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How interdisciplinary collaboration helps communicate engineering research to community audiences

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Abstract

Does interdisciplinary collaboration make a difference when it comes to communicating engineering concepts to community audiences? This research focuses on the effect of communication strategies on community attitudes toward engineering research. Two cohorts of four academic researchers each, representing eight different disciplinary backgrounds (aviation planning, cancer research, math education, musicology, chemical/biomolecular engineering, material science, soil science, and theater) developed research communication outputs for the public by creating: 1) an individual video presenting their research through the lens of their discipline alone; and 2) a convergent video where they collaboratively discussed their research with others in their cohort around a common theme, integrating all of their disciplinary lenses. Using a panel of respondents (n = 2,938) procured through Qualtrics, and purposefully recruited to create a diverse sample in age and racial/ethnic background, the research team randomly assigned respondents to watch one of three video treatments: one individual video, multiple individual videos, or a convergent video. Then, respondents answered a series of questions about their interest and knowledge of several STEM topics, both before and after watching the video(s). This retrospective pre/post questionnaire technique helps to alleviate response-shift bias present in self-assessed changes in learning attitudes. Our findings show that collaborative presentation videos increased self-reported audience interest in engineering, and perceptions of disciplinary relatedness more than the non-collaborative, individual presentations made by the same researchers. These results suggest a beneficial role for collaborative communication strategies to foster interest in engineering among public audiences, even among people without a background in STEM. Further, collaborative communication led to an increased sense of relatedness among different disciplines, which may be useful for effective public research communication about interdisciplinary engineering projects.

Introduction

There is a general understanding that engineering solves problems, but it is often hard to understand the direct context or implications of what engineers do without substantial scaffolding. Meanwhile, STEM is a familiar term within contemporary American educational systems, but it does not reflect a monolithic domain unto itself, and it is not always clear how engineering relates to science, technology, or math within this framing. While engineering alone is a rich area of exploration, contextualizing it with other disciplines can highlight engineers' contributions in real-world environments and applications. Addressing complex challenges facing society today requires collaboration incorporating tools, techniques, and insights from across the social, natural, and engineering sciences.

Education in formal and informal learning settings can provide opportunities to explore connections across seemingly distant ideas, thus sparking new creative solutions to complex societal challenges. In thinking about what engineering education might look like in community contexts, it is particularly important to consider *how* ideas are presented. In informal learning settings, public audiences are especially likely to enter with widely varying knowledge and interest in specific topics; and they may have priorities and expectations that are not specific to learning, such as having fun or spending time with others. In a virtual format that is even farther removed from a synchronous event or a shared physical space, variation in audiences' entry conditions is even more profound, because users themselves have more control over the terms of and context for their engagement. By making their research more approachable and understandable, engineers can help public audiences gain a more complete understanding of the work they do and become engaged in ways that might support greater motivation to keep learning or act. Most engagement with science occurs outside formal environments [1], and it is for these informal learning environments that researchers need to be prepared, both to share knowledge and to learn from others.

The research presented here comes from a novel multi-disciplinary program developed through a partnership between The Ohio State University and the Center of Science and Industry (COSI), both located in Columbus, OH. The program brings together researchers from divergent disciplinary perspectives to communicate science in informal learning settings and examines the effect of collaborative - now *convergent* - communication about a shared theme on attitudes and interest in STEM learning. The program pushes the frontier in science and research communication for lifelong learning with a collaborative and transdisciplinary approach that enables convergent learning through cognitive dissonance. We test the hypothesis that audiences will experience learning benefits from convergent communication; that convergent communication by researchers will increase positive learning attitudes among audiences, spark greater interest in STEM topics, increase desire to further explore topics, and increase likelihood that people might share their learning experience with others. By comparing changes in self-reported STEM learning attitudes across audiences that were shown convergent or individual disciplinary-focused videos, we assess the effectiveness of alternative research communication strategies. We find that collaborative presentations that include engineering perspectives are more effective in increasing interest in engineering relative to an individual presentation on an engineering topic. Respondents who watched transdisciplinary, collaborative presentations (those with engineers AND another disciplinary researcher present) reported being more likely to share something about the presentation with someone else. In addition, public audiences saw different disciplines as more related after convergent presentations than individual presentations. Both findings can be useful for preparing public-facing communications about engineering research.

In this paper, we do the following: discuss the theoretical background for the research, describe the researchers who participated in the research and their presentations, outline our analytical strategy, and present our findings. Lastly, we conclude with some comments on how this research can inform public engineering education and STEM learning broadly.

Theoretical Background

Research is the process of creating and sharing useful ideas. Dissemination of scientific research findings is important for other researchers to build on an existing body of knowledge, for funding agencies to determine research priorities, and for public audiences to engage with scientific discourse. Many funding agencies require public outreach as part of their grant application process. However, scientists are not often taught how to craft compelling narratives or share insights gleaned from their research in meaningful ways with the public. Effective communication of scientific breakthroughs with the public is as important as the content being shared, especially when the public is making decisions around science funding [2]. Furthermore, scientists' success in communication depends in large part on trustworthiness, competence, and expertise [3]. By engaging in discussion or teaching science topics with the public, trust in scientists and trust in science grows.

Critical thinking and creativity are inherently nonlinear and require divergent thought. Cognitive dissonance suggests that these creative leaps are likely to occur when people are presented with conflicting, divergent perspectives on a topic, creating a dissonance that people actively try to overcome [4], [5]. When a listener/viewer is presented with ideas from different researchers, it is too easy to compartmentalize the individual findings, even if the topics are actually related. Often, cognitive dissonance pushes researchers to find convergence when communicating ideas and this same process may help audiences make similar connections across disparate concepts or fields of knowledge.

Research supports the idea that learning occurs in three broad domains: the cognitive domain (knowledge), the psychomotor domain (physical skills), and the affective domain (attitudes) [6]. The process of finding convergence and making the connections explicit in research communication trigger different emotional responses in the presenters and the audience. For presenters, collaborative communication shifts one's own perception from being a topical expert to a learner and collaborator; for the audience, the confluence of multiple perspectives can influence learning in the affective domain by sparking curiosity and shifting away from long held attitudes of deficit-based education. Traditionally, communication methods between scientists and the public have focused on a knowledge deficit model rather than a discourse/dialogue-based approach [7]. When scientists use a dialogue model instead of deficit model to facilitate two-way engagement, understandings can be jointly developed. We especially need inclusive communication centered both on equity in access to information and on bringing excluded voices, experiences, and concerns to scientific dialogue [8], [9].

Adults use different frames of references to interact with the world that serve as sets of assumptions that help people make meaning of experiences and solve problems. An ideal environment for adult learning is one where transformative learning can flourish through effective discourse between the learner and the educator, followed by critical reflection by the learner to integrate the knowledge into their belief system [10]. In addition to cognitive learning, the process of developing convergent communication can influence conation, or the intention to act based on knowledge and skill [11], and the ability of a person to apply sustained effort toward actionable goals [12], [13].

Finally, beyond communicating research findings in a way that is more wholly understood by the public, developing this skill is useful for researchers wishing to increase their impact and productivity within their profession. Jensen et al. [14] conducted a bibliometric analysis and found that scientists who were active in wider dissemination activities (industry partnerships or outreach presentations) produced more scholarship than those who did not participate in wider dissemination activities. In fact, the most active researchers publish in traditional journals and then share in at least two of the following ways: communicating via popular media, collaborating with industry, or teaching. For these reasons, we set out to determine if researchers generally, and engineers specifically, could find ways to more effectively communicate their research findings with the public in several different informal learning environments.

Description of researcher experiences and communications formats

For this study, we recruited Ohio State faculty from a variety of colleges and departments to participate in a two-step process to improve their communication with the public. They 1) attended interactive training experiences to develop communication strategies for a variety of informal learning settings and 2) worked together in a pre-assigned cohort to create a series of informal learning experiences based on their areas of expertise and inquiry around a common theme. As the informal learning programming transitioned to virtual formats during the COVID-19 pandemic, the researchers prepared recorded presentations for a broad public audience. The typical sequence of activities for any researcher involved in the project was as follows:

> 1) attend a structured series of 2-hour training experiences (6 hours of total contact time for those participating during the COVID-19 pandemic)
>
> 2) prepare and deliver an individual presentation on their own research or area of expertise in an informal learning setting for adults

3) participate in semi-structured brainstorming sessions with 3-4 researchers from other disciplines (i.e., their cohort), with a goal of identifying areas of synergy and convergence across their disciplines

4) collaborate with their cohort to develop a hackathon challenge for high school learners that leveraged the entire cohort's expertise

5) collaborate with their cohort to develop a "convergent" presentation that leveraged all of the researchers' expertise in an informal learning setting for adults

For the cohorts described in this paper (one organized around the theme of Movement and one organized around the theme of Elements), the informal learning settings for their individual presentations, hackathon challenges, and convergent presentations were virtual. However, because these settings had analog counterparts that the project team used prior to the COVID-19 pandemic, the planning and execution of the five activities listed above were largely the same for the researchers. The major changes these cohorts experienced related to accessibility considerations, technical differences in how audiences for the experiences interacted with the programming, and tips for communicating in synchronous digital spaces. Each cohort consisted of four researchers; their areas of expertise, whether they identified as engineers, and their individual presentation topics are detailed in Table 1.

The primary difference between *individual presentations* and *convergent presentations* was that individual presentations were typically delivered serially, but separately. In contrast, convergent presentations represented an intentional weaving together of ideas from the researchers' distinct perspectives. Both the individual and convergent presentations described in this paper refer to informal learning experiences in the context of salon-style gatherings for adult audiences that were held on the Zoom video conferencing platform and were recorded. For the Movement cohort, individual presentations were pre-recorded videos developed by each researcher, and convergent presentations were held as featured events at virtual iterations of the local Columbus Science Pub, a monthly speaker series focused on science topics that generally reflect local interests, seasonal themes, and/or recent news items. For the Elements cohort, individual presentations were featured as part of a virtual edition of Franklinton Friday, a monthly "open house" community celebration that features opportunities to experience visual and performing arts, as well as science "microlectures" delivered in a cocktail party atmosphere. As with the Movement cohort, the convergent presentation developed by the Elements cohort was given at a virtual Columbus Science Pub event.

Table 1: Description of researcher individual presentations

Cohort theme area	**Researcher by area of expertise**	**Engineering discipline? (yes/no)**	**Individual presentation description**
Movement	Aviation planner	yes	Transportation impacts the individual, but must be designed as a system with nuanced angles of social and technical considerations. Urban planning interacts with other aspects of society such as with the environment, economy, and equity.
Movement	Cancer researcher	yes	Cancer biology is not typically studied in terms of how they spread (metastasis). Engineering concepts such as fluid mechanics and different engineering systems can be introduced as a means to study the properties of tumors.
Movement	Math education researcher	no	Math education and conjunctions of how access to math education is tied with identity. Social identities could be tied to math education in the form of digital mathematical storytelling for greater impact on students.
Movement	Musicologist	no	The theory of the purpose of music in evolutionary terms has been contested, but recent studies suggest that music creates group cohesion and bonding, which is critical for survival.
Elements	Chemical/Bio molecular engineer	yes	Polymers are identified by chains of repeated chemical units, which have specific properties that can be simulated computationally. Copolymers (polymers made up of two polymers) interact and can be simulated in software to discover interesting properties.
Elements	Material scientist	yes	Material science plays a large role in sustainability and in designing how materials with specific properties could be more efficient. The example of moving away from incandescent bulbs to LED bulbs is a result of material science engineering improving sustainability.

Elements	Soil scientist	no	Soil stores carbon and this soil organic carbon is sensitive to environmental changes such as temperature and moisture. Soil can be studied with its chemical, physical, and biological properties to potentially become a way to store and offset atmospheric carbon.
Elements	Theater artist	no	Story can be explored as a fundamental element of theater, and it is often relegated to be spatially constrained on a stage. Performances can become more engaging and tell a more intimate story when the fourth wall is removed and told directly to the audience.

Convergent presentations for the Elements and Movement cohorts employed various strategies to integrate narratives of differing disciplines together. The Movement cohort used a mutual interview strategy, where the researchers alternated roles in asking and answering questions, and facilitated a conversation that identified common ground across their disciplines. The cohort split up into pairs; the aviation planner and cancer researcher interviewed each other, and the math education researcher and musicologist interviewed each other. Overall, this style of co-presenting with carefully curated dialogue made it possible to weave common themes in the researchers' perspectives. This approach was also casual and conversational in nature compared to the individual presentations, and allowed for banter between the researchers. The Elements cohort presentation took a different approach and presented as a group of four. The theater artist, who assumed the role of moderator, asked each researcher to tie their presentation to a particular object that was displayed to the audience. This object was the central grounding point of the presentation and was continually referred back to by each researcher. Although the content of each presenter was generally preserved, using a specific object as a point of convergence allowed the presentations to transition smoothly. In highlighting intersections between disciplines, the cohort also recognized their emotional journey as researchers with powerful storytelling as a means to connect with the audience.

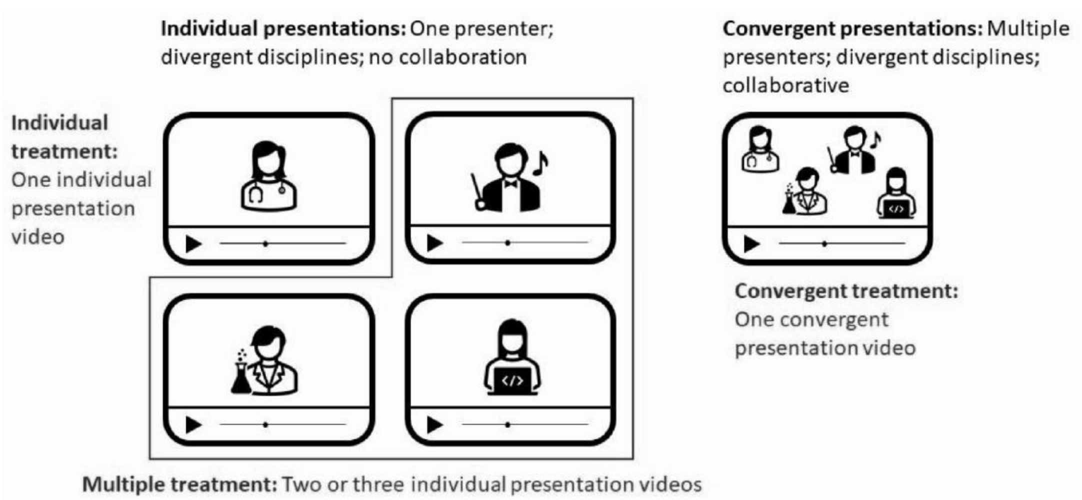
An additional advantage of digital formats was that recordings of the presentations could provide a reasonable proxy of the audience experience. The research team minimally edited the videos, both the individual presentations and the convergent presentations, for length and then used online survey panels assembled via Qualtrics to gather substantially more - and more diverse - audience survey data.

Analytical strategy

Experimental design with Qualtrics survey; post with retro-pre-method

The research team purchased Qualtrics-recruited respondent panels to approximate a generally diverse public audience. Panel respondents watched one of three different video treatments (Figure 1): 1) individual, which consisted of one video with a single researcher presenting (between 5 and 7 minutes); 2) multiple, which consisted of two or three of the individual videos (between 10 and 15 minutes); and 3) convergent, which consisted of one video with two or more researchers presenting together (between 10 and 20 minutes). Treatments were randomly assigned until quotas were achieved. We collected a total of 2,938 responses, split roughly evenly between the two cohorts (1,463 Movement and 1,475 Elements). The convergent treatment was purposefully oversampled as it is a key component of the research study, and because we wanted sufficient power to estimate a medium size effect (755 individual, 870 multiple, and 1,313 convergent). After watching the videos, respondents answered a series of questions about their interest and knowledge of several STEM topics, both before and after watching the video(s). This retrospective pre/post questionnaire technique helps to alleviate response-shift bias present in self-assessed changes in learning attitudes [15]. Respondents also answered other questions, including demographic and STEM identity questions.

Figure 1: Video treatments for Qualtrics panels



For the purposes of this paper, we grouped our respondents into six categories, based on the video treatment they received and the researchers present in those videos (see Table 2). These groups consist of respondents who watched: an individual video with an engineer presenting, multiple individual videos where all the presenters were engineers, multiple individual videos where at least one presenter was an engineer and other(s) were from different disciplines, a convergent video where both presenters were engineers, a convergent video where two of the presenters were engineers and two were from other disciplines, or video(s) of any treatment type where none of the presenters were engineers.

Table 2: Video treatment groups for analysis

Individual Videos	**Convergent Videos**
One Engineer (one video) (n=377)	N/A
Only Engineers (multiple videos) (n=227)	Only Engineers (n=370)*
Engineer + Others (multiple videos) (n=412)#	Engineer + Others (n=589)^
No Engineer (n=963)	

#multiple treatment from Elements cohort where the chemical/biomolecular engineer and/or material scientist were present
*convergent treatment from Movement cohort with aviation planner and cancer researcher
^convergent treatment from Elements cohort

Qualtrics panel sampling

The first Qualtrics panel, with videos from the Movement cohort, initially used a general U.S. sample with no demographic quotas (n = 1,061). However, the respondents did not represent a diverse audience — they were older (median age 65 years old) and primarily white, non-Hispanic (91%). So, we launched a smaller panel for the Movement videos (n= 402) with specific demographic quotas to increase the number of respondents sampled under the age of 50 and who identified as a race/ethnicity other than white, non-Hispanic. This way, we could be more confident that our results reflected the experiences of a diverse audience, in terms of age and ethnic/racial identity. The Elements panel (n=1,475) was run after the Movement panel so we included demographic quotas from the launch to ensure younger and more racially diverse respondents were represented.

Demographics of sample

For all respondents (n=2,938), the average age of respondents was 55 years, and the median age was 59 years. Nearly eight in ten respondents (77.5%) identified as white-only, and two in three respondents (65.9%) identified as female. Nearly half of the respondents (45.8%) reported completing a 4-year college degree or higher. Half of respondents (48.1%) reported annual household incomes under \$50,000, and 18.3% reported annual household incomes over \$100,000. Responses were received from all 50 states and DC. In the Elements panel questionnaire, respondents were asked to identify where they live as urban, suburban, or rural; almost half of respondents (47.5%) reported living in a suburban area. Full demographic details of the respondents can be found in Appendix A. We included these demographic variables in our analyses to ensure that we captured diverse identities and socioeconomic statuses (See *Statistical analysis and modeling* section below).

Respondents' background in STEM

We also asked respondents about their educational and professional backgrounds and identification with STEM topics, to provide a baseline for experiences and values respondents are 'bringing with them' when they watch these presentations. About one-third of respondents (34.7%) reported having a strong educational background in science, technology, engineering, and/or math. One-quarter of respondents (26.6%) reported having a strong professional background in those areas. Respondents were also asked to rate how much a series of statements, inspired by the LabX program [16], about leisure time activities related to STEM and informal learning describe them (on a 7-point scale from "1 - not me at all" to "7 - very much me"). Respondents were most likely to enjoy visiting science museums, zoos, and aquariums (mean = 5.27). Average scores hovered around the middle of the scale for seeking out arts-focused events (mean = 4.09), consuming science- or technology-focused media (mean = 4.34), and liking to stay up-to-date on news related to science and technology (mean = 4.31). Respondents were similarly likely to find scientific topics dry or boring (mean = 3.57) as they were to seek out opportunities to attend science festivals or other science-focused events (mean = 3.46). We also included STEM identity and background indicators in the models (See *Statistical analysis and modeling* section below).

Operationalizing learning outcomes

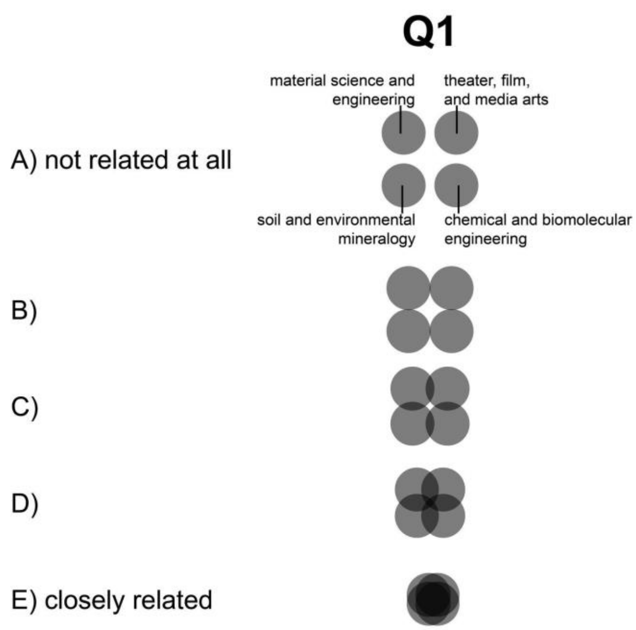
We focus on five, self-reported learning outcome indicators: **interest in engineering**, **knowledge of engineering**, **perceived relatedness of the disciplines represented**, **likelihood to share something about their experience**, and **likelihood to learn more about something in the presentation(s)**. We used affect response measures to indicate changes in learning attitudes and bigger picture cognitive measures to indicate changes in knowledge as a result of the presentations. Because the presentations represented several different topics and, at most, a 20-minute learning experience in a non-formal context (i.e. not a formal class), we did not directly measure content-specific learning outcomes.

We measured **interest in engineering** using retro-pre/post, 7-point Likert-like scale items. This means that after respondents watched a randomly assigned presentation treatment, we asked them to first think retrospectively about their interest in engineering *before* they watched the presentation and rate their interest on a scale of 1 = very little interest to 7 = a great deal of interest. Next, we asked them to think about *after* the presentation treatment and rate their interest in engineering on the same scale. This retro-pre/post technique has been shown to more accurately reflect change in learning attitudes as a result of an experience than a traditional pre/post, because it asks respondents to reflect on their learning attitudes with the experience in mind.

We measured **knowledge of engineering** using retro-pre/post, 7-point Likert-like scale items. This means that after respondents watched a randomly assigned presentation treatment, we asked them to first think about *before* the presentation treatment and rate their knowledge of engineering retrospectively, on a scale of 1 = very little knowledge to 7 = a great deal of knowledge. Next, we asked them to think about *after* the presentation treatment and rate their knowledge of engineering on the same scale.

We measured the **perceived relatedness of the disciplines** in order to detect the presence of higher-level, conceptual connections that audiences might pick up from the presentations. To do this, we used a 5-point scale with graphic representations of relatedness (see Figure 2). We used traditional pre/post technique, asking them about perceived relatedness before their presentation treatment and then after their presentation treatment. Perceiving disciplines as more related would indicate that audiences probably found similarities between them, potentially making a relatively less known discipline more familiar through its similarities with a more well-known discipline.

Figure 2: Graphic questionnaire item measuring perceived relatedness of disciplines



We measured **likelihood to share something about their experience** and **likelihood to learn more about something in the presentation(s)** using a post-only, 7-point Likert-like scale of 1 =

extremely unlikely to 7 = extremely likely. Higher scores in these measures (i.e. scores greater than 4) indicate positive learning attitudes, which would make people more open to more learning experiences.

Statistical analysis and modeling

First, we examined descriptive statistics for the learning outcomes, grouped by presentation treatment, to detect any general patterns (Appendix B). We then modeled respondent learning outcomes using both linear (Ordinary Least Squares) and nonlinear (logit) functions. We used linear models that approximate the learning outcomes as continuous, numeric variables. Doing so allowed us to estimate the *incremental effect* of different presentation treatments on outcomes, compared to a single, individual engineering presentation treatment. Since the outcome scales are subjective and not, strictly speaking, continuous variables, we also used a logit, nonlinear model to estimate the likelihood of a large change (>1 on the 5- and 7-point scales) in the **interest and knowledge of engineering and relatedness of disciplines** outcome variables, and the likelihood of a high score (>4 on a 7-point scale) occurring for the **likelihood to share** and **likelihood to learn more** outcome variables. For all of these models, we included demographic and STEM identity variables to account for diversity of respondents that influence learning outcomes (see Appendix C for a general specification of the models).

In estimating the effect of a specific presentation treatment on learning outcomes, we control for a range of demographic characteristics and unobservable factors that are common to each treatment experience. Because of a tendency for some respondents to overestimate the change in their learning attitudes as a result of their experience, we also had respondents answer retro-pre/post items about their interest in and knowledge of sports. Since none of the presentation treatments included anything about sports, we would not expect any change in knowledge of sports. If a respondent did indicate a change, controlling for this effect will reduce potential bias in how the respondent reported change in the outcomes of interest, i.e. interest and knowledge of engineering.

We also set up the analyses to model measures of learning outcomes *after* the presentation treatments, because not all had a pre- or retro-pre-measurement component. We included pre- / retro-pre-scores for outcomes with these components, as a way of controlling for the amount of change seen before and after. We also control for correlation between idiosyncratic error and control variables in the model and report (heteroskedasticity) robust standard errors. See Appendix C, *Xcont*, and Appendices D and E for more details.

Findings and Discussion

Consistent with our expectation, the presence of engineers affected respondents' reported interest and knowledge in engineering. After watching the video(s), respondents who saw at least one engineer present (in any treatment type) shared statistically significantly higher average ratings for interest and knowledge in engineering than did respondents who saw no engineers in the presentation. Differences in average reported levels of interest and knowledge are statistically significant at the 95% confidence level (Table 3). Because of this clear and unsurprising difference, we dropped the "no engineer" treatment from the rest of the analysis. This allowed us to focus on the effects of different combinations of presenters and treatment types focused specifically on engineers.

Table 3: Interest and knowledge of engineering by presence of engineers in presentation

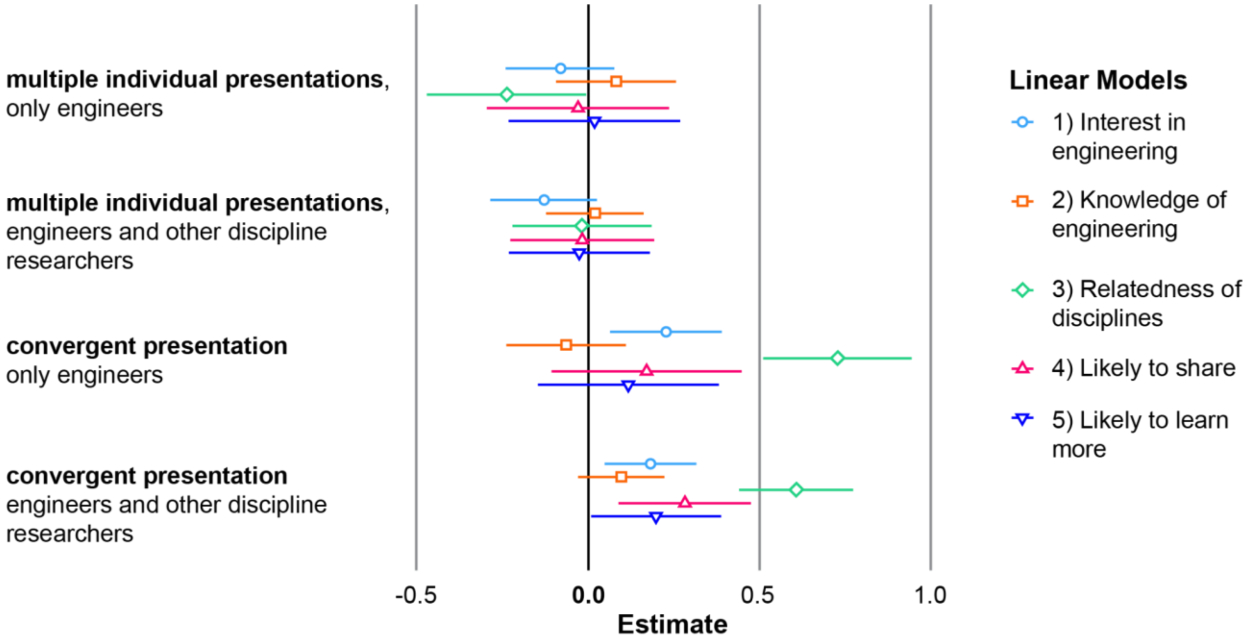
	Engineers present (mean)	Engineers not present (mean)	P-value of 2 sample t-test
Interest in engineering (after presentation)	4.513	4.198	.000031
Knowledge of engineering (after presentation)	3.867	3.598	.000311

After dropping the non-engineer presentation data (963 observations), we conducted both linear and non-linear regression analyses to understand differences in four presentation treatments *compared to the single, individual engineering presentation treatment.* The four treatments include:

- multiple individual presentations, only engineers;
- multiple individual presentations, engineers and other discipline researchers;
- convergent presentation with only engineers; and
- convergent presentation with engineers and other discipline researchers.

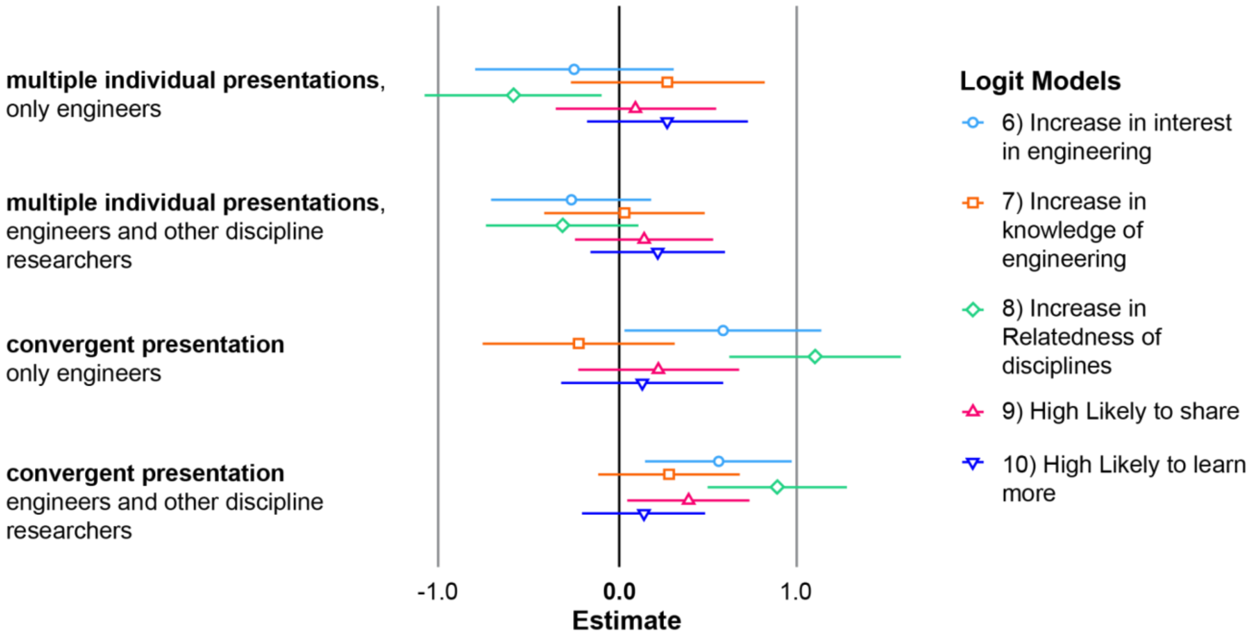
The linear models show a consistent, positive effect of convergent presentations compared to a single, individual engineer presentation (see Figure 3 for general results, and Appendix D for more technical model results). Multiple, individual presentations with the same researchers did not yield any obvious, positive learning outcomes compared to the single, individual engineer presentation. Convergent presentations with engineers and other discipline researchers, in particular, had significant, positive effects on more learning outcomes (all outcomes except the knowledge of engineering learning) relative to convergent presentations with only engineers. This suggests that collaboration across multiple disciplines in developing convergent research communication may influence learning in different and more ways than a collaboration among just engineers.

Figure 3: Presentation treatment effects, compared to seeing just one individual engineering presentation. Linear model, scaled estimates, with 95% confidence interval bands.



A continuous scale does not account for subjective differences across respondents. For example, a reported change in interest from 3 to 5 on a Likert scale is not necessarily comparable to a change from 5 to 7 by another individual. We therefore estimate non-linear logit models to recover the likelihood of increase in interest/knowledge in engineering. The logit models also suggest a significant, positive benefit of the collaborative, convergent presentations compared to a single, individual engineering presentation (see Figure 4 for general results, and Appendix E for more technical model results). While not yielding estimates with the same significance as in the linear models, the logit models show that respondents who saw the convergent presentation with engineers and other researchers were significantly more likely to have a higher learning outcome than those respondents who just saw a single, individual engineering presentation. Much like the linear models, multiple individual presentation treatments with the same researchers did not show any obvious learning outcome benefits compared to the single, individual engineering presentation.

Figure 4: Presentation treatment likelihoods (log odds ratios), compared to seeing just one individual engineering presentation. Logit model, scaled likelihood estimates with 95% confidence interval bands



Results from this study suggest that people who have exposure to collaborative research communication with multiple engineers are more likely to have higher learning outcomes relative to those who just see a single presentation with an engineer. Seeing the same combination of researchers present multiple times, but not in collaboration, does not appear to have as much positive benefit on audiences as the collaborative (convergent) presentations. Further, convergent presentations with engineers *and* researchers from other disciplines appear to have even more learning benefits on audiences, even those specific to engineering (such as interest). This suggests that collaborative *and* interdisciplinary research communication may be the best way to both communicate engineering topics to audiences, as well as get them interested in learning more and sharing more about their experience.

While we believe the results of our study suggest significant positive effects of convergent research communication (i.e. research communication that is collaborative *and* interdisciplinary around a common theme) on engineering learning attitudes among broadly diverse community audiences, the results should be extrapolated with caution. Comparisons in the effect of convergent communication are based on presentations across two different themes (Movement and Elements), and we do not know the degree to which the theme might have impacted learning outcomes. However, we do show in Appendix F that there was not a significant difference in general learning outcomes between audiences who saw Movement themed presentations and those who saw Elements themed presentations, with the exception of audience perception of disciplines' relatedness. We also cannot definitively rule out any individual researcher effects on learning outcomes. Continuing the study in the future with more researcher cohorts, as well as with more diverse researchers, would improve our ability to detect the impact that researcher identity, presentation skill, and other individual researcher characteristics have on audience learning attitudes. Further, while we made efforts to ensure that our sample of respondents (the ‘audience’) reflected some ethnic/racial, age, and gender diversity, we cannot claim that our sample was representative of the general population, nor that the sub-samples were large enough to make claims about the learning outcomes of specific groups of people (e.g., young, minority males). With that in mind, we still argue that our sampling strategy consisted of enough socioeconomic, demographic, and heritage diversity to sufficiently control for these differences while focusing our attention on the added impact of the presentation type on learning outcomes.

Conclusion

Effective research communication is an extremely valuable skill that prospective engineers need to develop. Strong communication of engineering research results can illuminate pathways toward engineering among public audiences and support more public interest and investment in the work of engineers. Increased interest and engagement with problems that require engineering solutions is a necessary first step to build a robust STEM workforce. In the United States, the STEM labor force represents 23% of the total labor force, involves workers at all educational levels, and includes higher proportions of men, Whites, Asians, and foreign-born workers than the proportions of these groups in the U.S. population [17]. Disparities in demographic and socioeconomic conditions present significant challenges in building an equitable and representative pipeline in STEM education. Informal learning platforms and the integration of STEM with the arts and humanities in communicating research ideas that are relevant and relatable to the society at large can broaden knowledge and engagement in engineering education. Engagement with science occurs largely outside formal environments [2] and it is for these informal learning environments that researchers need to be prepared, both to share knowledge and to learn from others. Exposure to STEM research through informal learning environments influences both interest in STEM fields [18] and STEM identities [19]. Our findings suggest that one way to improve research communication with public audiences is by having experts from different disciplines intentionally collaborate and converge around a topic. Collaborative communication skills can shift learning away from deficit models of science communication [20], and increase equitable public engagement with scientific research for bidirectional learning, especially when integrating arts and humanities with science and engineering.

Through response data that reflect diverse audiences’ takeaways from various combinations of presentation elements, our findings suggest that using a “convergent” style (i.e., presentations that explicitly combine different disciplinary perspectives through collaboration) holds particular promise for communicating engineering research. Compared to individual engineering presentations, convergent presentations that included at least one engineer supported significant growth in interest in engineering among respondents. As might be expected, this style of presentation also supported audiences in perceiving connections between presenters’ topics. Furthermore, convergent presentations that included an engineer and another kind of researcher showed a significant effect (compared to individual engineering presentations) on respondents' likelihood to share something about their experience, as well as their desire to learn more about the topic. Taken together, these outcomes reflect forms of engagement that can make engineering topics more meaningful and relevant, even to people who do not have an existing inclination to think about engineering.

Our research team is eager to build on the present study by exploring the boundaries of convergent presentations, namely by asking researchers and community members to collaborate around themes that communities themselves identify as important. Though not within the scope of this study, our team also considers *how* researchers collaborate and create successful convergent research communication, and necessary support structures, a vital area for future study. In this spirit, our ongoing research agenda includes substantial attention to the professional benefits of transdisciplinary collaboration. Within formal education spaces for engineers, it may be particularly productive to invest in professional learning opportunities that can support both better communication by engineers and those researchers who see the benefit of clearly articulating the content and value of their work. As an immediate takeaway from this work, we encourage readers to consider that intentional collaboration with other disciplines holds particular promise for helping engineers highlight the importance of what they do.

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Appendix A: Descriptive statistics of full Qualtrics Sample

Demographics for all respondents

Age (n=2938)	Mean = 55.18 years Std. Deviation = 17.11
Education Level (n=2937)	Some high school = 2.0% High school or equivalent (GED) = 30.9% Associate's or technical degree = 20.3% Bachelor's degree = 28.1% Graduate degree = 17.7% Prefer not to say = 1.0%
Residence *Zip Codes (n= 2928)* *urbanrural (n=1475)*	Respondents from all 50 states and DC. The five states with the most respondents are also the five most populous states in the U.S. (CA = 8.6%, FL = 8.3%, NY = 7.6%, TX = 6.7%, PA = 4.5%). In the second panel questionnaire (Elements cohort), respondents were asked to identify where they live as urban, suburban, or rural. Urban = 28.0% Suburban = 47.5% Rural = 24.5%
Income (n=2938)	Less than \$30,000 = 26.1% Between \$30,000 and \$49,999 = 22.0% Between \$50,000 and \$99,999 = 29.5% Between \$100,000 and \$149,999 = 12.2% \$150,000 or more = 6.1% Prefer not to answer = 4.2%
Ethnicity (n=2928)	White = 77.5% African American or Black = 9.2% Asian = 4% Latino/a/x or Hispanic = 3.6% American Indian or Alaskan Native = 0.6% Hawaiian or Pacific Islander = 0.1% Multiple races/ethnicities = 5.0%
Gender (n=2938)	Female = 65.9% Male = 33.6% Nonbinary = 0.4% Prefer not to answer = 0.2%

STEM background of total respondents

Strong educational background in science, technology, engineering, and/or math? (n=2937)	Yes = 34.7% No = 65.3%
Strong professional background in science, technology, engineering, and/or math? (n=2938)	Yes = 26.6% No = 73.4%
I enjoy visiting science museums, zoos, and aquariums in my free time (when it is safe to do so) (n=2938)	Mean = 5.27 Std. Deviation = 1.75 *7-point scale - 1 = not at all me; 7 = very much me (same below)
I seek out opportunities to attend science festivals and other science-focused events (n=2938)	Mean = 3.46 Std. Deviation = 1.97
I seek out opportunities to attend arts festivals and other arts-focused events (n=2938)	Mean = 4.09 Std. Deviation = 2.02
I enjoy radio shows/movies/TV programs/podcasts that are science- or technology-focused (n=2938)	Mean = 4.34 Std. Deviation = 1.94
I like to stay up-to-date on news related to science and technology (n=2938)	Mean = 4.31 Std. Deviation = 1.91
I generally find scientific topics to be dry or boring (n=2937)	Mean = 3.57 Std. Deviation = 2.03

Appendix B: Descriptive statistics of Outcome variables

Before and After interest in engineering

	P-values
Paired t-test	< 2.2e-16***
Paired Samples t-test (n = 50)*	0.3816
Wilcoxon Rank Sum test (sample n = 50)*	0.1266

Before and after knowledge of engineering

	P-values
Paired t-test	< 2.2e-16***
Paired Samples t-test (n = 50)*	0.07857
Wilcoxon Rank Sum test (sample n = 50)*	0.08669

Comparison of Pre-poll and Post-poll results for Relatedness of disciplines

	P-values
Paired Samples t-test (n = 50)*	0.03443***
Wilcoxon Rank Sum test (n = 50)*	0.07751

*random sampling w/ replacement to ensure independent samples. set.seed(2022) for reproducibility in R

Interest in and Knowledge of engineering by presentation treatment, before and after.
Scale of 1 = very little to 7 = a great deal

	Before presentation interest in engineering	After presentation interest in engineering	Before presentation knowledge of engineering	After presentation knowledge of engineering
One Engineer (one video)	Mean = 3.91 Std Dev = 1.89	Mean = 4.55 Std Dev = 1.94	Mean = 3.27 Std Dev = 1.87	Mean = 3.89 Std Dev = 2.05

Only Engineers (multiple videos)	Mean = 3.91 Std Dev = 1.83	Mean = 4.38 Std Dev = 1.84	Mean = 3.26 Std Dev = 1.84	Mean = 3.85 Std Dev = 1.82
Engineer + Others (multiple videos)	Mean = 3.69 Std Dev = 1.94	Mean = 4.23 Std Dev = 1.96	Mean = 3.06 Std Dev = 1.83	Mean = 3.72 Std Dev = 1.89
Only Engineers (convergent)	Mean = 3.92 Std Dev = 1.89	Mean = 4.68 Std Dev = 1.85	Mean = 3.30 Std Dev = 1.90	Mean = 3.91 Std Dev = 1.89
Engineer + Others (convergent)	Mean = 3.99 Std Dev = 1.89	Mean = 4.63 Std Dev = 1.87	Mean = 3.19 Std Dev = 1.86	Mean = 3.93 Std Dev = 1.90
No engineers	Mean = 3.70 Std Dev = 1.88	Mean = 4.20 Std Dev = 1.93	Mean = 3.18 Std Dev = 1.85	Mean = 3.60 Std Dev = 1.89
All	*Mean = 3.83* *Std Dev = 1.89*	*Mean = 4.41* *Std Dev = 1.92*	*Mean = 3.20* *Std Dev = 1.86*	*Mean = 3.78* *Std Dev = 1.89*

Perceived relatedness of disciplines before (prepoll_score) and after (postpoll_score) presentation.

Scale of 1 = not related at all to 5 = closely related

	prepoll_score	postpoll_score
One Engineer (one video)	Mean = 2.41 Std Dev = 1.46	Mean = 3.12 Std Dev = 1.43
Only Engineers (multiple videos)	Mean = 2.12 Std Dev = 1.29	Mean = 2.75 Std Dev = 1.34
Engineer + Others (multiple videos)	Mean = 2.52 Std Dev = 1.36	Mean = 3.09 Std Dev = 1.39
Only Engineers (convergent)	Mean = 1.93 Std Dev = 1.32	Mean = 3.44 Std Dev = 1.35
Engineer + Others (convergent)	Mean = 2.71 Std Dev = 1.34	Mean = 3.79 Std Dev = 1.21
No engineers	Mean = 2.29 Std Dev = 1.44	Mean = 2.90 Std Dev = 1.47

All	*Mean = 2.37* *Std Dev = 1.40*	*Mean = 3.19* *Std Dev = 1.42*

Likelihood to share and learn more by presentation treatment
Scale of 1 = extremely unlikely to 7 = extremely likely

	Likelihood to share	Likelihood to learn more
One Engineer (one video)	Mean = 3.89 Std Dev = 2.05	Mean = 4.10 Std Dev = 2.08
Only Engineers (multiple videos)	Mean = 3.58 Std Dev = 2.11	Mean = 3.81 Std Dev = 2.10
Engineer + Others (multiple videos)	Mean = 3.57 Std Dev = 2.08	Mean = 3.75 Std Dev = 2.10
Only Engineers (convergent)	Mean = 3.89 Std Dev = 2.15	Mean = 4.06 Std Dev = 2.15
Engineer + Others (convergent)	Mean = 4.04 Std Dev = 2.09	Mean = 4.15 Std Dev = 2.08
No engineers	Mean = 3.70 Std Dev = 2.10	Mean = 3.83 Std Dev = 2.10
All	*Mean = 3.79* *Std Dev = 2.10*	*Mean = 3.95* *Std Dev = 2.10*

Appendix C: Model specifications

General fitted model form:

Outcome variable =

intercept + [Bcont][Xcont] + [Btreat][Xtreat] + [Bdemo][Xdemo] + [Bid][Xid] + error

Where:

intercept is the intercept estimated by the model

Xcont are control variables, including:

> *RetroPre* is a retrospective and self-reported value of the outcome variable, on a scale of 1 = very little to 7 = a whole lot (only for models 1 - 3 and 6 - 8).
>
> *DK_sports* is the difference in self-reported knowledge of sports retrospectively before (1 = little to 7 = a whole lot, scale), and after (1 = little to 7 = a whole lot, scale) seeing a presentation. This variable is used to control for respondents who may overestimate their outcome variable measurement, because none of the presentations talked about sports.

Xtreat is a series of treatment dummy variables, whose reference is a treatment of one engineer presentation video (when all of the variables = 0). The treatment variables include:

> *just_engineers* is a dummy variable that indicates whether or not a respondent saw more than one video presentation, and only with engineers giving the presentations (1 = yes; 0 = no).
>
> *engineoth* is a dummy that indicates whether or not a respondent saw more than one video presentation, with engineers and another discipline researcher giving the presentations (1 = yes; 0 = no).
>
> *Convergent AND just_engineers* is a dummy variable that indicates whether or not a respondent saw the convergent video presentation, with only engineers giving the presentation (1 = yes; 0 = no).
>
> *Convergent AND engineoth* is a dummy variable that indicates whether or not a respondent saw the convergent video presentation, with engineers and other discipline researchers giving the presentation (1 = yes; 0 = no).

Xdemo is a series of demographic variables, including:

EduN is a self-reported, ordinal education attainment variable approximated as continuous on a scale of 1 = Some high school; 2 = High school or equivalent (GED); 3 = Associate's or technical degree; 4 = Bachelor's degree; or 5 = Graduate degree.

IncomeN is a self-reported ordinal household income variable approximated as continuous on a scale of 1 = less than $30,000; 2 = between $30,000 and $49,999; 3 = between $50,000 and $99,999; 4 = between $100,000 and $149,999; or 5 = $150,000 or more.

ETH_White is an on/off variable distinguishing whether a respondent identified as White, non-hispanic only (1) or whether they identified as an additional race/ethnicity (0).

Gender is a self-reported, categorical variable with the values of 'Male', 'Female', or 'Nonbinary.'

Age is a continuous variable, calculated using self-reported year of birth data.

Xid is a series of STEM identity variables, including:

edSTEM is a binomial variable indicating whether a respondent has a strong educational background in science, technology, engineering, and/or math (1) or not (0).

profSTEM is a binomial variable indicating whether a respondent has a strong professional background in science, technology, engineering, and/or math (1) or not (0).

STEMid.museums is a self-reported variable measuring how much someone enjoy[s] visiting science museums, zoos, and aquariums in [their] free time on a scale of 1 = not at all [] to 7 = very much [].

STEMid.scifest is a self-reported variable measuring how much someone seek[s] out opportunities to attend science festivals and other science-focused events, on a scale of 1 = not at all [] to 7 = very much [].

STEMid.artsfest is a self-reported variable measuring how much someone seek[s] out opportunities to attend arts festivals and other arts-focused events, on a scale of 1 = not at all [] to 7 = very much [].

STEMid.media is a self-reported variable measuring how much someone enjoy[s] radio shows/movies/TV programs/podcasts that are science- or technology-focused on a scale of 1 = not at all [] to 7 = very much [].

STEMid.news is a self-reported variable measuring how much someone like[s] to stay up-to-date on news related to science and technology on a scale of 1 = not at all [] to 7 = very much [].

STEMid.boring is a self-reported variable measuring how much someone generally find[s] scientific topics to be dry or boring on a scale of 1 = not at all [] to 7 = very much [].

Appendix D: Linear models approximating outcomes as continuous scales

Effects (and standard errors) of different presentation treatments compared to seeing one individual engineering presentation.

	Interest in Engineering (after video/s)	Knowledge of Engineering (after video/s)	Relatedness of topics (after video/s)	Likelihood to share something about the video	Likelihood to learn more about something in the video
Model number	1	2	3	4	5
(Intercept)	4.56 ***	3.98 ***	3.03 ***	4.03 ***	4.19 ***
	(0.10)	(0.10)	(0.12)	(0.14)	(0.13)
multiple individual presentations, only engineers	-0.08	0.08	-0.24 *	-0.03	0.02
	(0.08)	(0.09)	(0.12)	(0.14)	(0.13)
multiple individual presentations, engineers and other discipline researchers	-0.13	0.02	-0.02	-0.02	-0.03
	(0.08)	(0.07)	(0.10)	(0.11)	(0.10)
convergent presentation with only engineers (Movement cohort video)	0.23 **	-0.06	0.73 ***	0.17	0.12
	(0.08)	(0.09)	(0.11)	(0.14)	(0.13)
convergent presentation with engineers and other discipline researchers (Elements cohort video)	0.18 **	0.10	0.61 ***	0.28 **	0.20 *
	(0.07)	(0.06)	(0.09)	(0.10)	(0.10)
N	1846	1848	1646	1851	1851
R2	0.71	0.73	0.24	0.50	0.52

All continuous predictors are mean-centered and scaled by 1 standard deviation. Standard errors are heteroskedasticity robust. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. All variance inflation factor (VIF) scores are below 4. Demographics of respondents (Xdemo), STEM identity (Xid), and control variables (Xcont) not shown to save space.

Appendix E: Logit models (outcomes as ‘yes’ or ‘no’ variables)

Log odds ratio likelihoods (and standard errors) of different presentation treatments compared to seeing one individual engineering presentation.

	Interest in Engineering increased more than 1 point	Knowledge of Engineering increased more than 1 point	Relatedness of topics increased more than 1 point	High Likelihood to share Rating was >4	High Likelihood to learn more Rating was >4
Model #	6	7	8	9	10
multiple individual presentations, only engineers	-0.24	0.28	-0.58 *	0.10	0.28
	(0.28)	(0.28)	(0.25)	(0.23)	(0.23)
multiple individual presentations, engineers and other discipline researchers	-0.26	0.04	-0.31	0.15	0.22
	(0.23)	(0.23)	(0.22)	(0.20)	(0.19)
convergent presentation with only engineers (Movement cohort video)	0.59 *	-0.22	1.10 ***	0.23	0.14
	(0.28)	(0.27)	(0.25)	(0.23)	(0.23)
convergent presentation with engineers and other discipline researchers (Elements cohort video)	0.56 **	0.29	0.89 ***	0.40 *	0.15
	(0.21)	(0.20)	(0.20)	(0.18)	(0.18)
N	1846	1848	1646	1851	1851
AIC	1424.27	1384.93	1571.65	1728.56	1706.43
BIC	1540.20	1500.89	1685.18	1839.03	1816.90
Pseudo R2	0.28	0.35	0.40	0.48	0.51

All continuous predictors are mean-centered and scaled by 1 standard deviation. Standard errors are heteroskedasticity robust. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. All variance inflation factor (VIF) scores below 4. Demographics of respondents (Xdemo), STEM identity (Xid), control variables (Xcont), and intercept not shown to save space.

Appendix F: Differences in outcome variables by cohort

Outcome variable	Elements cohort mean	Movement cohort mean	degrees of freedom	t score	p-value
Interest in Engineering (after video/s)	4.41	4.41	2929.70	-0.04	0.97
Knowledge of Engineering (after video/s)	3.80	3.76	2930.00	0.63	0.53
Relatedness of disciplines (after video/s)	3.43	2.94	2740.00	9.09	**0.00*****
Likelihood to share something about the video	3.80	3.78	2936.00	0.25	0.80
Likelihood to learn more about something in the video	3.95	3.94	2936.00	0.04	0.97
Welch two sample t-test used, with alternative hypothesis: true difference in means is not equal to 0 (2-sided test), unequal variances. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$					