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Science Communication on Social Media: Examining Cross-Platform Behavioral Engagement

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Social media is a popular channel for scientists to communicate with the public. Still, it remains relatively unclear how social media users perceive and engage with scientific content across various platforms. Therefore, this study sought to examine how users engage with scientific content on different social media channels to help scientists and science communicators gain a deeper understanding of how audiences perceive their posts. A quasi-experimental survey methodology was conducted with a snowball sample of social media users. Participants ($N = 237$) were exposed to social media posts containing three scientific content areas (biology, social science, and engineering) across three social media platforms (Facebook, Instagram, and Twitter). Results from this study found that biology content on Facebook had higher behavioral engagement than other platforms, and there was no significant difference in content comprehension between social media platforms. Implications for scientists and science communicators using social media platforms to share knowledge and research findings are discussed.

Keywords: science communication, social media, Facebook, Twitter, Instagram, user engagement

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Throughout history, scientists have been called upon to disseminate research findings and engage audiences with their scientific discoveries. Today, this practice is formally known as science communication and is widely recognized as a critical component of the scientific process and a scientist's societal responsibility (Greenwood & Riordan, 2001; Leshner, 2003). Most recently, there has been a push for scientists and science communicators to utilize new media technology to reach audiences more directly and interactively (Brossard & Scheufele, 2013). As a result, scientists and science communicators are increasingly moving to social media channels to communicate science-related information (Gottfried & Shearer, 2016; Howell & Brossard, 2019).

Given the need for more strategic communication practices and evaluation of science communication efforts (Bennett et al., 2019; Pellegrini, 2021), there have been some efforts over the past several years to help scientists in this area. For example, organizations such as the American Association for the Advancement of Science (AAAS), the Alan Alda Center for Communicating Science, and COMPASS have provided scientists with valuable resources for designing effective messages and selecting appropriate channels (Bik & Goldstein, 2013; Cooke et al., 2017; Newman, 2019). However, the literature in this area is limited in substantiating which types of content across which platforms produce the most desired outcomes and user engagement.

Therefore, to provide perspective on the emerging presence of scientific content across social media channels, this study aims to experimentally examine how individuals respond to science content on social media across three of the most popular social media platforms (i.e., Facebook, Twitter, Instagram). By experimentally identifying which types of content produces desired outcomes (i.e., engagement and comprehension) on specific social media platforms, scientists and science communicators can be more strategic and efficient in their social media messaging and production. Given the affordances of social media to actively engage audiences with science, the Public Engagement with Science & Technology (PEST) model of science communication is utilized as a guiding framework to examine how public audiences engage with science content on interactive social media platforms.

LITERATURE REVIEW

Public Engagement with Science & Technology (PEST) Model of Science Communication

The PEST model of science communication was developed as an alternative to the Public Understanding of Science (PUS) model. The PUS model, also known as the information deficit model, assumes that the general public lacks scientific knowledge, leading to science skepticism. By simply providing more scientific facts, the public would develop a greater appreciation for and support science (Burns et al., 2003; Schäfer, 2011; Sturgis & Allum, 2004). However, despite its simplicity, the PUS model has lacked empirical support over time (Allum et al., 2008; Bauer & Gregory, 2007; Besley & Tanner, 2011) and did not account for the audiences' unique knowledge or values on different science-related issues (Allum et al., 2008).

In contrast, the PEST model emphasizes two-way communication between scientists and/or organizations and the public through interactive dialogue. By fostering open conversations that encourage the expression of different viewpoints, the PEST model views the public audience as citizen stakeholders and provides the opportunity to educate and converse about competing scientific findings and real-world implications of scientific results (Davies, 2008). In this way of thinking, engagement is construed as multiple, relational, and outcomes-oriented, with outcomes ranging from better science to individual empowerment, which contemporary social media platforms also utilize as a framework for enhancing the user experience (Davies, 2008).

However, despite the more recent adoption of the PEST model of science communication, many communication efforts still operate under an information deficit way of thinking. Research examining scientists' attitudes toward the public shows that information deficit thinking is still prevalent (Besley & Tanner, 2011). Simis and colleagues (2016) provide several reasons why this type of thinking persists, including the lack of formal training in communication skills, scientists' attitudes toward the public, and the audience's understanding of scientific information. Since the information deficit mindset is so entrenched in the very process of science, it is imperative to examine science communication efforts from a more inclusive framework that better reflects the multifaceted nature of society. Over the past several decades, there has been significant debate about different types of unified models of science communication (Bucchi, 2008; Bucchi & Trench, 2014). However, many now recognize the coexistence of multiple science communication models depending on the goal, audience, and context (Bucchi, 2008; Davies, 2013).

Therefore, by approaching science communication in a more inclusive, audience-centered manner, the current study utilizes the PEST model as a framework for examining how science content may appeal to varying audiences across different social media platforms. The PEST model allows us to consider interactive elements of social media platforms as part of the two-way dialogue between experts and audiences, giving audiences a more active role in engaging with science content using different features and audiences on different platforms. Given the multidimensional way the PEST model considers engagement and dialogic communication, interactive social media platforms provide unique spaces for audiences to access and engage with science.

Social Media User Engagement

Thanks to significant developments in standard features of social media platforms today (e.g., likes, comments, shares), user engagement has become more pronounced and subsequently more measurable (Sundar, 2012). Previous research has conceptualized social media engagement as having several subcomponents (Fredricks et al., 2004; Pugh et al., 2010), which most commonly include three elements: cognitive, affective, and behavioral engagement (Fredricks et al., 2004; Sinatra et al., 2015). Cognitive engagement refers to focused mental activity, affective engagement includes the emotional response to the object being engaged with, and behavioral engagement represents the actions of engagement (Dessart, 2017). The current study focuses on behavioral engagement as a visible form of engagement on social media platforms.

Sundar's (2008) MAIN model posits four distinct affordances that shape how users engage with digital media: modality (M), agency (A), interactivity (I), and navigability (N). The most visible social media engagement builds specifically on interactivity affordance, in which individuals have an active choice for interacting with content, allowing the user to serve as a source of communication instead of passively consuming content (Sundar, 2008). Interactive social media features such as likes, comments, and shares shape how users engage with content on these platforms (Barker, 2017; Rathnayake & Winter, 2018). Notably, despite the commonality of features across the spectrum of social media platforms (e.g., likes, shares, comments, tagging), these same features afford various uses, or perceived utility, on different social media platforms (Treem & Leonardi, 2013). Additionally, interactivity on social media platforms changes how we conceptualize and interpret engagement, moving towards more active outcomes, such as audiences sharing their attitudes via *likes*, disseminating content via *shares*, and connecting with others via *comments*, which aligns with contemporary conceptualizations of social media engagement (Dessart, 2017; Gilstrap & Holderby, 2016). Therefore, based on the affordance of interactivity, the current study operationalizes behavioral engagement on social media through the actions of likes, comments, shares, and tagging.

Engagement Across Social Media Platforms. Despite sharing similar affordances, behavioral engagement across social media platforms may have unique differences. Recently, Collins and colleagues (2016) found that scientists predominantly use Facebook, Twitter, and Instagram to share social media content. However, it is important to note that each social media platform has its own culture, with a complex combination of different affordances, cues, audience types (e.g., strong vs. weak ties), and norms for engagement. Thus, it is potentially unclear which type of content may be best suited for each platform (Bik & Goldstein, 2013) or how audiences will engage with content based on these affordances. For example, Facebook consists of audiences with both strong and weak ties to the user facilitating an environment that allows for more or less personal/intimate information. On the other hand, Twitter's affordances encourage a more direct and timely content style, leading to a more *newsworthy* environment where users are more likely to engage with weaker-tie audiences. Instagram, known for its emphasis on visual aesthetics, also allows for both strong- and weak-tie audiences to connect around special interest content (e.g., food, fashion, art, science, etc.; Waterloo et al., 2018).

While many studies have examined engagement on individual social media platforms, only a handful have focused on engagement across multiple platforms (Aldous et al., 2019; Tandoc et al., 2018). Nevertheless, cross-platform research allows for a more comprehensive picture of the role each social media platform may play in the process of disseminating information, especially given that most audiences have accounts on multiple platforms and perceive unique engagement on those platforms (Hall et al., 2018).

Given each platform's distinctive characteristics, it is also important to examine existing norms across platforms, as previous social media use has positively predicted social media engagement (DiGangi & Wasko, 2016; Skoric et al., 2016). Social media behaviors, such as liking, commenting, sharing, and tagging, require varying levels of cognitive effort and commitment (Kim & Yang, 2017). Each type of behavior is also associated with an aspect of self-presentation and/or community development. For example, a like could be considered an endorsement of a user's attitudes, a comment represents more dialogic communication, a tag invites others in your network to consume/contribute to content, and a share becomes part of a user's feed as a form of self-presentation (Kim & Yang, 2017). Additionally, behaviors have different norms depending on which social media channel is used (Singh & Srivastava, 2019). For example, a share on Facebook might hold more weight than a share on Twitter or Instagram because of the types of audiences, algorithm, and platform's interactivity.

Given the ubiquity of social media, and the emerging prevalence of scientific content on social media platforms, this study aims to better understand how audiences engage with different types of content. More specifically, this study examines content from three different science fields across three social media platforms. Therefore, we propose the following research questions to guide our methodology:

RQ1: How does behavioral engagement differ between each of the three social media platforms tested?

RQ2: How does behavioral engagement differ between each of the three science content areas tested?

If main effects are detected in RQ1 and RQ2, we ask:

RQ3: Is there an interaction effect between the type of social media platform and the type of scientific content on behavioral engagement?

RQ4: Do levels of message comprehension (for the same scientific content) differ between the type of social media platform on which the content is presented?

Reinforcing Science Information-Seeking and Social Media Engagement Behaviors. Social media users are becoming increasingly accustomed to engaging with science information, primarily on social media. For many adults, once formal science education ends, media sources become the most accessible, and sometimes the *only*, source of scientific information (Nisbet et al., 2002). Recently, social media has become a primary source for many individuals seeking scientific information (Funk et al., 2017). According to a study by the Pew Research Center, popular science-related Facebook pages have up to 44 million followers (Hitlin & Olmstead, 2018), indicating a genuine interest in scientific content for some social media users. The followers of these pages are likely to have more experience consuming and engaging with scientific content on social media (Segev & Baram-Tsabari, 2012). Further, more general prior engagement on social media channels may impact how they engage with future social media content (DiGangi et al., 2016). Specifically, they may be more likely to find it normal to engage with this content visibly.

Given that people who are turning to social media for science content are more likely to engage with it and learn from it, we predict the following:

H1: Previous engagement behaviors (e.g., likes, comments, shares, tags) on social media channels will have a positive influence on (a) engagement and (b) comprehension of scientific content on those platforms.

H2: Previous science information-seeking behaviors will positively influence (a) engagement and (b) comprehension of scientific content on social media platforms.

METHODS

This study employed a 3 (science content: biology, engineering, social science) x 3 (platform: Facebook, Twitter, Instagram) repeated-measures factorial experiment. The study's procedure and instrument were first approved by the researchers' University Institutional Review Board.

Participants

Participants were recruited using a snowball sampling method, beginning with researchers sharing a recruitment message on their social media platforms (Facebook, Twitter, Instagram, and Slack). Participants were also asked to share the recruitment information with their networks. A total of 237 participants were included in the final data set, with an average age of 32 (M = 31.60, SD = 9.74). The majority of participants were female (78.1%), middle class (78.9%), Caucasian (73.0%), and held either a bachelor's or master's degree (73.0%). The remaining participants identified as bi/multiracial (17.3%), Asian/Pacific Islander (8.0%), and African American/Black (1.7%). Additionally, most participants also considered themselves scientists or worked in a science-related field (75.5%). These individuals represented various science specialties, including biology, medicine, paleontology, social science, and engineering.

In examining participants' previous behaviors on social media, 92.0% of participants reported having a Facebook account, 86.5% of participants reported having a Twitter account, and 88.6% of participants reported having an Instagram account. When asked which social media platform they were most familiar with, 44.7% were most familiar with Facebook, 27% were most familiar with Twitter, and 28.3% were most familiar with Instagram. When asked which social media platform participants would be most likely to use, 43.0% reported Instagram, 30.8% reported Twitter, and 26.2% reported Facebook.

When asked which social media platform participants would be least likely to use, 42.6% reported Twitter, 32.9% reported Facebook, and 24.5% reported Instagram.

Procedure

Using a Qualtrics survey, participants were first asked about their previous social media engagement behaviors and previous science information-seeking behaviors. Participants were then randomly assigned to three of the nine experimental stimuli. Each viewed versions of a post with social science, biology, and engineering content shown as posted on Facebook, Twitter, or Instagram. To avoid potential fatigue from repetitive viewing of the same content type across each platform (i.e., all nine experimental stimuli), both content and platform were crossed and randomly presented. Each participant saw one category per content type and social media platform for a total of three different posts (e.g., an individual might have been presented the biology content on Facebook, the social science content on Twitter, and the engineering content on Instagram). This format resulted in approximately 35 (range between 30-40) responses per experimental stimuli. After viewing each stimulus, participants were asked their likelihood to engage with the post (i.e., like, share, comment, or tag). Participants were also presented with a multiple-choice comprehension check question for each post to which they were exposed. Following survey completion, respondents were offered a chance to win one of five $20 Amazon gift cards and were redirected to an external survey to provide information to be entered into the drawing.

Stimuli

When examining how scientists use social media, recent research has suggested that Facebook, Twitter, and Instagram are the most commonly used platforms. Therefore, we examined these three platforms in this study (Collins et al., 2016). Stimuli were created using Zeoob, an online social media post generator, to create realistic social media posts as they would appear on a person's social media feed. The posts' source was presented as The National Science Foundation, sharing a scientific article accompanied by the article's image, explanatory text, and field-specific hashtags (See Figure 1). The National Science Foundation was selected to serve as a consistent, objective, and credible source of science information. Content for each post was selected based on the relatively apolitical nature of each. The posts were developed using contemporary studies related to the fields of social science (e.g., cell phone technology's impacts on interpersonal relationships; Sbarra et al., 2018; see Figure 1), biomedical/health (e.g., sleep deprivation accelerating the development of Alzheimer's disease; Beil, 2018; see Figure 1), and engineering (e.g., 3D printing material structures in space; Gaget, 2017; see Figure 1).

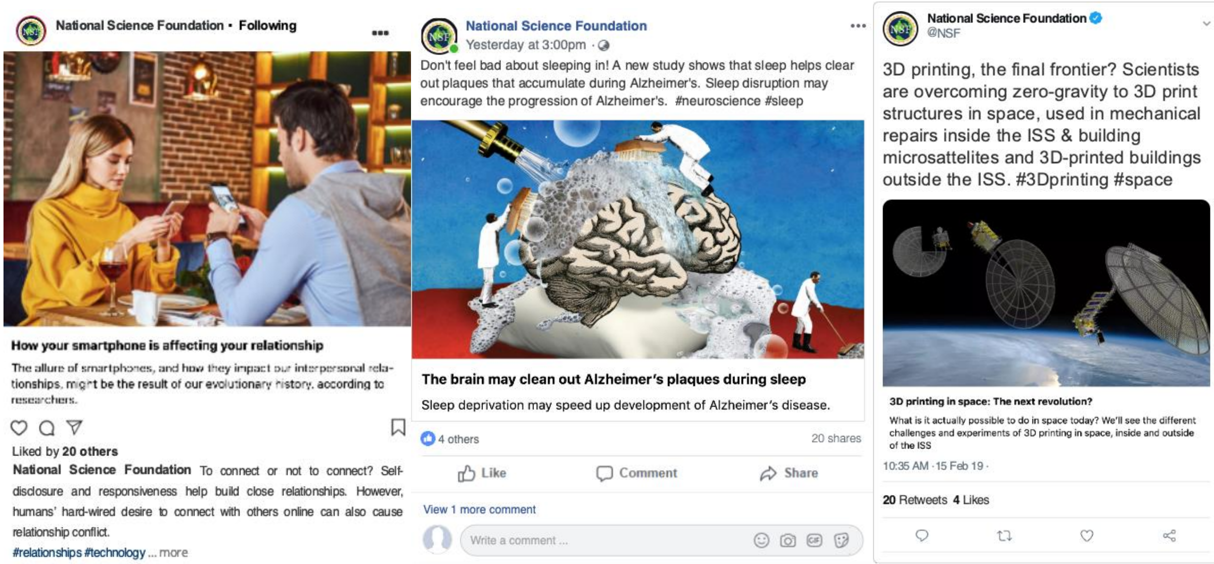

Figure 1. Sample social media posts: Instagram post with social science content (left), Facebook post with biology center (center), Twitter post with engineering content (right)

Pre-Stimuli Measures

Previous Social Media Behavioral Engagement. Participants were asked a series of questions about how they interact with content on Facebook, Twitter, and Instagram social media platforms. These questions asked participants if they had accounts on these platforms, how familiar they were with each platform, and which platforms they were (typically) most likely to use. Additionally, participants were also asked to consider how they (typically) engage with content on each platform, focusing specifically on likes, comments, shares, tags, and viewing stories. Participants respond to these questions using a 5-point Likert-type scale ranging from 1 = "strongly disagree" to 5 = "strongly agree." Example items included: "I like posts on Instagram," "I retweet posts on Twitter," and "I tag other people on Facebook posts" (M = 3.15, SD = .74, α = .772).

Previous Science Information-Seeking Behavior. Participants' previous science information-seeking behavior was measured using a modified version of Tella's (2009) information-seeking behavior scale. This 8-item scale utilized a 5-point Likert-type scale ranging from 1 = “strongly disagree” to 5 “strongly agree.” Example items include: “I tend to look for science content online,” and “I enjoy looking at science content online” (M = 3.32, SD = .83, α = .725).

Post-Stimuli Measures

Social Media Behavioral Engagement. Participants’ engagement with each social media post was measured using an abbreviated version of Baldwin et al.’s (2018) social media engagement scale. The shortened version included 4 items to assess how likely participants would be to like, share, comment, and tag someone. Each item was measured on a 5-point scale ranging from 1 = “extremely unlikely” to 5 “extremely likely.” Example items include “How likely would you be to comment on this post?” and “How likely would you be to share/repost this post?” Items were considered together as a total social media behavioral engagement score; See Table 1 for means and standard deviations (M = 2.38, SD = .77, α = . 991).

Message Comprehension. Participants’ knowledge comprehension of each social media post was measured using a multiple-choice question (4 response choices). Participants were asked to reflect on the post’s content and select the correct answer that most accurately described the content presented. For each question, the correct answer was scored as 1, and the other three incorrect answers were scored as 0. See Table 1 for means and standard deviations.

Table 1
Means and Standard Deviations of Behavioral Engagement Total Scores and Message Comprehension as a Function of a 3 (Science Content) x 3 (Platform) Design

	Facebook		Instagram		Twitter	
	M	*SD*	*M*	*SD*	*M*	*SD*
Behavioral Engagement						
Social Science	2.04	.98	2.09	.96	2.23	.99
Biology	3.32	.98	2.36	1.2	2.38	.99
Engineering	2.27	1.1	2.32	.95	2.37	1.1
Message Comprehension						
Social Science	.68	.47	.79	.41	.76	.43
Biology	.74	.44	.61	.49	.66	.48
Engineering	.98	.15	.97	.17	.99	.11

Notes. Total scores were measured using a 1-5 scale. Message comprehension was coded 0 = incorrect, 1 = correct.

RESULTS

All analyses were conducted using IBM SPSS Statistics Version 27. An acceptable significance level for hypothesis testing was set to an a-priori cut-off of .05.

Social Media Engagement

Research questions 1 and 2 asked about the main effects of social media platforms and science content areas on behavioral engagement. Research question 1 (RQ1) asked if there was a significant difference in behavioral engagement between the three social media platforms tested. A one-way repeated measures ANOVA was conducted for engagement on the social media platforms (Facebook, Instagram, and Twitter) with pairwise comparisons to determine differences between social media platforms (see Table 2 for pairwise comparison results). Mauchly's test indicated that the assumption of sphericity had been violated, χ^2 (2) = 27.5, $p < .001$. Therefore, the degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity, $\varepsilon = .90$. The results showed a significant difference in engagement between the three social media platforms, $F(1.8, 425.12) = 4.56$, $p < .05$. Pairwise comparisons revealed that engagement was significantly higher for Facebook ($M = 2.53$, $SD = 1.17$) compared to Instagram ($M = 2.28$, $SD = 1.03$, $p < .01$), but not Twitter ($M = 2.36$, $SD = 1.04$, $p = .06$). There was no significant difference in engagement between Instagram and Twitter ($p = .33$).

Table 2
One-Way Repeated Measures ANOVA Results on Behavioral Engagement with Pairwise Comparisons

	Mean Difference	*SE*	*p*	95% CI		*M*	*SE*
				LL	UL		
Facebook						2.54	.08
Instagram	.25*	.09	.00	.07	.42		
Twitter	.18	.09	.06	-.01	.36		
Instagram						2.29	.07
Facebook	-.25*	.09	.00	-.42	-.07		
Twitter	-.07	.07	.33	-.21	.07		
Twitter						2.36	.07
Facebook	-.18	.09	.06	-.36	.01		
Instagram	.07	.07	.33	-.07	.21		

Notes. SE = standard error; CI = Confidence Interval; *LL* = lower limit; *UL* = upper limit.
*p <.01

Research question 2 (RQ2) asked if there is a difference in behavioral engagement between each of the three science content areas tested. Again, a one-way repeated measures ANOVA was conducted for engagement with science content (biology, social science, and engineering) with pairwise comparisons to determine differences between science content (see Table 3 for pairwise comparison results). Mauchly's test indicated that the assumption of sphericity had been violated, χ^2 (2) = 12.3, $p < .01$. Again, the degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity, $\varepsilon = .95$. The results showed a significant difference in engagement between the three science content areas, $F(1.9, 449.10) = 22.2$, $p < .001$. Pairwise comparisons revealed that engagement for biology content ($M = 2.67$, $SD = 1.15$) was significantly higher than for social science ($M = 2.13$, $SD = .97$, $p < .001$), and engineering content ($M = 2.32$, $SD = 1.05$, $p < .001$). Additionally, engagement for engineering content was significantly higher than for social science content, $p < .01$.

Table 3
One-Way Repeated Measures ANOVA Results on Behavioral Engagement with Pairwise Comparisons

	Mean Difference	*SE*	*p*	95% CI		*M*	*SE*
				LL	UL		
Biology						2.67	.08
Social Science	.55*	.09	.00	.37	.72		
Engineering	.35*	.09	.00	.18	.53		
Social Science						2.13	.06
Biology	-.55*	.09	.00	-.72	-.37		
Engineering	-.19*	.07	.00	-.34	-.05		
Engineering						2.32	.07
Biology	-.35*	.09	.00	-.53	-.18		
Social Science	.19*	.07	.00	.05	.34		

Notes. SE = standard error; CI = Confidence Interval; *LL* = lower limit; *UL* = upper limit.
*p <.001

Research Question 3 (RQ3) asked if there is an interaction effect between the type of social media platform and the type of scientific content on behavioral engagement. For social media platforms, a one-way ANOVA was conducted for each of the three social media platforms (Facebook, Instagram, and Twitter) with a Tukey post hoc test to determine which science content area had the highest engagement on each social media channel. For Facebook, there was a significant difference in overall engagement between the three different science content areas, $F(2, 234) = 32.69$, $p < .001$. The Tukey post hoc test revealed that engagement was significantly higher for biology content ($M = 3.32$, $SD = 1.04$) compared to both social science ($M = 2.05$, $SD = .98$, $p < .001$) and engineering content ($M = 2.27$, $SD = 1.11$, $p < .001$). There was no significant difference between social science and engineering content ($p = .41$).

For Instagram, there was no significant difference in overall engagement between biology content ($M = 2.37$, $SD = 1.15$), social science content ($M = 2.18$, $SD = .94$), and engineering content ($M = 2.31$, $SD = .96$), $F(2, 234) = .73$, $p = .48$. For Twitter, there was also no significant difference in overall engagement between biology content ($M = 2.36$, $SD = .98$), social science content ($M = 2.36$, $SD = 1.06$), and engineering content ($M = 2.15$, $SD = 1.07$), $F(2, 234) = .00$, $p = 1.00$. Therefore, regarding RQ3, Facebook was the only social media channel to identify a significant difference in engagement amongst the three content areas of science tested. These findings provide compelling evidence that channel plays a significant role in the engagement process for scientific communication. See Table 4 for ANOVA results.

Table 4
Means, Standard Deviations, and One-Way Analyses of Variance Results Between Platform and Scientific Content on Behavioral Engagement

			Biology		Social Science		Engineering	
Platform	*F(2, 234)*	*p*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Facebook	32.69*	.00	3.32	1.04	2.05	.98	2.27	1.11
Instagram	.73	.48	2.37	1.15	2.18	.94	2.31	.96
Twitter	.00	1.00	2.36	.98	2.36	1.06	2.15	1.07

Notes. *p<.001

Again, for science content areas, one-way ANOVAs were conducted for each of the three content areas of science (biology, social science, engineering) with a post hoc Tukey test to determine which social media channel had the highest engagement for each science content area. For the biology posts, there was a significant difference in overall engagement between the three social media channels. A Tukey post hoc test revealed that engagement was significantly higher for Facebook ($M = 3.32$, $SD = 1.04$) compared to both Instagram ($M = 2.36$, $SD = 1.15$, $p < .001$) and Twitter ($M = 2.38$, $SD = .99$, $p < .001$). There was no significant difference in engagement for biology content between Instagram and Twitter ($p = .99$). For social science content, there was no significant difference in overall engagement between Facebook ($M = 2.04$, $SD = .98$), Instagram ($M = 2.11$, $SD = .96$), and Twitter ($M = 2.23$, $SD = .97$). For engineering science there was also no significant difference in overall engagement between Facebook ($M = 2.27$, $SD = 1.11$), Instagram ($M = 2.32$, $SD = .95$), and Twitter ($M = 2.37$, $SD = 1.08$). The biology posts were the only type of science content to show differences in engagement across social media channels. The results more specifically suggest that biology-based content on Facebook would likely produce the highest levels of engagement. See Table 5 for ANOVA results.

Table 5
One-Way ANOVA Results Between Scientific Content and Platform on Behavioral Engagement and Message Comprehension

			Facebook		Instagram		Twitter	
	F(2, 234)	*p*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Behavioral Engagement								
Facebook	20.7*	.00	3.32	1.04	2.36	1.15	2.38	.99
Instagram	.73	.48	2.04	.98	2.11	.96	2.23	.97
Twitter	.19	.83	2.27	1.11	2.32	.95	2.37	1.08
Message Comprehension								
Biology	1.47	.23	.74	.44	.61	.49	.66	.48
Social Science	1.24	.29	.67	.47	.78	.42	.76	.43
Engineering	.37	.69	.96	.15	.97	.17	.99	.11

Notes. *p<.001

Science Content Comprehension

Research question 4 (RQ4) sought to examine if there is a difference in message comprehension between each of the three social media platforms tested. A one-way ANOVA was conducted for each of the three science content area posts with a Tukey post hoc test to determine which social media channel had the highest comprehension for each science content area post. For biology, there was no significant difference in message comprehension between Facebook ($M = .74$, $SD = .44$), Instagram ($M = .61$, $SD = .49$), and Twitter ($M = .66$, $SD = .48$), $F(2, 234) = 1.47$, $p = .23$. For social science, there was no significant difference in message comprehension between Facebook ($M = .67$, $SD = .47$), Instagram ($M = .78$, $SD = .42$), and Twitter ($M = .76$, $SD = .43$), $F(2, 234) = 1.24$, $p = .29$. Finally, for engineering science, there was also no significant difference in message comprehension between Facebook ($M = .96$, $SD = .15$), Instagram ($M = .97$, $SD = .17$), and Twitter ($M = .99$, $SD = .11$), $F(2, 234) = .371$, $p = .69$. See Table 5 for ANOVA results. Thus, there were no significant differences in message comprehension between social media channels for any of the three types of science content. Given that participants mostly comprehended the science content in the social media posts (above 50%), this result shows that platform does not play a significant role in message comprehension of science content.

Previous Social Media Behavioral Engagement

Hypothesis 1 (H1) predicted that previous behaviors on social media channels would have a positive influence on (a) engagement and (b) comprehension of scientific content on those channels. Linear regressions were used to test this hypothesis. Three linear regressions were run for engagement to determine if previous behaviors on social media channels predicted behavioral engagement on Facebook, Instagram, and Twitter. Previous engagement behaviors significantly predicted behavioral engagement on Instagram. However, previous engagement behaviors did not positively influence behavioral engagement on Facebook or Twitter. For comprehension, three linear regressions were run to determine if previous behaviors on social media channels significantly predicted comprehension of biology, social science, and engineering content. Previous engagement behaviors did not positively influence comprehension of biology, social science, or engineering content. Overall, previous engagement behaviors on social media channels only predicted engagement on Instagram and did not predict comprehension for any science content areas. See Table 6 for regression analysis.

Table 6
Regression Analysis for Previous Social Media Behaviors Predicting Engagement and Comprehension

	ΔF	*df*	*p*	R^2
Behavioral Engagement				
Facebook	1.13	1	.29	.01
Instagram	14.63*	1	.00	.06
Twitter	.64	1	.43	.00
Message Comprehension				
Biology	1.00	1	.39	.00
Social Science	.94	1	.42	.01
Engineering	.89	1	.45	.01

Notes. *p<.001

Previous Science Information-Seeking Behaviors

Hypothesis 2 (H2) predicted that previous science information-seeking behaviors would have a positive influence on (a) engagement and (b) comprehension of scientific content on social media channels. First, to test the outcome of engagement, three linear regressions were run to examine if previous science information-seeking behaviors positively influenced engagement on Facebook, Instagram, and Twitter. Previous science information-seeking behaviors had a significant positive influence on engagement on Facebook and Instagram but did not significantly influence engagement on Twitter. Previous science information-seeking behaviors were a stronger predictor for Instagram compared to Facebook.

A second set of linear regressions were run to examine the influence of previous science information seeking on engagement with the different scientific content areas.

Previous science information-seeking behaviors significantly predicted engagement for biology and engineering content but did not predict engagement for social science content. Previous science information-seeking behaviors was a stronger predictor for engineering content than biology content.

Finally, to examine message comprehension, three linear regressions were run to determine if previous science information-seeking behaviors predicted message comprehension of biology, social science, and engineering content. Previous science information-seeking behaviors did not significantly predict comprehension for biology, social science, or engineering content. Overall, previous science information-seeking behaviors significantly predicted engagement on Facebook and Instagram as well as engagement for biology and engineering content and did not significantly predict message comprehension for any of the science content areas. See Table 7 for regression analysis.

Table 7
Regression Analysis for Previous Information-Seeking Behaviors Predicting Engagement and Comprehension

	ΔF	*df*	*p*	R^2	ß	*t*	*df*	*p*
Behavioral Engagement								
Platform								
Facebook	9.20*	1	.00	.04	.19	3.03*	235	.00
Instagram	19.57**	1	.00	.08	.28	4.42**	235	.00
Twitter	2.24	1	.14	.01				
Content Areas								
Biology	8.48*	1	.00	.04	.19	2.91*	235	.00
Social Science	2.05	1	.15	.01				
Engineering	23.14**	1	.00	.09	.30	4.81**	235	.00
Message Comprehension								
Biology	1.21	1	.27	.01				

Social Science	.03	1	.87	.00
Engineering	1.40	1	.24	.01

Notes. *p<.01, **p<.001

DISCUSSION

This study sought to examine behavioral engagement of three different scientific content areas (biology, social science, and engineering) across three different social media platforms (Facebook, Twitter, and Instagram). The results provide important insights into how audiences engage with different types of science content across different platforms and provide practical implications for scientists and science communicators seeking to maximize their audiences' behavioral engagement on social media platforms.

Following the PEST model of science communication, social media presents an opportunity for scientists and practitioners to interact with their audiences across multiple modalities (e.g., written text, photos, videos, memes, etc.), thus offering opportunities for unique behavioral engagement (Hines, 2019; Pavelle & Wilkinson, 2020). In considering both platform and science content area, this study found an interaction between the Facebook platform and biology content, such that higher reported behavioral engagement was identified for biology content posted on Facebook. These results could be due, in part, to the community-based nature of Facebook. Users tend to use Facebook to form reciprocal social connections as "friends" with individuals known offline (Ellison et al., 2007) and have higher levels of bonding social capital on Facebook compared to other platforms (Shane-Simpson et al., 2018). Additionally, the wider variety of affordances and features of Facebook may also contribute to the higher levels of engagement observed, as Facebook allows for longer text, images, video, and links for audience interaction.

In contrast, Instagram is primarily visual, has a social norm of using less text, and does not allow for links within content posts (Shane-Simpson et al., 2018). Following the PEST model of science communication, Facebook may provide the most flexibility for presenting engaging content and providing two-way dialogic communication between expert and audience. Also, since Facebook is the oldest of the three platforms examined and has previously been reported to be the primary platform for most Americans (Smith &

Anderson, 2018), users are likely more familiar with this platform and more comfortable engaging with content on Facebook. These results also align with previous research that found that young adults are more likely to engage with science content on Facebook than on Twitter (Hargittai et al., 2018). The results may have also shown higher engagement for biology-based content because of potentially higher personal/health relevance for the audience of biology-related content compared to posts focused on social sciences and/or engineering (Frewer et al., 1999). Additionally, these results may be attributed to the relative popularity of the biology field compared to other STEM fields (McFarland et al., 2019). These findings could suggest that the wider variety of social media platform affordances and the personal relevance of science content could contribute to behavioral engagement.

Previous social media engagement predicted stronger engagement with science content, but only on Instagram. In addition to being the newest of the three platforms studied, Instagram is focused more on visual aesthetics and has unique affordances that shape how audiences use this social media platform. For example, Sheldon and Bryant (2016) showed that Instagram users placed more emphasis on personal identity, surveillance, and self-promotion and less on connecting with other people or information-seeking. Given that these features require a unique, nuanced skill set to navigate in online environments, users without this prior experience on Instagram might be less likely to engage in this way. The PEST model of science communication also considers the intersection of science and society, providing audiences with connections between science and their own lives (Davies, 2013). In looking at identity and self-promotion in science communication on Instagram, Jarreau et al. (2019) showed that scientists who post selfies on Instagram were perceived as significantly warmer, more trustworthy, and no less competent than scientists who posted pictures only of their science research. In the same study, participants who viewed female scientists' selfies viewed science fields as less exclusively male. This research suggests that scientists posting selfies on Instagram can help mitigate negative attitudes toward scientists (Jarreau et al., 2019). Thus, given Instagram's social norms, affordances, and motivations centered on visuals and identity presentation, scientists and practitioners aiming to use Instagram should keep in mind the unique skill set and behavioral engagement on this platform.

Furthermore, previous science information-seeking behaviors significantly predicted engagement on Facebook and Instagram, as well as engagement with biology and engineering content. However, it did not predict message comprehension for any of the science content areas. While Twitter's social norms mainly focus on information-seeking (Osterreider, 2013), it was unexpected that information-seeking behaviors did not significantly predict engagement on Twitter. However, this result may tap into the more passive use of Twitter for science content (Côté & Darling, 2018). While users might be motivated to use Twitter to gain information, they might be more likely to only read or click on the content and engage with it off-platform rather than engage directly on Twitter. Thus, scientists and practitioners might want to consider expanding how they measure engagement to include clicks or eye-tracking when evaluating science content on Twitter (Kruikemeier et al., 2018).

Finally, there was no significant difference between any of the social media platforms for the three science content areas regarding message comprehension. Thus, message comprehension was comparable between the three science content areas presented. These results present an important finding for scientists and science communicators concerned about audiences understanding complex scientific information. Best practices for science communication suggest that a message should be clear, concise, jargon-limited, etc. (Rakedzon et al., 2017). Provided that these practices are followed, the current findings suggest that message comprehension is not directly impacted by the platform on which it is presented.

Implications

Given the findings in this study, scientists and science communicators need to consider the audiences, norms, and features of different social media platforms before posting content. Given the prevalence of the information deficit mindset (Besley & Tanner, 2011), scientists and communicators can use the PEST model as a framework for utilizing the interactive elements of social media platforms for two-way dialogue and engagement with audiences. Moving forward, social media presents a unique and critical space for audiences engaging in science content (Mueller-Herbst et al., 2020). Our findings suggest that science communication conducted on social media is not presented in isolation but is instead accompanied by various cues such as the source of the science content, the features and affordances of the social media channel, and the person/organization promoting the message (Brossard & Scheufele, 2013). The variety of cues, features, and affordances of social media platforms, such as Facebook, Twitter, and Instagram, presents various opportunities for engagement with science content. For example, all three platforms offer text, image, and video content and allow users to share content, have conversations, and build communities (Kietzmann et al., 2011).

However, each social media channel's content and behavior norms can influence how science communication content is presented and engaged with. In the current study, Facebook channel and biology content had the most significant difference in behavioral engagement compared to the other channels and science content areas. This result could reflect the popularity of both the Facebook channel and the biology science field. Facebook is the oldest and most popular social media platform out of the three tested in this study (Hitlin & Olmstead, 2018). Audiences could be more familiar and willing to engage with science content on this channel because of the social norms associated with Facebook. As scientists attempt to determine which social media channel to engage audiences with their research and science communicators choose which types of science content to position on different platforms, the current study can be seen as a starting point when considering behavioral engagement and comprehension factors.

Limitations

The current study has limitations that should be considered when interpreting the current findings. The external validity of our behavioral engagement measure must be interpreted within the context of the study's controlled setting. Participants indicated their likelihood to engage with posts, which served as an internally reliable measure of engagement. However, future research should corroborate this study's findings with analyses of engagement from a non-controlled real-world field examination. While we were able to exert consistent control across each of the content areas and platform types, the generalizability of findings may be limited, given the nature of the study's quasi-experimental design.

Next, it is important to acknowledge that scientific content encompasses a wide range of sub-disciplines, each with unique characteristics and challenges, including the potential for certain politicized topics (Munro et al., 2015). The current study purposely selected science content that was considered relatively apolitical to avoid unwanted bias in viewing the stimuli. Additionally, each science article presented in the stimuli was accompanied by its associated article image, a cartoon brain for the biology content, an image of a couple sitting together for the social science post, and an image of the international space station for the engineering post. These visual images could have presented a priming effect for participants viewing the science content stimuli. The application of findings for future scientific posts should consider the generalities and any associated characteristics of the three scientific fields chosen for the current study.

Finally, the generalizability of the study's sample may have limitations worth considering. This study recruited participants through snowball sampling on social media channels, and the demographics of this sample demonstrated that the majority of participants were well-educated, middle-class Caucasian females. Additionally, a large portion of participants also identified themselves as scientists or working in a science-related field. To help expand our findings to a broader and more generalizable sample of science communication consumers, a more diverse sample is needed, particularly seeking the inclusion of diverse races/ethnicities and socioeconomic status. Given the imperative need for science to be more diverse and disseminated amongst broader, more inclusive audiences, research studies need to obtain data from more diverse populations to achieve that goal (Canfield & Menezes, 2020).

Future Directions

Future research is needed to further examine the characteristics that drive engagement of science communication on social media. In particular, the construct of engagement should be further examined. In the current study, behavioral engagement in terms of likes, comments, shares, and tags was examined, but this only represents a portion of the engagement experience. Other subsets of engagement, such as emotional and cognitive forms, should be included in further studies for a more comprehensive understanding of a user's engagement experience with science content on social media. Future studies should also consider other features and uses of social media platforms, such as accuracy checks or the use of platforms for professional networking, and how those uses may be influencing audiences' perceptions and engagement with scientific content.

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