Journal of Personality and Social Psychology: Attitudes and Social Cognition

ISSN: 0022-3514

2025, Vol. 128, No. 2, 281–299
https://doi.org/10.1037/pspa0000430

Ideas Worth Spreading? When, How, and for Whom Information Load Hurts Online Talks' Popularity

Amir Sepehri[1], Rod Duclos[2], and Nasir Haghighi[3]
[1] Department of Marketing, ESSEC Business School
[2] Department of Marketing, Ivey Business School, Western University
[3] Milgard School of Business, University of Washington Tacoma

What makes cultural products such as edutainment (i.e., online talks) successful versus not? Asked differently, which characteristics make certain addresses more (vs. less) appealing? Across 12 field and lab studies, we explore when, why, and for whom the information load carried in TED talks causes them to gain (vs. lose) popularity. First and foremost, we uncover a negative effect whereby increases in the number of topics broached in a talk (i.e., information load) hurt viewer adoption. The cause? Processing disfluency. As information load soars, content becomes more difficult to process, which in turn reduces interest. Probing process further, we show this effect fades among audience members with greater need for cognition, a personality trait marking a penchant for deep and broad information processing. Similarly, the effect fades among edutainment viewers favoring education goals (i.e., cognitive enrichment) whereas it amplifies among those favoring entertainment (i.e., hedonic pleasure). Our investigation also documents the counterintuitiveness of our findings (i.e., how individuals mispredict which talks they would actually [dis] like). From these results, we derive theoretical insights for processing fluency research and the psychology of cultural products adoption (i.e., we weigh in on when, why, and for whom fluency has favorable vs. unfavorable downstream effects). We also derive *prescriptive* insights for (a) players of the edutainment industry whose very business hinges on curating appealing content (e.g., TED, Talks@Google, The Moth, Big Think, Spotify) and (b) communicators of all creeds wishing to broaden their reach and appeal (e.g., professors, scientists, politicians, journalists, bloggers, podcasters, content editors, online community managers).

Statement of Limitations

By recruiting broadly on Prolific Academic and by leveraging real behavioral data from the TED platform itself, we made every possible effort to increase the generalizability of our findings. For instance, our samples feature segments of the population diverse in terms of age, gender, education, occupation, and so forth. Despite these efforts, we warn the reader our research subjects still exhibit Western, educated, industrialized, rich, and democratic characteristics, which may limit the generalizability of our findings in developing regions. Moreover, though we go to great length to produce positive evidence for our process explanation (e.g., statistically, through mediation analyses, and experimentally, via theoretically derived moderators) while ruling out competing accounts, we recognize that our empirics suffer from limitations. Chief among them is that we do not manipulate information load in the *strictest* sense of the word (i.e., we do not manufacture from scratch TED talks wherein we decide ourselves the number of topics to be broached). Instead, we operationalize information load as naturally as possible, either by measuring it in the field (via text mining) or by varying it clinically in the lab (e.g., by randomly drawing talks with low, vs. high, load from TED's repository).

Keywords: processing fluency, online talks, virality

Supplemental materials: https://doi.org/10.1037/pspa0000430.supp

This article was published Online First December 12, 2024.
Mandy Huetter served as action editor.
Amir Sepehri https://orcid.org/0000-0002-3228-3127
Amir Sepehri and Rod Duclos contributed equally to this article. The authors report data, syntax, link to preregistrations, and sensitivity analyses for all studies on the Open Science Framework at https://osf.io/b6gdz/?view_only=ed168ffcecd54c6298b5997270980eb7. This research is based on Amir Sepehri's dissertation. This research was supported by CERESSEC funding awarded to Amir Sepehri and by an Ivey-Research-Policy grant awarded to Amir Sepehri and Rod Duclos. Amir Sepehri thanks Sarah Moore, David Hardisty, Mohammad Atari, and Roméo Tedongap for their support. Rod Duclos thanks Carly Vanderheyden and Mojgan Farahani for their support, as well as Jim Bettman, Fuzz, Spot, Paul, Mikey, Mandy, and Leo Messi.

Amir Sepehri played a lead role in data curation, formal analysis, and visualization and an equal role in conceptualization, funding acquisition,
continued

What makes cultural products such as online talks popular versus not? Asked differently, what attributes in a presentation tickle (vs. turn off) audiences' interest? We tackle these questions through the lens of information load and processing (dis)fluency.

Predicting the Success of Cultural Products

Across cultural products categories (e.g., books, songs, TV shows, movies), so-called "hits" far outshine the average market performance. Stated differently, hits sell disproportionally more (De Vany, 2004; Krueger, 2005; Vogel, 2004). Such stark discrepancies in market adoption suggest that certain products hold qualitatively distinct characteristics compared to the rest of the pack. Yet, prior research finds that connoisseurs (i.e., professionals equipped with ample market data and motivated to find the next best thing) exhibit low accuracy when forecasting which products will succeed (vs. fail) in the marketplace (Bielby & Bielby, 1994; Caves, 2000; De Vany, 2004; Peterson & Berger, 1971). Such unreliability on the part of experts sparked interest in the social sciences, particularly in psychology and management.

To account for outcome disparities, scholars first posited a convexity mechanism whereby one-unit differences in product quality spawn greater differences in market adoption (Rosen, 1981). In layman's terms, this convex quality-to-success mapping is sometimes referred to as the "superstar effect" or a "winner takes all" market (Frank & Cook, 1995). This interpretation is not without criticism, however. Such explanations assume indeed that the mapping from quality to market success is deterministic and that quality is known. For these reasons, such models are unable to explain the unpredictability of successes (and failures) actually observed in the market (Bond & Smith, 1996; Cialdini & Goldstein, 2004).

To account for this unpredictability of market outcomes, stochastic models emerged. These models posit that individuals' decisions are influenced by others. Once infused with social dynamics, these simulations reveal large variations both within and across realizations (De Vany, 2004; Richard, 1998; Watts, 2002), even when the underlying products are identical in intrinsic quality (Adler, 1985). As noted by Salganik et al. (2006), however, stochastic models have limitations of their own. Empirical tests of their predictions demand comparisons across multiple realizations of a stochastic process. In real life, however, only one history is ever observed.

To fill this gap, Salganik et al. (2006) launched the largest experiment to date on the psychology of cultural products adoption. After assembling 48 unknown songs from unknown bands, the authors randomly assigned >14,000 subjects to one of two conditions. First, in the control condition (aka "independent" decision making), participants viewed band names and song names before choosing which tune(s) to listen to. After each listen, subjects indicated their liking for the tune before choosing (or not) to download it for future consumption. The second condition (aka "social influence" condition) was itself subdivided into eight worlds (i.e., into eight separate subcells). In each of these eight worlds, participants saw the same 48 songs, but they witnessed in real time how often each song was being downloaded by peers within their world. Unlike theoretical models (i.e., simulations) and unlike real-world observational studies, this design enabled the authors to collect a natural measure of song quality through the control condition. This measure could then be compared to socially influenced judgements of individuals operating in eight independent worlds (i.e., in eight alternate realities).

Three lessons may be derived from Salganik et al.'s (2006) study. First, computing GINI coefficients, the authors found that social influence increases inequality (i.e., popular songs become more popular and unpopular songs more unpopular). Second, social influence increases unpredictability (i.e., though the very best songs rarely do poorly and the very worst songs rarely do splendidly, songs of just about *any* quality can experience a wide range of outcomes). Stated plainly, identifying winners (or losers) is impossible ex ante. Third, since these asymmetric outcomes emerge even with indistinguishable cohorts of individuals assessing the very same set of songs, unpredictability is inherent to the process and cannot be eliminated simply by knowing more about the songs or about market participants.

We contribute to this literature on cultural markets by identifying a product characteristic that *can* help predict adoption: the *information load* carried by TED talks. For clarity, we define information load as the number of topics broached in a presentation. For illustration, consider two 10-minute talks of equal duration. One is described as discussing ideas drawn from biology and environmental science; the second purports to cover insights from biology and environmental science amid principles of economics, ethics, and philosophy. Though the latter talk may *look* appealing to a wider audience for the richness/variety of topics it augurs, we posit that the accumulation of topics will in fact increase information load. And as information load soars, so does the difficulty to process it. Ultimately, the processing ease (vs. difficulty) experienced by viewers as they watch a talk causes them to like (vs. dislike) it.

In the next two sections, we unpack these notions by discussing how information load maps onto processing (dis)fluency and how, in turn, processing (dis)fluency affects audience adoption.

Information Load and Processing (Dis)Fluency

Cognitive psychologist and cofounder of psycholinguistics George Armitage Miller defined information as *bits* to be encoded, decoded, made sense of, and/or remembered. In his seminal review article, Miller (1956) stressed how limited human capacity is when it comes to processing information. On average, people can handle only seven chunks of information at a time, plus or minus two (e.g.,

investigation, methodology, writing–original draft, and writing–review and editing. Rod Duclos played a lead role in supervision and an equal role in conceptualization, funding acquisition, methodology, writing–original draft, and writing–review and editing. Nasir Haghighi played a supporting role in data curation, formal analysis, investigation, methodology, and visualization.

Correspondence concerning this article should be addressed to Amir Sepehri, Department of Marketing, ESSEC Business School, 3 Avenue Bernard Hirsch, 95000 Cergy, France, or Rod Duclos, Department of Marketing, Ivey Business School, Western University, 1255 Western Road, London, ON N6G 0N1, Canada. Email: sepehri@essec.edu or rduclos@ivey.ca

lists of digits, letters, words). Beyond this threshold, processing capacity saturates and errors accumulate.

In the same vein, Jacoby and colleagues demonstrated in a series of articles that individuals get overwhelmed fairly quickly with product information (Jacoby et al., 1973, Jacoby, Speller, & Berning, 1974; Jacoby, Speller, & Kohn, 1974). Historically operationalized as the number of options in a consideration set and/or as the number of attributes to be considered, information overload causes a variety of dysfunctions (e.g., decision inaccuracy, uncertainty, dissatisfaction; Jacoby, 1984; B. K. Lee & Lee, 2004; Malhotra, 1982; Sepehri et al., 2022, respectively). These dynamics are best summarized by Jacoby (1977, p. 569) himself:

> Information overload refers to the fact that there are finite limits to the ability of human beings to assimilate and process information during any given unit of time. Once these limits are surpassed, the system is said to be overloaded and human performance (including decision-making) becomes confused, less accurate, and less effective.

Though cultural products are somewhat different from the bulk of products examined by the extant literature, we posit that breaching a greater number of topics in a TED talk also increases information load for viewers (we will show the aforementioned is true even for talks of equal duration). And as information load soars, we predict viewers will find the experience disfluent (i.e., harder to process). This "information load → processing disfluency" link constitutes the first tenet of our argumentation; the next link concerns the effect of processing (dis)fluency on audience adoption.

Processing Disfluency and Audience Adoption

Processing (dis)fluency is commonly defined as the subjective ease (or difficulty) experienced by people as they process information (Schwarz, 2012; Schwarz et al., 1991). A wide variety of approaches have been used to manipulate (dis)fluency but, regardless of the approach, remarkably convergent consequences emerge for attitudes and behavior. Take "liking" as one such consequence. Reber et al. (1998) and Reber and Schwarz (1999) found that stimuli against less contrastive backgrounds (i.e., visual unease) are liked less than counterparts against highly contrastive backgrounds. Similarly, harder to imagine travel destinations (i.e., visualization unease) are liked less than counterparts that are easy to imagine (Mandel et al., 2006; Petrova & Cialdini, 2005). In the same vein, difficult-to-choose items (i.e., decision unease) are liked less than easy-to-choose counterparts (Iyengar & Lepper, 2000). Last and at the most basic level, Zajonc (1968) showed that less familiar stimuli (due to lesser exposure) are liked less than more familiar counterparts.[1]

In adjacent fields (i.e., consumer psychology), A. Y. Lee and Labroo (2004) found that fluency (induced by advertising exposure) inflates consumers' attitudes toward brands. Conversely, disfluency impedes brand liking. Similarly, Shen et al. (2010) found that processing disfluency (associated with a given product) hurts consumers' evaluations of the said product. Last, examining when message framing (loss vs. gain) proves more or less successful at driving recycling intentions, White et al. (2011) found that loss (gain) frames are more effective when consumers hold a low-level, concrete (high-level, abstract) mindset. Conversely, loss (gain) frames are *less* effective when consumers hold a high-level, abstract (low-level, concrete) mindset. The reason? Processing (dis)fluency. Processing a loss-frame message while holding an abstract mindset (or a gain-frame message while holding a concrete mindset) proves to be disfluent, which in turn hurts attitudes toward recycling.

Complementing the above streams of research and founding ours is the notion that an increase *in the amount* of information can decrease fluency (Reber et al., 2004). Documenting this effect in judgments of beauty, Garner (1974) found that figural goodness is rated superiorly when viewers need to extract *less* information to comprehend stimuli. Relatedly, Checkosky and Whitlock (1973) found that stimuli with less information are not only less challenging to process (as operationalized by identification speed) but also more pleasant.

In sum, the fluency literature points to a consistent finding. Whether its modality be visual, linguistic, spatial, perceptual, and so forth, processing difficulty tends to fuel people's subjective experience of disfluency. In turn, disfluency hurts attitudes toward a target stimulus. Bringing these findings to bear in our context, we propose that public addresses broaching more topics increase processing disfluency, which in turn hurts audience adoption. Broken down as main effect and process predictions, our hypotheses read as follows:

> *Hypothesis 1 (main effect):* More information load in TED talks (operationalized as the number of topics constituting a talk) hurts audience adoption.

> *Hypothesis 2 (mediation):* The deleterious impact of information load on audience adoption (Hypothesis 1) is mediated by processing disfluency.

Mitigating Role of Need for Cognition

If our theorizing above is correct, then it stands to reason that certain viewers may find information load to be less off-putting. Specifically, if processing disfluency is indeed the force causing viewers to dislike talks covering numerous topics, then we should see this effect weaken among individuals who exhibit a natural penchant for deep and broad information processing. One personality trait encapsulates this penchant: need for cognition (NFC).

NFC refers to one's propensity to engage in and enjoy thinking (Cacioppo & Petty, 1982). High NFC individuals put more effort into processing information (Cacioppo et al., 1983) and process information with more depth and breadth (Levin et al., 2000; White & Willness, 2009). Perhaps the best metaphor to understand NFC is that of magnets (Cacioppo et al., 1996, p. 199):

> If individuals could be thought of as magnets, information in daily life as fields of iron filings, and the acquisition, scrutiny, and retention of this information as the movement of the filings toward the magnets, then interindividual variations in need for cognition would be the strength of the magnetic fields.

Drawing from this literature, we posit that the deleterious impact of information load on audience adoption (Hypothesis 1)

[1] For completeness, we note that disfluency may prove beneficial under specific conditions (e.g., when effortful information processing is itself instrumental to goal pursuit; see Markowitz, 2023; Markowitz & Shulman, 2021). We revisit this notion in the General Discussion section.

should be mitigated for viewers exhibiting a stronger NFC. Stated formally:

> *Hypothesis 3 (moderation):* Need for cognition moderates (i.e., lessens) the deleterious impact of information load on audience adoption (Hypothesis 1).

Mitigating Role of Goals

Furthering our process exploration, we submit that enjoyment of edutainment depends in part on viewers' baseline motives.[2] Our reasoning is as follows.

When consumption is for entertainment purposes (i.e., for hedonic pleasure), the information load of TED talks should have a negative effect on liking because of processing disfluency. Indeed, as shown by Graf and Landwehr (2015), the quest for entertainment (i.e., hedonic pleasure) promotes automatic processing, which itself responds favorably (unfavorably) to processing fluency (disfluency). Stated differently, when one's baseline motive is entertainment (i.e., hedonic pleasure), an experience that proves easier (harder) to process than expected should foster positive (negative) dispositions toward the stimulus (i.e., pleasure, vs. displeasure, toward the talk).

In contrast, when consumption is for education purposes (i.e., for cognitive enrichment), the information load of TED talks should no longer exert a negative effect on liking. In such cases, the quest for education (i.e., cognitive enrichment) promotes controlled processing, which itself produces interest (provided the stimulus' disfluency does not prove sweepingly overwhelming; Graf & Landwehr, 2015). Stated differently, when one's baseline goal is education (i.e., cognitive enrichment), an experience that proves hard to process should not be off-putting (i.e., it should not foster displeasure toward the talk). Stated formally:

> *Hypothesis 4 (moderation):* Viewers' baseline motives moderate the deleterious impact of information load on audience adoption (Hypothesis 1) such that proclivities toward entertainment/hedonic pleasure (education/cognitive enrichment) magnify (dampen) it.

Message Delivery Mode as a Test of Robustness

Though our locus of interest lies in online talks, we are mindful that some public addresses take a written form (e.g., editorials, articles, white papers). To examine the generalizability of the proposed effect, we will compare the impact of information load in live addresses (i.e., a TED talk) versus in text-only addresses (i.e., transcripts of a TED talk wherein visual and auditory cues are absent). By keeping constant the very content of addresses, text-only conditions will test the robustness of our process explanation while casting doubt on a litany of alternative accounts. Various speaker-specific characteristics may indeed contribute to audience adoption (e.g., accent, charisma, facial expressions, fame, gender, hand gesturing, height, physical attractiveness, race, showmanship, smiling, speech speed, tonal accentuations, tone of voice, voice depth). Text-only conditions will neutralize these visual and auditory cues, thereby lending positive evidence in support of our process explanation. For clarity, our conceptual model follows in stylized form (Figure 1).

Transparency and Openness

We report data, syntax, link to preregistrations, and sensitivity analyses for all studies on the Open Science Framework at https://osf.io/b6gdz/?view_only=ed168ffcecd54c6298b5997270980eb7 (Sepehri et al., 2024). All studies received approval from the institutional review board at Western University and ESSEC Business School.

Studies 1A and 1B: What Do Viewers (Think They) Like?

Two talks may be on the same general theme (e.g., urban planning) but discuss those themes through a variety of angles (e.g., infrastructure mapping, the future of society, inequality, global development, economics, politics, government). Between one talk purporting to incorporate few of these perspectives and a counterpart intending to include many, which would you rather watch?

Participants and Design

We recruited 200 volunteers (M_{Age} = 30.26, 48% female) on Prolific Academic and assigned them to a single within-subjects condition (information load: low vs. high).

Procedure

Per the question introducing the present study, it makes intuitive sense that a talk intending to cover more angles will be more appealing. A greater number of topics may indeed augur a broader and richer discussion. And with the diversity of tastes existing in the world (i.e., given the heterogeneity of preferences among viewers), more topics are likelier to tickle more people's interest. With this in mind, Study 1A (S1A) seeks to capture viewers' spontaneous preference ex ante (i.e., *before* they actually experience/watch a talk). As alluded, we predict a talk promising to broach multiple topics *looks* more appealing on the surface than one set on broaching few. We test this proposition by going to the end user and asking candidly their preference. Preregistration details are available on AsPredicted. Org at https://aspredicted.org/GY2_VDW.

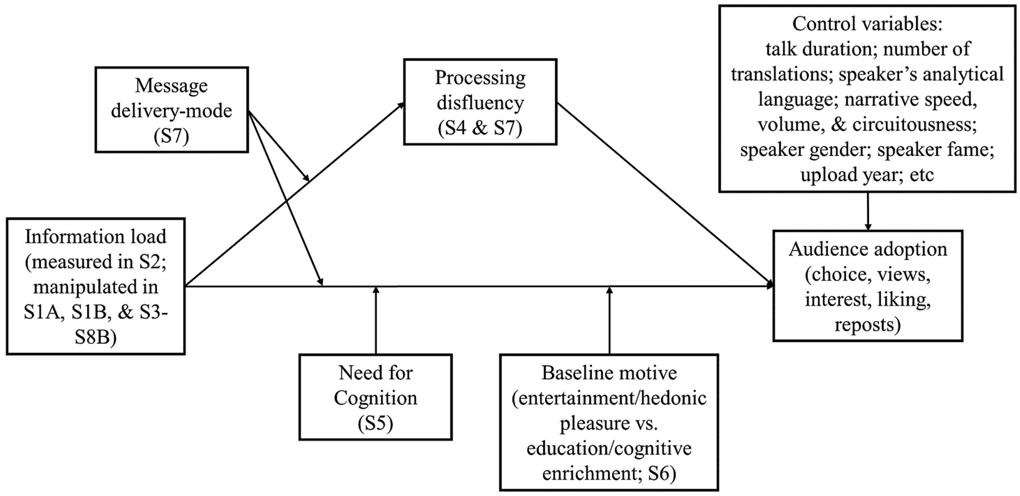
Upon signing a consent form, participants saw snippets (i.e., introductory teasers) of two TED talks. Per TED's presentation template, both snippets looked and felt similar. That is, they both showed a screenshot of the speaker in action, his name, and the talk's title (see Supplemental Material A).

The only difference between the two snippets came with our manipulation of information load. Staying true to the TED platform, each talk was accompanied by descriptive "tags" (i.e. 3 [vs. nine] tags in the low [vs. high] information load condition).

To capture participants' relative interest, we asked them "Which talk would you prefer to watch?." Answers were collected on a 7-point scale (1 = *I strongly prefer Talk A*, 2 = *I moderately prefer Talk A*, 3 = *I slightly prefer Talk A*, 4 = *Indifferent*, 5 = *I slightly prefer Talk B*, 6 = *I moderately prefer Talk B*, 7 = *I strongly prefer Talk B*).

[2] We thank an anonymous reviewer for this insight.

Figure 1
Conceptual Model



Note. S = study.

To rule out alternative explanations, we took a series of precautions. First, we selected talks on *the same* general theme (i.e., urban planning). To preserve realism, it was indeed essential that all tags apply legitimately to each talk. Without it, appearances might have been compromised. Second, we randomly drew which tags to assign to the low (vs. high) information load condition. Third, we rotated the allocation of tags across talks. Whatever the findings then, they could be confidently attributed to our information load manipulation and not to systematic idiosyncrasies in talk titles or in speakers' names, looks, perceived warmth, perceived competence, and so forth.

Results

For robustness, we tested our proposition not once but twice. First, we conducted a one-sample *t* test with a test value of 4 (i.e., the midpoint on our 7-point scale). For interpretability, let us preface our results by noting that a low response (i.e., up to 3) would connote preferences for the talk broaching three topics whereas a high response (i.e., 5 or more) would convey preferences for the talk broaching nine topics. Participants' M_{response} was 4.37 ($SD = 1.83$), which is significantly greater than the scale's midpoint, $t(199) = 2.86$, $p = .005$, Cohen's $d = .20$, 95% confidence interval (CI) [.06, .34].

To ease interpretability, our second analysis dichotomized participants' response, thereby turning our continuous measure into a binary dependent variable (DV). All participants responding 1, 2, or 3 (5, 6, or 7) were categorized as opting to watch the talk broaching three (nine) topics. Out of 200 participants, only 22 (i.e., 11% of the sample) were neutral between the two talks. Among the 178 participants who leaned one way, 104 (i.e., 58.4%) preferred to watch the talk with more topics, Observed $N_{\text{Low load}} = 74$, Observed $N_{\text{High load}} = 104$, $\chi^2(1) = 5.06$, $p = .02$.

In a follow-up study (i.e., Study 1B, S1B; preregistered on AsPredicted.Org at https://aspredicted.org/Y9F_W1B), we confirmed these proclivities while using slightly different outcome measures. Specifically, rather than presenting a bipolar item pitting one talk directly against the other, we instead featured four independent questions. Two assessed participants' interest in watching Talk A; two more did the same for Talk B. A repeated measures analysis of variance (ANOVA) yielded convergent findings. Viewers' preference went toward watching a talk purporting to cover more topics ($M_{\text{High load}} = 4.35$; $SD = 1.83$) rather than one set to broach few, $M_{\text{Low load}} = 4.06$, $SD = 1.69$; $F(1, 200) = 4.69$; $p = .03$, partial $\eta^2 = .023$. For details, we refer the reader to Supplemental Material B.

Discussion

We argued earlier that a talk purporting to discuss a greater number of topics is deceptively appealing. S1A and S1B provide support for *part* of this statement. Specifically, when choosing among options, a majority of people opt for a talk covering more topics. What S1A and S1B do not show—but what subsequent studies will—is that this preference is largely unfounded. Viewers may *think* they will enjoy rich, multitopic talks. In reality, we will show that they tend to prefer the opposite.

Study 2: Ideas Worth Spreading? Testing Hypothesis 1 in the Real World

Study 2 tests Hypothesis 1 in a naturalistic environment, the TED platform. Initially a brick-and-mortar conference held annually, TED morphed into an online repository of talks covering a gamut of themes (e.g., technology, entertainment, design, science, culture, politics, sports). The format is simple; speakers are given a few minutes to present their ideas as interestingly as possible through the art of storytelling. Notable speakers include Jeff Bezos, David Cameron, Bill Clinton, Richard Dawkins, Pope Francis, Bill Gates, Al Gore, Stephen Hawking, Elon Musk, and numerous Nobel laureates. With thousands of videos and over 3 billion views annually, TED constitutes a fertile context to examine the effect of information load on cultural products' adoption (https://www.ted.com/about/programs-initiatives/ted-talks).

Data

Our scope of inquiry consists of all talks uploaded to the TED platform until September 21, 2017 ($N = 2{,}460$; https://www.kaggle.com/datasets/rounakbanik/ted-talks).

Dependent Variable

Audience adoption was operationalized straightforwardly: by the number of views received by each talk. For context, the mean across talks is 1.74 million. Because the distribution of views is highly skewed,[3] however, we log-transformed the variable in our model specification (for robustness, regression results using the raw number of views as DV are available in Supplemental Material D).[4]

Independent Variable

The main independent variable consists of the number of distinct topics discernible in each talk. To compute this measure, we applied topic-modeling techniques (i.e., latent Dirichlet allocation, LDA; Blei et al., 2010) to the transcripts of all TED talks in our data set.[5] In layman's terms, LDA mines text to measure the co-occurrences of words both within and across transcripts. Doing so, the algorithm identifies (a) the topics discussed in each talk as well as their respective prevalence and (b) the words composing each topic (see Table 1, e.g., Berger & Packard, 2018; for a full review, see Berger et al., 2020).

To identify as precisely as possible the number of topics discussed within each talk, we employed an iterative approach. Following best practice and suggested benchmarks for LDA modeling, we began modeling topics by assuming a conservatively low number (i.e., 10 topics) and progressively increased to 100 topics (this was done in steps of three). As depicted in Figure 2, harmonic means of log-likelihood values from each number of topics identified the optimal number of topics to be 34. These log-likelihood values are a measure of "fit"; they determine the optimal number of topics summarizing a corpus of documents (Chen et al., 2015; Griffiths & Steyvers, 2004).

Next, we topic modeled all transcripts to extract the respective share of each of the 34 topics. Stated differently, we computed the proportion of each of the 34 topics in each of the 2,460 talks. If a talk were uniformly distributed across all 34 topics, each topic would have a share worth exactly $100/34 = 2.9412\%$. The natural threshold to count as a topic was therefore 3%. If a topic failed to reach this 3% threshold, it did not register as a topic. Results are robust, however, if 2.9412% or if 2.9% is used as the cutoff point.

Table 1
Sample Topics Emerged From Text Analysis and Their Constituting Words

Topic	Example of words constituting each topic
Health	Health, care, medical, patient, treatment
Family	Children, child, parent, baby, born
IT	Data, internet, information, online, web
War	War, military, Afghanistan, Iraq, peace
Energy	Energy, water, oil, carbon, power
Animals and environment	Fish, ocean, sea, animals, species

Note. IT = information technology.

Control Variables

Duration

One may argue that talks covering more topics are perhaps longer. As a result, it may be the duration (rather than information load) that causes a decay in views. To rule out this possibility, we control for each talk's length (in seconds). Of note, since duration is a good proxy for (and correlates highly with) word count, we controlled for the former only, not the latter. Identical results emerge, however, if we covary out word count rather than duration.

Primary Topic

Another consideration may be the primary topic of a talk (i.e., its general genre/theme). For instance, some topics may be inherently complex, others inherently trendy. In turn, this may cause talks discussing said topics to be liked less or more. To account for this possibility, we added fixed effects (FEs) for the primary topic of each talk (i.e., the topic holding the highest share of speech in each talk). This fixed effect rules out all alternative explanations pertaining to topical genres/themes.

Speaker's Gender

Prior work in the social perceptions and stereotypes literature suggests men tend to be viewed as competent (i.e., confident, skillful, capable) while women as warm (e.g., likable, good-natured, friendly, sincere; Fiske et al., 1999, 2018). Since these characteristics may in turn influence audience adoption, we sought to control for speakers' gender. This variable being unavailable to us, we synthesized it from speakers' first name using an R-Studio "gender" package. In the end, 59.5% of speakers were identified as male, 30% as female, and 10.5% as undetermined. We included all three levels as fixed effects.

Upload Year

To account for the passing of time (e.g., older talks having earned more views over the years), we included fixed effects for each talk's year of publication.

Number of Languages

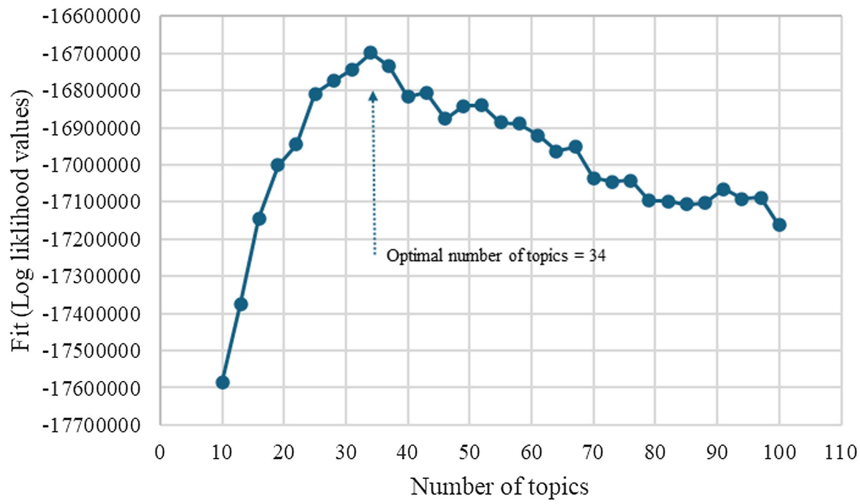
Some talks were transcribed in foreign languages ($M = 28.29$), thereby making them more accessible worldwide. To unconfound accessibility from market adoption, we controlled for the number of languages in which each talk was available.

[3] See histograms of original and log-transformed views in Supplemental Material C.

[4] Note that TED is not transparent on what threshold it uses to record a view (e.g., 1 s, half a talk, the whole talk). We remedy this shortcoming in subsequent studies by using a variety of adoption DVs to test our theorizing.

[5] Transcriptions are done by TED itself and posted on the platform.

Figure 2
Fit (Log-Likelihood Values for Each Number of Topics)



Note. See the online article for the color version of this figure.

Analytic Language Style

Analytical language corresponds to words indicative of formal, logical, connective, and/or hierarchical thinking (Pennebaker et al., 2014). For intuition, someone displaying greater analytical language would use more articles and prepositions relative to negations, adverbs, or pronouns (Chung & Pennebaker, 2007). These stylistic characteristics do not influence content per se, but they may impact storytelling (e.g., by establishing connections between concepts). To freeze such influences, we controlled for analytic language style. To this end, we submitted all transcripts to Linguistic Inquiry and Word Count, one of the most recognized text-mining softwares to date (Humphreys & Wang, 2018; Pennebaker et al., 2015; Tausczik & Pennebaker, 2010). We then used analytic language style as a covariate in our regressions.

Shape of Stories

The shape of stories refers to the way in which narratives unfold (e.g., how quickly they move across topics, how much semantic ground they cover, or how often they circle back to prior themes). Examining characteristics such as narrative speed, narrative volume, and narrative circuitousness; Toubia et al. (2021), we found differences in what makes these stories appealing across different types of content. For instance, whereas faster moving movies are enjoyed more, academic articles that cover more ground or loop back on ideas tend to get cited more.

Following Toubia et al.'s (2021) work, we measured the speed, volume, and circuitousness of our talks to covary them out. This enables us to test conservatively the predictive power of our own hypotheses (i.e., above and beyond the shape of stories). For clarity, narrative speed may be likened to vehicle speed. Much like a car can move slowly or quickly (i.e., move through smaller or larger distances in a given period), so can content (e.g., dwelling on semantically related concepts or moving a larger distance to content that is less semantically related).

Narrative volume is conceptually closest to our work. While some content may cover a lot of ground and touch on many distinct themes, other content may cover less ground. Volume, therefore, refers to the total ground covered in a narrative (i.e., "higher volume means that more ground was covered in the same number of periods"; Toubia et al., 2021, p. 2).

Last, narrative circuitousness refers to paths taken by a story. This variable derives from the well-known traveling salesman problem. That is, regardless of speed or the total volume of semantic ground covered, a story may travel back and forth between topics in a number of ways. Circuitousness captures how narratives travel (i.e., the paths through which topics are visited).

Fame of Speaker

Famous speakers draw curiosity, hence, online views. To rule this out as an alternative explanation for our findings, we undertook to measure speakers' fame and covary it out. Our approach was straightforward. We googled each speaker's name; the resultant number of search results served as a proxy for fame in our full-model specification (see descriptive statistics in Supplemental Material E). For illustration, Al Gore (the 45th Vice President United States, now climate advocate) returns 2,289,000,000 search results. This number testifies to Al Gore's relative fame compared to his fellow TED speakers (the median in our data set is 21,650,000 search results).

Model-Free Evidence

Table 2 reports model-free evidence in the form of zero-level correlations between (a) the number of topics, (b) the log-transformed number of views, and (c) the raw number of views. As can be seen, the number of topics covered in each talk is negatively correlated with views in both their log-transformed and raw forms.

Table 2
Correlation Matrix Between Number of Topics and Number of Views

Variable	1	2	3
1. Number of topics			
Pearson's r	—	$-.086^{***}$	$-.075^{***}$
Spearman's ρ	—	$-.079^{***}$	$-.079^{***}$
Kendall's τ B	—	$-.057^{***}$	$-.057^{***}$
2. Number of views (log transformed)			
Pearson's r		—	$.749^{***}$
Spearman's ρ		—	1.000^{***}
Kendall's τ B		—	1.000^{***}
3. Number of views (raw)			
Pearson's r			—
Spearman's ρ			—
Kendall's τ B			—

*** $p < .001$.

Model Specification and Results

Using ordinary least squares regression in Equation 1, we specify our model as follows:

$$\begin{aligned}\text{In(Number of Viwes)} = {} & \beta_0 + \beta_1\text{Number of topics} \\ & + \beta_2\text{Talk duration} \\ & + \beta_3\text{Number of languages} \\ & + \beta_4\text{Analytical language} + \beta_5\text{Speed} \\ & + \beta_6\text{Volume} + \beta_7\text{Circuitousness} \\ & + \beta_8\text{Speaker fame} \\ & + \theta'\text{Pimary topic fixed effects} \\ & + \gamma'\text{Gender fixed effects} \\ & + \eta'\text{Year fixed effects} + \in . \end{aligned} \tag{1}$$

Tables 3 and 4 report the regression results for our model specification. Supporting Hypothesis 1, we find a negative effect by the number of topics ($B = -.028$, $p < .001$). In plain terms, each additional topic broached (i.e., each one-unit increase in the number of topics) causes a 3% loss in views (i.e., $\exp(-.028) = .97$).

As expected given their conceptual relatedness, narrative volume (Toubia et al., 2021) and our measure of information load (i.e., number of topics) correlated positively, but this correlation was only moderate ($r = .16$, $p < .001$). Moreover, the 3% drop in views caused by each incremental topic discussed is above and beyond the effect of volume on views. Combined, these elements confirm that our methodological approach is *both* unique and robust in its capacity to predict adoption.

Table 3
Study 2 Results—Model Fit Measures

Model	R^2	Adjusted R^2	AIC	BIC
Model fit measures	0.539	0.529	3,648	3,973

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion.

Robustness Check 1

To help site visitors search through its repository, TED attaches thematic tags (aka "categories") to its talks. For instance, Malala Yousafzai's talk titled *Activism, changemakers, and hope for the future* is ascribed the following tags: gender equality, activism, education, social change, and coronavirus. Since tags are generated by the platform and are meant to describe a talk's contents, it is reasonable to assume that more tags attached to a talk reflect a greater number of topics covered. For robustness, then, we used the number of tags describing each talk as an alternative (and admittedly coarser) proxy for information load.

Running again our model specification, we find convergent support for Hypothesis 1. As the number of tags attached to a talk increases, the number of views it receives decreases ($B = -.009$, standard error [SE] = .003, $p = .004$; full results in Supplemental Material F).

We pause here to underscore the *counterintuitiveness* of our findings. Indeed, as the number of descriptive tags attached to a talk increases, so does the frequency at which said talk appears in search results. Stated differently, the more descriptive tags are ascribed to a talk, the more often will said talk match someone's locus of interest. Hence, the negative effect (of information load) on views is large enough to *outweigh* the otherwise positive effect that keyword matches have on views.

Robustness Check 2

For completeness, we considered yet another measure: the standard deviation across topic proportions. Our rationale is as follows.

Per our LDA analyses, the entirety of TED talks is best described along 34 topics. Accordingly, each talk varies in the extent to which it discusses each of these 34 topics (from 0% to 100%). For illustration, imagine that Talk A broaches five topics (e.g., Topic 4 has a weight of 30%, Topic 11: 25%, Topic 15: 20%; Topic 22: 15%, Topic 34: 10%; total = 100%) and leaves the remaining 29 topics untouched (i.e., the latter receive a weight/proportion of 0% each). By contrast, Talk B broaches 10 topics (e.g., each with a weight varying from 5% to 15% but adding cumulatively to 100%) and leaves the remaining 24 topics untouched (i.e., the latter receive a weight/proportion of 0% each). *Across the 34 possible topics*, then, Talk A (which broaches only five topics) exhibits a greater standard deviation in topic proportions than Talk B (which broaches 10 topics).

With the above in mind, Robustness Check 2 substituted the number of topics (i.e., our main independent variable) by the standard deviation in topic proportions. Next, using the same model specification as before, we find that more standard deviation in topic proportions is associated with more views ($B = 3.53$, $SE = 1.01$, $p < .001$; full results in Supplemental Material G). That is, greater standard deviation in topic proportions (which implies that fewer topics were broached overall, as in the case of Talk A) correlates with greater adoption. Conversely, less standard deviation in topic proportions (which implies that more topics were broached overall, as in the case of Talk B) correlates with lesser adoption.

Table 4
Study 2 Results—Model Coefficients

Predictor	Raw coefficient	*SE*	*t*	*p*
Model coefficients—views (log-transformed)				
Intercept[a]	10.9878	0.278764	39.4161	<.001
Number of topics	−0.02792	0.007374	−3.78672	<.001
Duration	0.000707	4.49E-05	15.76645	<.001
Number of languages	0.075819	0.00173	43.83637	<.001
Analytic	−0.0022	0.000759	−2.89529	.004
Speed	1.803972	0.671914	2.684827	.007
Volume	−15.0536	2.785863	−5.40357	<.001
Circuitousness	0.090199	0.483424	0.186584	.852
Speaker fame	4.04E-12	1.53E-12	2.644083	.008
Primary topic	FEs included			
Speaker gender	FEs included			
Upload year	FEs included			

Note. *SE* = standard error; FEs = fixed effects.
[a] Represents reference level.

Discussion

The purpose of Study 2 was to test Hypothesis 1 in a real-world, naturalistic setting. For robustness, we approached the task from three different angles. We operationalized information load first and foremost as the number of topics broached in a talk, second as the number of tags used by TED to describe its talks, and third as the standard deviation in topic proportions. Regardless of the approach, results converge. The greater the information load, the fewer views earned. Stated differently, for each additional topic a talk broaches, market adoption shrinks. This remains true after controlling for a litany of confounding factors (e.g., a talk's duration, a talk's primary topic, speaker gender, speaker fame, time elapsed since the talk was uploaded, number of languages in which the talk was transcribed, speaker writing style, narrative speed, narrative volume, and narrative circuitousness).

Studies 3A and 3B: Replicating the Effect in the Lab

Building on its predecessor, Study 3A takes our investigation to the lab to test Hypothesis 1 in a controlled environment (i.e., with the benefits of random assignment).

Participants and Design

We randomly assigned 201 participants recruited on Prolific Academic (M_{Age} = 30.44; 34% female) to one of two conditions following a between-subjects design (information load: low vs. high). Preregistration details may be found on AsPredicted.Org at https://aspredicted.org/MY5_JPZ.

Procedure

As alluded earlier, TED posts on its platform the transcripts of its talks. In Study 2, we topic modeled all transcripts to identify how many distinct topics are discussed in each talk. Bringing this intel to Study 3A, we randomly drew two talks from our repository with the intent to administer one talk discussing fewer topics than the other (i.e., four topics in the low-load cell vs. eight topics in the high-load cell). This made for a seamless/unobtrusive manipulation of information load.

DV, Manipulation Check, and Covariate

Whereas Study 2 captured audience adoption via the number of views received by each talk, Study 3A does so through interest and liking (i.e., "How interesting did you find the talk? How much did you like the talk?" r = .88). To avoid order effects, these questions appeared in a random sequence, with answers collected from 1 (*not at all*) to 7 (*very much*).

In addition, we assessed whether viewers have a sense of the number of topics broached in a talk (i.e., "How many different topics do you think were covered in the talk you just watched?"). This measure may be thought of as procedural validation for our automated topic modeling in Study 2. Note that we did not provide participants any information about the talk they were about to watch (e.g., no descriptive tags); we let them form their own impressions.

Last, to control for personal habits, we asked subjects how often they watch TED talks (i.e., 1 = *never*; 2 = *once a year*; 3 = *once a month*; 4 = *1–2 times a week*; 5 = *3–4 times a week*; 6 = *5–6 times a week*; 7 = *every day*). By covarying out the latter, we were able to neutralize interindividual differences. Stated differently, in case TED draws to its website a special kind of people, we were now able to proactively control for such a self-selection bias.

Results and Discussion

Manipulation Check

Controlling for participants' consumption of TED talks, an analysis of covariance revealed that viewers do have a sense of the number of topics discussed in a talk, $M_{\text{Low load}}$ = 2.04, SD = 1.18 versus $M_{\text{High load}}$ = 3.00; SD = 1.41; $F(1, 198) = 27.47$; $p < .001$, partial η^2 = .12. This result lends credence to our methodological approach in Study 2.

Dependent Variable

Our analysis of covariance revealed that viewer response worsens as information load increases, $M_{\text{Low load}}$ = 5.52, SD = 1.36 versus $M_{\text{High load}}$ = 4.44; SD = 1.92; $F(1, 198) = 19.93$; $p < .001$, partial η^2 = .09. Hence, through two new proxies of adoption (i.e., interest and liking) and with the benefits of random assignment, Study 3A echoes the field results of Study 2 and supports Hypothesis 1.

A follow-up, preregistered study (i.e., Study 3B) used a slightly different approach to confirm these proclivities. Specifically, rather than adopting a between-subjects design, Study 3B asked volunteers to watch not one but two randomly drawn talks (information load: low vs. high; within-subjects design). Once again, as information load increased, viewer response worsened, $M_{\text{Low load}}$ = 5.62; SD = 1.41 versus $M_{\text{High load}}$ = 4.93; SD = 1.81; $F(1, 99) = 11.92$; $p < .001$, partial η^2 = .11. For details, we refer the reader to Supplemental Material H.

Study 4: Mechanism Through Mediation

To explain the deleterious impact of information load on audience adoption witnessed in Studies 2–3 (Hypothesis 1), we proposed in Hypothesis 2 that processing disfluency is at play. Study 4 tests our reasoning by way of mediation.

Participants and Design

We recruited 249 volunteers on Prolific Academic to partake in a "TED study" ($M_{\text{Age}} = 30.01$, 45% female) and assigned them to one of two conditions following a between-subjects design (information load: low vs. high).

Procedure

The procedure resembles Study 3A. Upon signing a consent form, participants watched a talk discussing either few or numerous topics. Though two talks would suffice to test Hypothesis 1 (i.e., one discussing few topics and another discussing many), we opted to feature eight talks in the present study. Specifically, we rotated talks *within* each condition such that our overall findings would not be driven by a given talk. To this end, we drew eight new talks from our repository (i.e., four new talks broaching four topics in the low-load condition and four new talks broaching eight topics in the high-load condition).[6] The drawing was semirandom by design. First, for realism, we sought talks that were relatively short so that participants could fully consume them within the bounds of our study. Second, to rule alternative explanations related to length (e.g., talks covering four [eight] topics are liked more [less] simply because they are shorter [longer]), we sought eight talks of similar duration (i.e., $M_{\text{Low load}} = 318$ s; $M_{\text{High load}} = 337$ s). Third, in compliance with research ethics, stimuli shall not cause sadness, anxiety, interpersonal prejudice, and so forth.

DV and Mediator

Upon watching their respective video, participants reported their interest and liking for it ($r = .81$); these measures served as proxies for adoption. To test Hypothesis 2, we next gauged processing disfluency by using measures typical of this literature (Alter & Oppenheimer, 2009; A. Y. Lee & Aaker, 2004; Schwarz, 2004). We asked: How complex was this talk? How difficult to understand was this talk? How complicated was this talk? These items have been used extensively in previous research to measure processing (dis)fluency (for a review, see Graf et al., 2018). Once again, to avoid order effects, we presented items in a random sequence (Cronbach's $\alpha = .86$) and collected answers from 1 (*not at all*) to 7 (*very much*).

Results

Mirroring the results of Studies 2–3, an analysis of variance revealed a negative main effect. As information load increased, viewer response worsened, $M_{\text{Low load}} = 5.84$; $SD = 1.38$ versus $M_{\text{High load}} = 4.95$; $SD = 1.48$; $F(1, 247) = 24.11$; $p < .001$, partial $\eta^2 = .09$. This validates Hypothesis 1.

To test Hypothesis 2, we then examined processing disfluency as a function of information load. As expected, talks with greater information load proved harder to process, $M_{\text{Low load}} = 1.91$; $SD = 0.94$ versus $M_{\text{High load}} = 3.11$; $SD = 1.46$; $F(1, 247) = 58.99$; $p < .001$, partial $\eta^2 = .19$. We thus proceeded to testing the information load → processing disfluency → audience adoption chain of events with PROCESS Model 4 (Hayes, 2022). We find that increases in information load spike processing disfluency, which in turn erodes interest and liking ($B_{\text{Indirect effect}} = -.13$; $SE = .05$; 95% CI [−.23, −.03]; see illustration in Figure 3).

Discussion

The purpose of Study 4 was twofold. First, using eight new talks, we sought evidence corroborating the findings unearthed in Studies 2–3. Supporting Hypothesis 1, we find again that information load hurts viewer adoption. Second, supporting Hypothesis 2, we find that processing disfluency underpins our effect. As the number of topics discussed in a talk increases, it becomes harder for audience members to understand it, which in turn erodes interest and liking.

Study 5: Mechanism Through Moderation: NFC to the Rescue

We designed Study 5 (S5) with two goals in mind. First, to further generalize our findings, we test Hypothesis 1 by employing a set of eight new videos. Second and more importantly, we seek to build on Study 4's mediation evidence by exploring process, this time by way of moderation. If our theorizing at the onset is correct (i.e., if processing disfluency drives the negative impact of information load on audience adoption), then it stands to reason that certain viewers may find information load to be less off-putting. To this effect, we posited that a personality trait speaks directly to the mechanism uncovered in Study 4: NFC (Cacioppo & Petty, 1982). Lower (higher) NFC marks an aversion toward (a penchant for) debate, idea evaluation, problem solving, and deep and broad information processing. Stated differently, with NFC grows the desire to think through issues and learn, even when doing so is effortful. Accordingly, we predicted in Hypothesis 3 that the negative main effect hypothesized in Hypothesis 1 should be moderated (i.e., lessened) among audience members exhibiting greater NFC.

Participants and Design

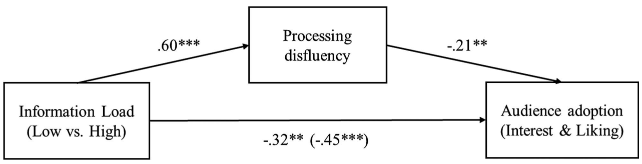
We recruited 200 volunteers on Prolific Academic ($M_{\text{Age}} = 29.08$, 49% female) and assigned them to one of two conditions following a between-subjects design (information load: low vs. high). We measured NFC, the second factor of interest in this study, on an individual difference scale.

Procedure

As in Study 4, participants (a) signed a consent form, (b) watched a talk discussing either few or many topics (i.e., IV), and (c) reported their interest and liking for it (i.e., DV). The main differences between Studies 4 and 5 are as follows.

[6] The number of topics had been identified by mining talks' transcripts (i.e., through topic modeling; see details in Study 2).

Figure 3
Mediation Results (Study 4)



** $p < .01$. *** $p < .001$.

First, to instill further confidence in our findings, we semirandomly drew yet a new set of eight videos from TED's repository.[7] Participants in the low (high) information load condition viewed one of four possible talks that each discussed three (nine) topics.[8] Using eight talks (rather than two) reduces once again the likelihood that our results be driven by the idiosyncrasies of any particular talk.

Second, to test Hypothesis 3, we administered at the end of the session Cacioppo et al.'s (1984) Need For Cognition scale. Made of 18 items, this scale is arguably the most recognized in the literature. Sample items include: I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought; I usually end up deliberating about issues even when they do not affect me personally; I really enjoy a task that involves coming up with new solutions to problems; Thinking is not my idea of fun (reverse coded); I would rather do something that requires little thought than something that is sure to challenge my thinking abilities (reverse coded); and I try to anticipate and avoid situations where there is likely a chance I will have to think in depth about something (reverse coded). We collected answers from 1 (*very uncharacteristic of me*) to 5 (*very characteristic of me*).

Results

Echoing the results of Studies 2–4, an ANOVA revealed that information load had a negative main effect. As information load increased, viewer response worsened, $M_{\text{Low load}} = 5.30$, $SD = 1.76$ versus $M_{\text{High load}} = 4.64$, $SD = 1.52$; $F(1, 198) = 8.07$; $p = .005$, partial $\eta^2 = .04$. This validates Hypothesis 1.

To test Hypothesis 3, we then examined the interaction of information load and NFC. After mean centering NFC, an ordinary least squares regression revealed a positive Information Load × NFC coefficient ($B = .44$, $SE = .19$, $p = .022$, Hayes, 2022; PROCESS Model 1, full results in Table 5). In plain terms, increases in NFC counteract the negative main effect of information load. Beyond a certain threshold in NFC (i.e., beyond 3.8 on a 5-point scale), high information load no longer obstructs viewer adoption. For perspective, 35% of our sample scored 3.8 or more in NFC. These results validate Hypothesis 3.

Table 5
Study 5 Results

Term	Estimate	*SE*	*p*	95% CI *LL*	95% CI *UL*
Constant	4.958	0.114	.000	4.732	5.183
Information load	−0.345	0.114	.003	−0.570	−0.119
NFC (centered)	0.450	0.190	.019	0.075	0.825
Information Load × NFC	0.438	0.190	.022	0.063	0.813

Note. Interaction between information load and NFC (centered). *SE* = standard error; CI = confidence interval; *LL* = lower limit; *UL* = upper limit; NFC = need for cognition.

For interpretability, we refer the reader to the conditional effects in Table 6 and to the floodlight analysis in Figure 4. The grayed area on the right corresponds to the 35% of subjects with highest NFC. At such levels of NFC, the deleterious impact of high information load loses statistical significance (i.e., the CI includes 0). In plain terms, participants are no longer deterred from finding high-load talks interesting or enjoyable.

Still for illustration purposes, Figure 5 uses a median split procedure and a bar graph to convey the same insight. At lower levels of NFC (i.e., leftmost bars), high information load impedes adoption. At higher levels of NFC (i.e., rightmost bars), the effect fades.

For completeness, we note that NFC showed a positive main effect on interest and liking ($B = .45$, $SE = .19$, $p = .019$, $\beta = .16$), which is easily explained. Watching TED talks is an intellectual activity; accordingly, high NFC individuals enjoy the experience more than low NFC counterparts.

Discussion

S5 makes two contributions. First, it validates Hypothesis 1 under yet another set of experimental conditions (i.e., with eight new talks). This adds robustness to our findings.

Second, as it validates Hypothesis 3, S5 also supports our process explanation. Indeed, we posited in Hypothesis 2 (and showed in Study 4) that processing disfluency mediates the deleterious impact of information load on audience adoption. If this mechanism is reliable, then it stands to reason that NFC should buffer viewers against the damaging effect of information load. NFC marks indeed a penchant for deep and broad information processing. As such, viewers who exhibit higher NFC should experience less disfluency (than counterparts with lower NFC) as they watch talks with high information load. The interactive pattern of results uncovered herein suggests just that (see Figures 4 and 5).

Study 6: Baseline Goals as an Additional Moderator

Study 6 (S6) has two objectives: providing corroborating evidence for our base effect (Hypothesis 1) and probing the underlying process by way of moderation (Hypothesis 4).

Participants and Design

We recruited 401 volunteers on Prolific Academic ($M_{\text{Age}} = 44.43$, 54% female) and assigned them to one of two conditions following a between-subjects design (information load: low vs. high). The second factor of interest in this study, baseline motives (i.e., entertainment/hedonic pleasure vs. education/cognitive enrichment), was assessed as an individual difference. Preregistration details are available on AsPredicted.Org at https://aspredicted.org/VML_78Q.

[7] See in previous study the bases for a semirandom draw.
[8] The number of topics had been identified by mining talks' transcripts (i.e., through topic modeling; see details in Study 2).

Table 6
Conditional Effects of Information Load on Audience Adoption (i.e., Interest and Liking) at Mean ±1 SD of NFC

Value point	NFC	Effect	*SE*	*p*	95% CI *LL*	95% CI *UL*
M −1 *SD*	2.952	−0.6113	0.1634	.0002	−0.9335	−0.2892
M	3.5608	−0.3448	0.1143	.0029	−0.5703	−0.1194
M +1 *SD*	4.1697	−0.0783	0.162	.6295	−0.3979	0.2413

Note. NFC = need for cognition; *SE* = standard error; CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Procedure

Our theorizing posited that viewers' enjoyment of edutainment depends in part on their baseline motive (Hypothesis 4). To test this proposition, S6 captures viewers' primary goal when they engage with TED talks (i.e., entertainment/hedonic pleasure vs. education/cognitive enrichment).

The procedure resembles S5's. Upon signing a consent form, participants in the low (high) information load condition viewed one of eight possible talks that each discussed either four or eight topics before reporting their interest and liking for it (i.e., DV). To test Hypothesis 4, S6 also captures subjects' primary motive in watching edutainment. To this end, we instructed participants that,

> People may have quite different motives for watching TED talks. Some people watch TED talks for pleasure. These people report consuming TED talks much like they consume other online-content. Their primary goal is to distract or to entertain themselves. Other people watch TED talks for cognitive enrichment. These people report consuming TED talks much like they consume educational content. Their primary goal is self-growth, to learn something new and to better themselves.

Next, we asked "What is YOUR primary motive for watching TED talks?" Mindful of the potential for social desirability, we stressed "There is no 'right' or 'wrong' answer here. On the scale below, please indicate what is most characteristic of you." We collected answers from 1 (*I watch TED talks for pleasure exclusively*) to 5 (*I watch TED talks for pleasure as much as for cognitive enrichment*) to 9 (*I watch TED talks for cognitive enrichment exclusively*).

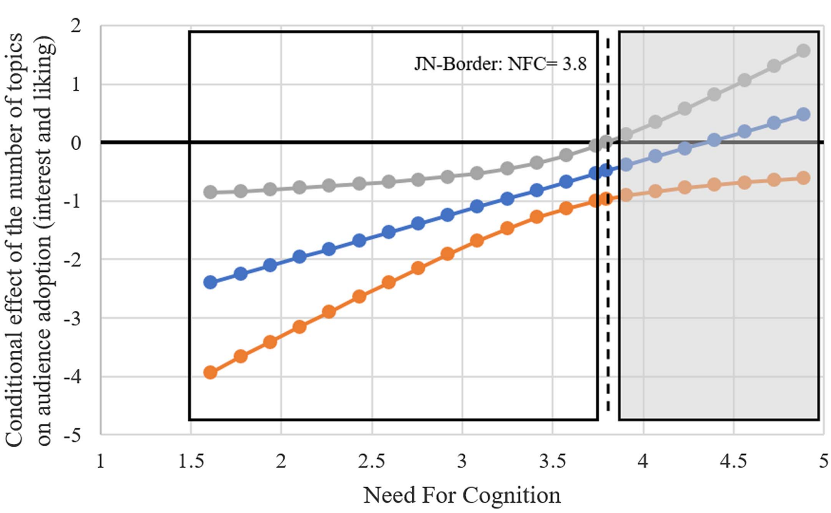
Results and Discussion

Mirroring our earlier findings, an ANOVA revealed that information load has a negative main effect on viewer adoption. As the number of topics discussed increased, liking and interest worsened, $M_{\text{Low load}} = 5.84$, $SD = 1.38$ versus $M_{\text{High load}} = 5.04$, $SD = 1.89$; $F(1, 399) = 23.57$; $p < .001$, partial $\eta^2 = .06$. This validates Hypothesis 1 yet again.

More importantly, we find support for Hypothesis 4. Upon mean centering baseline motives, an ordinary least squares regression revealed indeed a positive Information Load × Baseline Motive interaction ($B = .09$, $SE = .05$, $p = .086$, Hayes, 2022; PROCESS Model 1, full results in Table 7). In plain terms, baseline motives moderate (i.e., lessen) the negative impact of information load on viewer adoption. The floodlight analysis below describes the shape of this interaction.

For individuals on the left who watch TED talks primarily for entertainment (i.e., for hedonic pleasure), information load spoils liking and interest substantially. But as viewers' baseline motive moves to the right (i.e., toward education/cognitive enrichment), this negative effect weakens. Past a certain threshold (i.e., beyond 8.02

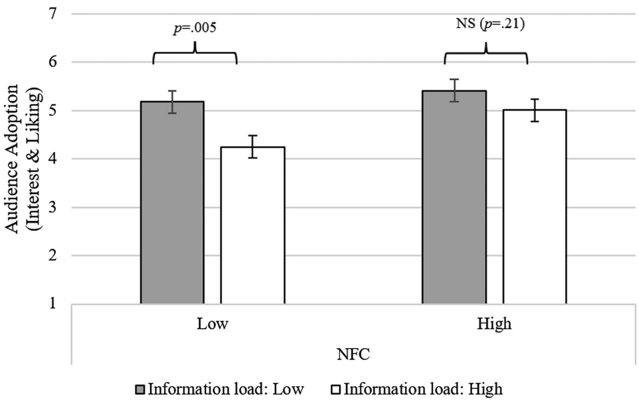
Figure 4
Conditional Effect of Information Load on Audience Adoption (i.e., Interest and Liking) at Varying Levels of NFC (Study 5)



Note. Gray and orange lines represent the upper and lower bounds of the confidence interval. For illustration purposes, original (i.e., noncentered) NFC values were used to plot the floodlight graph. NFC = need for cognition; JN = Johnson Neyman. See the online article for the color version of this figure.

Figure 5

Effect of Information Load on Audience Adoption (i.e., Interest and Liking) at Median Split Levels of NFC (Study 5)



Note. NFC = need for cognition; NS = not significant.

on a 9-point scale), high information load no longer impedes viewer adoption. For perspective, 17.7% of our sample scored 8 or higher on our Relative Motive scale. Albeit weaker, these results echo S5's findings (i.e., moderation by NFC of our base effect) and provide further process insights into when and for whom edutainment proves attractive (Figure 6).

Study 7: From Video to Text: Does the Effect Replicate?

As announced at the onset, online talks constitute our locus of interest. Accordingly, our empirical investigation focused on videos, a medium mixing visual, motion, and auditory signals. In Study 7 (S7), we consider the generalizability of our findings to a mode of delivery where visual and auditory cues are absent: text. Mindful indeed that public addresses can take various forms (e.g., in person vs. in text), we test Hypothesis 1 (i.e., the effect of information load on audience adoption) and Hypothesis 2 (i.e., mediation by processing disfluency) for each mode of delivery. Similar results in both mediums would validate our theorizing and highlight yet again the robustness of our findings. Moreover, from an internal validity standpoint, symmetric findings across modes of delivery would rule out a litany of confounds related to speaker idiosyncrasies (e.g., body language, showmanship, charisma, smiling, tone of voice, attractiveness).

Participants, Design, and Procedure

We recruited 402 volunteers on Prolific Academic ($M_{\text{Age}} = 28.46$, 51% female) and assigned them to one of four conditions following a 2 (information load: low vs. high) × 2 (message delivery-mode: video vs. text) between-subjects design.

The procedure resembles Study 4's. Upon signing a consent form, participants in the low (high) information load condition viewed one of eight possible talks that each discussed four (eight) topics (i.e., IV) before reporting their interest and liking for it (i.e., DV). The main difference between Studies 4 and 7 is as follows.

Per Study 7's goals and design, the mode of delivery manipulation had participants either (a) watch a TED talk or (b) read its transcript (see sample transcript in Supplemental Material I). This implies that content remained *identical* across modes of delivery. The latter is important because it enables the clean testing of Hypotheses 1 and 2 in each medium (i.e., without introducing content-related confounds). Everything else follows Study 4 (i.e., same eight talks, same three mediation-items,[9] and same two adoption DVs[10]).

Results

Dependent Variable

Echoing our earlier findings, an ANOVA revealed that information load has a negative main effect on audience adoption. On average, higher load eroded liking and interest, $M_{\text{Low load}} = 5.28$, $SD = 1.67$ versus $M_{\text{High load}} = 4.61$, $SD = 1.74$; $F(1, 398) = 15.35$, $p < .001$, partial $\eta^2 = .04$; this validates Hypothesis 1. And as may be expected due to its less effortful nature, we also observe a main effect by mode of delivery whereby watching videos was on average preferred to reading text, $M_{\text{Video}} = 5.14$, $SD = 1.73$ versus $M_{\text{Text}} = 4.75$, $SD = 1.72$; $F(1, 398) = 5.34$, $p = .02$, partial $\eta^2 = .01$. The two factors did not interact, $F(1, 398) = .68$, $p = .41$, partial $\eta^2 = .002$; Figure 7, but the most important results of Study 7 are as follows.

Mechanism

As alluded, Study 7 tests a moderated-mediation model wherein information load acts as IV, mode of delivery as moderator, processing disfluency as mediator, and adoption (i.e., interest and liking) as DV. Testing this framework, PROCESS Model 8 (Hayes, 2022) revealed that the indirect effect (information load → processing disfluency → audience adoption) is significant in *both* modes of delivery ($B_{\text{Video}} = -.07$, $SE = .03$, 95% CI [−.14, −.01]; $B_{\text{Text}} = -.13$, $SE = .05$, 95% CI [−.24, −.03]; Table 8). In layman's terms, whether content is delivered by video or in text, increases in information load spike processing disfluency, which in turn erodes interest and liking. These process results replicate Study 4's results and validate Hypothesis 2 yet again. We note in passing that the indirect effect was significantly more pronounced (i.e., more deleterious) when addresses were delivered in text than through videos ($B_{\text{Index of Moderated Mediation}} = -.064$; $SE = .037$; 95% CI [−.147, −.006]); we discuss the practical implications of this subtlety in the discussion.

Discussion

Supporting Hypotheses 1 and 2, S7 finds once again that load-laden talks prove harder to process, which in turn causes viewers to lose interest. But in addition to producing positive evidence for the mechanism posited, S7 discounts several alternative explanations. We draw the reader's attention to the text conditions in this study. By providing some participants only transcripts of talks, we stripped stimuli of *all* their visual and audio attributes. A litany of alternative accounts were thereby controlled for experimentally (e.g., hand gesturing, facial expressions, tonal accentuations, voice depth, speech speed, accent, physical attractiveness, smiling, height, race, speaker gender, speaker fame). Even then, our process explanation held true by way of mediation.

[9] Cronbach's $\alpha = .87$.

[10] $r = .83$.

Table 7
Study 6 Results

Term	Estimate	*SE*	*p*	95% CI *LL*	95% CI *UL*
Constant	5.443	0.082	<.001	5.281	5.605
Information load	−0.402	0.082	<.001	−0.564	−0.240
Baseline motives (centered)	0.101	0.053	.060	−0.004	0.205
Information Load × Baseline Motives	0.092	0.053	.086	−0.013	0.196

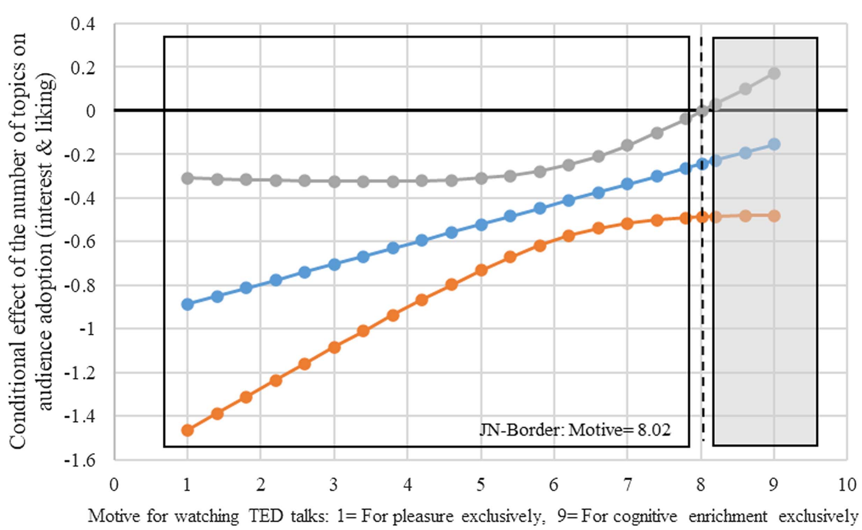
Note. Interactionbetween information load and baseline motives (centered). *SE* = standard error; CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Though the focus of our inquiry lies squarely in what makes online talks popular versus not, S7 took a sidestep to enlarge our realm of investigation. Mindful indeed that some real-world addresses occur through text (e.g., blogs, corporate websites, political newsletters, op eds, scientific articles), we briefly examined our propositions beyond videos. To this effect, we found that the *total* effect of information load on audience adoption is significant in *both* delivery modes, but it tends to be more damaging for in-person communications (e.g., video addresses; $M_{\text{Difference}} = -.803$, $SE = .24$, CI [.329, 1.277], $p < .001$) than for text communications ($M_{\text{Difference}} = -.525$, $SE = .24$, CI [.057, .992], $p = .028$). This insight is somewhat counterintuitive since in-person exchanges afford communicators a greater range of signals to address their audience (e.g., hand gesturing, facial expressions, tonal accentuations, voice depth), which should in turn ease information processing for recipients.

Moreover, we note that the total effect's breakdown varies across modes of delivery. In the "video" condition, though both direct and indirect effects were negative and significant on their own, by far the larger influence came from the direct effect, that is, $B_{\text{Video (Direct)}} = -0.33$, CI [−.54, −.10]; $B_{\text{Video (Indirect)}} = -0.07$, CI [−.14, −.01]. The opposite was true in the "text" condition. Therein, the direct effect was also negative but not significant on a 95% CI, that is, $B_{\text{Text (Direct)}} = -0.13$, CI [−.38, .12]; it is the indirect effect that drove the total effect, that is, $B_{\text{Text (Indirect)}} = -0.13$, CI [−.24, −.03].

From a practice standpoint, these nuances offer an opportunity to overcome the challenges of text communication. For instance, by mindfully infusing their writing with proper language, syntax, or structuring headers, informed writers may be able to mitigate disfluency and, hence, alleviate the damaging effect of information load on liking/interest. Given the respective total effect sizes, however, the same task seems more arduous for oral communicators

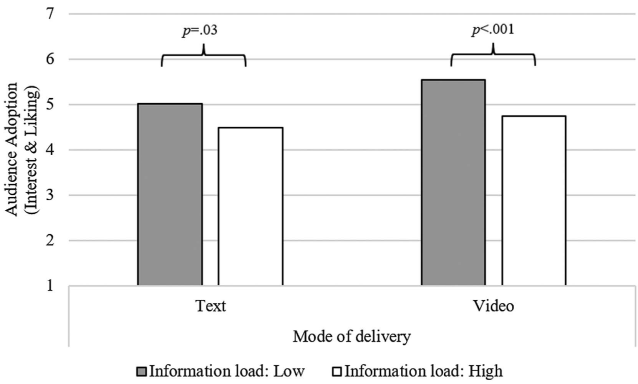
Figure 6
Conditional Effect of Information Load on Audience Adoption (i.e., Interest and Liking) at Varying Levels of Motives for Watching TED Talks



Note. Lower (higher) values on the moderator indicate a preference for watching TED talks for entertainment/hedonic pleasure (education/cognitive enrichment). For illustration purposes, original (i.e., noncentered) NFC values were used to plot the floodlight graph (Study 6). Grey and orange lines represent the upper and lower bounds of the confidence interval. The blue line represents the conditional effect of information load on audience adoption at varying levels of motives for watching TED talks. NFC = need for cognition; JN = Johnson Neyman. See the online article for the color version of this figure.

Figure 7

Effect of Information Load on Audience Adoption (i.e., Interest and Liking) by Mode of Delivery (Study 7)



(e.g., in-person or on-camera addresses). For the latter, staying clear from high information load altogether is preferable.

In the General Discussion section, we revisit the implications of these findings for communicators of all creeds (e.g., professors, politicians, news commentators, editorialists, scientists). As they alternate between modes of delivery, we detail when, why, and for whom they should adjust their messaging.

Studies 8A and 8B: From Individual Responses to Market Adoption

S1A–S1B showed that, as they consider competing options, viewers generally opt to watch talks purporting to broach more (rather than fewer) topics. If this is true, however, why do talks with more topics garner *fewer* views ultimately (per the field data of Study 2)? We believe the answer to this paradox lies in people's sharing behavior. Specifically, we posit that shares and referrals on social platforms are made primarily by satisfied viewers. Stated plainly, if viewers did not like a talk, they would unlikely post/refer it on their social media for friends and family. On average, then, we argue that talks exhibiting more (fewer) views are those that were not only (a) more (less) enjoyable and interesting to begin with but also (b) relayed most (least) by prior viewers.

Participants and Design

We randomly assigned 200 participants recruited on Prolific Academic (M_{Age} = 36.7; 59% female) to one of two conditions following a between-subjects design (information load: low vs. high). Preregistered details are available on AsPredicted.Org at https://aspredicted.org/XD8_F3Y.

Procedure

The procedure resembles Study 3. Invited to partake in a "TED talk" study, volunteers signed a consent form before watching their assigned video. Two new talks were randomly drawn from our repository. One broached four topics (low information load) while the other broached eight topics (high information load).

To proxy audience adoption, we collected once again participants' interest in and liking for the content they watched (r = .91). But in line with Study 8A's primary goal, we included this time a measure of virality. Specifically, we assessed subjects' propensity to promote the talk by reposting it on social media (i.e., Would you share this talk on your social media [e.g., Twitter, LinkedIn, Facebook]?). We collected answers from 1 (*definitely no*) to 7 (*definitely yes*).

Results and Discussion

Once again, an analysis of variance revealed that viewers' response worsens as information load increases, $M_{\text{Low load}} = 5.35$, $SD = 1.58$ versus $M_{\text{High load}} = 4.20$, $SD = 1.84$; $F(1, 198) = 22.44$; $p < .001$, partial $\eta^2 = .10$. Using yet a new set of videos, then, Study 8A echoes the results of Studies 2–7 and validates Hypothesis 1.

But more interesting is the measure of virality. Participants were more likely to share the content on their social media when the talk they watched had lesser information load, $M_{\text{Low load}} = 3.57$, $SD =$ 1.84 versus $M_{\text{High load}} = 2.39$; $SD = 1.69$; $F(1, 198) = 22.21$; $p <$ .001, partial $\eta^2 = .10$. The latter insight helps explain why seemingly richer talks (e.g., talks described by many tags) look appealing on the surface but garner fewer views ultimately.

Note that a follow-up study (i.e., Study 8B; preregistered on AsPredicted.Org at https://aspredicted.org/GCP_773) confirmed these proclivities while using a single outcome measure. Specifically, to rule out a potential pressure for participants to respond consistently, we reran Study 8A while capturing only sharing behavior (i.e., independently of "interest" and "liking"). An ANOVA yielded convergent findings. On average, viewers were more likely to post/refer the talk they had just watched when its content covers fewer topics, $M_{\text{Low load}} = 4.03$, $SD = 1.96$ versus $M_{\text{High load}} = 3.18$, $SD =$ 2.00; $F(1, 199) = 9.12$; $p = .003$, partial $\eta^2 = .04$. For details, we refer the reader to Supplemental Material J.

Table 8

Direct and Indirect Effects of Information Load on Audience Adoption for Video and Text Delivery (Study 7)

	Indirect effect through disfluency			Direct effect	
	Delivered in video	Delivered in text		Delivered in video	Delivered in text
Dependent variable	*B* [95% CI]	*B* [95% CI]	IMM [95% CI]	*B* [95% CI]	*B* [95% CI]
Audience adoption (interest and liking)	**−0.07 [−.14, −.01]**	**−0.13 [−.24, −.03]**	**−0.064 [−.147, −.006]**	**−0.33 [−.57, −.10]**	−0.13 [−.38, .12]

Note. Hayes Model 8 (bootstrap samples = 5,000, 95% CI). Moderation is supported only if the IMM (index of moderated mediation) excludes 0 (Hayes, 2022). Bold coefficients are significant on a 95% confidence interval (CI).

General Discussion

We began our inquiry into the psychology of taste with a clear anchor: What makes cultural products such as online talks popular versus not? Asked differently, what attributes in a presentation tickle (vs. turnoff) audiences' interest? Guided by information processing and fluency theories, we examined the impact of information load (i.e., the number of distinct topics/ideas discussed in a talk) on audience adoption. Across 12 studies, we find that talks characterized by less (more) information load prove more (less) popular (Hypothesis 1).

This phenomenon may look surprising at first. S1A and S1B show indeed that, between a talk purporting to cover many topics (as signaled by descriptive tags) and one intending to broach few, prospective viewers opt to watch the former. Accordingly, how can load-laden talks earn fewer views online? Postexperience sharing behavior helps answer the question. Viewers not only find more (less) interesting and more (less) enjoyable a talk with lesser (greater) information load, but they also relay it more (less) afterward on their social media. The latter helps explain market penetration.

Speaking to robustness, our findings manifest both in the real world (i.e., through 2,460 videos on the TED platform) and in laboratory settings (i.e., through 20+ talks). They also manifest whether audience adoption is gauged by: (a) views garnered online, (b) interest, (c) liking, or (d) one's propensity to relay content on social media. Two sets of theoretical insights may be derived from these findings.

Theoretical Contributions

Our first contribution is to the *psychology of cultural products*. Noting how poor industry experts are at forecasting the next big movie, book, or song (Bielby & Bielby, 1994; De Vany, 2004; Peterson & Berger, 1971), scholars began to examine the making of popularity. In perhaps the largest and most rigorous experiment on the topic, Salganik et al. (2006) showed that social dynamics make it impossible to predict which songs will turn into hits versus busts. They find indeed that intrinsic product quality plays only a marginal role in market outcomes; songs of just about *any* quality can experience a wide range of fates.

Three noteworthy efforts have since nuanced Salganik et al.'s (2006) conclusions. First, Nunes et al. (2015) showed that the repetitiveness of lyrics, an intrinsic product characteristic, increases song popularity. Second, in a clever suite of studies examining microreels of 1–5 s, Stuppy et al. (2024) found that slowing down such videos boosts consumer evaluations. Third and last, introducing an innovative natural language processing technique, Toubia et al. (2021) showed that the "shape of stories" helps predict market acceptance (see Study 2).

We complement and extend these efforts in a variety of ways. For instance, whereas Stuppy et al. (2024) examined the *visual* complexity inherent in microreels (e.g., GIFs), we investigate *discourse* complexity. Methodologically, whereas Stuppy et al.'s (2024) use video editing (i.e., slow motion), we employ text-modeling and machine-learning techniques. Last, whereas Toubia et al. (2021) explored movies and journal articles, we examine a new type of target (i.e., edutainment) and a new antecedent to processing fluency (i.e., information load). Conceptually and empirically, our combined similarities and differences help build a richer, more complex, and more trustworthy body of knowledge on the psychology of cultural products.

Our second contribution is to the *processing fluency literature* and comes in three layers. First, standing on Reber et al.'s (2004) seminal review, we note that the extant literature has focused overwhelmingly on hedonic (i.e., dominantly pleasant) stimuli. By contrast, TED talks are qualitatively special, from a processing fluency perspective, because they contain not only entertaining but also educational components. Speaking to the latter, our process insights in S6 show that one's primary motivation for watching edutainment (i.e., hedonic pleasure vs. cognitive enrichment) moderates the deleterious impact of information load on audience adoption.

Second, our findings contribute to the debate (and conflicting findings) on when processing fluency has positive (vs. negative) downstream effects. It is worth noting indeed that different models of processing fluency make different predictions. As alluded already, the majority of the extant research finds that fluency produces favorable outcomes (Checkosky & Whitlock, 1973; Garner, 1974; Iyengar & Lepper, 2000; A. Y. Lee & Labroo, 2004; Mandel et al., 2006; Nunes et al., 2015; Reber et al., 1998, 2004; Reber & Schwarz, 1999; Shen et al., 2010; Stuppy et al., 2024; White et al., 2011; Zajonc, 1968). By contrast, a small but mounting body of work suggests that *dis*fluency may produce favorable outcomes (Alter, 2013; Alter et al., 2007; Bjork & Bjork, 2020; Graf & Landwehr, 2015; Markowitz, 2023). We contribute to this debate by shedding light on not only process but also boundary conditions. Specifically, we identify when, why, and for whom (dis)fluency helps (vs. impede) interest (e.g., NFC in S5; goals in S6).

Our third contribution to the processing fluency literature comes in the form of another boundary condition: messages' delivery medium. A priori, which mode of communication is best to convey information-laden long-form messages? On the one hand, text communications have the benefit of being self-paced. Accordingly, readers can make sense of information at their own speed, which should ease processing fluency. On the other hand, whether in person or on camera, oral communications grant speakers advantages that text does not (e.g., hand gesturing, body language, showmanship, facial expressions, tonal accentuations, voice depth, speech speed). This too should ease processing fluency for recipients. Ex ante, then, it is unclear which delivery medium is best to convey high-load, multitopic messages. Fortunately, the insights uncovered herein shed light on the question and begin to answer it. S7 shows indeed that the total effect of information load (on audience adoption) is more damaging when people *view* an address than when they read one. This finding has practical implications for communicators of all creeds (e.g., professors, politicians, journalists, scientists, bloggers, podcasters, content editors, online community managers) when they alternate between modes of delivery (more on this in the next section).

Practical Implications

From a societal standpoint, our findings benefit four constituencies. The first beneficiaries are consumers of edutainment. S1A and S1B indeed unearthed a disutility issue for audiences whereby consumers are naturally attracted by talks intending to cover more topics. Ultimately, however, most viewers will prefer addresses discussing fewer topics. By documenting the gap between choice and enjoyment of cultural products, we hope to (a) free prospective viewers from faulty intuitions and (b) restore a bit of personal welfare (more on this in the Limitations and Future Directions section below).

The second beneficiaries are suppliers of edutainment. Indeed, our findings yield *prescriptive* insights to direct suppliers of talks (e.g., presenters) and to institutional suppliers (e.g., TED, Talks@Google, The Moth, Big Think, Idea City, Spotify, and all other platforms that curate, promote, and distribute edutainment). In an industry whose very business hinges on attracting eyeballs, our results inform these players on what to do (and what to avoid) when producing their content.

The third beneficiaries are communicators at large. Looking beyond the edutainment industry (i.e., beyond TED speakers and beyond institutional players), we see a constellation of potential beneficiaries from the insights uncovered herein. Take B2C firms and nongovernmental organizations as examples. Through costly advertising and through their own websites, these organizations engage in storytelling in hopes to fuel brand liking and interest. Similarly, politicians, op-ed columnists, critics, bloggers, and journalists compete for eyes, ears, and brain share. To communicators of many creeds then, our findings offer insights (with tailored boundary conditions) that help maximize (minimize) interest, liking, and sharing (disinterest, disliking, disengagement). We note the appetite for such insights is evident; the market is indeed full of books, press articles, workshops, and blogs promising to turn anyone into a master communicator (see Supplemental Material K).

Fourth and last, we sound a tune of caution for our fellow academics. Worldwide, the trend nowadays is to enrich scientific pursuits through interdisciplinary research. Neuroscientists and anthropologists team up with economists, biologists and engineers join forces with astrophysicists, and so forth. Inevitably, interdisciplinary research entails the juxtaposition of multiple ideas, concepts, and methodologies. While much is to be gained scholarly from such an approach, special care should be given when (a) communicating its merits to funding agencies (e.g., in grant applications) and (b) disseminating its findings (particularly to laymen, low NFC audiences).

Limitations and Future Directions

The limitations of our research (see Table 9) pave the way for future directions. For instance, whereas we focused on audience adoption (approximated through choice, number of views received, interest, liking, and one's propensity to repost content for friends and family), a distinct outcome may be worth examining: *learning*. How does information load impact what people understand and retain from a talk? Does information load interact with NFC or with other personality dimensions? And, if so, positively or negatively? We took one modest step in answering this call. Extending the results of Studies 2–8, Study 9 suggests that information load hurts not only audience adoption but also audience learning (for procedural and statistical details, we refer the reader to Supplemental Material L). Sensitivity analyses for this and all preceding studies are reported in Supplemental Materials M.

A second avenue for research regard the disentangling of (hedonic) choice and impression management. Asked plainly, could self-presentation motives contribute to our findings? Impression management can indeed be a powerful driver of behavior, to the point where individuals willfully forego immediate enjoyment to signal something about themselves to others or to the self (e.g., a consumer choosing a less preferred dish at a restaurant to signal uniqueness vis-a-vis friends at the table; Ariely & Levav, 2000). Future research may explore whereas self-presentation motives cause viewers to seek/watch a talk intending to cover more topics (as signaled by the number of descriptive tags attached) even though, on average, they are likelier to prefer an alternative broaching fewer topics.

To conclude, whether it is through processing fluency or via other theoretical lenses, we hope our work will spur interest in the psychology of adoption, particularly as it relates to cultural products. Indeed, communicators of all creeds stand to gain from better understanding how to address their audiences (e.g., researchers, politicians, journalists, bloggers, podcasters, novelists, movie directors).

Table 9
Table of Limitations

Limitation	Source
Our Prolific Academic samples are more varied (e.g., in age, education, income) than typical university student samples. Yet, by virtue of being North American residents (U.S. residents to be exact), our samples boast Western, educated, industrialized, rich, and democratic characteristics. This causes uncertainty regarding the generalizability of our findings in developing regions.	Sample used in lab studies
Our "real-world" data from the TED platform is international, but we do not know the geographic or ethnic breakdown of viewers.	Viewers' demographics in field data
Organic viewers of TED talks (i.e., individuals who are not experimentally assigned to viewing talks) may not be representative of the general population. We suspect such viewers may indeed be above average in a variety of traits and characteristics (e.g., education, income, need for cognition).	Viewers' characteristics in field data
Despite a multipronged approach to produce positive evidence for our process explanation while discounting competing accounts (e.g., mediation analyses and conceptually derived moderations), caution is warranted regarding our empirical work. Indeed, we do not manipulate information load in the *strictest* sense of the word (i.e., we do not manufacture from scratch TED talks wherein we decide ourselves the number of topics to be broached). Instead, we operationalize information load as naturally as possible, either by measuring it in the field (via text mining) or by varying it clinically in the lab (e.g., by randomly drawing talks with low, vs. high, load from TED's repository).	Operationalization of information load

References

Adler, M. (1985). Stardom and talent. *The American Economic Review*, *75*(1), 208–212. https://www.jstor.org/stable/1812714

Alter, A. L. (2013). The benefits of cognitive disfluency. *Current Directions in Psychological Science*, *22*(6), 437–442. https://doi.org/10.1177/0963721413498894

Alter, A. L., & Oppenheimer, D. M. (2009). Uniting the tribes of fluency to form a metacognitive nation. *Personality and Social Psychology Review*, *13*(3), 219–235. https://doi.org/10.1177/1088868309341564

Alter, A. L., Oppenheimer, D. M., Epley, N., & Eyre, R. N. (2007). Overcoming intuition: Metacognitive difficulty activates analytic reasoning. *Journal of Experimental Psychology: General*, *136*(4), 569–576. https://doi.org/10.1037/0096-3445.136.4.569

Ariely, D., & Levav, J. (2000). Sequential choice in group settings: Taking the road less traveled and less enjoyed. *The Journal of Consumer Research*, *27*(3), 279–290. https://doi.org/10.1086/317585

Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., & Schweidel, D. A. (2020). Uniting the tribes: Using text for marketing insight. *Journal of Marketing*, *84*(1), 1–25. https://doi.org/10.1177/0022242919873106

Berger, J., & Packard, G. (2018). Are atypical things more popular? *Psychological Science*, *29*(7), 1178–1184. https://doi.org/10.1177/0956797618759465

Bielby, W. T., & Bielby, D. D. (1994). "All hits are flukes": Institutionalized decision making and the rhetoric of network prime-time program development. *American Journal of Sociology*, *99*(5), 1287–1313. https://doi.org/10.1086/230412

Bjork, R. A., & Bjork, E. L. (2020). Desirable difficulties in theory and practice. *Journal of Applied Research in Memory and Cognition*, *9*(4), 475–479. https://doi.org/10.1016/j.jarmac.2020.09.003

Blei, D., Carin, L., & Dunson, D. (2010). Probabilistic topic models: A focus on graphical model design and applications to document and image analysis. *IEEE Signal Processing Magazine*, *27*(6), 55–65. https://doi.org/10.1109/MSP.2010.938079

Bond, R., & Smith, P. B. (1996). Culture and conformity: A meta-analysis of studies using Asch's (1952b, 1956) line judgment task, 119 PSYCHOL. *Psychological Bulletin*, *111*(1), 124–128. https://doi.org/10.1037/0033-2909.119.1.111

Cacioppo, J. T., & Petty, R. E. (1982). The need for cognition. *Journal of Personality and Social Psychology*, *42*(1), 116–131. https://doi.org/10.1037/0022-3514.42.1.116

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. *Psychological Bulletin*, *119*(2), 197–253. https://doi.org/10.1037/0033-2909.119.2.197

Cacioppo, J. T., Petty, R. E., & Kao, C. F. (1984). The efficient assessment of need for cognition. *Journal of Personality Assessment*, *48*(3), 306–307. https://doi.org/10.1207/s15327752jpa4803_13

Cacioppo, J. T., Petty, R. E., & Morris, K. J. (1983). Effects of need for cognition on message evaluation, recall, and persuasion. *Journal of Personality and Social Psychology*, *45*(4), 805–818. https://doi.org/10.1037/0022-3514.45.4.805

Caves, R. E. (2000). *Creative industries: Contracts between art and commerce* (Issue 20). Harvard University Press.

Checkosky, S. F., & Whitlock, D. (1973). Effects of pattern goodness on recognition time in a memory search task. *Journal of Experimental Psychology*, *100*(2), 341–348). https://doi.org/10.1037/h0035692

Chen, B., Chen, X., & Xing, W. (2015). "Twitter archeology" of learning analytics and knowledge conferences. *ACM International conference proceeding series, 16–20-Marc* (pp. 340–349). ACM Digital Library. https://doi.org/10.1145/2723576.2723584

Chung, C., & Pennebaker, J. W. (2007). The psychological functions of function words. In K. Fiedler (Ed.), *Social communication* (pp. 343–359). Psychology Press.

Cialdini, R. B., & Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annual Review of Psychology*, *55*(1), 591–621. https://doi.org/10.1146/annurev.psych.55.090902.142015

De Vany, A. (2004). *Hollywood economics: How extreme uncertainty shapes the film industry*. Routledge.

Fiske, S. T., Cuddy, A. J. C., Glick, P., & Xu, J. (2018). A model of (often mixed) stereotype content: Competence and warmth respectively follow from perceived status and competition. In S. Fiske (Ed.), *Social cognition* (pp. 162–214). Routledge. https://doi.org/10.4324/9781315187280-7

Fiske, S. T., Xu, J., Cuddy, A. C., & Glick, P. (1999). (Dis) respecting versus (dis) liking: Status and interdependence predict ambivalent stereotypes of competence and warmth. *Journal of Social Issues*, *55*(3), 473–489. https://doi.org/10.1111/0022-4537.00128

Frank, R. H., & Cook, P. J. (1995). *The winner-take-all: Society*. Penguin.

Garner, W. R. (1974). The stimulus in information processing. In H. R. Moskowitz, B. Scharf, & J. C. Stevens (Eds.), *Sensation and measurement* (pp. 77–90). Springer. https://doi.org/10.1007/978-94-010-2245-3_7

Graf, L. K. M., & Landwehr, J. R. (2015). A dual-process perspective on fluency-based aesthetics: The pleasure-interest model of aesthetic liking. *Personality and Social Psychology Review*, *19*(4), 395–410. https://doi.org/10.1177/1088868315574978

Graf, L. K. M., Mayer, S., & Landwehr, J. R. (2018). Measuring processing fluency: One versus five items. *Journal of Consumer Psychology*, *28*(3), 393–411. https://doi.org/10.1002/jcpy.1021

Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(Suppl. 1), 5228–5235. https://doi.org/10.1073/pnas.0307752101

Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford Press.

Humphreys, A., & Wang, R. J. H. (2018). Automated text analysis for consumer research. *The Journal of Consumer Research*, *44*(6), 1274–1306. https://doi.org/10.1093/jcr/ucx104

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology*, *79*(6), 995–1006. https://doi.org/10.1037/0022-3514.79.6.995

Jacoby, J. (1977). Information load and decision quality: Some contested issues. *Journal of Marketing Research*, *14*(4), 569–573. https://doi.org/10.1177/002224377701400414

Jacoby, J. (1984). Perspectives on Information Overload Linked references are available on JSTOR for this article: Perspectives on information overload. *The Journal of Consumer Research*, *10*(4), 432–435. https://doi.org/10.1086/208981

Jacoby, J., Kohn, C. A., & Speller, D. E. (1973). Time spent acquiring product information as a function of information load and organization. *Proceedings of the annual convention of the American psychological association* (pp. 817–818). American Psychological Association.

Jacoby, J., Speller, D. E., & Berning, C. K. (1974). Brand choice behavior as a function of information load: Replication and extension. *The Journal of Consumer Research*, *1*(1), 33–42. https://doi.org/10.1086/208579

Jacoby, J., Speller, D. E., & Kohn, C. A. (1974). Brand choice behavior as a function of information load. *Journal of Marketing Research*, *11*(1), 63–69. https://doi.org/10.1177/002224377401100106

Krueger, A. B. (2005). The economics of real superstars: The market for rock concerts in the material world. *Journal of Labor Economics*, *23*(1), 1–30. https://doi.org/10.1086/425431

Lee, A. Y., & Aaker, J. L. (2004). Bringing the frame into focus: The influence of regulatory fit on processing fluency and persuasion. *Journal of Personality and Social Psychology*, *86*(2), 205–218. https://doi.org/10.1037/0022-3514.86.2.205

Lee, A. Y., & Labroo, A. A. (2004). The effect of conceptual and perceptual fluency on brand evaluation. *Journal of Marketing Research*, *41*(2), 151–165. https://doi.org/10.1509/jmkr.41.2.151.28665

Lee, B. K., & Lee, W. N. (2004). The effect of information overload on consumer choice quality in an on-line environment. *Psychology and Marketing*, *21*(3), 159–183. https://doi.org/10.1002/mar.20000

Levin, I. P., Huneke, M. E., & Jasper, J. D. (2000). Information processing at successive stages of decision making: Need for cognition and inclusion-exclusion effects. *Organizational Behavior and Human Decision Processes*, *82*(2), 171–193. https://doi.org/10.1006/obhd.2000.2881

Malhotra, N. K. (1982). Information load and consumer decision making. *The Journal of Consumer Research*, *8*(4), 419–430. https://doi.org/10.1086/208882

Mandel, N., Petrova, P. K., & Cialdini, R. B. (2006). Images of success and the preference for luxury brands. *Journal of Consumer Psychology*, *16*(1), 57–69. https://doi.org/10.1207/s15327663jcp1601_8

Markowitz, D. M. (2023). Instrumental goal activation increases online petition support across languages. *Journal of Personality and Social Psychology*, *124*(6), 1133–1145. https://doi.org/10.1037/pspa0000333

Markowitz, D. M., & Shulman, H. C. (2021). The predictive utility of word familiarity for online engagements and funding. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(18), Article e2026045118. https://doi.org/10.1073/pnas.2026045118

Miller, G. A. (1956). The magical number seven plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, *63*(2), 81–97. https://doi.org/10.1037/h0043158

Nunes, J. C., Ordanini, A., & Valsesia, F. (2015). The power of repetition: Repetitive lyrics in a song increase processing fluency and drive market success. *Journal of Consumer Psychology*, *25*(2), 187–199. https://doi.org/10.1016/j.jcps.2014.12.004

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). *The development and psychometric properties of LIWC2015*. University of Texas at Austin. https://doi.org/10.15781/T29G6Z

Pennebaker, J. W., Chung, C. K., Frazee, J., Lavergne, G. M., & Beaver, D. I. (2014). When small words foretell academic success: The case of college admissions essays. *PLOS ONE*, *9*(12), Article e115844. https://doi.org/10.1371/journal.pone.0115844

Peterson, R. A., & Berger, D. G. (1971). Entrepreneurship in organizations: Evidence from the popular music industry. *Administrative Science Quarterly*, *16*(1), 97–106. https://doi.org/10.2307/2391293

Petrova, P. K., & Cialdini, R. B. (2005). Fluency of consumption imagery and the backfire effects of imagery appeals. *The Journal of Consumer Research*, *32*(3), 442–452. https://doi.org/10.1086/497556

Reber, R., & Schwarz, N. (1999). Effects of perceptual fluency on judgments of truth. *Consciousness and Cognition*, *8*(3), 338–342. https://doi.org/10.1006/ccog.1999.0386

Reber, R., Schwarz, N., & Winkielman, P. (2004). Processing fluency and aesthetic pleasure: Is beauty in the perceiver's processing experience? *Personality and Social Psychology Review*, *8*(4), 364–382. https://doi.org/10.1207/s15327957pspr0804_3

Reber, R., Winkielman, P., & Schwarz, N. (1998). Effects of perceptual fluency on affective judgments. *Psychological Science*, *9*(1), 45–48. https://doi.org/10.1111/1467-9280.00008

Richard, S. (1998). *Social mechanisms: An analytical approach to social theory*. Cambridge University Press.

Rosen, S. (1981). The economics of superstars. *The American Economic Review*, *71*(5), 845–858. https://www.jstor.org/stable/1803469

Salganik, M. J., Dodds, P. S., & Watts, D. J. (2006). Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, *311*(5762), 854–856. https://doi.org/10.1126/science.1121066

Schwarz, N. (2004). Metacognitive experiences in consumer judgment and decision making. *Journal of Consumer Psychology*, *14*(4), 332–348. https://doi.org/10.1207/s15327663jcp1404_2

Schwarz, N. (2012). Feelings-as-information theory. In P. A. M. Van Lange, A. W. Kruglanski, & E. T. Higgins (Eds.), *Handbook of theories of social psychology* (pp. 289–308). Sage Publications.

Schwarz, N., Bless, H., Strack, F., Klumpp, G., Rittenauer-Schatka, H., & Simons, A. (1991). Ease of retrieval as information: Another look at the availability heuristic. *Journal of Personality and Social Psychology*, *61*(2), 195–202. https://doi.org/10.1037/0022-3514.61.2.195

Sepehri, A., Duclos, R., & Haghighi, N. (2022). Too much of a good thing? The unforeseen cost of tags in online retailing. *International Journal of Research in Marketing*, *39*(2), 336–348. https://doi.org/10.1016/j.ijresmar.2021.10.004

Sepehri, A., Duclos, R., & Haghighi, N. (2024). *Ideas worth spreading? When, why, and for whom information load hurts online talks' popularity*. https://osf.io/b6gdz

Shen, H., Jiang, Y., & Adaval, R. (2010). Contrast and assimilation effects of processing fluency. *The Journal of Consumer Research*, *36*(5), 876–889. https://doi.org/10.1086/612425

Stuppy, A., Landwehr, J. R., & McGraw, A. P. (2024). The art of slowness: Slow motion enhances consumer evaluations by increasing processing fluency. *Journal of Marketing Research*, *61*(2), 185–203. https://doi.org/10.1177/00222437231179187

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, *29*(1), 24–54. https://doi.org/10.1177/0261927X09351676

Toubia, O., Berger, J., & Eliashberg, J. (2021). How quantifying the shape of stories predicts their success. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(26), Article e2011695118. https://doi.org/10.1073/pnas.2011695118

Vogel, H. L. (2004). *Entertainment industry economics* (6th ed.). Cambridge University Press.

Watts, D. J. (2002). A simple model of global cascades on random networks. *Proceedings of the National Academy of Sciences of the United States of America*, *99*(9), 5766–5771. https://doi.org/10.1073/pnas.082090499

White, K., MacDonnell, R., & Dahl, D. W. (2011). It's the mind-set that matters: The role of construal level and message framing in influencing consumer efficacy and conservation behaviors. *Journal of Marketing Research*, *48*(3), 472–485. https://doi.org/10.1509/jmkr.48.3.472

White, K., & Willness, C. (2009). Consumer reactions to the decreased usage message: The role of elaborative processing. *Journal of Consumer Psychology*, *19*(1), 73–87. https://doi.org/10.1016/j.jcps.2008.12.010

Zajonc, R. B. (1968). Attitudinal effects of mere exposure. *Journal of Personality and Social Psychology*, *9*, 1–27. https://doi.org/10.1037/h0025848

Received November 1, 2023
Revision received August 15, 2024
Accepted September 5, 2024 ■