

UC Davis

UC Davis Electronic Theses and Dissertations

Title

Leveraging Multimodal Features in Short Videos to Communicate Risks in a Sensational Media Environment

Permalink

<https://escholarship.org/uc/item/7422m1w6>

Author

Xue, Haoning

Publication Date

2024

Peer reviewed|Thesis/dissertation

Leveraging Multimodal Features in Short Videos to Communicate Risks in a Sensational Media Environment

By

HAONING XUE
DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Communication

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA

DAVIS

Approved:

Jingwen Zhang, Chair

Cuihua Shen

Magdalena Wojcieszak

Committee in Charge
2024

Acknowledgments

I would like to express my deepest gratitude to my advisor Dr. Jingwen Zhang for her invaluable guidance and support throughout the past five years. Her mentorship has shaped my growth as an independent researcher. I am grateful for her constant faith in me, especially during times when I doubted myself. I look forward to continuing our collaboration and maintaining our connection in the years to come.

I would like to extend my heartfelt thanks to my amazing committee members, Dr. Cuihua Shen and Dr. Magdalena Wojcieszak, for serving on my thesis, qualification exam, and now my dissertation committee. I appreciate their consistent support and guidance as committee members, collaborators, and mentors throughout my PhD journey. It is an honor to work with such distinguished scholars, and I look forward to continued collaboration.

I am deeply grateful to all my collaborators as well as the faculty and staff in the Department of Communication for their support and encouragement throughout my PhD journey. I would like to extend my gratitude to my cohort as well as the members of the CHATR lab for their camaraderie and for all the memorable moments at Davis.

I owe my greatest thanks and love to my parents. Their unwavering love, support, and understanding give me strength and perseverance. I want to thank my best friend, Haihao Zhu, for his steadfast companion and for sharing every bit of the ups and downs of my journey. I also want to thank Spade for being the perfect cat and my best purring company.

Table of Contents

Acknowledgments.....	ii
Abstract.....	v
Chapter 1 Introduction	1
1.1 Dissertation Overview	4
Chapter 2 Literature Review	6
2.1 Short Video Platforms as Science Information Hub.....	6
2.2 Message Sensation Value: Theorizing Short Videos' Effects	10
Chapter 3 A Holistic Approach to Multimodal Features: A Validated Computational Measure of Message Sensation Value in Short Videos	19
3.1 Introduction.....	20
3.2 Message Sensation Value: Objective versus Perceived.....	21
3.3 Theoretical Perspectives of MSV	24
3.4 Audiovisual Features in the Present Study	28
3.5 Methods.....	32
3.6 Results.....	46
3.7 Discussion	55
Chapter 4 Message Sensation Value in Short Videos Enhances Message Processing and Persuasion, Especially for Young Adults	59
4.1 Introduction.....	60
4.2 MSV: Attention-Attractor or Attention-Distractor?	63
4.3 Sensation-seeking Beyond Young Adulthood.....	66
4.4 The Influence of Motivated Reasoning.....	68
4.5 Methods.....	69
4.6 Results.....	81
4.7 Discussion	88

Chapter 5 Discussion and Conclusion	94
5.1 Limitations and Future Directions	97
5.2 Conclusion	98
Reference	99
Appendices.....	123

Abstract

Short video platforms have emerged as key information sources, while the proliferation of misinformation on these platforms poses challenges for science and risk communication to adapt to emerging media formats and provide effective scientific surveillance on these platforms. This dissertation proposes that sensational short videos should be considered as an innovative solution to effectively communicate science and risk information in the current information ecosystem. Grounded on the theoretical framework of Message Sensation Value (MSV), this dissertation (a) investigates the relationship between MSV and public engagement and develops a computational measure of MSV with a computational observational study, and (b) examines the theoretical mechanism by which MSV in short videos impacts message attention, processing, and persuasiveness in the context of COVID-19 and climate change with an online experiment.

Relying on a computational analysis of $N = 1,200$ short videos, the observational study reveals a consistent inverted U-shaped relationship between MSV and engagement, where videos with moderate levels of MSV are most engaging. This study also presents a computational measure of MSV using multimodal features with high reliability and validity. Built upon the insights in the observational study, the online experiment uses a within-subject experimental design and investigates the impacts of MSV (low, mid, high) in short videos for $N = 1,467$ participants in the United States. Results showed that MSV enhanced message processing and persuasiveness across varying belief congruence, while MSV did not affect attention or risk perception. In addition, contrary to existing research that emphasizes the impact of sensation-seeking and belief congruence, age was found to moderate MSV's effects, which were particularly prominent for young adults.

Overall, with both observational and experimental evidence, this dissertation demonstrates that MSV enhances message engagement and persuasiveness to a certain extent and suggests the possibility of leveraging sensational multimodal features in short videos to improve message persuasiveness and engagement for effective science and risk communication. This dissertation provides significant theoretical contributions and practical implications for communicating risks in the contemporary media landscape. First, this dissertation advances our understanding of MSV's persuasive impacts and provides a useful theoretical framework for understanding multimodal information. Second, this computational measure of MSV provides a robust and automated tool for estimating MSV in short videos, facilitating the empirical research of short videos and MSV. Lastly, this study provides theory-informed practical implications and actionable guidelines for content production on short video platforms, which could increase the visibility of scientific information and establish scientific surveillance on short video platforms.

Chapter 1 Introduction

The contemporary high-sensation and high-choice social media environment, exemplified by short-video platforms such as TikTok, YouTube Shorts, and Instagram Reels, provides both challenges and opportunities to communicate important science, health, environment, and risk information. Short video platforms have transformed into key sources for news and information due to their massive user base. As of 2020, TikTok has garnered 50 million daily active users in the U.S. (Sherman, 2020); Instagram Reels reached 2.35 billion monthly active users in 2023 (Ruby, 2023). Remarkably, 43% of U.S. adults regularly get news from TikTok (Matsa, 2023), equaling Facebook's reach for news audience and right below X (formerly Twitter, 53%). These platforms not only serve as information hubs but also empower ordinary users to create and share content to participate in discussions on science, health, and environmental issues (McCashin & Murphy, 2023). Over half of TikTok users have posted videos, with 25% of its user base generating 98% of the platform's content (Bestvater, 2024). During the COVID-19 pandemic, there was a surge in videos from both experts and the general public advocating for vaccinations and healthy practices (Basch et al., 2021; Li et al., 2021; Southwick et al., 2021).

However, Short video platforms have become a major source of misinformation (Alonso López et al., 2021; Hsu, 2022), particularly concerning critical issues like the COVID-19 vaccine (Little & Richards, 2021) and climate change (Basch et al., 2022). Accompanying recent extreme weather and deadly floods are the uproaring climate change denialism and conspiracy theories on social media (Calma, 2023; Romero-Vicente, 2023). Conspiracy theories such as the fear of “green agenda” and climate change denialism undermine public understanding and climate

actions (Richards, 2022). Likewise, the COVID-19 pandemic and the monkeypox outbreak have seen a proliferation of misinformation on short video platforms (Czopek, 2023; Zadrozny, 2021), including the fear of the “mystery virus” on TikTok with a new variant of COVID-19 (Choi, 2024).

On the contrary, public health and science communication efforts have not sufficiently engaged with this emerging information hub that “lacks scientific oversight” (Eghtesadi & Florea, 2020, p. 391). Fact-checking video content is still rare on short video platforms (Newman, 2022); videos communicating science and risk information are predominantly produced by non-authoritative and non-expert accounts (McCashin & Murphy, 2023). In addition, a lot of science and risk communications on social media tend to be generic and impersonal, resulting in ineffective communication and sometimes even backfiring effects (Kreps & Neuhauser, 2013; Y. Wang et al., 2019). Traditional risk communication style that features standard information presentation may be becoming obsolete and hard to compete for attention on short video platforms that prioritize sensational multimodal features (Collie & Wilson-Barnao, 2020). To date, although there is some research examining science communication on social media and short video platforms (e.g., Richards, 2022; Southerton, 2021; van Kampen et al., 2022), it remains largely unknown how we can employ short video features to increase the engagement and persuasion of risk communication on these platforms to the general public. With the ongoing plague of misinformation critical issues like COVID-19 and climate change, it is urgent to investigate the theoretical mechanisms of multimodal features’ persuasive effects and identify effective public risk communication strategies to counter misinformation influence and update accurate risk perceptions on COVID-19 and climate change.

Observing how misinformation and scientific short videos are produced and disseminated on social media (O’Sullivan et al., 2022; Sharevski et al., 2023; Southwick et al., 2021), I propose that sensational short videos should be considered as an innovative solution to effective risk communication in the current social media information ecosystem. Message sensation value (MSV) is a theoretical construct that connects multimodal features of short videos with public attention and subsequent persuasive outcomes (e.g., credibility judgment and risk perception). Developed in the era of television programs, MSV quantifies the extent to which objectively measured message features and audiovisual content attract attention and elicit affective responses (Everett & Palmgreen, 1995; Kang et al., 2006; Palmgreen et al., 1991). MSV provides a theoretical foundation to assess the collective impact of multimodal features in short videos, a unified perspective that is missing in the current research on short videos’ effects.

While MSV serves as a useful theoretical framework for evaluating short videos’ impacts, there are two notable research gaps in the current research landscape. First, there is an urgent need for an accurate, current, and efficient measure of MSV to investigate its impacts. The existing measure of MSV (Morgan et al., 2003) was developed 20 years ago in the context of Public Service Announcements (PSAs) and relies on human annotation of multimodal features. An updated measure is needed to capture the nuances and dynamics of today’s media landscape more accurately and effectively. Second, while there is substantial empirical research exploring MSV’s effects on high-risk behaviors among young adults, it remains unclear how MSV in short videos impacts message processing and persuasive outcomes, especially across broader demographic groups. To bridge this gap, it is necessary to examine the precise theoretical mechanisms underlying the persuasive effects of MSV in short videos for the general population in broader risk communication contexts.

Employing a combination of computational video analysis and online experiment, this dissertation aims to (a) develop a computational measure of MSV with multimodal features and investigate the relationship between MSV and public engagement, and (b) examine the theoretical mechanism by which MSV in science short videos impacts message attention, processing, persuasiveness, and risk perceptions in the context of COVID-19 and climate change. This dissertation can expand our understanding of how individuals process multimodal video information in a complex media environment, which addresses a significant gap in decision-making and information-processing research. This comprehensive approach provides both observational and experimental evidence for enhancing our understanding of the contemporary media landscape.

1.1 Dissertation Overview

This dissertation is organized as follows. To overview the existing research on short videos for science communication and understand the conceptual space of MSV, Chapter 2 reviews the existing literature on short videos' impacts in the context of science, health, environment, and risk communication. In addition, Chapter 2 introduces the concepts of and theoretical frameworks related to MSV, highlighting its relevance and importance to the study context.

Chapter 3 details a study that uses computational video analysis and machine learning techniques to develop and validate a computational measure of MSV in short videos. This computational measure that automatically assesses the MSV of short videos is developed based on a comprehensive dataset of short videos and further validated the measure with an additional dataset. The computational measure adapts the existing objective measure of MSV in PSAs to the contemporary context of short videos and supports its theoretical foundation by

demonstrating the inverted U-shaped relationship between MSV and public engagement in multiple contexts. This measure demonstrates high reliability and validity. This research advances both empirical and theoretical research on short videos' effects and provides theory-informed practical guidelines for effective public communication on short video platforms.

Given the correlational nature of the relationship between MSV and engagement in the study presented in Chapter 3, Chapter 4 presents an online experiment that examines the causal persuasive impact of MSV and investigates the underlying theoretical mechanism. Built upon the computational measure and insights in Chapter 3, this experiment crafts video stimuli with both internal and external validity to examine how short videos with varying levels of MSV affect attention, cognitive and affective information processing, perceived credibility, engagement intentions, and risk perceptions. Results showed that [TBC].

Chapter 5 concludes this dissertation by summarizing the major findings, discussing both theoretical and practical implications, addressing the limitations of this dissertation, and proposing future research directions.

Chapter 2 Literature Review

2.1 Short Video Platforms as Science Information Hub

Short video platforms, characterized by portrait videos that usually last less than 60 seconds, have emerged as an important information source (Matsa, 2023), particularly for Generation Z (Huang, 2022). Remarkably, 43% of U.S. adults regularly get news from TikTok (Matsa, 2023), equaling Facebook's reach for news audience and right below X (formerly Twitter, 53%). These platforms boost a substantial audience base: TikTok has garnered 50 million daily active users in the U.S. (Sherman, 2020), while YouTube Shorts has amassed 50 billion daily views (Mehta, 2023).

The popularity of short video platforms is contributed by attention-grabbing and visually engaging formats of short videos (Butler, 2023). Short video platforms' technical infrastructure supports high-sensation, visually engaging, and immersive multimodal features, such as chroma keying, lip-syncing, and augmented reality (AR) filters (Collie & Wilson-Barnao, 2020) (see Figure 2.1). These features can greatly enhance the entertainment values of short videos and allow any user to make complex videos that juxtapose texts, pictures, videos, and animations. A higher content contribution has been observed on short video platforms compared with other video platforms: over half of TikTok users have posted videos, with 25% of its user base generating 98% of the platform's content (Bestvater, 2024).

Short videos featured by these multimodal features are inherently more engaging and have stronger influences on individual perception, cognition, and emotion (Y. Wang, 2020).

First, multimodal information can be perceived as more credible and persuasive in comparison to text-based information, because the “seeing is believing” *realism heuristic* of multimodal content can better assemble the real world and easily amplify the persuasiveness of video content (Sundar, 2008). Second, from the perspective of cognitive processing, according to the dual coding theory (DCT; Paivio, 1991), individuals process multimodal information with both visual and verbal systems, resulting in more cognitive resources allocated as well as better memory and learning outcomes with both systems activated (Mayer & Sims, 1994). Lastly, multimodal information is more engaging because it is easier for people to get immersed in information that activates multiple senses and creates a higher level of social presence and immersion (Biocca et al., 2003; Y. Wang, 2020). Overall, short videos represent a powerful format of information.

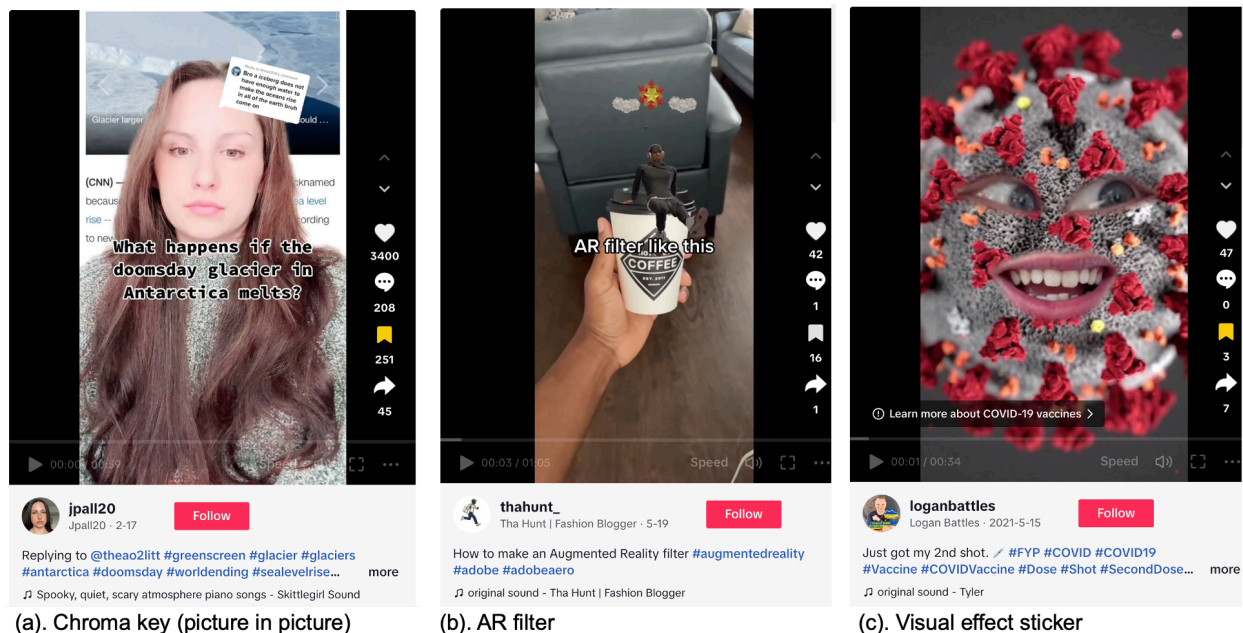


Figure 2.1 Examples of multimodal features and platform built-in functions on short video platforms.

Along with the soaring popularity, short video platforms have become a major source of misinformation (Bhargava et al., 2023; Hsu, 2022). During the early stage of the COVID-19 pandemic, more than 20% of short videos contained misinformation (Southwick et al., 2021). TikTok has seen the proliferation of climate change conspiracy videos with more than 150 million views (Richards, 2022). Misinformation videos have fully utilized these technical affordances to attract public attention, at the same time complicating and hindering automated misinformation detection and correction. A prime example is the stitch function that allows users to integrate others' videos with misinformation directly into one's video production. Such functions smooth the re-creation and virality of short videos (Bhargava et al., 2023). The proliferation of misinformation on these popular platforms poses significant risks to individual decision-making and public safety.

This proliferation of misinformation in short videos is concerning because misinformation communicated via multimodal video formats has stronger negative influences (Lee & Shin, 2022). On the one hand, misinformation tends to be more emotionally arousing, and various multimodal features such as negative facial expressions and visual effect stickers can further intensify emotional involvement (Carrasco-Farré, 2022). For instance, anti-vaccine short videos utilized distinctive visual appeal strategies than pro-vaccine videos, including persuasive gestures, negative facial emotions, and text stickers (Van Poucke, 2023). Misinformation videos often leverage platform built-in multimodal features, such as audio memes, video filters, and the stitch/duet function, to attract attention and increase virality (Alonso López et al., 2021). The accessibility of misinformation content and soundtracks with just one click allows for low-cost mass production of misinformation, and the built-in technical meshing of various contents makes misinformation detection and correction even more challenging to implement. On the other hand,

misinformation videos can easily go viral because the platform recommendation algorithm prioritizes content with high sensation value in terms of message content and message features. Misinformation often combines both for attention (Baptista & Gradim, 2020): eye-catching misinformation claims and emotionally charging visual effects. For instance, one research shows although TikTok prohibits misinformation, its algorithm recommends viral misinformation on the “For You” page (Little & Richards, 2021).

In contrast to how short videos are produced to disseminate misinformation, the traditional public communication style of scientific information is slow in adapting to the new media environment. A majority of science and risk information on social media tends to be generic and impersonal, resulting in ineffective communication and sometimes even backfiring effects (Kreps & Neuhauser, 2013; Y. Wang et al., 2019). Traditional risk communication style that features standard information presentation may be becoming obsolete and hard to compete for attention on short video platforms that prioritize sensational multimodal features (Collie & Wilson-Barnao, 2020). Regarding existing scientific information on short video platforms, fact-checking video content is still rare on short video platforms (Newman, 2022). Videos communicating science and risk information are predominantly produced by non-authoritative and non-expert accounts (McCashin & Murphy, 2023); a network analysis showed that authoritative accounts were less influential than individual influencers in the diffusion of climate change news on Douyin (Sun et al., 2024). There is an urgent need to improve the effectiveness of science communication on short video platforms.

The current literature has revealed the engaging and persuasive effects of multimodal features. Numerous studies suggest that multimodal features can enhance public engagement with science, such as scientific memes (Zeng et al., 2020) and the lip-syncing function

(Southerton, 2021). A recent study on fact-checking short videos revealed that video length, audio volume, and scientific memes positively predicted engagement, while visual complexity was revealed as a negative indicator of engagement (Y. Lu & Shen, 2023). These studies provide useful insights into the effects of individual features of short videos, however, this approach that analyzes multimodal features in isolation or simply aggregates them overlooks the unified and holistic perspective in processing multimodal information (Lahat et al., 2015). Through the theoretical lens of Message Sensation Value (MSV; Palmgreen et al., 1991), this study unifies various multimodal features and connects links multimodal features with short videos' impacts on public engagement and subsequent persuasive outcomes. Considering how multimodal features interact with each other rather than function in isolation provides a more nuanced understanding of the collective processing of multimodal information. The section below reviews existing research on MSV.

2.2 Message Sensation Value: Theorizing Short Videos' Effects

2.2.1 Message Sensation Value: Objective versus Perceived

Message Sensation Value (MSV) quantifies the extent to which *objectively* measured multimodal features of a message attract attention and elicit affective responses (Palmgreen et al., 1991). This concept focuses on the objective attributes of a message that contribute to human perceptions and affective responses, whereas Perceived Message Sensation Value (PMSV) represents the extent to which individuals *subjectively* perceive, react to, and evaluate a message (Palmgreen et al., 2002).

Distinguishing between MSV and PMSV—two conceptually related but distinct constructs—provides both theoretical clarity and practical utility. On the one hand, clarifying how objective message attributes are related to human perceptions helps us understand the

(dis)association between sensational message features and human evaluations. This is particularly relevant considering how individual dispositions such as sensation-seeking influence the perception of audiovisual features, such that individuals with high sensation-seeking tendencies are more susceptible to audiovisual features, while individuals with low sensation-seeking preferences prefer less sensational audiovisual features (Everett & Palmgreen, 1995). On the other hand, existing approaches to measuring MSV often conflate it with PMSV. For example, existing studies often use the PMSV scale as a proxy to assess the manipulation of MSV in stimuli, while the actual MSV in messages—rather than how MSV is perceived—is neglected. In addition, clarifying the concept and measurement of MSV is particularly insightful for real-world content production and experimental stimuli, with which creators and researchers have more control in the development phase (Morgan et al., 2003). This conceptual and operational ambiguity necessitates a clearer distinction between MSV and PMSV.

Morgan and colleagues (2003) introduced an *objective* MSV scale that relies on human annotation of audiovisual features in Public Service Announcements (PSAs). This measure encompasses three dimensions: (a) formal (structural) video features, (b) formal audio features, and (c) content features (Morgan et al., 2003). First, there are five video features, including the number of cuts and the presence of special visual effects, slow motion, unusual colors, and intense images. Second, audio features include the presence of sound saturation (background sound), background music, and (unusual) sound effects. Lastly, content features include three common persuasive/narrative techniques in PSAs, including the presence of acted-out (versus talking head), unexpected format, and surprise/twist ending.

While this structured approach systematically considers a wide range of multimodal features, there are several limitations. The primary concern lies in the subjective nature of

annotating certain message features that are supposed to be objectively defined and quantified. The ambiguity in defining what constitutes *unusual* sound effects, *unexpected* format, or *surprise* endings leads to significant variability in human evaluations and perceptions. This ambiguity may also compromise the measure's reliability since what is considered *surprising* often changes with time. Second, content-related features such as surprise endings go beyond the scope of multimodal features: they predominantly address the overarching message content rather than the audiovisual features of videos. It would be more relevant to MSV's definition to primarily focus on multimodal features that are unique to video content rather than those that transcend modalities. Third, this measure heavily relies on dichotomized annotation of message features, with 10 out of 11 features being coded as binary variables—the presence or absence of a given feature. This approach oversimplifies a rich spectrum of multimodal features and may potentially neglect nuanced details that are crucial to individual sensory processing. Lastly, although the method of aggregating 11 feature scores to compute the MSV score is standard for measures with a fixed scale point, it may not be an appropriate computation approach for this objective measure of multimodal features. This is because this method does not account for the varying relationships and interactions among features and the varying influence of different features on MSV. Despite these limitations, this MSV measure provides a useful framework to quantify the influence of multimodal features under the theoretical framework of MSV.

Regarding the measure of PMSV, Everett and Palmgreen (1995) initially developed the PMSV scale as a part of a pretest to assess the validity of the manipulation of MSV in televised PSAs. This semantic differential scale included 4 dimensions: emotional response (e.g., dramatic–undramatic), sensory response (e.g., strong sound effects–weak sound effects), novelty (e.g., unusual–usual), and physiological response (e.g., exciting–boring). This scale was

systematically updated and validated in a later study (Palmgreen et al., 2002), where three dimensions emerged from the 17 items: *emotional arousal* (e.g., arousing–not arousing), *dramatic impact* (e.g., creative–uncreative), and *novelty* (e.g., unique–not unique). This PMSV scale demonstrates high internal reliability and high construct and predictive validity across multiple contexts for individuals with varying sensation-seeking preferences. While PMSV and MSV have different focuses, PMSV is still theoretically aligned with MSV, representing the human perceptions of objective message attributes. Both concepts share the common ground of sensory experiences elicited by and perceptions of sensational message attributes. This theoretical alignment is supported by a highly positive correlation between PMSV and MSV in the literature (Morgan et al., 2003).

2.2.2 MSV: Attention-Attractor or Attention-Distractor?

MSV influences an individual's attention to persuasive messages (Stephenson, 1999). MSV activates the neural system, triggers the sensory processing of information, and impacts attention allocation (Imhof et al., 2017; Mesulam, 1998). Although attention is acknowledged as one of the most important outcome variables of MSV (Donohew et al., 1994), how MSV influences attention as well as the subsequent message processing and persuasive outcomes is debatable. Whether MSV functions as an *attention-attractor* or *attention-distractor* is predicted by different theoretical perspectives on the role of MSV in persuasive messages (Xu, 2017).

The first theoretical perspective argues for the *attention-attracting* effect of MSV. MSV represents message features that are integrated with persuasive messages. Both the Activation Model of Information Exposure (AMIE; Donohew et al., 1980) and the Limited Capacity Model of Mediated Message Processing (LC4MP; Lang, 2000) highlight the attention-attracting role of MSV. This attention-attracting effect comes from AMIE's assumption that individuals are

motivated to seek sensory experiences that are characterized by “newness, change, sensation, or inconsistency” (Donohew et al., 1980, p. 296). Persuasive messages with sensational message features would satisfy this motivation for sensory experiences, thereby receiving more attention. LC4MP shares a similar argument that compared with neutral information, arousing and novel information tends to have more cognitive resources and attention allocated for information processing, given the limited cognitive capacity assumption (Lang, 2000).

The second theoretical perspective argues for the *attention-distracting* effect of MSV. The Elaboration Likelihood Model (ELM; Petty & Cacioppo, 1986) adopts a unique theoretical perspective of dual message processing, which perceives message content and message features as separate components in a persuasive message. With dual message processing, message content undergoes the central route and receives more cognitive efforts, which contrasts message features that are processed with the peripheral route with fewer cognitive resources. MSV represents sensational message features that activate the peripheral message processing (Kang et al., 2006), whereas the main message content is processed using the central route which requires more cognitive effort (Petty & Cacioppo, 1986). Therefore, ELM highlights the *attention-distracting* role of MSV: as high MSV attracts attention to message features, fewer cognitive resources are allocated to the central route for individuals to carefully process the message content, given the assumption of limited cognitive capacity in information processing. In this way, with limited cognitive resources, individuals are less likely to process message content, neither cognitively nor affectively.

In addition to these two competing theoretical arguments, AMIE provides a more nuanced “matching hypothesis” that emphasizes the significance of individual sensation-seeking preferences. Sensation seeking represents “the need for varied, novel, and complex sensations

and experience and the willingness to take physical and social risks for the sake of such experience” (Zuckerman, 1990, p. 313). AMIE argues that persuasive messages with MSV that match one’s optimal sensation-seeking tendencies would maximize attention. Hence, when a message’s MSV is lower or higher than one’s optimal sensation-seeking preferences, individuals are motivated to withdraw attention from the current message and shift focus to seek more or less sensational content that matches the individual need for sensation and to satisfy one’s motivation for optimal sensory experiences. However, it is still not conclusive regarding the optimal MSV in general (Stephenson & Southwell, 2006).

These different theoretical arguments have received empirical support. Regarding the *attention-attracting* role of MSV, a wide range of empirical studies support a universal effect of MSV in enhancing attention, message processing, and persuasiveness. Noar and colleagues (2010) found that safer sex PSAs with high MSV were more effective among young adults with either high or low sensation-seeking tendencies. Anti-marijuana PSAs with high MSV were found to enhance (e.g., Kang & Cappella, 2008; Noar et al., 2010; Quick, 2013; Xu, 2015a) message processing and mitigate drug-related attitudes and behaviors for young adults, regardless of sensation-seeking preferences (Stephenson & Palmgreen, 2001). This attention-attracting effect has been confirmed across multiple high-risk behaviors among teenagers and young adults, such as smoking (Xu, 2015a), driving under influence (Xu, 2015b), and violence (Kang & Cappella, 2008).

In addition to experimental evidence, content analyses of MSV in persuasive messages have supported the *attention-attracting* effect as well. Relying on content analyses and surveys of 45 anti-smoking PSAs, MSV, operationalized as the number of sensational message features, was found to positively relate to message recall for teenagers, with the correlation stronger for

high sensation-seekers than for low sensation-seekers (Niederdeppe et al., 2007). Using the existing objective measure of MSV (Morgan et al., 2003), Zhang and colleagues (2021) found that MSV in health-related TikTok videos was positively associated with video engagement. Further, they analyzed 354 short videos related to COVID-19 on TikTok, showing the same positive correlation (W. Zhang et al., 2023). Similarly, MSV in antismoking videos on YouTube was found to be positively associated with the number of views and comments (Paek et al., 2010).

Contradicting empirical evidence exists to support the *attention-distracting* effect of MSV as well. When high MSV in antimarijuana PSAs distracted attention, the effect of argument strength diminished because people were distracted by message features and had limited cognitive resources to process the main argument or pay attention to argument strength (Kang et al., 2006). This distraction can be useful when it comes to counter-attitudinal messages. For counter-attitudinal antimarijuana PSAs, MSV was found to effectively distract the audience's attention to the uncomfortable main argument and reduce psychological reactance, which supports the thought disruption hypothesis (Quick, 2013). Additionally, neuroimaging studies revealed that anti-smoking and safer-sex PSAs with low MSV generated more brain activities, higher levels of cognitive processing, and more accurate message recall compared with high-MSV PSAs (Langleben et al., 2009; Seelig et al., 2014). These findings challenged the notation that MSV facilitates message processing.

Lastly, empirical research also shows a dynamic interaction between MSV and individual sensation-seeking preferences in influencing attention, message processing, and persuasiveness. Lorch and colleagues (1994) found that high sensation-seeking young adults preferred high-MSV television programs, while low sensation-seekers preferred low-MSV programs. In the

context of anti-cocaine PSAs, Everett and Palmgreen (1995) found a clear preference for messages with high MSV among high sensation-seeking individuals and a preference for low-MSV messages among low sensation-seekers. In addition to self-reported preference, Wang and colleagues (2015) discovered physiological evidence that anti-drug PSAs with high MSV activated the approach tendency among high sensation-seekers, whereas high-MSV PSAs triggered the avoidance tendency among low sensation-seekers.

2.2.3 The Influence of Individual Predispositions

These mixed findings illustrate the complicated effect of MSV and the potential interaction with message content and individual predisposing factors. As AMIE pinpoints sensation-seeking as a key predisposing factor that conditions MSV's effects, indicating that MSV is most effective when it aligns with one's sensation-seeking preference (Donohew et al., 1980; Zuckerman, 1990). While the conditioning effect of sensation-seeking received empirical support (e.g., Everett & Palmgreen, 1995; Lorch et al., 1994; Z. Wang et al., 2015), this effect was not consistently observed in empirical studies (e.g., Kang & Cappella, 2008; Niederdeppe et al., 2007; Quick, 2013; Xu, 2015a).

One potential explanation for this inconsistency lies in the unique demographic focus of most MSV research: a majority of studies primarily focus on teenagers and young adults. This demographic focus is theoretically and practically meaningful because young adults are more susceptible to high-risk behaviors and therefore are key populations in risk communication contexts. However, the fact that teenagers and young adults are likely to be high sensation-seekers complicates this issue with the correlation between age and sensation-seeking. Zuckerman (2014) notes that individual sensation-seeking tendencies change over time, peaking in early adulthood and generally declining. Therefore, young adults may have very similar

sensation-seeking preferences. The homogeneity with little variability in sensation-seeking preference might explain why various studies observed minimal differences between high sensation-seekers and low sensation-seekers.

This specific demographic focus, along with the development of sensation-seeking over time, underscores the significance of considering age as an individual predisposition in the study of MSV effectiveness (Lang et al., 2005). Although sensation-seeking and age are highly correlated with each other, they are essentially two separate constructs and may have different implications for MSV's effectiveness. For example, Lang and colleagues (2005) have observed notable differences in message processing and recognition between college students and adolescents, while no significant difference in cognitive effort or self-reported arousal was found between high sensation-seekers and low sensation-seekers. This finding underscores the significance of age with significant differences observed even between two closely related age groups of college students and adolescents.

Previous studies have demonstrated age differences in attention, message processing, and message perceptions. A physiological study revealed that older adults experienced lower levels of physiological reactions and less attention to affective pictures while reporting higher levels of subjective pleasure and arousal, compared with young adults (Smith et al., 2005). The processing speed theory also argues that older adults tend to require longer cognitive processing time and have decreased cognitive performance, especially under time constraints (Salthouse, 1996). These findings suggest the significance of considering age in the study of MSV.

Overall, this review presents a comprehensive overview of the study of short videos and MSV. The following chapters delve into each of the research gaps identified and address the pertinent research questions in the existing literature.

Chapter 3 A Holistic Approach to Multimodal Features: A Validated Computational Measure of Message Sensation Value in Short Videos

Abstract

The contemporary media landscape is characterized by its highly sensational and immersive multimodal audiovisual features on short video platforms. While empirical studies have identified diverse effects of multimodal features on engagement, the significance of these individual findings is constrained by the fact that multimodal features do not operate in isolation but interact collectively to influence video processing and engagement. Drawing upon the theoretical framework of Message Sensation Value (MSV), this study aims to examine and quantify the holistic effects of multimodal features in short videos. MSV captures the degree to which objectively assessed message features and audiovisual content attract attention and elicit affective responses. Relying on computer video analysis and human evaluation of 1200 short videos as well as machine learning, this research developed and validated a computational measure of MSV in short videos that demonstrates high reliability and validity. In addition, consistent with existing literature on MSV, the findings revealed an inverted U-shaped relationship between MSV and engagement, where videos with moderate levels of MSV are most engaging. This research opens avenues for future studies to use this computational measure and explore short video performances and impacts.

Keywords: message sensation value, multimodal feature analysis, short video analytics, social media engagement, video-as-data

3.1 Introduction

Public and authoritative institutions have been increasingly turning to social media to communicate critical public issues, such as the COVID-19 pandemic (Hyland-Wood et al., 2021; J. Zhang et al., 2021). A range of theoretical and empirical works have systematically examined effective persuasive techniques, providing foundations for effective public communication on social media. These research efforts focus on various message features (see L. Shen & Bigsby, 2013 for an overview), including both message content (e.g., evidence type, Hoeken & Hustinx, 2009; Xue & Taylor, 2022) and message styles (e.g., message framing, Rothman & Salovey, 1997). This body of work has been extended to the contemporary media environment featuring short videos: recent empirical studies highlighted the effects of multimodal features, such as lip-syncing function on short video platforms (Southerton, 2021) and visual complexity (Y. Lu & Shen, 2023). However, the significance of these individual findings is constrained by the fact that multimodal features do not operate in isolation but interact collectively to influence video processing. Therefore, a theoretical investigation is necessary to understand the holistic effect of multimodal features.

Message Sensation Value (MSV) provides a theoretical framework for analyzing message effects that transcend message modality. MSV quantifies the extent to which objectively measured message features and audiovisual content attract attention and elicit affective responses (Palmgreen et al., 1991). Grounded on the literature on MSV, Morgan and colleagues (2003) developed an objective measure of MSV by annotating both formal (e.g., shot changes) and content (e.g., surprise ending) features. This measure which was developed 20 years ago can be updated for three reasons. First, the focus on the context of Public Service Announcements (PSAs) limits the measure's applicability to the contemporary media landscape

and the broader information processing context, since MSV is a theoretical concept that goes beyond health and risk communication (Xu, 2017). Second, this measure relies on the labor-intensive human annotation of video features that can be automated through computational video analysis. Lastly, this measure incorporates both formal and content features, despite the Elaboration Likelihood Model (ELM; Petty & Cacioppo, 1986) arguing that these two types of features should be examined separately to understand the dual processing of messages (i.e., central and peripheral processing of formal and content features). Therefore, an updated measure that automatically assesses the holistic effect of multimodal features in short videos is needed to address these limitations. Such a measure would advance empirical and theoretical research on short videos' effects and provide practical guidelines for effective video production for science, health, environment, and risk communication in the contemporary media environment.

The goal of the present study is to develop and validate a measure that computationally quantifies the MSV of multimodal features in short videos. Specifically, this study used computational video analysis to extract 18 multimodal features of $N = 1200$ short videos on Instagram Reels, covering 8 critical issues. Machine-learning techniques were used to pinpoint relevant multimodal features and connect these features with human evaluations ($N_{\text{participant}} = 1007$) of the perceived MSV. This measure, therefore, automatically predicts the MSV of a given video. Next, this study examined the reliability and predictive validity of this measure and further tested it with two unseen datasets.

3.2 Message Sensation Value: Objective versus Perceived

Message Sensation Value (MSV) quantifies the extent to which *objectively* measured multimodal features of a message attract attention and elicit affective responses (Palmgreen et al., 1991). This concept that focuses on the objective attributes of a message contrasts with the

Perceived Message Sensation Value (PMSV), which reflects an individual's *subjective* perception and evaluation of a message (Palmgreen et al., 2002). Distinguishing between MSV and PMSV—two conceptually related but distinctive constructs—provides both theoretical and practical clarity. On the one hand, clarifying how objective message attributes are related to human perceptions helps us understand the (dis)association between MSV and PMSV. This is particularly relevant considering how individual characteristics such as sensation-seeking influence the reception of audiovisual features, such that individuals with high sensation-seeking preferences are more influenced by audiovisual features (Everett & Palmgreen, 1995). On the other hand, existing approaches to measuring MSV often conflate it with PMSV. For example, existing studies often use the PMSV scale as a proxy to assess the manipulation of MSV in stimuli, while the actual MSV in messages—rather than how MSV is perceived—is neglected. This conceptual and operational ambiguity necessitates a clearer distinction between MSV and PMSV.

Morgan and colleagues (2003) introduced an MSV scale that relies on human annotation of audiovisual features in videos. This measure encompasses three dimensions: (a) formal (structural) video features, (b) formal audio features, and (c) content features (Morgan et al., 2003). First, there are five video features, including the number of cuts and the presence of special visual effects, slow motion, unusual colors, and intense images. Second, audio features include the presence of sound saturation (background sound), background music, and (unusual) sound effects. Lastly, content features incorporate three common persuasive/narrative techniques in PSAs, including the presence of acted-out (versus talking head), unexpected format, and surprise/twist ending.

While this structured approach systematically incorporates a wide range of multimodal features, there are several limitations. The primary concern lies in the subjective nature of annotating certain message features that are supposed to be objectively defined and quantified. The ambiguity in defining what constitutes *unusual* sound effects, *unexpected* format, or *surprise* endings leads to considerable variability in human evaluations and perceptions. Second, content-related features such as surprise endings go beyond the scope of multimodal features: they predominantly address the overarching message content rather than the specific audiovisual characteristics of videos. It is more relevant to the concept of MSV to primarily focus on multimodal features that are unique to video content rather than those that transcend modalities. Third, this measure heavily relies on dichotomized annotation of message features, with 10 out of 11 features being coded as binary variables, namely, the presence or absence of a given feature. This approach oversimplifies a rich spectrum of multimodal features and potentially neglects nuanced details that are crucial to individual sensory processes. Lastly, although the method of aggregating 11 feature scores to compute the MSV score is standard for measures with a fixed scale point, it may not be appropriate for this objective measure of multimodal features because this method does not account for the varying relationships among features and the varying influence of different features on MSV. Despite these limitations, this MSV measure provides a useful framework to quantify the influence of multimodal features under the theoretical framework of MSV.

Everett and Palmgreen (1995) initially developed the PMSV scale as a part of a pretest to assess the validity of the manipulation of MSV in televised PSAs. Using focus group discussions and pretest surveys, the final PMSV scale was reduced from 40 items to 17 items. This semantic differential scale included 4 dimensions: emotional response (e.g., dramatic–undramatic),

sensory response (e.g., strong sound effects–weak sound effects), novelty (e.g., unusual–usual), and physiological response (e.g., exciting–boring). This scale was systematically updated and validated in a later study (Palmgreen et al., 2002), where three dimensions emerged from the 17 items: *emotional arousal* (e.g., arousing–not arousing), *dramatic impact* (e.g., creative–uncreative), and *novelty* (e.g., unique–not unique). This revised PMSV scale demonstrates high internal reliability and high construct and predictive validity across multiple contexts for individuals with varying sensation-seeking preferences. Although PMSV and MSV are distinct concepts, PMSV is theoretically aligned with MSV, representing the human perceptions of objective message attributes. Both concepts share the common ground of sensory experiences elicited by sensational message attributes. This theoretical alignment is supported by a high correlation between PMSV and MSV in the literature (Morgan et al., 2003). Therefore, the current study follows suit and uses PMSV to assess the construct validity of the updated MSV scale.

***RQ1.** Does an MSV measure using multimodal features in short videos demonstrate reliability?*

***RQ2.** Does an MSV measure using multimodal features in short videos demonstrate construct validity?*

3.3 Theoretical Perspectives of MSV

MSV influences an individual's attention to persuasive messages (Stephenson, 1999). MSV activates the neural system, triggers the sensory processing of information, and impacts attention allocation (Imhof et al., 2017; Mesulam, 1998). Various theoretical frameworks emphasize the importance of attention as an important outcome of MSV in human communication (Donohew et al., 1994). The Activation Model of Information Exposure (AMIE;

Donohew et al., 1980) describes how individual attention changes with MSV. It is based on the premise that individuals are motivated to seek out sensory experiences—“newness, change, sensation, or inconsistency”—that align with one’s optimal sensation level (Donohew et al., 1980, p. 296). In the context of information exposure and selection, individuals would pay attention to messages with MSV that match one’s optimal sensation level. However, when MSV is lower or higher than one’s optimal sensation value, an individual is motivated to withdraw attention from the current message and shift focus to more or less sensational content to satisfy one’s need for sensation. Similarly, the Limited Capacity Model of Mediated Message Processing (LC4MP; Lang, 2000) posits that arousing and novel information tends to receive more cognitive resources allocated for information processing and therefore receive more attention and affective responses. Both theories highlight attention as an important outcome of information processing. In the social media context, attention is often gauged via social media engagement metrics (e.g., the number of views, likes, comments, and shares) (Berger et al., 2023). Although engagement metrics do not perfectly capture human attention, they do quantify the extent to which the general public pays attention (i.e., the number of views) and allocates cognitive and affective efforts to a message (e.g., the number of likes, comments, and shares). The current study employs engagement to assess the predictive validity of the updated MSV scale.

***RQ3.** Does an MSV measure using multimodal features in short videos demonstrate predictive validity?*

While these theoretical frameworks highlight the significance of attention, there are debating theoretical arguments and empirical evidence regarding the relationship between MSV and attention. It remains uncertain whether MSV functions as an attention-getter or attention-distractor, as various theoretical perspectives offer different predictions (Xu, 2017). LC4MP

argues for a general effectiveness of high MSV, such that sensational messages are overall more likely to receive attention and cognitive resources (Lang et al., 2005). However, the AMIE model emphasizes the role of one's optimal sensation level in conditioning the effect of MSV.

Sensation seeking describes the individual variations in the preference for sensory experiences, defined as "the need for varied, novel, and complex sensations and experiences and the willingness to take physical and social risks for the sake of such experience" (Zuckerman, 2014, p. 10). The AMIE model argues that individuals pursue sensory experiences "in moderate amounts" (Donohew et al., 1980, p. 296), showing a preference for messages that align with a moderate level of MSV. Consequently, messages with high or low MSV are less likely to captivate the audience's attention.

Both the AMIE model and LC4MP perceive a message as a whole, while the Elaboration Likelihood Model (ELM; Petty & Cacioppo, 1986) adopts a unique perspective of dual message processing, wherein message content and message features are treated as separate message components. MSV is considered a message feature that activates the peripheral message processing (Kang et al., 2006), while the main argument undergoes the central route, requiring more cognitive effort (Petty & Cacioppo, 1986). ELM highlights the attention-distracting role of MSV: as high MSV attracts attention to message features, fewer cognitive resources are allocated to carefully process the message content, given the limited cognitive capacity. Hence, with limited cognitive resources, individuals are less likely to process messages cognitively or affectively.

Empirical evidence supports these different theoretical perspectives on the effect of MSV. On the one hand, research shows a dynamic interaction between MSV and individual sensation-seeking preferences in influencing message processing and effectiveness. Everett and

Palmgreen (1995) found a clear preference for messages with high MSV among high sensation-seekers and a preference for messages with low MSV among low sensation-seekers. In addition to self-reported data, Wang and colleagues (2015) discovered physiological evidence that videos with high MSV can activate the approach tendency among high sensation-seekers, while it might trigger the avoidance tendency among low sensation-seekers. These findings support the AMIE model, which posits that the effectiveness of messages with high MSV is under the influence of the alignment with the optimal sensation levels (Zuckerman, 1990).

On the other hand, empirical studies also support a universal effect of MSV in enhancing message processing and audience engagement with messages, regardless of individual differences in sensation seeking. Experimental evidence showed that PSAs with high MSV are perceived as more effective among individuals with varying sensation-seeking tendencies (Noar et al., 2010). Anti-marijuana PSAs with high MSV have been found to enhance message processing and mitigate drug-related attitudes and behaviors for both high and low sensation-seekers (Stephenson & Palmgreen, 2001). In addition, the number of sensational message features is positively associated with message recall, with the slope steeper for high sensation-seekers than for low sensation-seekers (Niederdeppe et al., 2007). Social media data support this idea as well: using the annotation-based MSV scale (Morgan et al., 2003), Zhang and colleagues (W. Zhang et al., 2021) found that message content rather than MSV of message features determines the popularity of health-related TikTok videos. A more recent study on 354 authoritative short videos on TikTok showed that MSV positively predicted public engagement (W. Zhang et al., 2023). Antismoking videos on YouTube with higher levels of MSV have received higher numbers of views and comments (Paek et al., 2010). Specifically, the number of

cuts and the presence of suspenseful features that are considered to be highly sensational were found to increase message processing (Niederdeppe, 2005).

However, contradicting evidence also exists to support the attention-distracting effect of MSV. When high MSV distracts attention, the effect of argument strength diminishes as people do not carefully process the message content (Kang et al., 2006). Neuroimaging data suggest that PSAs with low MSV generated more brain activities, higher levels of cognitive processing, and more accurate message recall (Langleben et al., 2009; Seelig et al., 2014), thereby challenging the notation that MSV facilitates message processing. Given the mixed evidence supporting different theoretical arguments regarding the relationship between MSV and engagement, RQ4 was proposed. In addition, the final research question to assess the external validity of the MSV measure was proposed.

***RQ4.** What is the optimal MSV level to achieve a high level of engagement?*

***RQ5.** Does an MSV measure using multimodal features in short videos demonstrate external validity with unseen data?*

3.4 Audiovisual Features in the Present Study

The present study incorporates a different set of audiovisual features in the context of short videos in the contemporary media landscape. These features are selected considering the concept of MSV, the existing MSV scale (Morgan et al., 2003), the current research on short videos' effects and content features, as well as the literature on audiovisual communication.

3.4.1 Visual/Aesthetic Features

The present study investigates six basic visual features: (1) brightness, (2) saturation, (3) temperature, (4) visual complexity, (5) shot count per second, and (6) shot duration per second.

The first four features represent intrinsic color features (Wyszecki & Stiles, 2000). Brightness is defined as “the attribute of a visual sensation according to which a given visual stimulus appears to be more or less intense” (Wyszecki & Stiles, 2000, p. 487). Saturation represents “the attribute of a visual sensation which permits a judgment to be made of the degree to which a chromatic stimulus differs from an achromatic stimulus regardless of their brightness” (Wyszecki & Stiles, 2000, p. 487). Color warmth refers to the extent to which colors on a visual fall in the warm spectrum, such as red and orange, out of both warm and cold colors (Motoki et al., 2019). Visual complexity refers to “the level of detail or intricacy contained within an image”, representing the diversity of information that image pixels convey (Z. Shen et al., 2022). These color features influence individual affect, cognition, and behavior (Elliot & Maier, 2014). For example, bright and saturated colors are more arousing and can elicit stronger physiological reactions (Wilms & Oberfeld, 2018). Warm colors facilitate comprehension in multimedia learning (Plass et al., 2014) and increase engagement with tourism-related visuals on Instagram (Yu & Egger, 2021). Visual complexity is positively related to perceived visual informativeness and intentions to seek information (Deng & Poole, 2010; King et al., 2020).

The last two features revolve around video motion, representing the number of shot changes and the duration of a single shot in a given video. In the filmmaking context, the number of cuts/shot changes is more likely to capture the audience’s attention (Cutting, 2016). The original MSV measure quantifies the number of cuts in a given video, but this approach does not account for the confounder of video length variation, as a higher number of cuts is naturally associated with longer videos. To address this issue and provide a more accurate measure, the present study adjusts video motions for video length as an important factor (Z. Wang et al.,

2015), thereby having the number of shot changes per second and the average duration of shots per second to provide a cleaner representation of video pace and motion.

3.4.2 Audio Features

Three basic auditory features are included in the present study: loudness, tempo, and sound brightness. Loudness is also known as acoustic intensity, measuring sound energy (Bannister, 2020). Tempo describes the sound pace or speed, defined as “the rate at which underlying beat or pulse of music progresses” (Schubert, 2004, p. 568). Sound brightness is quantified as spectral centroid, reflecting “the proportion of high to low frequencies in a sound” (Bannister, 2020). A higher value of spectral centroid signals a brighter sound, while a lower value indicates a darker sound. These audio features are crucial in eliciting both individual emotional and physiological reactions and boosting engagement (Bannister, 2020; Trochidis et al., 2011). For example, loudness and tempo positively predicted both subjective and physiological emotional arousal (Coutinho & Cangelosi, 2011). Lu and Shen (2023) found that audio loudness positively indicates engagement with short videos on TikTok. These audio features’ impact on emotional and sensory engagement underscores including these features in the current study. Audio features in the original MSV scale such as the presence of background music and sound effects are not included. This is because these fundamental features such as tempo and loudness can effectively capture the core properties underlying these high-level features and represent the essence of sound.

3.4.3 Face Presence Features

In addition to basic visual features, the present study also includes face presence features, including the number of faces per second, the duration of faces per second, face age, and facial

expressions (i.e., disgust, anger, fear, happiness, sadness, and surprise). This is because the presence of faces and facial expressions are important syntactic features in visual communication (Joo et al., 2014). On the one hand, messages with human facial expressions are powerful in eliciting sensory experiences in the audience through emotional contagion (Hess & Blairy, 2001). Although emotional contagion is mostly studied as a social phenomenon (e.g., Barsade, 2002; Kramer et al., 2014), emotions can be internalized during the process of understanding information (Howard & Gengler, 2001). Studies found that emotion contagion occurs through facial mimicry—when watching short videos depicting various facial expressions, participants tend to show similar facial expressions and experience similar emotions as portrayed in the videos (Hess & Blairy, 2001). This finding indicates that showcasing human faces creates a more emotionally engaging and more sensational experience for the audience.

On the other hand, the presence of human faces activates the *social presence heuristic*, with which individuals feel they are “communicating with a social entity rather than an inanimate object” (Sundar, 2008, p. 84). The activation of the social presence heuristic fosters a greater sense of involvement and engagement with the videos (Lackmann et al., 2021). Similarly, the number and duration of faces are adjusted with video length to have a more precise measurement of face presence features in videos.

Table 3.1 outlines the multimodal features that are considered in the study, although not every multimodal feature may prove pertinent to the MSV of short videos. To ensure the precision of the updated MSV measure, a systematic feature selection is paramount. The following section details the methodology of data collection and measure development.

Table 3.1 The description of multimodal features.

#	Category	Multimodal feature	Definition
---	----------	--------------------	------------

1		Brightness	Intensity of color luminance
2		Color saturation	Intensity of color vividness
3	Visual	Color warmness	Percentage of warm colors in all colors
4		Visual complexity	Diversity of visual brightness/texture
5		Shot count/s	Number of shot changes per second
6		Shot duration/s	Average duration per shot per second
7		Loudness	Energy of a sound wave
8	Audio	Tempo	Sound rhythm, beats per minute
9		Sound brightness	Brightness of a sound wave
10		Face count/s	Number of faces present per second
11		Face duration/s	Average duration per face per second
12		Face age	Detected age of faces in a video
13			Disgust
14	Face		Anger
15			Fear
16		Facial expression	Happiness
17			Sadness
18			Surprise

3.5 Methods

Relying on a dataset of 1200 short videos from Instagram Reels, this study outlines four key steps (Figure 3.1) in developing a computational measure of MSV, including (a) extracting multimodal features from short videos, (b) having human evaluations of PMSV in short videos, (c) selecting relevant multimodal features and developing a measure using supervised machine learning, as well as (d) evaluating the reliability and validity of the measure. This study will follow open science practice with pre-registration and open data available.

3.5.1 Data Collection and Sampling

This dataset consists of 1200 short videos on Instagram Reels, covering eight critical societal issues: alternative medicine, climate change, COVID-19, GMO, health, the presidential election, vaccination, and the Russian-Ukraine conflict. A part of this dataset originated from Qian and colleagues (2024): they identified the top 20 hashtags related to each topic and

pinpointed a pool of popular accounts (i.e., with more than 1 million followers) on Instagram Reels associated with each topic. All historical data from these popular accounts during the timeframe from August 2020 to April 2022 were collected, including both the videos and related metadata. Using 4K Stogram, a data-extraction software, a total of 39,634 videos were extracted (4K Stogram, 2024). In addition, Apify was used to extract video metadata for $n = 39230$ videos (Apify, 2023). The discrepancy in these numbers results from certain videos becoming unavailable or set to private throughout the data collection period.

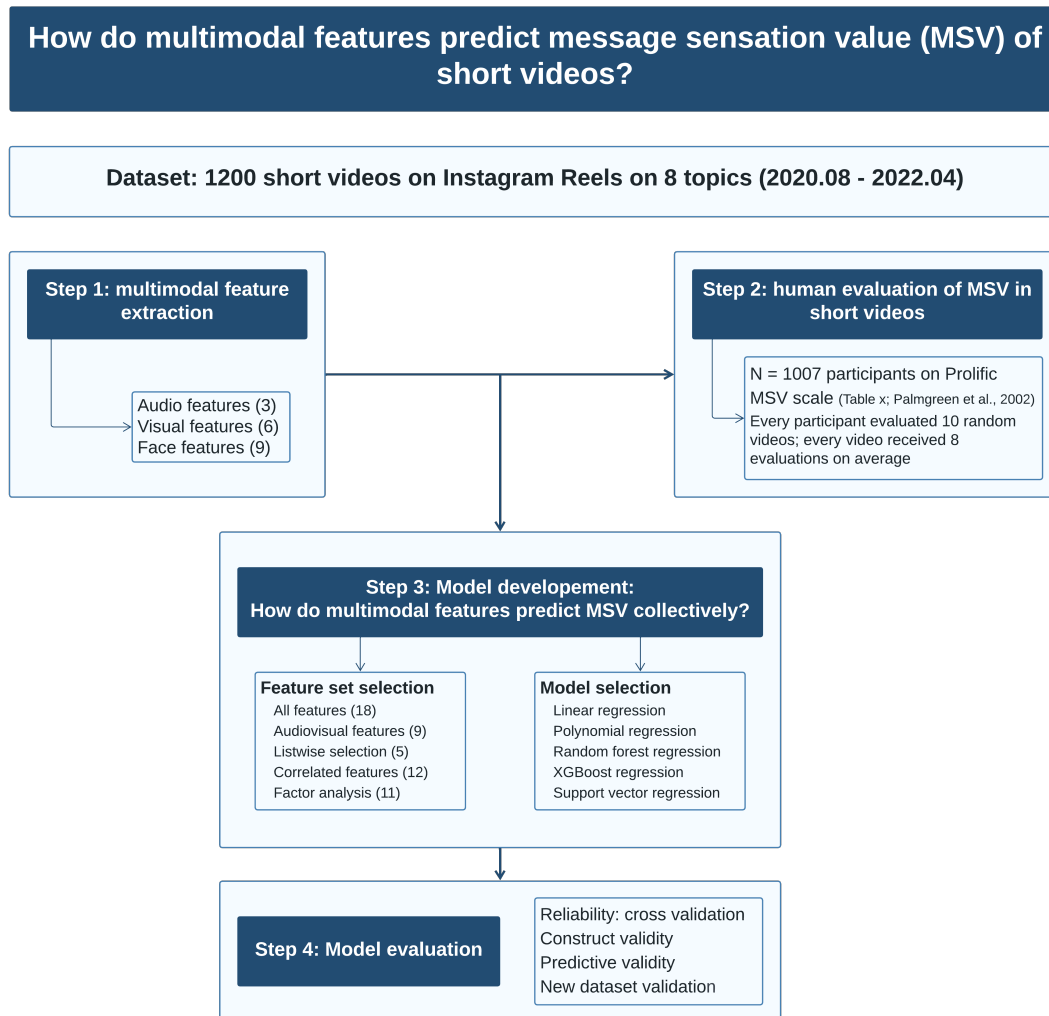


Figure 3.1 Flow diagram of study procedures.

In addition to videos from popular accounts, to increase the generalizability, this study considered the potential influence of account popularity on MSV. Hence, this study further identified 8 unpopular accounts (i.e., with fewer than 50,000 followers) from the existing hashtags for each issue. Within the identical timeframe, this study collected $n = 8,819$ videos from these accounts and extracted metadata for $n = 7,699$ videos.

Given the large scale of the dataset and the constraints of computational capacity, a stratified sampling procedure was implemented to refine the dataset to a manageable sub-dataset of $N = 1,200$ videos for analysis. This approach took into account both account popularity and issue type: among the 1,200 videos sampled, 800 videos were published by popular accounts and 400 were from unpopular videos, ensuring a balanced representation of both popular and unpopular accounts. Similarly, this sub-dataset was prepared to equally represent all 8 issues so that 150 videos were sampled for each issue (100 videos from popular accounts, 50 videos from unpopular accounts).

These videos in the sub-dataset were created by 153 unique accounts on Instagram Reels with an average video length of 39.6 seconds ($SD = 57.0$; $Min = 0.9$; $Max = 559.7$). This dataset demonstrated a wide range of engagement, with an average of 1.53 million views ($SD = 3,512,845$; $Min = 75$; $Max = 63,334,902$), 67,963 likes ($SD = 190,390$; $Min = 0$; $Max = 3,458,418$), and 1421 comments ($SD = 3906$; $Min = 0$; $Max = 50,199$). Additionally, videos about COVID-19, GMOs, and vaccinations tend to elicit more engagement (see Table 3.2 for summary statistics). Further, short videos from popular and unpopular accounts show significant differences in engagement metrics.

Measure of video engagement. This study operationalized video engagement as the sum of the number of views, likes, and comments because all engagement behaviors contribute to the

visibility of short videos (C. Kim & Yang, 2017). Video engagement is adjusted by a factor of 10,000 for visual simplicity.

Table 3.2 Summary statistics of short videos by issue and account popularity.

Issue	N	N_{account}	Duration (s)	#View	#Like	#Comment
Alternative medicine	155	15	25.86	1200644.60	109448.31	833.57
Climate change	188	25	56.79	402720.50	54906.28	457.43
COVID-19	280	20	35.73	2408484.90	208814.56	4883.89
Presidential election	150	13	31.29	164893.70	24441.28	1007.89
GMO	236	16	33.12	1736174.30	132133.65	5018.76
Health	150	24	38.90	197741.20	14020.91	120.83
Russian-Ukraine conflict	182	24	47.64	484576.30	70221.91	493.68
Vaccination	296	32	37.50	1524542.70	116390.26	4259.48
Popularity	N	N_{account}	Duration (s)	#View	#Like	#Comment
Popular	800	110	32.30	1082807.12	102653.69	2122.58
Unpopular	400	43	54.29	3945.82	381.59	18.38

3.5.2 Multimodal Feature Extraction

To extract the multimodal features depicted in Table 3.1, several computational analysis tools that have been widely used were employed. The feature extraction methods and descriptive statistics are detailed in Table 3.3.

Table 3.3 Descriptive statistics of multimodal features.

#	Category	Multimodal feature	Range	Min	Max	Mean (SD)
1	Visual	Brightness	0, 255	4.49	250.80	121.03 (40.21)
2		Color saturation	0, 255	0.00	248.54	74.52 (36.51)
3		Color warmness	0, 1	0.00	0.89	0.24 (0.18)
4		Visual complexity	0, 8	0.15	7.76	6.47 (1.31)
5		Shot count/s	0, $+\infty$	0.00	2.44	0.24 (0.29)

6		Shot duration/s	0, 1	0.01	1.01	0.50 (0.40)
7		Loudness	0, 1	0.00	0.47	0.05 (0.07)
8	Audio	Tempo	0, $+\infty$	0.00	215.33	118.42 (31.26)
9		Sound brightness	0, $+\infty$	0.00	4890.05	1919.06 (658.32)
10		Face count/s	0, $+\infty$	0.00	7.35	0.37 (0.62)
11		Face duration/s	0, 1	0.00	1.00	0.27 (0.33)
12		Face age	0, $+\infty$	4.39	74.33	34.29 (9.82)
13		Disgust		0.00	75.50	5.77 (7.96)
14	Face	Anger		0.00	92.99	6.49 (10.30)
15		Facial Fear	0, 100	0.00	97.20	4.41 (8.76)
16	expression	Happiness		0.00	100.00	23.83 (23.43)
17		Sadness		0.00	96.06	9.36 (11.60)
18		Surprise		0.00	99.99	11.28 (13.24)

3.5.2.1 Visual Feature Extraction

Frame Sampling. The OpenCV Library in Python (Bradski, 2000) was used to extract aesthetic visual features included in this study: brightness, color warmness, color saturation, and visual complexity. Given computational constraints, this study used the equal interval frame sampling method with which a frame in every 6 frames is selected for analysis (L. Wang et al., 2016). This approach allows for the computation of average values of aesthetic features in the sampled frames, which represent the overall aesthetics of a video. Despite the critique that equal interval frame sampling lacks flexibility in motion detection (Zhi et al., 2021), it remains an effective technique for aesthetic feature estimation in videos. Unlike motion detection which requires keyframe identification, aesthetic features are less dependent on keyframes and can be effectively captured with equally spaced frames.

Brightness, saturation, and warmness. Brightness and saturation are basic color attributes. Frame-level brightness and color saturation are calculated by averaging the brightness and saturation values of every pixel in a frame, where brightness spans from 0 (zero luminance,

absence of light) to 255 (maximum luminance) and saturation also ranges from 0 (lacking color, gray) to 255 (vibrant, pure color). Moreover, to capture the proportion of warm colors within a frame, this study calculated the percentage of pixels with a hue falling within a hue range of 0 (red) to 30 (yellow) based on the HSV (i.e., hue, saturation, and value) color scheme. This measure ranges from 0 to 1, representing the extent to which a frame contains warm colors.

Visual complexity. Grounded on the concept of entropy in information theory, visual complexity is calculated as the diversity of pixel intensity in the grayscale version of a frame (Y. Lu & Pan, 2022; Qi et al., 2021; Yang et al., 2019). This measure quantifies visual complexity by using Shannon's entropy formula, which calculates the probability of occurrence of each unique pixel intensity level. Visual complexity ranges from 0 to 8 (maximum), with a higher value representing a higher level of variability and complexity of visual patterns in a given frame. Therefore, a frame with a broad range of brightness intensity and texture would have a higher visual complexity score, while a frame lacking visual variation would receive a zero visual complexity score.

Shot change counts and duration per second. This study used Google Cloud Video Intelligence API (Google Cloud, 2024) to extract the number of shots and the duration for each shot in a video. This tool enables us to calculate the number of shot changes and the average duration of each shot in a video. These two variables were adjusted by video length, thereby having the shot change counts and duration per second. This decision is both theory-driven and data-driven. First, standardization by time unit enables an accurate comparison of video pace across different video lengths. Second, this approach, compared with having video length as an additional variable to shot changes and duration, comes with a lower collinearity score (see Appendix Table C.1 for details).

3.5.2.2 Audio Feature Extraction

The *Librosa* Library in Python (McFee et al., 2015) was used to extract three audio features included in this study: loudness, tempo, and sound brightness. This tool has been widely used in audio-related studies across computer science and social science disciplines (e.g., Brown et al., 2020; Kong et al., 2020). Loudness ranges from 0 to 1, indicating the energy of a sound wave. Tempo ranges from 0 to positive infinity, with a higher value indicating a faster pace. Lastly, sound brightness (measured via spectral centroid) also spans from 0 to positive infinity, with a higher value representing a brighter sound that contains more high-frequency content and a lower value representing a darker sound with more low-frequency content.

3.5.2.3 Face Presence Feature Extraction

Face counts and duration per second. This study used Google Cloud Video Intelligence API (Google Cloud, 2024) to extract the number of faces and the average duration of faces in a given video. Similarly, these two features were adjusted for video length.

Face age and facial expressions. Additionally, this study used Face++ (Face++, 2023), a face recognition software, to extract the estimated ages and facial expressions of faces in a given video. This tool can detect faces in an image and analyze various face attributes, including estimated face age and 6 discrete facial expressions (i.e., disgust, anger, fear, happiness, sadness, and surprise). The face age ranges from 0 to positive infinity, whereas facial expressions span from 0 to 100, with higher scores indicating a more pronounced facial expression. Given the capacity of Face++ to analyze still images only, this study adopted the same frame-level approach by extracting the face age and facial expressions of all identified faces within a frame and computing the averages to represent the overall face age and facial expressions depicted in a video.

3.5.3 Human Evaluation of Short Video PMSV

To evaluate the perceptions of MSV in the sample short videos, an online survey with $N = 1,007$ participants was conducted on Prolific in October 2023. All study procedures were approved by the university's Institutional Review Board. Initially, $n = 1086$ U.S. adults were recruited on Prolific to participate in this survey. The responses of $n = 79$ participants were excluded for failed attention checks, resulting in $N = 1,007$ valid responses. The survey was programmed on the Qualtrics platform (Qualtrics, 2022). Each of the participants evaluated the perceived MSV for 10 random short videos. The median time to complete the survey was 17.6 minutes. On average, each video was independently evaluated by 8 participants, providing a comprehensive and diverse set of perceptions. Following the video evaluations, participants were asked to answer questions about their sensation-seeking preferences. The survey ends with questions on demographics (see Appendix Table B.1 for the summary of demographics).

Perceived Message Sensation Value. PMSV was measured with a PMSV scale (Palmgreen et al., 2002). This instrument contains 17 items on a 7-point semantic differential scale, covering three dimensions of PMSV: emotional arousal (8 items, e.g., arousing–not arousing), dramatic impact (6 items, e.g., didn't give me goosebumps–gave me goosebumps), and novelty (3 items, e.g., unique–common) ($n = 10069$, $Min = 1$, $Max = 7$, $M = 3.65$, $SD = 1.42$, Cronbach's $\alpha = .94$). See Appendix Table A.1 for the full scale.

Sensation seeking. The sensation-seeking preference was measured by a brief sensation-seeking scale (Hoyle et al., 2002). Participants are asked to evaluate the extent to which they agree or disagree with 8 statements on a 5-point scale (1: strongly disagree, 5: strongly agree), such as “I would like to take off on a trip with no pre-planned routes or timetables” ($N = 1,007$,

$Min = 1$, $Max = 5$, $M = 2.59$, $SD = 0.85$, Cronbach's $\alpha = .81$). See Appendix Table A.2 for the full scale.

3.5.4 Measure Development with Machine Learning

Two critical issues need to be addressed to develop a computational measure of MSV based on multimodal features. The first challenge involves pinpointing which among the 18 multimodal features are relevant to PMSV. On the one hand, given the diversity of these multimodal features, not all of them may directly contribute to PMSV. Eliminating the less relevant features would enhance the accuracy of the computational measure of MSV. On the other hand, removing redundant features that are highly correlated can improve computational efficiency and reduce measure complexity.

The second challenge revolves around understanding how these relevant multimodal features contribute to PMSV. The aggregating approach by Morgan and colleagues (2003) did not account for the potential nonlinear relationships among multimodal features or the unequal weighting of these features. To address these two challenges, this study adopts a machine learning approach that (a) systematically filters relevant multimodal features and (b) evaluates a range of linear and non-linear machine learning models to identify the most suitable model that illustrates the relationship between multimodal features and PMSV.

3.5.4.1 Feature Selection

Building on the initial feature set which includes all 18 multimodal features, this study relies on both data-driven and theory-driven approaches to identify four feature sets for further evaluation (Maass et al., 2018). Table 3.4 below lists the composition of features in 5 distinct feature sets. Considering the continuous nature of multimodal features and PMSV, three appropriate data-driven approaches—correlation-based feature selection, stepwise feature

selection, and exploratory factor analysis (EFA)—are considered (Hogarty et al., 2004; Jović et al., 2015).

Table 3.4 Five sets of multimodal features.

#	Feature set 1 All features	Feature set 2 Correlation	Feature set 3 Stepwise	Feature set 4 EFA	Feature set 5 Audiovisual
1	Brightness	Brightness	Brightness		Brightness
2	Color saturation			Color saturation	Color saturation
3	Color warmth			Color warmth	Color warmth
4	Visual complexity		Visual complexity	Visual complexity	Visual complexity
5	Shot count/s	Shot count/s		Shot count/s	Shot count/s
6	Shot duration/s	Shot duration/s	Shot duration/s	Shot duration/s	Shot duration/s
7	Loudness	Loudness			Loudness
8	Tempo			Tempo	Tempo
9	Sound brightness	Sound brightness	Sound brightness	Sound brightness	Sound brightness
10	Face count/s	Face count/s			Face count/s
11	Face duration/s	Face duration/s	Face duration/s	Face duration/s	Face duration/s
12	Face age	Face age			
13	Disgust	Disgust			
14	Anger	Anger	Anger		
15	Fear	Fear			
16	Happiness			Happiness	
17	Sadness	Sadness		Sadness	
18	Surprise				

First, feature set 2 is curated to include 12 features with significant correlations with PMSV in Pearson’s correlation tests (see Appendix Table B.2 for detailed correlation results). Second, by conducting forward, backward, and bidirectional stepwise linear regressions, feature set 3 emerged with 6 multimodal features that were consistently selected across three stepwise regressions.

Third, although EFA is often used to construct underlying factors or reduce data dimension, EFA is used in this study to identify multimodal features that have substantial

contributions to the underlying dimensions, as indicated by factor loadings exceeding 0.2 (see Appendix Table B.3 for factor loadings). This is because the notion that EFA identifies underlying factors matches the study's aim to uncover the theoretical construct of MSV's underlying multimodal features. However, the linear approach of EFA in constructing factors may not fit the nature of the dataset. Therefore, the selective use of EFA results in feature set 4, comprising 10 multimodal features with relatively high factor loadings.

Lastly, feature set 5 is narrowed down to only 11 multimodal features, excluding facial attributes and facial expressions. First, this decision stems from the fact that audiovisual features are universally present and consistently measured across video content, while facial attributes and expressions are less universal. Therefore, by zooming in on audiovisual features solely, this feature set may increase the measure's applicability and accuracy. Furthermore, while exploring the potential impact of face presence features on MSV may provide meaningful insights, evaluating audiovisual features provides a valuable baseline to understand low-level multimodal features' impact on MSV.

3.5.4.2 Regression Model Selection and Evaluation

This study examines five regression models for MSV measure development: linear regression, polynomial regression, random forest regression (Segal, 2004), XGBoost regression (Chen & Guestrin, 2016), as well as support vector regression (F. Zhang & O'Donnell, 2020). These regression models were selected to account for both linear and non-linear models. In addition, regression models that are known for their accuracy and robustness in previous studies are included (e.g., Rodriguez-Galiano et al., 2015; Shahani et al., 2021).

Evaluation metrics. The performance of these regression models is assessed using two metrics: Mean Squared Error (MSE) and Akaike Information Criterion (AIC). MSE measures

prediction accuracy by quantifying the average squared difference between the estimated value and the actual value, with lower scores indicating higher accuracy and better model performance. AIC gauges model complexity and fit, with lower values representing higher levels of model parsimony and simplicity. This study values both metrics to develop a MSV measure with high accuracy and fit.

Data preprocessing. Prior to model development, this study went through three steps for data preprocessing: (a) data imputation, (b) data standardization, and (c) train-test split. First, the missing values in the data were imputed with variable mean. Second, given the varying scales of multimodal features, standardization was applied to all features. Lastly, the data was randomly split into a training set (90%, $n = 1080$) and a test set (10%, $n = 120$). The variance of PMSV ($Var = 0.664$) in the test set serves as the baseline MSE for model performance comparison. This value signals the minimum error achievable without predictive modeling. It sets a straightforward threshold; any model yielding MSE above the baseline would be considered ineffective.

Model development. Across 5 distinct feature sets and 5 regression models, this study developed 25 models in total. Performance metrics (i.e., MSE and AIC) for all models are summarized in Table 3.5. All models achieve better performance than the baseline ($MSE_{baseline} = 0.664$). Notably, the random forest regression model that uses 11 audiovisual features ($MSE = 0.441$, $AIC = -76.25$) demonstrated the top performance with the lowest MSE and the second lowest AIC score in the cohort.

Table 3.5 MSE and AIC of models predicting PMSV with multimodal features. The baseline of MSE is 0.664.

MSE (AIC)

Feature set (#features)	Linear	Polynomial	Random Forest	XGBoost	Support Vector
All features (18)	0.527 (-40.83)	0.600 (-25.39)	0.488 (-50.20)	0.486 (-50.68)	0.528 (-40.72)
Correlation (12)	0.538 (-50.29)	0.535 (-51.00)	0.471 (-66.42)	0.479 (-64.21)	0.502 (-58.79)
Stepwise (6)	0.529 (-64.51)	0.489 (-73.81)	0.513 (68.19)	0.491 (-73.36)	0.541 (-61.70)
EFA (10)	0.509 (-60.95)	0.447 (-76.73)	0.478 (-68.70)	0.481 (-67.77)	0.473 (-69.88)
Audiovisual (11)	0.519 (-56.74)	0.510 (-58.82)	0.441 (-76.25)	0.469 (-68.84)	0.476 (-67.13)

In contrast to linear regression models that quantify variable impacts with regression coefficients, random forest regression provides feature importance statistics to explain the contribution of each feature in model prediction. The feature importance is summarized in Table 3.6 below. The key multimodal features contributing to the model's prediction are the duration of faces and shots per second along with brightness, collectively accounting for 55% importance. Using this model, this study computed the estimated MSV ($N = 1200$, $Min = 2.32$, $Max = 4.77$, $M = 3.51$, $SD = 0.37$) for further analysis.

Table 3.6 Feature importance of 11 multimodal features in the feature set 5 in the random forest regression model.

Feature	Importance
Face duration/s	0.24
Shot duration/s	0.20
Brightness	0.10
Shot count/s	0.09
Visual complexity	0.07
Sound brightness	0.06
Face count/s	0.05
Color saturation	0.05
Color warmth	0.05
Loudness	0.05
Tempo	0.03

3.5.5 Assessment Plan of Measure Validity and Reliability

To answer RQ1 about the reliability of the MSV measure, a k-fold cross-validation was conducted across all 25 models (Fushiki, 2011). Since this MSV measure is a non-linear composition of computer-captured multimodal features, traditional methods for evaluating reliability, such as test-retest reliability and internal consistency tests, are not suitable in this context. In the machine learning context, k-fold cross-validation assesses the consistency of a model's prediction across various partitions of the data. Specifically, a 10-fold cross-validation was conducted: the dataset is partitioned into 10 equal folds, with each fold containing $n = 120$ data points. In each validation cycle, a model would be trained on 9 of these segments and tested on the remaining segment. This process will be repeated 10 times, with each fold serving as a test set for once. This cross-validation procedure mitigates the potential biases that arise from the random train-test split in the training process and provides a robust evaluation of the model's reliability in predicting MSV across different subsets of data.

To answer RQ2 about the construct validity of the MSV measure, this study conducted a linear regression with the PMSV as the dependent variable and the predicted MSV as the independent variable. This model incorporated covariates including video posting time, video duration, video topic, and posting account popularity. Further, this study assessed the construct validity across different age groups and individual preferences for sensation-seeking by conducting similar regression models.

To answer RQ3 about the predictive validity of the MSV measure and to answer RQ4 about the optimal level of MSV to maximize engagement, this study conducted negative binomial regression models with video engagement as the dependent variable and the predicted MSV as the independent variable. Reflecting on the literature that suggests a potential linear or

non-linear relationship between MSV and engagement, this study explored the predicted MSV in both linear and polynomial terms. This model also incorporated covariates including video posting time, video duration, video topic, and posting account popularity.

Lastly, to answer RQ5 about the external validity of the MSV measure, the same negative binomial regression models were conducted with video engagement as the dependent variable and the predicted MSV as the independent variable for two new datasets including (a) science-related short videos on TikTok ($n = 10,000$) and (b) short videos recommended to kids on TikTok, Instagram Reels, and YouTube Shorts ($n = 4,492$) to demonstrate generalizability and stability of the MSV measure across contexts and short video platforms.

3.6 Results

3.6.1 Reliability Assessment

To assess reliability (RQ1), this study conducted a 10-fold cross-validation across 25 models in the model development stage. Table 3.7 below summarizes the average MSE for every model in the 10-fold cross-validation. Notably, the random forest regression model that incorporates 11 audiovisual features consistently achieved the best performance with the lowest MSE. By comparing MSE across different models, this study validated the stable performance and reliability of the chosen model.

Table 3.7 Average MSE of models predicting PMSV with multimodal features in 10-fold cross-validation. The baseline of MSE is 0.664.

Feature selection	#Features	MSE (AIC)				
		Linear	Polynomial	Random Forest	XGBoost	Support Vector
All features	18	0.560	0.654	0.523	0.540	0.579
Correlation	12	0.561	0.578	0.519	0.533	0.561

Stepwise	6	0.556	0.545	0.533	0.535	0.556
EFA	10	0.564	0.555	0.518	0.542	0.592
Audiovisual	11	0.558	0.555	0.517	0.532	0.556

3.6.2 Validity Assessment

3.6.2.1 Construct Validity

To assess construct validity (RQ2), this study conducted two linear regression models on the association between the predicted MSV and PMSV (see Figure 3.2 below for the visualization; see Appendix Table C.2 for the details of regression models). The predicted MSV was a positive indicator of PMSV ($b = 1.50$, $SE = 0.05$, $95\% CI = [1.40, 1.59]$, $p < .001$), with or without adjusted for covariates. In addition, a Pearson's correlation test confirmed the positive association between the predicted MSV and PMSV ($r = .70$, $p < .001$). These results collectively support that this computational MSV measure demonstrates high construct validity by accurately measuring the underlying construct of PMSV.

Whether the relationship between MSV and PMSV is consistent across demographic groups is another important aspect of assessing construct validity. Two important individual differences are age and sensation-seeking preferences. Younger participants aged from 19 to 38 ($N = 503$, $M = 29.40$, $SD = 5.05$); older participants aged from 39 to 83 ($N = 503$, $M = 52.68$, $SD = 9.37$). High sensation-seekers have an average sensation-seeking preference of 3.30 ($N = 500$, $Min = 2.63$, $Max = 5.00$, $M = 3.30$, $SD = 0.54$), compared with the average of 1.90 for low sensation-seekers ($N = 509$, $Min = 1.00$, $Max = 2.50$, $M = 1.90$, $SD = 0.43$). For each video, the average PMSV provided by each age or sensation-seeking group was calculated. Older participants ($N = 1198$, $Min = 1.18$, $Max = 6.03$, $M = 3.63$, $SD = 0.98$) tended to evaluate a video as more sensational compared with younger participants ($N = 1196$, $Min = 1.00$, $Max = 6.47$, $M =$

3.43, $SD = 0.93$; $t = 5.31$, $p < .001$). However, there was no significant difference in PMSV between high sensation-seekers ($N = 1191$, $Min = 1.00$, $Max = 5.76$, $M = 3.56$, $SD = 0.93$) and low sensation-seekers ($N = 1196$, $Min = 1.00$, $Max = 6.82$, $M = 3.49$, $SD = 0.96$; $t = 1.87$, $p = .062$).

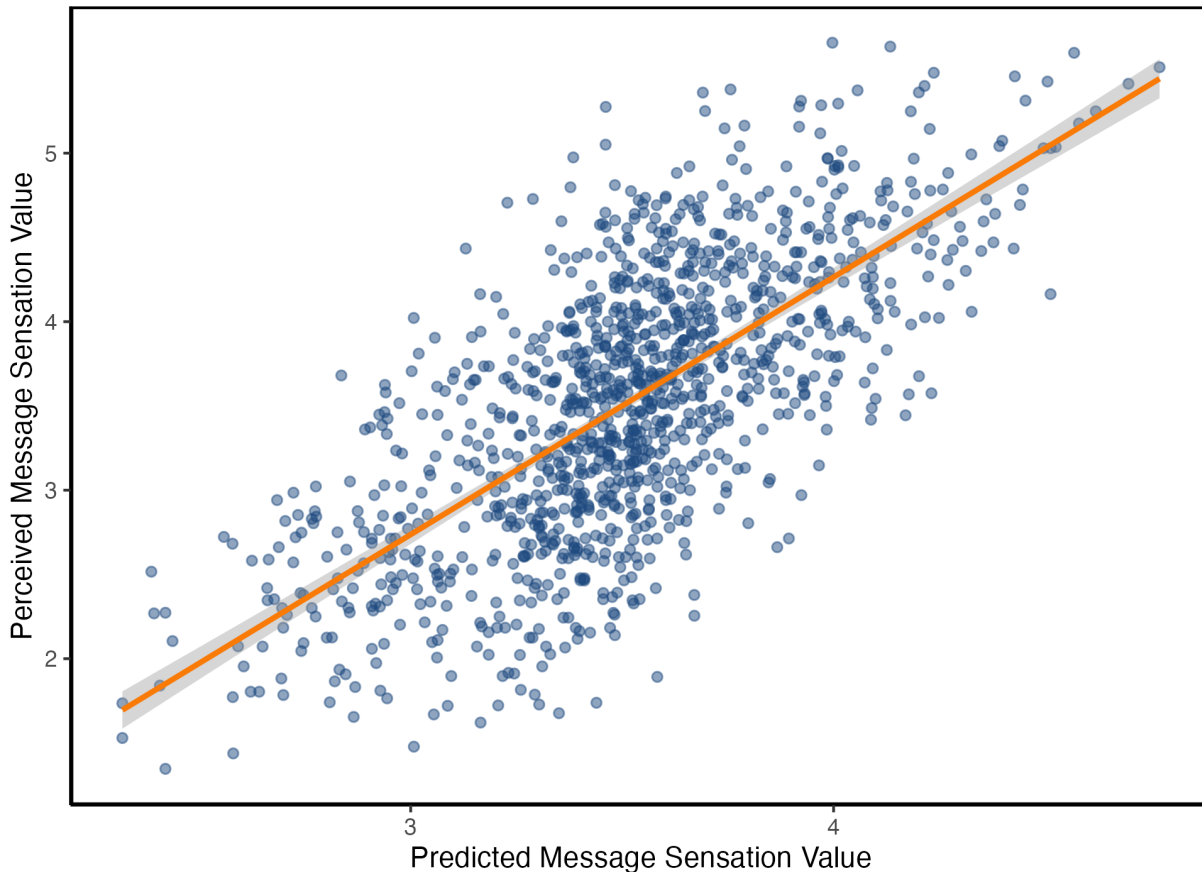


Figure 3.2 The relationship between the predicted Message Sensation Value and the Perceived Message Sensation Value.

Similar linear regression models were conducted on the relationship between the predicted MSV and the PMSV of younger (Appendix Table C.3) versus older participants (Appendix Table C.4), and high sensation-seekers (Appendix Table C.5) versus low sensation-seekers (Appendix Table C.6). Results showed that MSV remained a significant positive

predictor of PMSV for younger participants ($b = 1.43$, $SE = 0.06$, $95\% CI = [1.31, 1.55]$, $p < .001$), older participants ($b = 1.53$, $SE = 0.07$, $95\% CI = [1.39, 1.66]$, $p < .001$), low sensation-seekers ($b = 1.53$, $SE = 0.06$, $95\% CI = [1.40, 1.66]$, $p < .001$), and high sensation-seekers ($b = 1.46$, $SE = 0.06$, $95\% CI = [1.33, 1.58]$, $p < .001$). In addition, similar linear regressions were conducted to assess construct validity across different contexts; Figure 3.3 below illustrates the consistent positive relationship between perceived and predicted MSV across issues. These results support the construct validity of the computational measure of MSV across contexts and individual variations.

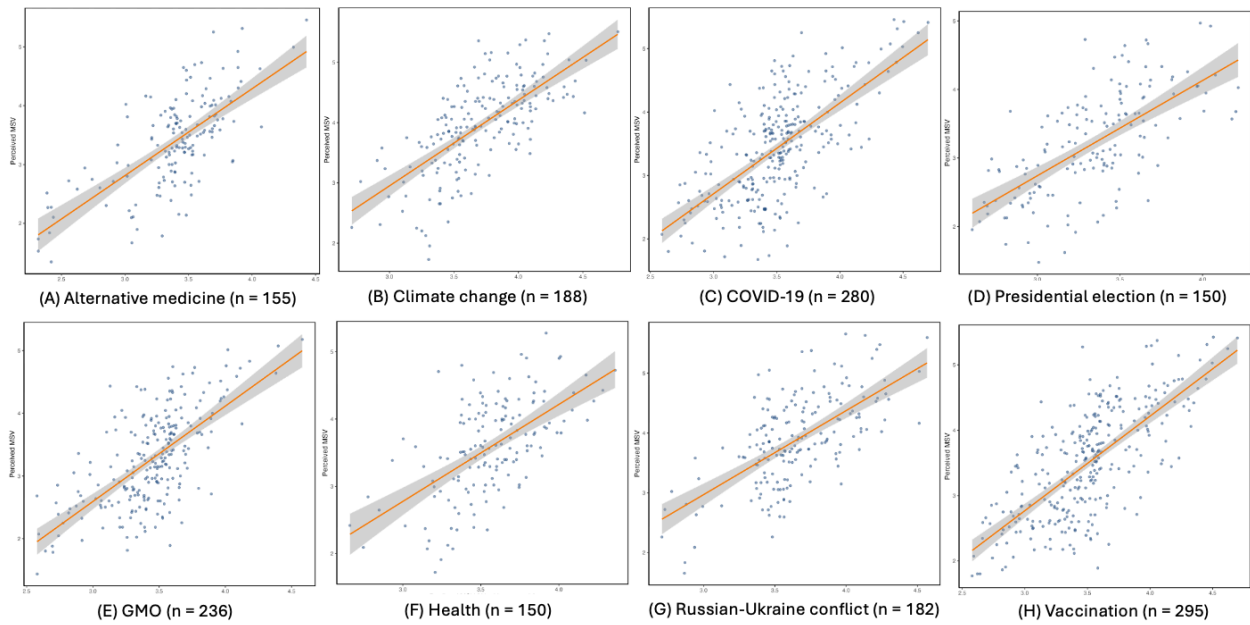


Figure 3.3 The relationship between the predicted Message Sensation Value (X-axis) and the Perceived Message Sensation Value (Y-axis) across 8 topics: (A) alternative medicine, (B) climate change, (C) COVID-19, (D) presidential election, (E) GMO, (F) health, (G) Russian-Ukraine conflict, and (H) vaccination. The numbers in parentheses indicate the number of videos in each topic, with some overlap across topics.

3.6.2.2 Predictive Validity

To assess predictive validity (RQ3), this study conducted negative binomial regression models to examine the relationship between the predicted MSV and video engagement (see

Appendix Table C.7 for details). In the linear term, the predicted MSV positively predicted video engagement in the unadjusted Model ($b = -0.54$, $SE = 0.16$, $95\% CI = [-0.92, -0.17]$, $p = .001$), while this relationship did not hold significance with covariates adjusted ($b = -0.12$, $SE = 0.12$, $95\% CI = [-0.39, 0.15]$, $p = .289$).

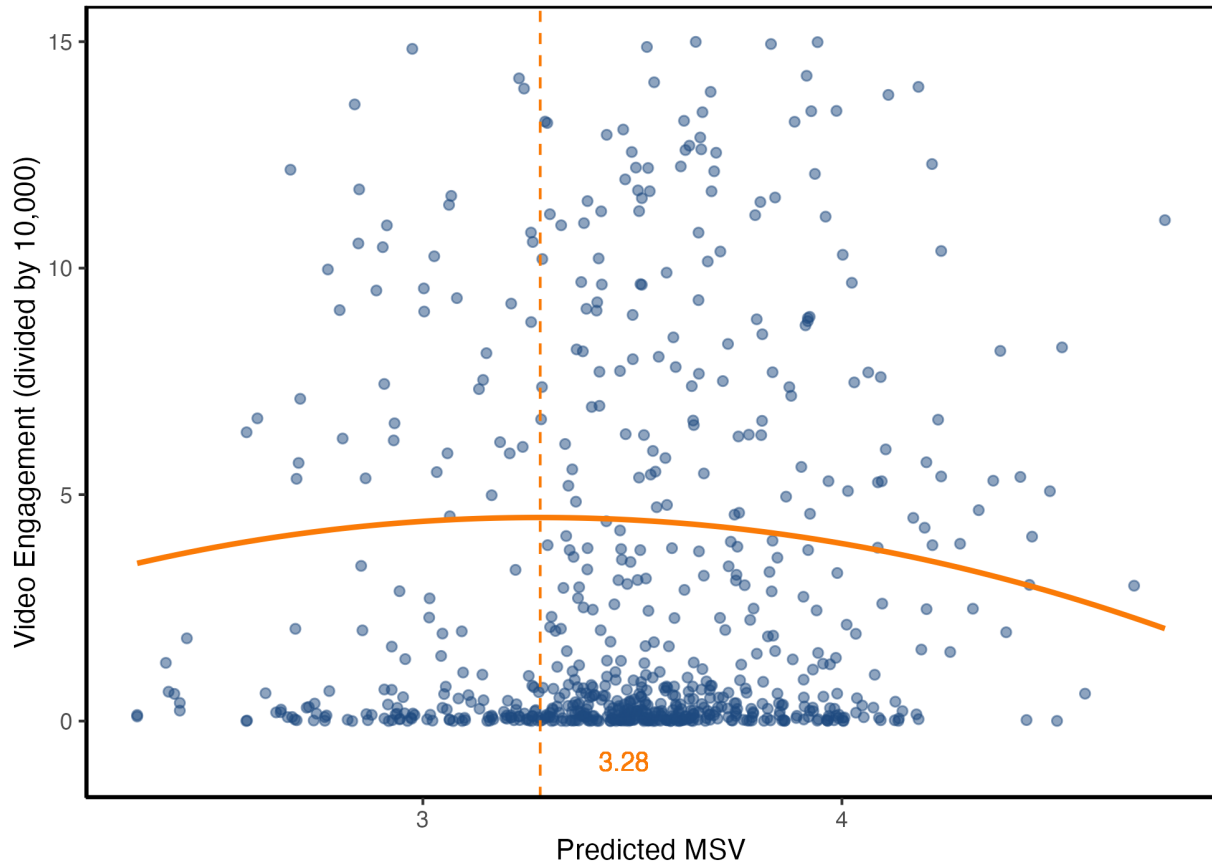


Figure 3.4 The relationship between the predicted MSV and video engagement, as illustrated in the orange curve. Video engagement is maximized with the optimal predicted MSV = 3.28.

On the contrary, incorporating the predicted MSV as a polynomial term revealed a consistent and significant relationship with video engagement, with or without covariate adjustment (polynomial term: $b = -1.10$, $SE = 0.27$, $95\% CI = [-1.62, -0.53]$, $p < .001$; linear term: $b = 7.21$, $SE = 1.89$, $95\% CI = [3.20, 10.91]$, $p < .001$). Given the consistency of results,

the polynomial regression demonstrated a higher level of robustness, illustrating an inverted U-shaped relationship between the predicted MSV and video engagement (see Figure 3.4 above for visualization; see Appendix Table C.8 for model details). Therefore, the measure of MSV demonstrates predictive validity.

Table 3.8 Summary statistics of multimodal features and engagement across three levels of predicted MSV, revolving around the optimal MSV level of 3.28.

Predicted MSV	Low	Mid	High
N	129	507	564
Predicted MSV range	[1, 3.03)	[3.03, 3.53)	[3.53, 7]
Brightness	137.00	128.53	110.64
Color saturation	70.48	72.39	77.36
Color warmness	0.23	0.25	0.23
Visual complexity	5.78	6.52	6.58
Shot count/s	0.17	0.18	0.31
Shot duration/s	0.91	0.63	0.29
Loudness	0.04	0.05	0.06
Tempo	118.94	117.51	119.12
Sound brightness	1921.80	1951.48	1889.95
Face count/s	0.23	0.29	0.48
Face duration/s	0.87	0.33	0.08
Predicted MSV	2.82	3.36	3.81
PMSV	2.55	3.23	4.01
#Views	737038.90	845474.20	610089.70
#Likes	67090.47	81072.38	57438.38
#Comments	1385.62	1780.43	1106.36

Based on the negative binomial model with polynomial terms in RQ3, this study was able to address RQ4 and identified the optimal level of predicted MSV was approximately 3.28 to maximize video engagement (Figure 3.4). To delve into multimodal features of short videos with the optimal MSV, the average multimodal features across low (predicted MSV between 1.00 and

3.03), mid (predicted MSV between 3.03 and 3.53), and high (predicted MSV between 3.53 and 7.00) predicted MSV are summarized in Table 3.8 above. Results indicated that short videos with the optimal MSV were neither oversimplistic nor excessively fast-paced—these videos tended to display a moderate pace with moderate levels of audiovisual features. For example, to optimize engagement for a 60-second video, the findings suggest that approximately 10 shots would be ideal, contrasting the high-MSV version with 20 shots on average may potentially distract attention with the rapid pace. This finding suggested that short videos with a moderate to low level of predicted MSV were likely to achieve higher levels of engagement.

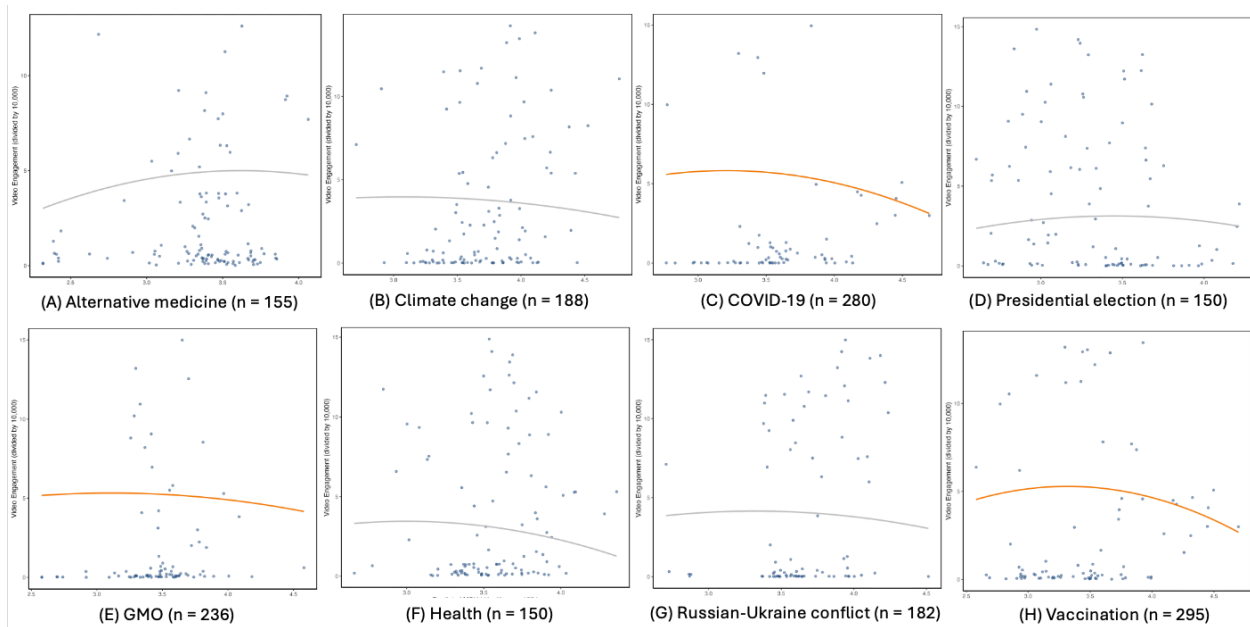


Figure 3.5 The relationship between the predicted MSV and video engagement across 8 topics: (A) alternative medicine, (B) climate change, (C) COVID-19, (D) presidential election, (E) GMO, (F) health, (G) Russian-Ukraine conflict, and (H) vaccination. The numbers in parentheses indicate the number of videos in each topic, with some overlap across topics. The orange curves illustrate significant polynomial regression coefficients, and the gray curves indicate non-significant relationships.

Similar polynomial regressions were conducted for each topic to examine the consistency of this inverted U-shaped curve across different contexts (see Figure 3.5 above). While similar patterns emerged across all topics, statistically significant relationships were observed in the

contexts of COVID-19, GMOs, and vaccines. This finding suggests the significance of contexts in the relationship between MSV and engagement. In addition, the variation in statistical significance may be attributed to the difference in sample sizes: three topics showing significant results having more than 200 data points, respectively, which was substantially higher compared with other topics.

3.6.2.3 External Validity

Lastly, to assess the external validity (RQ5), this study applied the same negative binomial regression models with polynomial terms of the predicted MSV as the independent variable and video engagement as the dependent variable to two comprehensive datasets of short videos (combined $n = 14,492$). The dataset details and findings were presented in this section.

Dataset description. This study collected two diverse datasets of short videos in October 2023: science-related short videos on TikTok and short videos recommended to children on TikTok, Instagram Reels, and YouTube Shorts. First, science-related short videos covering vaccines and climate change on TikTok were collected ($n = 10,000$). The data collection started with identifying 10 trending hashtags for each issue with both stances considered. The TikTok Research API (TikTok, 2024) was used to search all short videos available with these hashtags from January 2020 to September 2023 ($n = 103,888$). After removing duplicates, $n = 96,242$ short videos remained, from which a stratified sample of $n = 10,000$ was drawn. This sample includes $n = 6,520$ vaccine-related videos ($n_{pro-vaccine} = 4,181$, $n_{anti-vaccine} = 2,339$) and $n = 3,480$ climate change-related videos ($n_{pro-climate\ action} = 3,319$, $n_{anti-climate\ action} = 161$). Second, children-related short videos include $n = 4,492$ short videos recommended to child profiles on TikTok ($n = 2,686$), Instagram Reels ($n = 810$), and YouTube Shorts ($n = 996$) in an algorithm audition study. This was part of an algorithm audit study that created child profiles across a range of ages,

genders, and races to gather a set of unique short videos recommended for these profiles. See

Table 3.9 below for summary statistics.

Table 3.9 Summary statistics of video engagement, video duration, and predicted MSV for short videos across datasets and platforms.

Dataset		Science		Kids	
Platform		TikTok	Instagram Reels	TikTok	YouTube Shorts
n		10000	810	2686	996
#Likes	M	1311.82	1126104.70	1143366.00	3432550.00
	SD	18630.00	1748228.00	2801893.00	4574511.00
#Comments	M	48.53	3786.41	8109.86	14351.34
	SD	383.75	6666.32	21938.43	21255.04
#Views	M	10434.10	10243781.00	13732715.00	98729873.00
	SD	132775.50	15948761.00	38576165.00	149508867.00
Video duration	M	44.04	12.71	106.20	43.15
	SD	55.40	8.56	118.10	16.34
Predicted MSV	M	3.56	3.30	3.40	3.40
	SD	0.36	0.19	0.23	0.14

The details for the negative binomial models can be found in Appendix Table C.9, where engagement is the sum of the number of views, likes, and comments. Similar inverted U-shaped relationships between the predicted MSV and engagement were confirmed for both datasets. In addition, this study was able to identify the optimal level of predicted MSV is approximately 3.64 to maximize video engagement for the dataset of science-related short videos and 3.36 for the dataset of short videos for kids, which supports the finding that short videos with moderate to low levels of MSV tend to maximize video engagement (see Figure 3.6 below for visualization; see Appendix Table C.9 for details). Given the consistency of the inverted U-shaped relationship across different datasets, this study concludes that the computational measure of MSV demonstrates external validity.

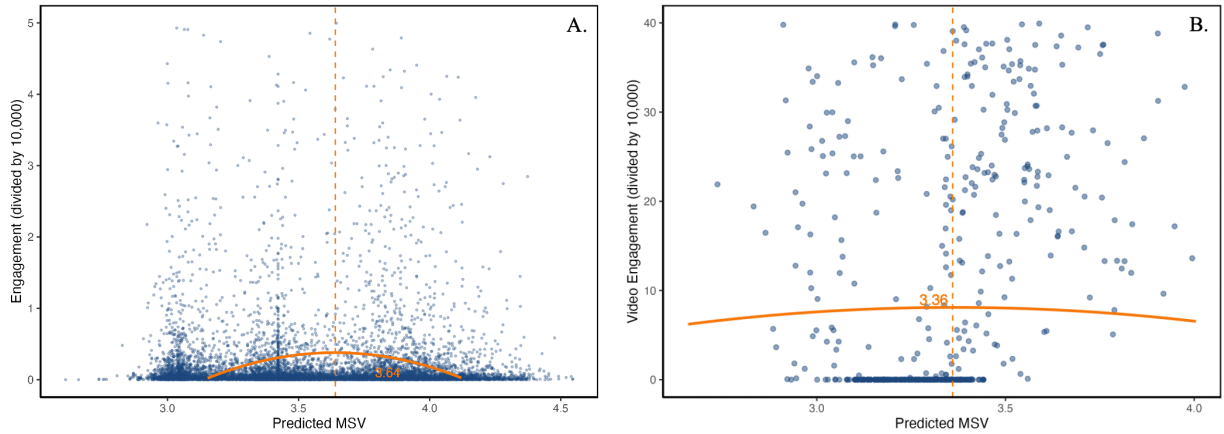


Figure 3.6 The relationship between the predicted MSV and video engagement, as illustrated in the orange curve, for (A) the dataset of science-related short videos ($n = 10,000$) and (B) the dataset of short videos for kids ($n = 4,492$).

3.7 Discussion

With short videos on the rise as crucial information hubs and formats in this contemporary media environment, it is urgent to understand how multimodal features influence the processing, engagement, and persuasion of short video content. Addressing this question advances both empirical and theoretical research on short videos' effects and provides theory-informed practical guidelines for effective public communication on short video platforms. Grounded on the literature on Message Sensation Value, this study theorizes the holistic effects of short videos and develops an updated objective measure of MSV with computational methods. Relying on a computational analysis of $N = 1,200$ short videos across eight generic topics on Instagram Reels, this study develops a machine learning-based model that predicts MSV using computationally extracted multimodal features. This study validates the measure's reliability and validity across multiple contexts and demographic groups, offering a robust and automated tool for estimating MSV in short videos.

This updated computational measure of MSV presents three key enhancements over the existing objective measure of MSV (Morgan et al., 2003). First, the computational measure incorporates a broader set of 11 multimodal features that were selected from an initial set of 18 features. This selection is more inclusive compared with the original measure with 7 multimodal features and 3 content-specific features, allowing for a more comprehensive study of multimodal features. Second, adopting machine learning techniques captures the complex interactions among various features and allows for a non-linear aggregation of multimodal features in this computational measure. This approach provides a more sophisticated and accurate estimation of MSV than the linear summary approach in the existing measure. Lastly, the shift from human annotation to computational extraction of multimodal features marks a significant improvement in reliability, consistency, and efficiency. While the existing measure relies on subjective human annotations of binary multimodal features, this computational provides an objective and continuous scale to represent multimodal features, which reduces human errors and human perception variability. This computational approach not only boosts measurement reliability and accuracy but also provides a more cost-effective solution to measurement.

This study provides additional empirical to the ongoing study of the impacts of MSV by presenting an inverted U-shaped relationship between MSV and engagement. Existing research has demonstrated contradicting results regarding how MSV impacts attention and message processing and identified the significant role of individual sensation-seeking in determining the optimal level of MSV, such that high-MSV content is more optimal for high sensation-seekers, while low-MSV content is preferred for low sensation-seekers (Everett & Palmgreen, 1995; Z. Wang et al., 2015; Zuckerman, 1990). However, the optimal level of MSV remains non-conclusive (Stephenson & Southwell, 2006). Drawing from this analysis of real-world, large-

scale datasets across multiple contexts and platforms, this research enriches the empirical evidence by demonstrating that short videos with a moderate level of MSV optimized engagement. It provides initial, correlational evidence on the relationship between MSV and engagement. It is worth noting that while engagement is not equivalent to attention, it is often perceived as an indirect indicator of viewers' attention to and engagement with the video. Further, existing studies often dichotomize MSV into high and low levels, overlooking the middle spectrum of MSV (e.g., Kang et al., 2006). This study's finding highlights the potential importance of the "middle ground" of MSV and advocates for a more granular examination of MSV in future research.

By pinpointing that mid-level MSV maximizes engagement, this study provides practical implications and actionable guidelines for content production on short video platforms in the context of science, environment, health, and risk communication. Building upon prior research on the impacts of individual multimodal features (e.g., Y. Lu & Shen, 2023; Southerton, 2021), this study addressed the gap in the collective impact of multimodal features and a comprehensive guideline on content production. This research demonstrated that short videos with the optimal level of MSV tended to possess a balanced pace and appropriate audiovisual features that are neither oversimplistic nor excessively sensational. This study moves beyond identifying individual multimodal features in isolation and provides a holistic and quantifiable guideline for systematically improving user engagement.

3.7.1 Limitations and Future Directions

This study is not without limitations. First, one significant limitation revolves around the scope of multimodal features examined. Although this study delves into 18 multimodal features, it does not extend to high-level, sophisticated features such as key objects and platform built-in

features such as chroma key, video filters, and AI-generated voiceover. Future research could explore a wider range of multimodal features, including both the individual and collective effects, to broaden our understanding of short videos as a unique message format.

Second, it is worth noting that the study's finding on the inverted U-shaped relationship between MSV and engagement remains correlational. More experimental research is needed to provide more causal evidence on MSV's effects and examine the theoretical mechanism underlying such effects. Both correlational and causal evidence would contribute to a more robust conclusion on the impacts of MSV.

Lastly, this study is limited to the context of English short videos in the United States. The fact that MSV is a concept that varies across linguistic and cultural contexts (A. C. C. Lu et al., 2017) limits the generalizability of the study's findings and the applicability of the computational measure of MSV. To enhance the generalizability of the results, future research should replicate this study across a variety of cultural and linguistic settings and explore how the relationship between MSV and engagement changes with different media landscapes.

Chapter 4 Message Sensation Value in Short Videos Enhances Message Processing and Persuasion, Especially for Young Adults

Abstract

Short video platforms have become critical information sources, but how to effectively communicate science with short videos remains unclear. This study explores using sensational short videos as an innovative solution. Grounded on the literature of Message Sensation Value (MSV), this study examines whether MSV in short videos functions as an attention-attractor or attention-distractor of persuasive messages, and how individual predispositions come in place. This study presents an online experiment ($N = 1,467$) in the U.S. that tested the persuasive effects of MSV (low, mid, or high) on attention, message processing, and persuasiveness in the contexts of COVID-19 and climate change. MSV enhanced message processing and persuasiveness across varying belief congruence but did not affect attention or risk perception. Contrary to existing research, age, rather than sensation-seeking, moderated MSV's effects, which were particularly prominent for young adults. Leveraging sensational short videos could be an effective approach to communicating science to young audiences.

Keywords: climate change, COVID-19, engagement, message processing, message sensation value, persuasion, risk perception, short videos

4.1 Introduction

Featured by visually engaging multimodal features such as chroma keying, lip-syncing, and augmented reality (AR) filters (Butler, 2023; Collie & Wilson-Barnao, 2020), short video platforms have emerged as critical information sources (Matsa, 2023), particularly appealing to Generation Z (Huang, 2022). The wide reach of short video platforms presents new challenges for science and risk communication with the proliferation of misinformation on these popular platforms (Bhargava et al., 2023; Hsu, 2022) and the misalignment between the generic, obsolete formats of scientific information presentation and the sensational, dynamic media environment (Collie & Wilson-Barnao, 2020; Kreps & Neuhauser, 2013; Y. Wang et al., 2019). The viral spread of misinformation short videos and the disconnection between science and audience needs underscores the critical need for effective scientific oversight on these popular platforms, with science and risk communication adapting to the contemporary media environment and engaging the targeted audiences.

This study argues that sensational short videos can be an innovative solution to effective science and risk communication in the current information ecosystem. Existing research highlights the overall effectiveness of sensational multimodal features for enhancing message processing and audience engagement. In the context of short videos, platform-specific features such as scientific memes (Zeng et al., 2020) and lip-syncing functions (Southerton, 2021) are associated with increased audience engagement. Further, Lu and Shen (2023) found that short video engagement was positively predicted by video length and audio volume while negatively predicted by visual complexity. In the context of Public Service Announcements (PSAs), shot changes and special audio effects were positively associated with both cognitive and affective processing of messages (Niederdeppe, 2005; Potter & Callison, 2000). By pinpointing the

impacts of specific multimodal features in isolation, this literature provides valuable correlational insight. However, there remains a research gap in adopting a more unified and holistic perspective in understanding how multimodal features interact and collectively influence short videos' effectiveness (Lahat et al., 2015).

This study addresses this gap and employs the concept of Message Sensation Value (MSV; Palmgreen et al., 1991) to theoretically unify the synergic effects of multimodal features. MSV is defined as the extent to which objectively measured message features and audiovisual content attract attention and elicit affective responses (Palmgreen et al., 1991). By considering how multimodal features interrelate rather than function in isolation, this approach provides a more nuanced understanding of the collective processing of multimodal information by linking multimodal features with short videos' impacts via the theoretical lens of MSV.

MSV influences an individual's attention to persuasive messages by activating the neural system, triggering the sensory processing of information, and impacting attention allocation (Imhof et al., 2017; Mesulam, 1998). However, competing theoretical arguments exist in predicting how exactly MSV influences attention. Theories grounded in communication and cognitive science, such as the Activation Model of Information Exposure (AMIE; Donohew et al., 1980), the Limited Capacity Model of Mediated Message Processing (LC4MP; Lang, 2000), and the Elaboration Likelihood Model (ELM; Petty & Cacioppo, 1986), have argued for opposite mechanisms for the impact of MSV. AMIE and LC4MP propose that MSV functions as an *attention-getter* that facilitates information processing whereas ELM argues the *attention-distracter* role of MSV in impeding the processing of core arguments of the message. Both arguments have received empirical support, but the precise theoretical mechanisms of how MSV in short videos impacts message processing and persuasion outcomes are still not well

understood. This is especially crucial in the contemporary media ecosystem where people are increasingly consuming and being addicted to sensational short videos (Petrillo, 2021).

Further, MSV's persuasive effects are often intertwined with predisposition factors such as issue-relevant personal involvement and sensation-seeking tendency (Miller & Quick, 2010; Palmgreen et al., 1991). In particular, AMIE highlights the role of sensation-seeking by arguing that MSV is most effective when it aligns with one's optimal sensation-seeking. However, research suggests that the influence of sensation-seeking is very limited (Xu, 2017), particularly among studies focusing on teenagers and young adults who are susceptible to high-risk behaviors like unprotected sex and substance use. While this unique focus provides valuable insights for a specific demographic, how broader with varied sensation-seeking preferences respond to universal risks such as COVID-19 and climate change is overlooked. This study bridges this gap by exploring the role of sensation-seeking and age in a broader risk communication context.

This research seeks to address two fundamental questions: (a) Does MSV in short videos function as an attention-attractor or attention-distractor in influencing attention to message, message processing, and persuasive outcomes? and (b) How do individual differences moderate the impact of MSV in short videos? Using a within-subject experimental design, this study investigates the theoretical mechanism by which MSV in short videos influences attention, message processing, and persuasiveness, in the context of COVID-19 and climate change. This study provides a more comprehensive understanding of MSV's effects by extending the focus of this line of research from high-risk behaviors among young adults to a broader science and risk communication context applicable to the general population, and from PSAs on television to short videos in the contemporary media environment.

4.2 MSV: Attention-Attractor or Attention-Distractor?

Attention is acknowledged as one of the most important outcomes of MSV (Donohew et al., 1994). MSV influences an individual's attention to persuasive messages (Stephenson, 1999). Messages with high MSV activate the neural system, trigger the sensory processing of information, and impact attention allocation (Imhof et al., 2017; Mesulam, 1998). Whether MSV functions as an *attention-attractor* or *attention-distractor* depends on different theoretical perspectives on the role of MSV in persuasion (Xu, 2017).

On the one hand, MSV represents important message features that are integrated with the persuasive message. Both AMIE and LC4MP highlight the attention-attracting role of MSV. This attention-attracting effect comes from AMIE's assumption that individuals are motivated to seek sensory experiences—"newness, change, sensation, or inconsistency" (Donohew et al., 1980, p. 296). Persuasive messages that incorporate sensational message features satisfy this motivation for sensory experiences and thereby receive more attention. Similarly, LC4MP posits that arousing and novel information tends to receive more cognitive resources allocated for information processing and therefore receive more attention and affective responses (Lang, 2000).

On the other hand, ELM (Petty & Cacioppo, 1986) adopts the perspective of dual message processing, arguing that message content and message features are separate components of a persuasive message. MSV represents sensational message features that activate the peripheral message processing (Kang et al., 2006), whereas the main message content is processed using the central route which requires more cognitive effort (Petty & Cacioppo, 1986). Therefore, ELM highlights the attention-distracting role of MSV: as high MSV attracts attention to message features, fewer cognitive resources are allocated to the central route for individuals to

carefully process the message content, given the assumption of limited cognitive capacity in information processing. Hence, with limited cognitive resources, individuals are less likely to process messages cognitively or affectively.

In addition to the competing theoretical arguments, AMIE provides a more nuanced matching hypothesis that involves individual sensation-seeking preferences. Sensation seeking is defined as “the need for varied, novel, and complex sensations and experience and the willingness to take physical and social risks for the sake of such experience” (Zuckerman, 1990, p. 313). AMIE posits that persuasive messages with MSV that match one’s optimal sensation-seeking preferences would maximize attention. Hence, when a message’s MSV is lower or higher than one’s optimal sensation-seeking preferences, an individual is motivated to withdraw attention from the current message and shift focus to seek more or less sensational content that matches one’s need for sensation. However, it is not conclusive regarding the optimal MSV in general (Stephenson & Southwell, 2006).

These varied theoretical arguments have received empirical support. First, empirical studies support a universal effect of MSV in enhancing attention, message processing, and persuasiveness. Noar and colleagues (2010) found that safer sex PSAs with high MSV are perceived as more effective among young adults, regardless of sensation-seeking tendencies. Anti-marijuana PSAs with high MSV were found to enhance message processing and mitigate drug-related attitudes and behaviors for both high and low sensation-seekers (Stephenson & Palmgreen, 2001). Consistently, the attention-attracting effect was observed across multiple risk communication contexts, such as smoking (Xu, 2015a), driving under influence (Xu, 2015b), and violence (Kang & Cappella, 2008). In addition to experimental evidence, content analyses of MSV in persuasive messages have supported the attention-attracting effect as well. Relying on

content analyses and surveys of 45 anti-smoking advertisements, MSV, as indicated by the number of sensational message features, was positively associated with message recall for teenagers, with the slope steeper for high sensation-seekers than for low sensation-seekers (Niederdeppe et al., 2007). Using the annotation-based MSV scale (Morgan et al., 2003), Zhang and colleagues (2021) found that MSV in health-related TikTok videos was positively associated with video engagement. Further, they analyzed 354 short videos related to COVID-19 on TikTok, showing the same positive correlation (W. Zhang et al., 2023). Similarly, MSV in antismoking videos on YouTube was found to be positively associated with the number of views and comments (Paek et al., 2010).

Second, contradicting evidence exists to support the attention-distracting effect of MSV. When high MSV in antimarijuana PSAs distracts attention, the effect of argument strength diminishes as people process the main argument less carefully (Kang et al., 2006). When it comes to counter-attitudinal antimarijuana PSAs, MSV was found to effectively distract the audience's attention and reduce psychological reactance, which supports the thought disruption hypothesis (Quick, 2013). Neuroimaging data demonstrated that anti-smoking and safer sex PSAs with low MSV generated more brain activities, higher levels of cognitive processing, and more accurate message recall compared with high-MSV PSAs (Langleben et al., 2009; Seelig et al., 2014), thereby challenging the notation that MSV facilitates message processing.

Lastly, research shows a dynamic interaction between MSV and individual sensation-seeking preferences in influencing attention, message processing, and persuasiveness. Lorch and colleagues (1994) found that high sensation-seeking young adults preferred high-MSV television programs, while low sensation-seekers preferred low-MSV programs. In the context of anti-cocaine PSAs, Everett and Palmgreen (1995) found a clear preference for messages with high

MSV among high sensation-seeking college students and a preference for low-MSV messages among low sensation-seekers. In addition to self-reported preference, Wang and colleagues (2015) discovered physiological evidence that anti-drug PSAs with high MSV activated the approach tendency among high sensation-seekers, whereas high-MSV PSAs triggered the avoidance tendency among low sensation-seekers. Given the mixed theoretical arguments and empirical evidence, this study proposed the following competing hypotheses on attention and message processing as well as a research question on the persuasive effects of MSV.

***H1a (attention-attracting hypothesis).** MSV in short videos increases attention to short videos and message processing.*

***H1b (attention-distracting hypothesis).** MSV in short videos decreases attention to short videos and message processing.*

***RQ1.** How does MSV in short videos influence perceived message credibility, engagement intention, and risk perception?*

4.3 Sensation-seeking Beyond Young Adulthood

As detailed above, AMIE pinpoints sensation-seeking as a key predisposing factor that conditions MSV's effects, indicating that MSV is most effective when it aligns with one's sensation-seeking preference (Donohew et al., 1980; Zuckerman, 1990). This matching hypothesis has received empirical support (e.g., Everett & Palmgreen, 1995; Lorch et al., 1994; Z. Wang et al., 2015), confirming the effectiveness of the optimal MSV. However, there is also significant evidence suggesting a universally consistent effect of MSV on attention and message processing, which challenges the significance of sensation-seeking and the matching hypothesis. One potential explanation for this discrepancy lies in the unique demographic focus of much MSV research, with a majority of studies primarily focusing on teenagers and young adults. This

demographic focus is meaningful because young adults are more susceptible to high-risk behaviors. Meanwhile, the fact that teenagers and young adults are likely to be high sensation-seekers complicates this issue. Zuckerman (2014) notes that individual sensation-seeking tendencies evolve over time, peaking in early adulthood and generally declining. Therefore, the homogeneous sensation-seeking preference that comes with this specific demographic might explain why various studies observed minimal differences between high sensation-seekers and low sensation-seekers.

This specific demographic focus, along with the development of sensation-seeking over time, underscores the significance of incorporating age as an individual predisposition in the study of MSV effectiveness (Lang et al., 2005). Although sensation-seeking and age are closely related, they are essentially distinct constructs and may have different implications for MSV's effectiveness. For instance, by comparing college students and adolescents, Lang and colleagues (2005) have observed notable differences in message processing and recognition, while no significant difference in cognitive effort or self-reported arousal was found between high sensation-seekers and low sensation-seekers.

Age differences have been observed in attention, message processing, and message perceptions. A physiological study found that, for the same affective pictures, older adults experienced lower levels of physiological reactions and less attention while reporting higher levels of subjective pleasure and arousal, compared with young adults (Smith et al., 2005). The processing speed theory also highlights age differences, arguing that older adults tend to require longer cognitive processing time and have decreased cognitive performance, especially under time constraints (Salthouse, 1996). Further, younger and older adults are different in media usage and news consumption (Boulianne & Shehata, 2022), with more younger adults regularly

consuming news on TikTok than older adults (Matsa, 2023). Considering these findings on the significance of sensation-seeking and age in message processing, this study proposed the following research questions.

***RQ2.** How does sensation-seeking moderate the effects of MSV in short videos on message attention, processing, and persuasiveness?*

***RQ3.** How does age moderate the effects of MSV in short videos on message attention, processing, and persuasiveness?*

4.4 The Influence of Motivated Reasoning

In the study contexts of COVID-19 and climate change, pre-existing attitudes toward these issues motivate people to process persuasive messages differently. People tend to approach pro-attitudinal messages favorably while adopting a more critical judgment toward counter-attitudinal messages (Kunda, 1990). The critical judgment is reflected in more systematic processing of counter-attitudinal messages; people are motivated to argue against these messages and defend their existing positions (Jain & Maheswaran, 2000).

Considering one's issue-relevant pre-existing attitude, MSV may have distinctive effects on message processing for pro-attitudinal and counter-attitudinal persuasive messages by influencing the attention to messages and psychological reactance. Psychological reactance is a form of cognitive dissonance that specifically focuses on the threat to freedom of choice (Brehm & Brehm, 1981; Rosenberg & Siegel, 2018). It is a more pertinent psychological factor in the study contexts where the freedom of choice is a major argument of anti-vaxxers and climate change skeptics (Bayes & Druckman, 2021; Kriss et al., 2022). Building upon the attention-attracting literature, researchers pointed out the potential backfiring effect of sensational persuasive messages that attract attention and further provoke high-risk behaviors (Miller &

Quick, 2010). Empirical research found that MSV could backfire by posing a threat to the freedom of choice (Miller & Quick, 2010), especially when high MSV is coupled with high-controlling language (Xu, 2015a).

However, grounded on the attention-distracting literature, the dominant thought interrupting hypothesis suggests that MSV can enhance the persuasiveness of counter-attitudinal messages (Petty et al., 1976). This occurs because MSV diverts attention away from the threatening message content, reduces message processing, and consequently enhances message effectiveness. Previous studies have partially supported this hypothesis, such that only one dimension of MSV, message novelty, effectively reduces psychological reactance (Quick, 2013). Given the mixed evidence, this study proposed the following research question about the role of belief congruence in moderating MSV's effects.

***RQ4.** How does belief congruence moderate the effects of MSV in short videos on message attention, processing, and persuasiveness?*

4.5 Methods

4.5.1 Experiment Design and Procedure

To investigate the effect of MSV in short videos, an online experiment using a within-subject design was conducted. Two within-subject factors were included in this study, including three levels of MSV (i.e., low, mid, high) and two issues (i.e., COVID-19, climate change). Figure 4.1 below details the experimental design and procedure. A within-subject design was chosen because it allows for a direct comparison across the varying levels of MSV while minimizing individual variability, increasing the study's internal validity. This design also enhances the study's external validity by reflecting the real-world short video exposure experience.

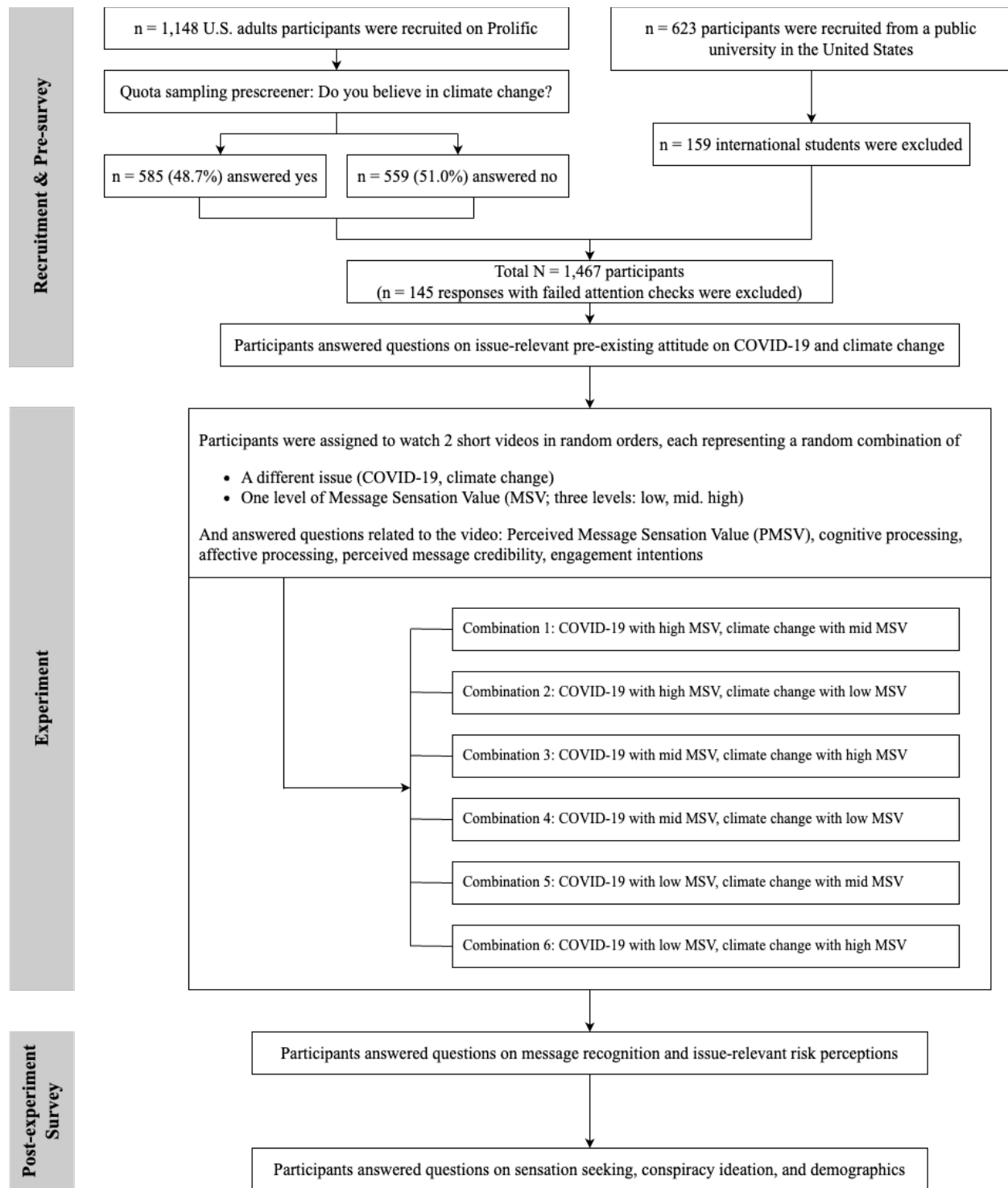


Figure 4.1 Flow diagram of experiment design and procedure.

The experiment was programmed on the Qualtrics platform (Qualtrics, 2022). All study procedures were approved by the university's Institutional Review Board. Participants ($n = 1,612$) were recruited from both Prolific (Prolific, 2023) and a public university in the U.S. in April 2024. Power analysis using G*Power showed that the sample size was sufficient to detect statistically significant effects ($\alpha = .05$, power = .95, Cohen's $d = .10$) (Faul et al., 2009). Eligible participants were U.S. adults. To ensure inclusivity and equal participation opportunities, in the student sample, international students could participate in this study as well, but their responses ($n = 60$) were later excluded from the analysis to maintain the study's focus on the targeted population. Further, an attention check was integrated into the study to maintain data quality; participants who failed the attention check question were excluded from the analysis. $N = 1,467$ participants were retained as the final sample for analysis.

Sampling procedure. Given the significance of belief congruence in this study, having a balanced representation of pre-existing beliefs on COVID-19 and climate change is important. According to the Pew Research Center, Americans' concerns with COVID-19 have decreased, yet there remains a divide with half of the population still concerned with the long COVID while the other half is not (Tyson & Pasquini, 2024). On the contrary, Americans's views on climate change are more aligned with the majority of expressing concerns (Tyson et al., 2023). To address the potential imbalance in the pre-existing attitude toward climate change, quota sampling was employed on Prolific. Relying on the responses to the prescreening question on Prolific: "Do you believe in climate change?", this study recruited 50% of participants who answered yes and the other 50% answering no and excluded those undecided or preferring not to answer.

Experiment procedure. The study started with two questions on the participant's pre-existing attitudes toward COVID-19 and climate change. Next, participants were assigned to watch two short videos on COVID-19 and climate change, presented one by one. These two short videos were randomly matched with a different level of MSV and an issue (see Figure 4.1 for all potential combinations). During this phase, the short videos were programmed to play automatically, and the option to pause or stop was disabled. The "next" button was programmed to become available only after the full playback of a video, which was when participants were able to proceed to the next section. After finishing watching a video, participants were asked to evaluate the video in terms of its perceived MSV, cognitive and affective processing, perceived credibility, and intention to engage with the video. Participants were also prompted to list 3-5 thoughts related to each video. While responding to these questions, the video was still accessible for further viewing if necessary. Afterward, participants proceeded to the next section where they answered questions on message recognition and issue-relevant risk perceptions without access to the video anymore. The study ended with questions on sensation seeking, conspiracy ideation, and demographics.

Demographics. Among the $N = 1,467$ participants, $n = 952$ participants were female (65.2%), with a mean age of 36.6 years, 65.8% white, 33.3% with a bachelor's degree or above, and with a median annual household income between \$50,000 and \$74,999. See Appendix Table B.4 for a summary of demographics.

4.5.2 Stimuli Development

The development of experimental stimuli of short videos with three distinct levels of MSV (i.e., low, mid, high) involves three steps: (a) script writing, (b) MSV manipulation, and (c) manipulation check.

4.5.2.1 Script Development

The scripts for short videos about COVID-19 and climate change were created to serve as the foundational content for all stimuli variations (See Appendix Table A.3 for the video scripts). To ensure internal validity, stimuli across all conditions follow the same script, keeping the content constant. To ensure external validity, this study created scripts mirroring the style of the existing informational videos on popular short video platforms and integrated the most current news for each topic. The COVID-19 script centered on the recent surge of COVID-19 in 2024 (Hohman, 2024), highlighted the emerging variants and healthcare challenges (Loesch, 2024), and concluded with a call for COVID-19 vaccination. The climate change script focused on recent environmental crises, pinpointed significant events such as the wildfire in Hawaii (Siegler, 2023) and the mass bleaching in the Great Barrier Reef (BBC, 2020), and concluded with a call for action.

4.5.2.2 MSV Manipulation

To create experimental stimuli short videos with varying levels of MSV (i.e., low, mid, high), it is necessary to understand how multimodal features contribute to MSV in existing informational short videos, thereby ensuring the external validity of this manipulation. This understanding was informed by (a) a dataset of $n = 10,000$ short videos related to climate change and vaccination and (b) a computational measure of MSV established in Chapter 3.

Dataset overview. This dataset of short videos related to vaccines and climate change was sampled from a dataset of $n = 96,242$ short videos on TikTok. The full dataset was curated using TikTok Research API (TikTok, 2024), where 10 popular hashtags for each issue with both stances considered were included, and all short videos spanning from January 2020 to September 2023 were collected. This subset ($n = 10,000$) includes $n = 6,520$ vaccine-related videos (n_{pro-

$n_{vaccine} = 4,181$, $n_{anti-vaccine} = 2,339$) and $n = 3,480$ climate change-related videos ($n_{pro-climate\ action} = 3,319$, $n_{anti-climate\ action} = 161$). This dataset was selected as the reference for stimuli production due to its relevance to the study's emphasis on science-related issues and its reflection on the current trends in short video production practices. Although it does not specifically align with the context of COVID-19, it remains pertinent with a substantial portion of the dataset ($n = 2,401$) containing keywords related to COVID-19 (e.g., COVID-19, coronavirus).

Computational analysis of MSV. This study extracted multimodal features and estimated MSV for this dataset with the computational measure of MSV in Chapter 3. The analysis involved segmenting the dataset into three quantiles based on the predicted MSV and conducting pairwise t-tests of multimodal features across three quantiles. The analysis revealed significant differences for 8 multimodal features (see Appendix Table B.5 for summary statistics). Specifically, short videos with higher MSV were featured by (a) a higher number of faces and shots per second and therefore a shorter duration of faces and shots per second, as well as (b) lower levels of visual and sound brightness, color warmth, and visual complexity. The insights from this computational analysis informed the adjustment of multimodal features and guided the manipulation of MSV in stimuli videos.

MSV manipulation details. Drawing from the analysis above, experimental stimuli short videos were tailored to reflect varying levels of MSV (see Table 4.1 below for details). Consistently, the greenscreen technique was used across all videos as the basic format, featuring a human narrator, a white female, against varied backgrounds. This format follows the prevalent style on short video platforms, ensuring external validity. MSV was manipulated through three features: the number of shots, background music, and visual stickers. First, high-MSV stimuli incorporated at least 15 shots, mid-MSV stimuli included 6 shots, and low-MSV stimuli were

featured by one shot only, with the video duration constant. Second, high-MSV stimuli included dynamic news article scroll-downs and supplementary video clips related to the discussed scenes; mid-MSV stimuli included news article screenshots corresponding to the narratives; low-MSV stimuli were characterized by a single, static, context-relevant background image. Lastly, high-MSV stimuli were further intensified by including fast-paced background music and additional visual stickers, enhancing the overall MSV. This study included in total of 6 short videos, with climate change videos lasting for 65 seconds and the COVID-19 videos running 75 seconds.

Table 4.1 Description of multimodal feature adjustments for MSV manipulation.

		Low	Mid	High
MSV manipulation	Human face	Y	Y	Y
	Background screenshot	N	Still screenshot	Scroll-down
	#shots	1	6	15+
	Background music	slow-paced	slow-paced	fast-paced
	Visual stickers	N	N	Y

4.5.2.3 Manipulation Check

This study assessed the effectiveness of MSV manipulation in the short videos with both MSV and perceived MSV. This study examined (a) the predicted MSV with the computational MSV measure and (b) the perceived MSV with the PMSV scale in a pilot test ($n = 317$). Table 4.2 below details the summary. On the one hand, the computational analysis of MSV showed a successful manipulation of MSV, with High-MSV stimuli achieving a predicted MSV of 4.04, mid-MSV stimuli at 3.59, and 3.24 for low-MSV stimuli.

Table 4.2 Summary statistics of multimodal features, predicted MSV, and PMSV of experimental stimuli short videos across three levels of MSV.

		Low	Mid	High
Multimodal features	Brightness	116.18	130.24	126.92
	Color saturation	71.58	40.05	85.17
	Color warmness	0.35	0.15	0.22
	Visual complexity	7.27	4.96	6.21
	Shot count/s	0.01	0.11	0.47
	Shot duration/s	1.00	0.13	0.03
	Loudness	0.01	0.01	0.00
	Tempo	134.58	134.58	134.58
	Sound brightness	2564.45	2557.91	2751.35
	Face count/s	0.01	0.15	0.80
	Face duration/s	1.00	0.17	0.02
Predicted MSV		3.24	3.59	4.04
PMSV		3.25	3.62	3.98

Consistently, on the other hand, the pilot test of PMSV confirmed the success of MSV manipulation. This study surveyed $n = 317$ participants in March 2024 on Prolific (Prolific, 2023). Similar to the experiment design, participants were assigned to watch two short videos on COVID-19 and climate change, presented one by one. These two short videos were randomly matched with a different level of MSV and an issue to better capture the perceptual differences across individual variations (see Figure 4.1 for all potential combinations). Participants were asked to evaluate the PMSV of each video, using the PMSV scale ($n = 633$, $Min = 1$, $Max = 7$, $M = 3.66$, $SD = 1.28$, Cronbach's $\alpha = .95$) (Palmgreen et al., 2002). This study conducted a pairwise t-test to assess the PMSV contrasting three MSV levels and revealed significant differences, with high-MSV stimuli ($M = 3.98$, $SD = 1.26$) being perceived as more sensational than mid-MSV stimuli ($M = 3.62$, $SD = 1.29$, $p = .011$) and low-MSV stimuli ($M = 3.25$, $SD = 1.25$, $p < .001$), and mid-MSV stimuli being perceived as more sensational than low-MSV stimuli ($p = .035$). Overall, both manipulation checks confirmed the effectiveness of MSV manipulation.

4.5.3 Measures

Pre-existing attitude. On a 4-point scale (1– not serious at all/not concerned at all to 4– very serious/very concerned), the pre-existing attitude toward COVID-19 ($n = 1,467$, $Min = 1$, $Max = 4$, $M = 2.11$, $SD = 0.88$) and climate change ($n = 1,467$, $Min = 1$, $Max = 4$, $M = 2.79$, $SD = 1.14$) were measured with two questions, respectively: “How serious a problem would you say the COVID-19 pandemic is right now?” and “How concerned are you about the impacts of climate change?”

Perceived Message Sensation Value. PMSV was measured with a PMSV scale (Palmgreen et al., 2002). This instrument contains 17 items on a 7-point semantic differential scale, covering three dimensions of PMSV: emotional arousal (8 items, e.g., arousing–not arousing), dramatic impact (6 items, e.g., didn’t give me goosebumps–gave me goosebumps), and novelty (3 items, e.g., unique–common) ($n = 2,933$, $Min = 1$, $Max = 7$, $M = 3.31$, $SD = 1.23$, Cronbach’s $\alpha = .94$). See Appendix Table A.1 for the full scale.

Cognitive processing. Cognitive processing ($n = 2,932$, $Min = 1$, $Max = 7$, $M = 3.41$, $SD = 0.83$, Cronbach’s $\alpha = .89$) was measured by the extent to which participants agreed with 12 statements on a message elaboration scale that ranged from 1–strongly disagree to 7–strongly agree (Reynolds, 1997). Example items include “deep in thought about the video” and “not really exerting your mind.” See Appendix Table A.4 for the full scale.

Affective processing. On a 7-point scale, affective processing ($n = 2,933$, $Min = 1$, $Max = 5$, $M = 1.85$, $SD = 0.55$, Cronbach’s $\alpha = .67$) was measured by the extent to which participants feel 7 discrete emotions while watching the video, including surprised, angry, fearful, sad, guilty, happy, and contented (Dillard & Peck, 2001).

Perceived credibility. Perceived credibility of short videos was measured by participants' credibility perceptions (Sundar, 2000), using five pairs of adjectives (e.g., biased–unbiased, unfair–fair) on a 7-point semantic differential scale ($M = 3.60$, $SD = 1.45$, Cronbach's $\alpha = .93$). See Appendix Table A.5 for the full scale.

Engagement intention. Intention to engage with short videos was measured by the extent to which participants would like, comment, or share the short videos (J. W. Kim, 2018) by asking them to agree or disagree with 5 statements (e.g., “This short video is worth sharing with others on social media” from 1–strongly disagree to 7–strongly agree) ($M = 2.54$, $SD = 1.24$, Cronbach's $\alpha = .91$). See Appendix Table A.6 for the full scale.

Attention. The attention to short videos was measured by the dwell time spent on the short video's page (Epstein et al., 2022). The dwell time was automatically recorded by the Qualtrics survey. Given that some participants paused in between surveys, the dwell time shorter than 10 minutes was included ($n = 2,927$, $Min = 1.02$, $Max = 9.86$, $M = 1.39$, $SD = 0.60$). In addition to the dwell time, attention was further measured by the accuracy of the recognition task (Kuhajda et al., 2002). It includes 10 multiple-choice questions on the information details in short videos, with 5 questions for COVID-19 ($n = 1,467$, $Min = 0$, $Max = 5$, $M = 4.35$, $SD = 0.95$, Cronbach's $\alpha = .50$) and 5 for climate change ($n = 1,467$, $Min = 0$, $Max = 5$, $M = 4.30$, $SD = 0.90$, Cronbach's $\alpha = .37$). Example questions include “What is the name of the latest COVID-19 variant mentioned in the video?” and “What major environmental event affected the Great Barrier Reef according to the video?” See Appendix Table A.7 for all question items.

Risk perception of climate change. The risk perception of climate change ($n = 1,467$, $Min = 0$, $Max = 7$, $M = 4.57$, $SD = 2.12$, Cronbach's $\alpha = .98$) was measured by a risk perception scale on a 7-point scale (van der Linden, 2015). This scale includes 8 questions, covering both the

perception of societal risk and personal risk related to climate change, such as “How concerned are you about the impacts of climate change?” and “How serious of a threat do you think climate change is to the natural environment?” See Appendix Table A.8 for the full scale.

Risk perception of COVID-19. Based on the existing measure of COVID-19 risk perception (Mejia et al., 2021; Wagner et al., 2021), the risk perception of COVID-19 ($n = 1,467$, $Min = 1$, $Max = 7$, $M = 3.43$, $SD = 1.51$, Cronbach’s $\alpha = .75$) includes 4 items on a 7-point scale, such as “Do you think you will be infected with COVID-19 over the next 12 months?” and “I think the pandemic has already ended.” See Appendix Table A.9 for the full scale.

Sensation seeking. The sensation-seeking preference was measured by a brief sensation-seeking scale (Hoyle et al., 2002). Participants are asked to evaluate the extent to which they agree or disagree with 8 statements on a 5-point scale (1: strongly disagree, 5: strongly agree), such as “I would like to take off on a trip with no pre-planned routes or timetables” ($n = 1,467$, $Min = 1$, $Max = 5$, $M = 2.67$, $SD = 0.91$, Cronbach’s $\alpha = .73$). See Appendix Table A.2 for the full scale.

Conspiracy ideation. Conspiracy ideation influences science acceptance and the attitude toward critical issues such as COVID-19 and climate change (Biddlestone et al., 2022; Granados Samayoa et al., 2022; Lewandowsky et al., 2013). It was measured by the conspiracy ideation scale (Brotherton et al., 2013) using 9 items (e.g., “The spread of certain viruses and/or diseases is the result of the deliberate, concealed efforts of some organization.”), with a 5-point scale (1 for definitely not true and 5 for definitely true) ($M = 3.08$, $SD = 0.98$, Cronbach’s $\alpha = .92$). See Appendix Table A.10 for the full scale.

Demographics. As additional covariates, participants were asked to report their age, gender, race, education, and income. Gender and race were converted to binary variables (gender: 1 for female, 0 for male; race: 1 for white, 0 for non-white).

4.5.4 Analysis Plan

To test competing hypotheses H1a and H1b regarding the effects of MSV on attention and message processing, the *lmerTest* package in R (Kuznetsova et al., 2017) was used to conduct linear mixed effects models. For this study with a within-subject design, the random order presenting two short videos was controlled as a random effect, in addition to the random intercept for participant variability. Two models were conducted with attention, cognitive processing, and affective processing as the dependent variable, respectively. In the unadjusted Model 1, the MSV of short videos was the only independent variable. In the adjusted Model 2, seven covariates were added, including the issue, pre-existing attitude, sensation seeking, conspiracy ideation, age, education, and income level.

To answer RQ1 about the effects of MSV on perceived message credibility, engagement intention, and risk perceptions, for each dependent variable, this study conducted two similar linear mixed effects models, one unadjusted and one adjusted for the same 7 covariates.

To answer RQ2 about the moderating effect of sensation-seeking, this study conducted two similar linear mixed effects models (i.e., one unadjusted and one adjusted for covariates) for each dependent variable (i.e., attention, cognitive and affective processing, perceived message credibility, engagement intention, and risk perceptions). The independent variables are MSV, sensation-seeking, and their interaction term. Given the significance of simple slope analysis in testing moderation effects (Robinson et al., 2013), this study further conducted simple slope analyses using the *interaction* package in R (Long, 2022).

Similarly, to answer RQ3 about the moderating effect of age, this study conducted similar linear mixed effects models (i.e., one unadjusted and one adjusted for covariates) for each dependent variable. The independent variables are MSV, age, and their interaction term.

To answer RQ4 about the moderating effect of belief congruence, a dichotomized variable was created based on issue-relevant pre-existing attitudes. The video on climate change was counter-attitudinal for individuals who were not concerned with climate change; the video on COVID-19 was counter-attitudinal for individuals who considered COVID-19 as not serious. This study conducted similar linear mixed effects models for each dependent variable, with MSV, belief congruence, and their interaction term as independent variables.

4.6 Results

Manipulation check. Before testing hypotheses and answering research questions, this study conducted another manipulation check with a pairwise t-test of PMSV across three levels of MSV in the experiment. Consistently, this study found significant differences contrasting three levels of MSV. The manipulation of MSV is still successful. See Panel A in Figure 4.2 below for details.

The competing hypotheses H1a and H1b hypothesize the positive and negative effects of MSV in short videos on attention, cognitive processing, and affective processing (see Panels B-E in Figure 4.2 below for visualization; see Appendix Tables C.10-C.13 for results of linear mixed effects models). First, MSV was not a significant predictor of attention in the likelihood ratio tests of the significance of including MSV in the linear mixed effects models (dwell time: $\chi^2(2) = 1.31, p = .270$; message recognition: $\chi^2(2) = 0.99, p = .372$); MSV did impact dwell time or message recognition (Appendix Tables C.11-C.12). Second, MSV increased both cognitive and affective processing. MSV was identified as a significant factor in the likelihood ratio tests for

both cognitive ($\chi^2(2) = 19.78, p < .001$) and affective processing ($\chi^2(2) = 6.95, p < .001$). Specifically, both mid-MSV ($b = 0.06, SE = 0.02, 95\% CI = [0.01, 0.11], p = .019$) and high-MSV ($b = 0.15, SE = 0.02, 95\% CI = [0.11, 0.20], p < .001$) videos elicited higher levels of cognitive processing than low-MSV videos. Although affective processing did not differ across low-MSV and mid-MSV videos, high-MSV videos elicited more affective processing than low-MSV videos ($b = 0.06, SE = 0.02, 95\% CI = [0.03, 0.10], p = .001$). Therefore, neither of the competing hypotheses on MSV's effects on attention were accepted, however, H1a, the attention-attracting hypothesis was partially accepted for MSV's positive effects on cognitive and affective processing.

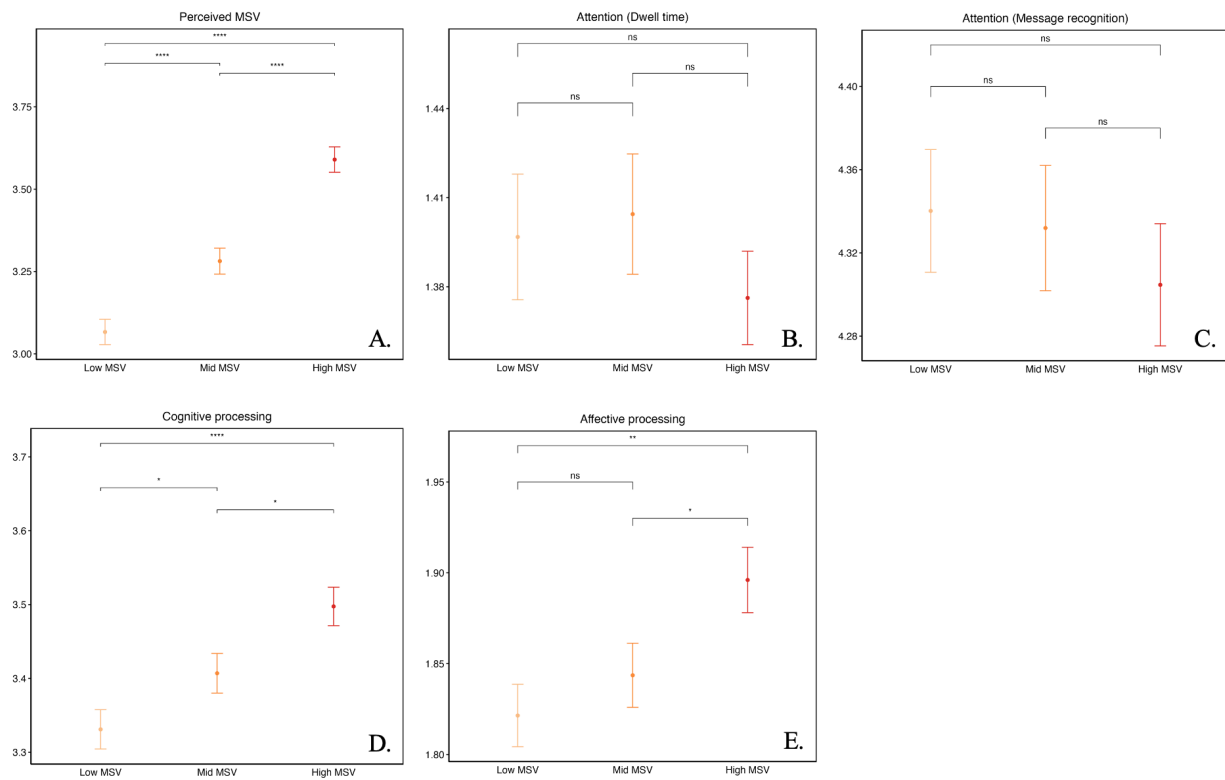


Figure 4.2 Means and confidence intervals of (A) Perceived Message Sensation Value (PMSV), (B) attention (dwell time), (C) attention (message recognition), (D) cognitive processing, and (E) affective processing across three levels of MSV. ns $p \geq .05$, * $p < .05$, ** $p < .01$, *** $p < .001$, **** $p < .0001$ in pairwise t-tests.

RQ1 inquired about the persuasive effects of MSV on perceived message credibility, engagement intention, and risk perceptions (see Figure 4.3 below for visualization; see Appendix Tables C.14-C.16 for results of linear mixed effects models). Overall, the likelihood ratio tests showed that MSV was a significant indicator of perceived message credibility ($\chi^2(2) = 5.82, p = .003$) and engagement intention ($\chi^2(2) = 9.91, p < .001$), but not for risk perceptions ($\chi^2(2) = 1.34, p = .261$). Specifically, high-MSV ($b = 0.13, SE = 0.04, 95\% CI = [0.06, 0.21], p = .001$) videos were perceived as more credible than low-MSV videos. Compared with low-MSV videos, individuals were more willing to engage with mid-MSV ($b = 0.07, SE = 0.03, 95\% CI = [0.00, 0.14], p = .036$) and high-MSV ($b = 0.15, SE = 0.03, 95\% CI = [0.08, 0.22], p < .001$) videos. However, issue-relevant risk perceptions did not differ across MSV. Therefore, MSV positively affected perceived message credibility and engagement intention.

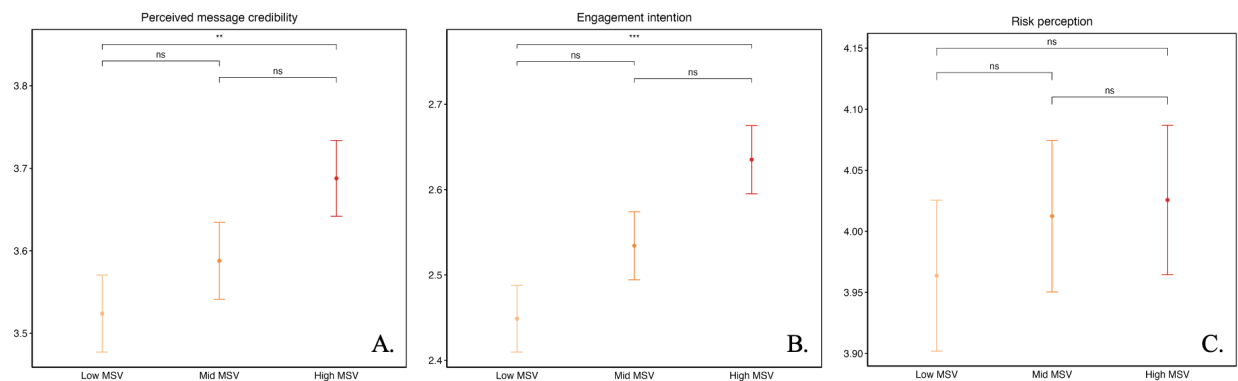


Figure 4.3 Means and confidence intervals of (A) perceived message credibility, (B) engagement intention, and (C) issue-relevant risk perception across three levels of MSV. ns $p \geq .05$, * $p < .05$, ** $p < .01$, *** $p < .001$, **** $p < .0001$ in pairwise t-tests.

Still, this effect did not translate to issue-relevant risk perceptions, even when considering the mediation effects of cognitive processing (proportion mediated = $-.13, 95\% CI = [-4.84, 7.89], p = .870$), affective processing (proportion mediated = $.01, 95\% CI = [-3.91, 2.88], p$

= .990), perceived message credibility (proportion mediated = .36, 95% CI = [-7.87, 8.54], p = .772), and engagement intention (proportion mediated = .21, 95% CI = [-6.25, 7.09], p = .920).

See Appendix Table C.17 for the details of exploratory mediation analyses).

4.6.1 The Influence of Sensation-seeking, Age, and Motivated Reasoning

RQ2 and RQ3 asked about the moderating effect of sensation-seeking and age. Before discussing the moderating effects, the relationship between sensation-seeking and age as well as the main effects of sensation-seeking and age are described in detail (see Appendix Tables C.10-C.16 for details). First, as Zuckerman (1994) noted, there was a negative correlation between sensation-seeking and age ($N = 1,466$, $r = -0.32$, $p < .001$), supporting the idea of decreased sensation-seeking over time. Further, there was a negative correlation between age and PMSV of experimental stimuli ($r = -0.12$, $p < .001$) and a positive correlation between sensation-seeking and PMSV ($r = 0.10$, $p < .001$), such that younger participants perceived the same content more sensational than older participants; high sensation-seekers perceived the same content more sensational than low sensation-seekers.

Second, without including the interaction terms, sensation-seeking negatively predicted message recognition and positively predicted dwell time, perceived message credibility, and engagement intention. These findings suggest that compared with low sensation-seekers, high sensation-seekers spent more time on the message content, remembered less from the message, perceived the videos as more credible, and were more likely to engage with the videos. In addition, age positively predicted attention (message recognition) and cognitive processing but negatively predicted perceived message credibility. Older adults remembered more from the short videos meanwhile being more suspicious.

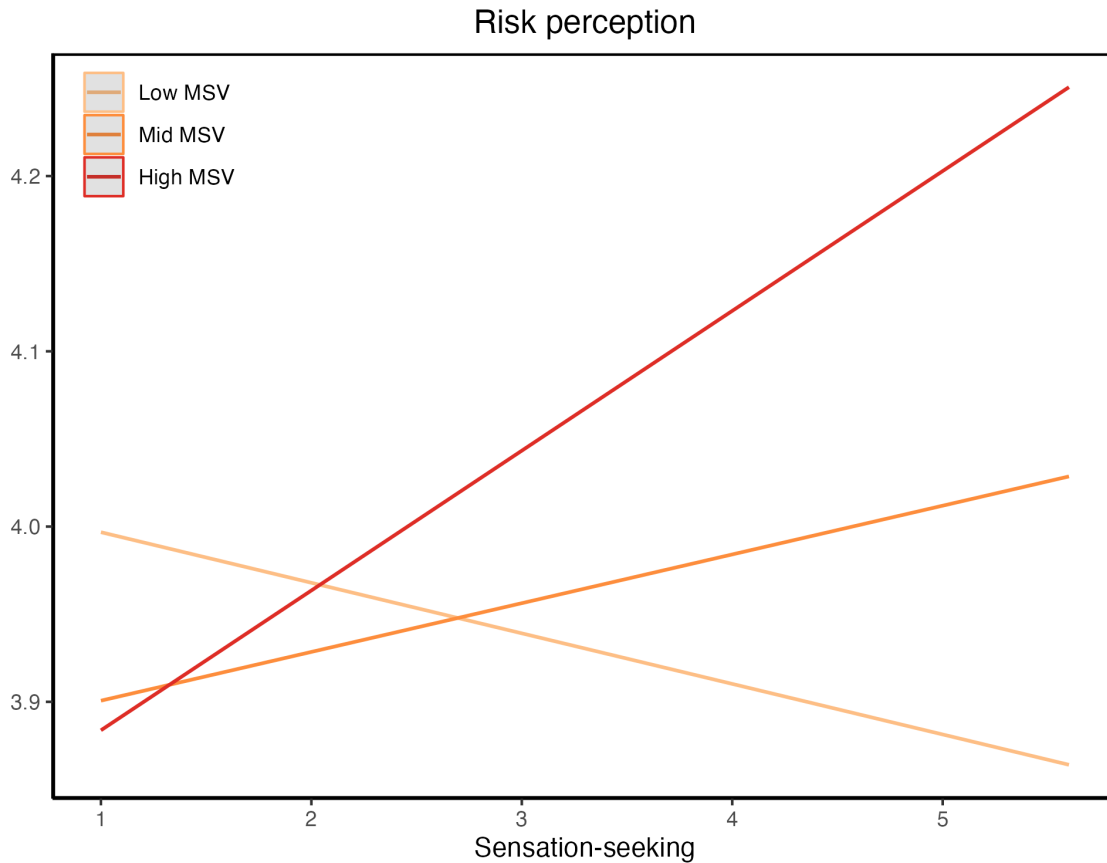


Figure 4.4 Predicted marginal means of risk perceptions in relation to sensation-seeking across three levels of Message Sensation Value (i.e., high, mid, low).

To answer RQ2, linear mixed effects models including the interaction term between sensation-seeking and MSV were conducted (see Appendix Tables C.18-C.24 for details). While there was no significant interaction between sensation-seeking and MSV for attention or message processing, there was a significant interaction between sensation-seeking and high MSV for risk perception ($b = 0.11$, $SE = 0.05$, $95\% CI = [0.01, 0.21]$, $p = .037$; see Appendix Table C.24 for details). This interaction effect was relatively small, which was not detected in the likelihood ratio test ($\chi^2(2) = 2.17$, $p = .114$). However, a closer look at the simple slope analysis revealed that sensation-seeking positively predicted risk perception for high-MSV videos ($b = 0.08$, $SE = 0.04$, $95\% CI = [0.00, 0.16]$, $p = .039$), but not for low-MSV ($b = -0.03$, $SE = 0.04$, $95\% CI = [-$

0.11, 0.05, $p = .466$) or mid-MSV ($b = 0.03$, $SE = 0.04$, 95% $CI = [-0.05, 0.11]$, $p = .490$) videos (see Figure 4.4 above for visualization). Further, separate models on MSV's impact on risk perceptions for high sensation-seeking and low sensation-seeking individuals were conducted (see Appendix Table C.25 for details). High-MSV videos increased risk perceptions for high sensation-seekers ($b = 0.19$, $SE = 0.09$, 95% $CI = [0.02, 0.35]$, $p = .029$), while MSV had no significant impact for low sensation-seekers.

The findings suggest that low-MSV and mid-MSV had no impact on risk perceptions regardless of sensation-seeking preferences, whereas high sensation-seekers exposed to high-MSV videos experienced improved risk perceptions. Overall, although sensation-seeking did not moderate MSV's effect on attention, message processing, or message perception, high-MSV videos increased risk perceptions for high sensation-seekers.

To answer RQ3, this study conducted linear mixed effects models including the interaction term between age and MSV (see Figure 4.5 above for visualizations; see Appendix Tables C.26-C.32 for details). Overall, the likelihood ratio tests showed that there was a significant interaction effect between age and MSV on cognitive processing ($\chi^2(2) = 3.17$, $p = .042$), affective processing ($\chi^2(2) = 5.38$, $p = .005$), and engagement intention ($\chi^2(2) = 7.02$, $p < .001$). Although the interaction overall was not a significant factor for perceived message credibility ($\chi^2(2) = 2.06$, $p = .127$), there was a notable interaction between high MSV and age (see Appendix Table C.30 for details).

Simple slope analyses revealed that (a) the positive effect of age on cognitive processing decreased with MSV, (b) age positively predicted affective processing for low-MSV videos only, (c) MSV intensified the negative effect of age on perceived message credibility, and (d) age negatively predicted engagement intention for high-MSV videos only. These results suggested

that younger participants experienced higher levels of message processing and had higher levels of perceived message credibility and engagement intention with high-MSV videos, while the opposite was for older participants.

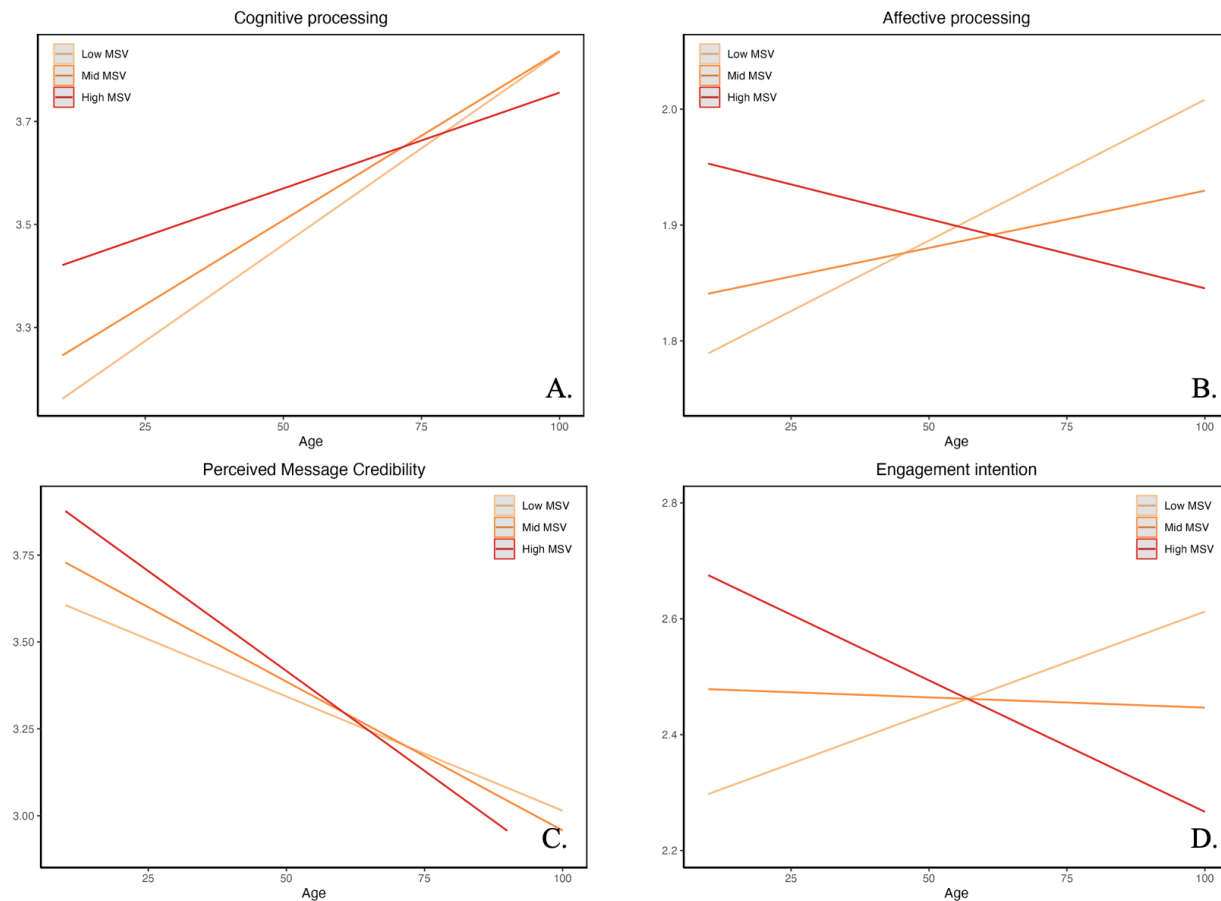


Figure 4.5 Predicted marginal means of (A) cognitive processing, (B) affective processing, (C) perceived message credibility, and (D) engagement intention in relation to age across three levels of Message Sensation Value (i.e., high, mid, low).

Specifically, this study conducted similar linear mixed effects models for two age groups, younger and older than 35 years old (see Appendix Tables C.33-C.36 for details). First, compared with low-MSV videos, both high-MSV ($b = 0.20$, $SE = 0.04$, $95\% CI = [0.13, 0.27]$, $p < .001$) and mid-MSV videos ($b = 0.08$, $SE = 0.04$, $95\% CI = [0.01, 0.16]$, $p = .025$) enhanced

cognitive processing for younger adults, while only high-MSV videos enhanced cognitive processing for older adults ($b = 0.11$, $SE = 0.03$, $95\% CI = [0.05, 0.18]$, $p = .001$). Second, MSV positively influenced the affective processing of short videos for participants aged below 35, such that high-MSV elicited more affective processing than low-MSV videos ($b = 0.11$, $SE = 0.03$, $95\% CI = [0.06, 0.16]$, $p < .001$). On the contrary, MSV did not impact affective processing for participants older than 35. Third, high-MSV videos increased perceived message credibility for younger adults ($b = 0.19$, $SE = 0.05$, $95\% CI = [0.09, 0.29]$, $p < .001$), while MSV did not impact credibility judgment for older adults. Lastly, regarding the intention to engage with short videos, younger participants were more willing to engage with both high-MSV ($b = 0.27$, $SE = 0.05$, $95\% CI = [0.17, 0.36]$, $p < .001$) and mid-MSV ($b = 0.12$, $SE = 0.05$, $95\% CI = [0.02, 0.21]$, $p = .017$) videos, compared with low-MSV videos. Similarly, the engagement intentions of participants aged above 35 did not vary across MSV. Overall, age moderated the effects of MSV in short videos, and younger individuals were more susceptible to the impact of MSV in short videos.

RQ4 inquired about the moderating effect of belief congruence (see Appendix Tables C.37-C.43 for details). Overall, belief congruence had a positive main effect on message processing and persuasiveness. However, belief congruence did not moderate MSV's impact, which suggests that MSV influenced attention, message processing, and persuasiveness consistently when the videos were pro-attitudinal or counter-attitudinal for participants.

4.7 Discussion

This study relies on an online experiment to examine the persuasive effects of Message Sensation Value in short videos in the risk communication contexts of COVID-19 and climate change. This study addresses gaps in our knowledge regarding (a) the collective impact of

multimodal features and (b) the theoretical mechanism through which MSV attracts or distracts attention and enhances or impedes persuasion. The major findings are discussed below.

4.7.1 Overall Effectiveness of MSV

First, MSV in short videos has shown an overall positive effect on message processing and persuasiveness, such that high-MSV and mid-MSV videos enhanced cognitive and affective processing as well as perceived message credibility and the intention to engage with short videos, compared with low-MSV videos. Contrary to the thought-disruption hypothesis that posits that sensational message features distract the attention and cognitive resources from the message content (Petty et al., 1976), this finding supports the attention-attracting argument that sensational message features satisfy individual motivation for sensory experiences, receive more cognitive resources allocated for information processing, and elicit higher levels of affective responses (Lang, 2000). This result not only supports existing research that mainly focuses on message perceptions but also provides experimental evidence for the activating role of MSV in motivating the intention to engage with short videos. This finding indicates the possibility of leveraging sensational multimodal features in short videos to improve message persuasiveness and engagement for effective science and risk communication.

Despite MSV's overall positive effects on message processing and persuasion, this positive effect did not extend to attention, complicating the mixed findings in prior research. Xu (2015b) found a positive effect of MSV on attention, where attention was measured by heart rate decelerations (Lang, 2000). Using human observation of participants' visual attention, Lorch and colleagues (1994) found that high-MSV videos increased attention for high sensation-seekers only. These mixed findings could be explained by measurement differences, with each measure capturing a distinct facet and stage of the complex process of attention. For example, heart rate

decelerations represent the immediate physiological engagement with messages (Lacey & Lacey, 2017), whereas self-reported message recognition quantifies the encoding of messages (Lang, 2000). It is worth noting that these approaches only approximate real human attention, and the validity and accuracy of these measures are subject to different limitations (e.g., see Carroll & Anastasiades, 1978 for criticism of the heart rate deceleration approach). Therefore, the conclusion drawn from these studies should be considered within the specific aspects of attention rather than attention as a whole complex process. It is possible that MSV influences different aspects and stages of attention differently. In the current study that focuses on observed dwell time and self-reported message recognition, this study observed a consistent null effect for both measures. This underscores the need for a more nuanced understanding of how MSV impacts attention throughout the process of message exposure.

4.7.2 Sensation-seeking Moderates MSV's Effect on Risk Perception

This study revealed that sensation-seeking did not moderate MSV's effects on message processing or persuasiveness. The positive impacts of MSV were consistently observed for both high and low sensation-seekers, with the effect being more pronounced for high sensation-seekers. The positive effect of MSV among low sensation-seekers does not contradict AMIE's argument on optimal sensory preference. This is because these mid-MSV and even high-MSV videos may still fall within the acceptable sensory range for low sensation-seekers and therefore these videos are not overwhelmingly sensational to elicit negative perceptions (Noar et al., 2010). The average PMSV ratings of short videos showed that high-MSV videos were not perceived as excessively sensational in the study, which further supports this explanation.

Despite MSV's overall positive effects on message processing and persuasion, this study showed that high-MSV short videos specifically improved issue-relevant risk perceptions only

among high sensation-seekers. This finding may partially support AMIE's proposition that MSV that matches one's optimal sensation-seeking preferences would maximize attention and message processing (Donohew et al., 1980). For high sensation-seekers, high-MSV videos may represent optimal sensory experiences, thereby making the messages more persuasive for them in increasing risk perceptions. This finding suggests that although MSV enhances message processing and persuasiveness overall, its impact on changing risk perceptions may require a better alignment with the optimal sensation-seeking preference.

4.7.3 The Preference for High MSV among Young Adults

Instead of sensation-seeking, age was found to moderate MSV's effects on message processing and persuasiveness, such that MSV's positive impacts were more notable for young adults and MSV did not influence persuasiveness for older adults. It suggests that the attention-attracting effect of MSV is primarily effective for young adults, and this effect diminishes with age. This observation highlights a significant gap in the current research that predominantly focuses on teenagers and young adults. While this demographic focus is meaningful for the study of high-risk behaviors, this finding suggests the importance of exploring MSV's effects across a broader age spectrum, particularly in risk communication contexts that are relevant to the general population. Overall, this finding suggests that young adults are more susceptible to the influence of MSV, which suggests the potential of using sensational multimodal features on short video platforms with a majority of young audiences for effective science and risk communication.

4.7.4 The (Null) Moderating Effect of Belief Congruence

Lastly, belief congruence did not moderate MSV's effects. Although counter-attitudinal videos generally elicited lower levels of message processing and persuasive effects compared

with pro-attitudinal videos, MSV enhanced these outcomes consistently across varying belief alignments. The existing literature has suggested that sensational messages may increase psychological reactance and the perceived threat of freedom (Miller & Quick, 2010). However, such backfiring effects were not evident in this study. This could be explained by issue-relevant personal involvement or perceived severity of study contexts, such that issues like COVID-19 and climate change may not be perceived as immediately threatening personal freedom of choice, thereby allowing MSV to have positive effects on message processing and persuasiveness regardless of pre-existing attitudes. This result further supports the effectiveness of adopting sensational content for effective science and risk communication.

4.7.5 Limitations and Future Directions

This study has several limitations that could be addressed in future research. First, although this study operationalized three levels of MSV in experimental stimuli by manipulating multimodal features, this study only considers a limited set of features, which may limit the generalizability of the study's findings. Future research could include a wider range of multimodal features or experiment with different combinations of features to replicate the study's findings.

Second, the study's reliance on dwell time and self-reported message recognition as proxies for estimating attention may not accurately capture the complex process of viewers' attention to and visual engagement with short videos. Since participants were required to watch the entire video before proceeding to enhance the internal validity in the experimental setting, the measurement of attention could be less reliable. Future research could replicate this study with more direct and diverse measures of attention, such as eye-tracking experiments, to provide a more accurate and comprehensive understanding of MSV's effects on attention.

Third, this study relies on a static exposure platform with embedded short videos, which does not mimic the dynamic scrolling experience of actual short video platforms. This could limit the external validity of the findings because user behaviors may differ significantly in the real information exposure environment. In addition, engagement intention was measured with self-reported questions rather than observing actual engagement behaviors. Future research could replicate this study with a field experiment or on a simulated short video platform to validate the findings with higher levels of external validity.

Chapter 5 Discussion and Conclusion

The contemporary high-sensation media environment provides both challenges and opportunities to communicate important science, health, environment, and risk information. Short video platforms have emerged as key information sources with a massive user base, along with the ongoing plague of misinformation about critical issues like COVID-19 and climate change on short video platforms (Alonso López et al., 2021; Hsu, 2022). It is urgent for traditional public communication to adapt to the new media formats and effectively engage the audience on these emerging platforms. Key questions arise: How can we effectively employ short video features for effective science and risk communication? Which multimodal features of short videos are crucial for persuasion? What is the precise theoretical mechanism explaining multimodal features' persuasive effects?

The current dissertation tackles these pressing questions by proposing that sensational short videos should be considered as an innovative solution to effective risk communication in the current social media information ecosystem. This dissertation is grounded in the theoretical framework of Message Sensation Value (MSV; Palmgreen et al., 1991), theorizing and examining how MSV of short videos functions as an attention-attractor or attention-distractor. This research includes a combination of (a) an observational study analyzing multimodal features in short videos (Chapter 3) and (b) an online experiment that tests the causal impact of MSV on attention, message processing, and persuasion in the context of COVID-19 and climate change (Chapter 4). Findings from both studies suggest that leveraging sensational short videos could be an effective approach to engaging and persuading the public, particularly young audiences, on critical science and risk issues. This dissertation offers significant theoretical contributions and practical implications for communicating risks in the contemporary media landscape.

First, with both observational and experimental evidence, this dissertation demonstrates that MSV enhances message engagement and persuasiveness to a certain extent. Chapter 3 identifies a consistent inverted U-shaped relationship between MSV and engagement through computational analysis of short videos across two datasets, highlighting the effectiveness of mid-MSV content in maximizing audience engagement. Chapter 4 presents causal evidence from an experiment and indicates that MSV enhances message processing, perceived message credibility, and engagement intentions. Both studies underscore the attention-attracting role of MSV, yet they present contradicting evidence on the extent of MSV's impacts: Chapter 3 suggests that video engagement peaks at the moderate level of MSV ($MSV = 3.28$ or 3.34 across two datasets), while Chapter 4 reveals that high-MSV videos ($PMSV = 3.59$) are more effective than mid-MSV ($PMSV = 3.28$) and low-MSV videos ($PMSV = 3.07$). This discrepancy could be attributed to differences in measurement and contexts. On the one hand, engagement measured with the observed number of views, likes, and shares is not conceptually equivalent to self-reported engagement intentions in experimental settings. The conceptual and measurement differences may lead to potential variations in outcomes. On the other hand, the significant differences in perception and effectiveness of MSV across contexts may contribute to the discrepancy in the findings. Chapter 3 includes short videos across eight general issues from 2018 to 2023, while Chapter 4 focuses on COVID-19 and climate change in 2024. Despite these differences, both studies agree on the MSV's effectiveness up to a point. Future research could further explore and pinpoint a more accurate optimal MSV that maximizes engagement and persuasiveness across varied contexts.

Second, this dissertation advances the research of short videos' impacts by examining the collective impact of multimodal features in short videos and developing a computational measure

of MSV in short videos. Relying on a computational analysis of $N = 1,200$ short videos across eight generic topics, Chapter 3 develops a machine learning-based model that predicts MSV using computationally extracted multimodal features with high reliability and validity. This approach updates the existing objective measure of MSV (Morgan et al., 2003) by (a) incorporating a comprehensive feature set, (b) adopting machine learning methods for accurate MSV estimation, and (c) shifting from human annotation to computational extraction of features. This advanced measure offers a robust and automated tool for estimating MSV in short videos, facilitating the empirical research of short videos and MSV. In addition, this study provides practical implications and actionable guidelines for content production on short video platforms in the context of science, environment, health, and risk communication.

Lastly, this dissertation explores the theoretical mechanism through which (a) MSV attracts or distracts attention and enhances or impedes persuasion, as well as (b) how individual predispositions moderate these effects. Chapter 4 confirms the overall positive effect of MSV in short videos in enhancing message processing and persuasiveness, which supports the attention-attracting argument that sensational message features receive more cognitive resources and elicit more affective responses (Lang, 2000). Further, this study identified age, rather than sensation-seeking or belief congruence as indicated in prior research, as a more significant moderator of MSV's effects. Specifically, the attention-attracting effect of MSV is primarily effective for young adults, and this effect diminishes with age. However, high-MSV short videos were found to improve issue-relevant risk perceptions only among high sensation-seekers, and MSV's impact did not vary across belief congruence. These findings advance our understanding of the role of MSV in a broader risk communication context for the general population, suggesting that

sensational short videos may potentially serve as effective public risk communication strategies to counter misinformation influence and update accurate risk perceptions on critical issues.

5.1 Limitations and Future Directions

This dissertation has several limitations that could be addressed in future research. First, the findings of this dissertation have limited generalizability with its focus on English-language short videos in the United States. Chapter 3 examined English short videos on Instagram Reels and TikTok. The experiment in Chapter 4 recruited U.S. adults from online survey panels and included experimental stimuli in English only. This focus on specific content, platforms, and populations narrows the generalizability of this dissertation's findings to other cultural and linguistic contexts. Given the significance of cultural context in the research of MSV (A. C. C. Lu et al., 2017), future research should broaden the scope by examining a variety of video content across diverse cultural and linguistic settings for different populations.

Second, this dissertation presents correlational evidence on the relationship between MSV and engagement and causal evidence with an online experiment. However, how MSV influences engagement and persuasive outcomes over time remains unclear. Since attitude change is often a longitudinal process, exploring how MSV in the long run influences the changes in attitudes and risk perceptions could provide a more nuanced understanding of its effect. Further, investigating the long-term effects would enhance the external validity of the findings because sustained message exposure reflects actual information consumption behaviors more accurately.

Lastly, this dissertation primarily relies on self-reported data from participants, which may not fully capture the actual information consumption behaviors and preferences. To bridge this gap, future research could rely on more behavior-based approaches such as physiological

measures, eye-tracking studies, and field experiments. These methods could provide a more direct observation of participants' responses and behaviors, which could further provide a more robust validation of the dissertation's findings.

5.2 Conclusion

Using a multi-method design, this dissertation reveals the attention-attracting effect of MSV in short videos and suggests that sensational short videos should be considered as an innovative solution for effective risk communication in the contemporary media environment. Specifically, both observational and experimental evidence showed that MSV enhances message engagement and persuasiveness to a certain extent. This dissertation not only advances our understanding of MSV's persuasive impacts but also provides a useful theoretical framework and a robust measure for understanding multimodal information in future research. This dissertation has practical implications for science communication and social media practitioners. Incorporating sensational multimodal features, this research provides a theory-informed and actionable guideline to increase the visibility of scientific information, establish scientific surveillance on short video platforms, and effectively compete for public attention against misinformation.

Reference

- 4K Stogram. (2024). *4kstogram: Best IG downloader by URL*. 4kstogram: Best IG Downloader by URL. <https://www.4kstogram.com/>
- Alonso López, N., Sidorenko Bautista, P., Giacomelli, F., & others. (2021). Beyond challenges and viral dance moves: TikTok as a vehicle for disinformation and fact-checking in Spain, Portugal, Brazil, and the USA. *Anàlisi*, 64. <https://doi.org/10.5565/rev/analisi.3411>
- Apify. (2023). *Apify: Full-stack web scraping and data extraction platform*. Apify. <https://apify.com/>
- Bannister, S. (2020). A Vigilance Explanation of Musical Chills? Effects of Loudness and Brightness Manipulations. *Music & Science*, 3, 2059204320915654. <https://doi.org/10.1177/2059204320915654>
- Baptista, J. P., & Gradim, A. (2020). Understanding Fake News Consumption: A Review. *Social Sciences*, 9(10). <https://doi.org/10.3390/socsci9100185>
- Barsade, S. G. (2002). The Ripple Effect: Emotional Contagion and its Influence on Group Behavior. *Administrative Science Quarterly*, 47(4), 644–675. <https://doi.org/10.2307/3094912>
- Basch, C. H., Mohlman, J., Fera, J., Tang, H., Pellicane, A., & Basch, C. E. (2021). Community Mitigation of COVID-19 and Portrayal of Testing on TikTok: Descriptive Study. *JMIR Public Health Surveill*, 7(6), e29528. <https://doi.org/10.2196/29528>
- Basch, C. H., Yalamanchili, B., & Fera, J. (2022). #Climate Change on TikTok: A Content Analysis of Videos. *Journal of Community Health*, 47(1), 163–167. <https://doi.org/10.1007/s10900-021-01031-x>

- Bayes, R., & Druckman, J. N. (2021). Motivated reasoning and climate change. *Human Response to Climate Change: From Neurons to Collective Action*, 42, 27–35.
<https://doi.org/10.1016/j.cobeha.2021.02.009>
- BBC. (2020, October 14). Great Barrier Reef has lost half of its corals since 1995. *BBC*.
<https://www.bbc.com/news/world-australia-54533971>
- Berger, J., Moe, W. W., & Schweidel, D. A. (2023). What Holds Attention? Linguistic Drivers of Engagement. *Journal of Marketing*, 87(5), 793–809.
<https://doi.org/10.1177/00222429231152880>
- Bestvater, S. (2024, February 22). How U.S. Adults Use TikTok. *Pew Research Center: Internet, Science & Tech*. <https://www.pewresearch.org/internet/2024/02/22/how-u-s-adults-use-tiktok/>
- Bhargava, P., MacDonald, K., Newton, C., Lin, H., & Pennycook, G. (2023). How effective are TikTok misinformation debunking videos? *Harvard Kennedy School Misinformation Review*. <https://doi.org/10.37016/mr-2020-114>
- Biddlestone, M., Azevedo, F., & van der Linden, S. (2022). Climate of conspiracy: A meta-analysis of the consequences of belief in conspiracy theories about climate change. *Current Opinion in Psychology*, 46, 101390.
<https://doi.org/10.1016/j.copsyc.2022.101390>
- Biocca, F., Harms, C., & Burgoon, J. K. (2003). Toward a More Robust Theory and Measure of Social Presence: Review and Suggested Criteria. *Presence: Teleoperators and Virtual Environments*, 12(5), 456–480. <https://doi.org/10.1162/105474603322761270>

- Boulianne, S., & Shehata, A. (2022). Age Differences in Online News Consumption and Online Political Expression in the United States, United Kingdom, and France. *The International Journal of Press/Politics*, 27(3), 763–783. <https://doi.org/10.1177/19401612211060271>
- Bradski, G. (2000). The openCV library. *Dr. Dobb's Journal: Software Tools for the Professional Programmer*, 25(11), 120–123.
- Brehm, S. S., & Brehm, J. Williams. (1981). *Psychological reactance: A theory of freedom and control*. Academic Press.
- Brotherton, R., French, C. C., & Pickering, A. D. (2013). Measuring Belief in Conspiracy Theories: The Generic Conspiracist Beliefs Scale. *Frontiers in Psychology*, 0(MAY), 279. <https://doi.org/10.3389/FPSYG.2013.00279>
- Brown, C., Chauhan, J., Grammenos, A., Han, J., Hasthanasombat, A., Spathis, D., Xia, T., Cicuta, P., & Mascolo, C. (2020). Exploring Automatic Diagnosis of COVID-19 from Crowdsourced Respiratory Sound Data. *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 3474–3484. <https://doi.org/10.1145/3394486.3412865>
- Butler, M. (2023, November 15). The Rise and Expansion of Short-Form Video: From Social Media to B2B Marketing | LinkedIn. *LinkedIn*. <https://www.linkedin.com/pulse/rise-expansion-short-form-video-from-social-media-b2b-marc-butler-kpdrc/>
- Calma, J. (2023, May 24). A fake climate change theory is going viral on TikTok after Joe Rogan talked about it. *The Verge*. <https://www.theverge.com/2023/5/24/23733231/tiktok-joe-rogan-podcast-climate-misinformation>

- Carrasco-Farré, C. (2022). The fingerprints of misinformation: How deceptive content differs from reliable sources in terms of cognitive effort and appeal to emotions. *Humanities and Social Sciences Communications*, 9(1), 162. <https://doi.org/10.1057/s41599-022-01174-9>
- Carroll, D., & Anastasiades, P. (1978). The behavioural significance of heart rate: The Laceys' hypothesis. *Biological Psychology*, 7(4), 249–275. [https://doi.org/10.1016/0301-0511\(78\)90059-5](https://doi.org/10.1016/0301-0511(78)90059-5)
- Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. <https://doi.org/10.1145/2939672.2939785>
- Choi, J. (2024, February 28). TikTok's 'mystery virus' is a pandemic side effect [Text]. *The Hill*. <https://thehill.com/policy/healthcare/4492268-tiktok-mystery-virus-pandemic-side-effect/>
- Collie, N., & Wilson-Barnao, C. (2020). 11. Playing with TikTok: Algorithmic culture and the future of creative work. In G. Hearn (Ed.), *The Future of Creative Work: Creativity and Digital Disruption* (pp. 172–188). Edward Elgar Publishing. <https://doi.org/10.4337/9781839101106.00007>
- Coutinho, E., & Cangelosi, A. (2011). Musical emotions: Predicting second-by-second subjective feelings of emotion from low-level psychoacoustic features and physiological measurements. *Emotion*, 11(4), 921–937. APA PsycArticles®. <https://doi.org/10.1037/a0024700>
- Cutting, J. E. (2016). The evolution of pace in popular movies. *Cognitive Research: Principles and Implications*, 1(1), 30. <https://doi.org/10.1186/s41235-016-0029-0>
- Czopek, M. (2023, July 31). PolitiFact—How health incidents like Bronny James' cardiac arrest fuel COVID-19 vaccine misinformation. *PolitiFact*.

- <https://www.politifact.com/article/2023/jul/31/how-health-incidents-like-bronny-james-cardiac-arr/>
- Deng, L., & Poole, M. S. (2010). Affect in Web Interfaces: A Study of the Impacts of Web Page Visual Complexity and Order. *MIS Quarterly*, 34(4), 711–730. JSTOR.
<https://doi.org/10.2307/25750702>
- Dillard, J. P., & Peck, E. (2001). Persuasion and the structure of affect. *Human Communication Research*, 27(1), 38–68. <https://doi.org/10.1111/j.1468-2958.2001.tb00775.x>
- Donohew, L., Palmgreen, P., & Duncan, J. (1980). An activation model of information exposure. *Communication Monographs*, 47(4), 295–303.
<https://doi.org/10.1080/03637758009376038>
- Donohew, L., Palmgreen, P., & Lorch, E. (1994). Attention, Need for Sensation, and Health Communication Campaigns. *American Behavioral Scientist*, 38(2), 310–322.
<https://doi.org/10.1177/0002764294038002011>
- Eghtesadi, M., & Florea, A. (2020). Facebook, Instagram, Reddit and TikTok: A proposal for health authorities to integrate popular social media platforms in contingency planning amid a global pandemic outbreak. *Canadian Journal of Public Health*, 111(3), 389–391.
<https://doi.org/10.17269/s41997-020-00343-0>
- Elliot, A. J., & Maier, M. A. (2014). Color Psychology: Effects of Perceiving Color on Psychological Functioning in Humans. In *Annual Review of Psychology* (Vol. 65, Issue Volume 65, 2014, pp. 95–120). Annual Reviews. <https://doi.org/10.1146/annurev-psych-010213-115035>
- Epstein, Z., Lin, H., Pennycook, G., & Rand, D. (2022). *Quantifying attention via dwell time and engagement in a social media browsing environment*.

- Everett, M. W., & Palmgreen, P. (1995). Influences of Sensation Seeking, Message Sensation Value, and Program Context on Effectiveness of Anticocaine Public Service Announcements. *Health Communication*, 7(3), 225–248.
https://doi.org/10.1207/s15327027hc0703_3
- Face++. (2023). *Face++ Cognitive Services*. <https://www.faceplusplus.com/>
- Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, 41(4), 1149–1160. <https://doi.org/10.3758/BRM.41.4.1149>
- Fushiki, T. (2011). Estimation of prediction error by using K-fold cross-validation. *Statistics and Computing*, 21(2), 137–146. <https://doi.org/10.1007/s11222-009-9153-8>
- Google Cloud. (2024). *Video AI and intelligence*. Google Cloud. <https://cloud.google.com/video-intelligence>
- Granados Samayoa, J. A., Moore, C. A., Ruisch, B. C., Boggs, S. T., Ladanyi, J. T., & Fazio, R. H. (2022). A gateway conspiracy? Belief in COVID-19 conspiracy theories prospectively predicts greater conspiracist ideation. *PLOS ONE*, 17(10), e0275502.
<https://doi.org/10.1371/journal.pone.0275502>
- Hess, U., & Blairy, S. (2001). Facial mimicry and emotional contagion to dynamic emotional facial expressions and their influence on decoding accuracy. *International Journal of Psychophysiology*, 40(2), 129–141. [https://doi.org/10.1016/S0167-8760\(00\)00161-6](https://doi.org/10.1016/S0167-8760(00)00161-6)
- Hoeken, H., & Hustinx, L. (2009). When is Statistical Evidence Superior to Anecdotal Evidence in Supporting Probability Claims? The Role of Argument Type. *Human Communication Research*, 35(4), 491–510. <https://doi.org/10.1111/j.1468-2958.2009.01360.x>

- Hogarty, K. Y., Kromrey, J. D., Ferron, J. M., & Hines, C. V. (2004). Selection of variables in exploratory factor analysis: An empirical comparison of a stepwise and traditional approach. *Psychometrika*, 69(4), 593–611. <https://doi.org/10.1007/BF02289857>
- Hohman, M. (2024, January 13). The US is starting 2024 in its second-largest COVID surge ever, experts say. *TODAY.Com*. <https://www.today.com/health/news/covid-wave-2024-rcna132529>
- Howard, D. J., & Gengler, C. (2001). Emotional Contagion Effects on Product Attitudes. *Journal of Consumer Research*, 28(2), 189–201. <https://doi.org/10.1086/322897>
- Hoyle, R. H., Stephenson, M. T., Palmgreen, P., Lorch, E. P., & Donohew, R. L. (2002). Reliability and validity of a brief measure of sensation seeking. *Personality and Individual Differences*, 32(3), 401–414. [https://doi.org/10.1016/S0191-8869\(01\)00032-0](https://doi.org/10.1016/S0191-8869(01)00032-0)
- Hsu, T. (2022, November 4). Worries Grow That TikTok Is New Home for Manipulated Video and Photos. *The New York Times*. <https://www.nytimes.com/2022/11/04/technology/tiktok-deepfakes-disinformation.html>
- Huang, K. (2022, September 16). For Gen Z, TikTok Is the New Search Engine. *The New York Times*. <https://www.nytimes.com/2022/09/16/technology/gen-z-tiktok-search-engine.html>
- Hyland-Wood, B., Gardner, J., Leask, J., & Ecker, U. K. H. (2021). Toward effective government communication strategies in the era of COVID-19. *Humanities and Social Sciences Communications*, 8(1), 30. <https://doi.org/10.1057/s41599-020-00701-w>
- Imhof, M. A., Schmälzle, R., Renner, B., & Schupp, H. T. (2017). How real-life health messages engage our brains: Shared processing of effective anti-alcohol videos. *Social Cognitive and Affective Neuroscience*, 12(7), 1188–1196. <https://doi.org/10.1093/scan/nsx044>

- Jain, S. P., & Maheswaran, D. (2000). Motivated Reasoning: A Depth-of-Processing Perspective. *Journal of Consumer Research*, 26(4), 358–371. <https://doi.org/10.1086/209568>
- Joo, J., Li, W., Steen, F. F., & Zhu, S.-C. (2014, June). Visual Persuasion: Inferring Communicative Intents of Images. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.
- Jović, A., Brkić, K., & Bogunović, N. (2015). A review of feature selection methods with applications. *2015 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, 1200–1205. <https://doi.org/10.1109/MIPRO.2015.7160458>
- Kang, Y., Cappella, J., & Fishbein, M. (2006). The Attentional Mechanism of Message Sensation Value: Interaction between Message Sensation Value and Argument Quality on Message Effectiveness. *Communication Monographs*, 73(4), 351–378. <https://doi.org/10.1080/03637750601024164>
- Kang, Y., & Cappella, J. N. (2008). Emotional Reactions to and Perceived Effectiveness of Media Messages: Appraisal and Message Sensation Value. *Western Journal of Communication*, 72(1), 40–61. <https://doi.org/10.1080/10570310701827604>
- Kim, C., & Yang, S. U. (2017). Like, comment, and share on Facebook: How each behavior differs from the other. *Public Relations Review*, 43(2), 441–449. <https://doi.org/10.1016/J.PUBREV.2017.02.006>
- Kim, J. W. (2018). Rumor has it: The effects of virality metrics on rumor believability and transmission on Twitter: *New Media & Society*, 20(12), 4807–4825. <https://doi.org/10.1177/1461444818784945>

- King, A. J., Lazard, A. J., & White, S. R. (2020). The influence of visual complexity on initial user impressions: Testing the persuasive model of web design. *Behaviour & Information Technology*, 39(5), 497–510. <https://doi.org/10.1080/0144929X.2019.1602167>
- Kong, Q., Cao, Y., Iqbal, T., Wang, Y., Wang, W., & Plumbley, M. D. (2020). PANNs: Large-Scale Pretrained Audio Neural Networks for Audio Pattern Recognition. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 28, 2880–2894. <https://doi.org/10.1109/TASLP.2020.3030497>
- Kramer, A. D. I., Guillory, J. E., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences*, 111(24), 8788. <https://doi.org/10.1073/pnas.1320040111>
- Kreps, G. L., & Neuhauser, L. (2013). Artificial intelligence and immediacy: Designing health communication to personally engage consumers and providers. *Patient Education and Counseling*, 92(2), 205–210. <https://doi.org/10.1016/j.pec.2013.04.014>
- Kriss, L. A., Quick, B. L., Rains, S. A., & Barbati, J. L. (2022). Psychological Reactance Theory and COVID-19 Vaccine Mandates: The Roles of Threat Magnitude and Direction of Threat. *Journal of Health Communication*, 27(9), 654–663. <https://doi.org/10.1080/10810730.2022.2148023>
- Kuhajda, M. C., Thorn, B. E., Klinger, M. R., & Rubin, N. J. (2002). The effect of headache pain on attention (encoding) and memory (recognition). *PAIN*, 97(3). https://journals.lww.com/pain/fulltext/2002/06000/the_effect_of_headache_pain_on_attention.5.aspx
- Kunda, Z. (1990). The case for motivated reasoning. *Psychological Bulletin*, 108(3), 480–498. <https://doi.org/10.1037/0033-2909.108.3.480>

- Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, 82(1), 1–26.
<https://doi.org/10.18637/JSS.V082.I13>
- Lacey, B. C., & Lacey, J. I. (2017). Studies of heart rate and other bodily processes in sensorimotor behavior. In *Cardiovascular psychophysiology* (pp. 538–564). Routledge.
- Lackmann, S., Léger, P.-M., Charland, P., Aubé, C., & Talbot, J. (2021). The Influence of Video Format on Engagement and Performance in Online Learning. *Brain Sciences*, 11(2).
<https://doi.org/10.3390/brainsci11020128>
- Lahat, D., Adali, T., & Jutten, C. (2015). Multimodal Data Fusion: An Overview of Methods, Challenges, and Prospects. *Proceedings of the IEEE*, 103(9), 1449–1477.
<https://doi.org/10.1109/JPROC.2015.2460697>
- Lang, A. (2000). The Limited Capacity Model of Mediated Message Processing. *Journal of Communication*, 50(1), 46–70. <https://doi.org/10.1111/j.1460-2466.2000.tb02833.x>
- Lang, A., Chung, Y., Lee, S., Schwartz, N., & Shin, M. (2005). It’s an Arousing, Fast-Paced Kind of World: The Effects of Age and Sensation Seeking on the Information Processing of Substance-Abuse PSAs. *Media Psychology*, 7(4), 421–454.
https://doi.org/10.1207/S1532785XMEP0704_6
- Langleben, D. D., Loughead, J. W., Ruparel, K., Hakun, J. G., Busch-Winokur, S., Holloway, M. B., Strasser, A. A., Cappella, J. N., & Lerman, C. (2009). Reduced prefrontal and temporal processing and recall of high “sensation value” ads. *NeuroImage*, 46(1), 219–225. <https://doi.org/10.1016/j.neuroimage.2008.12.062>

- Lee, J., & Shin, S. Y. (2022). Something that They Never Said: Multimodal Disinformation and Source Vividness in Understanding the Power of AI-Enabled Deepfake News. *Media Psychology*, 25(4), 531–546. <https://doi.org/10.1080/15213269.2021.2007489>
- Lewandowsky, S., Gignac, G. E., & Oberauer, K. (2013). The Role of Conspiracist Ideation and Worldviews in Predicting Rejection of Science. *PLOS ONE*, 8(10), e75637. <https://doi.org/10.1371/JOURNAL.PONE.0075637>
- Li, Y., Guan, M., Hammond, P., & Berrey, L. E. (2021). Communicating COVID-19 information on TikTok: A content analysis of TikTok videos from official accounts featured in the COVID-19 information hub. *Health Education Research*, 36(3), 261–271. <https://doi.org/10.1093/her/cyab010>
- Little, O., & Richards, A. (2021, August 18). TikTok’s algorithm is amplifying COVID-19 and vaccine misinformation | Media Matters for America. *Media Matters for America*. <https://www.mediamatters.org/tiktok/tiktoks-algorithm-amplifying-covid-19-and-vaccine-misinformation>
- Loesch, C. (2024, January 22). “Full-Blown Crisis:” Mass General Out Of Hospital Beds. *Across Massachusetts, MA Patch*. <https://patch.com/massachusetts/across-ma/full-blown-crisis-mass-general-out-hospital-beds>
- Long, J. A. (2022). *interactions: Comprehensive, User-Friendly Toolkit for Probing Interactions*. <https://cran.r-project.org/package=interactions>
- Lorch, E. P., Palmgreen, P., Donohew, L., Helm, D., Baer, S. A., & Dsilva, M. U. (1994). Program Context, Sensation Seeking, and Attention to Televised Anti-Drug Public Service Announcements. *Human Communication Research*, 20(3), 390–412. <https://doi.org/10.1111/j.1468-2958.1994.tb00328.x>

- Lu, A. C. C., Chi, C. G.-Q., & Lu, C. Y. R. (2017). Sensation Seeking, Message Sensation Value, and Destinations: A Cross-Cultural Comparison. *Journal of Hospitality & Tourism Research*, 41(3), 357–383. <https://doi.org/10.1177/1096348014550872>
- Lu, Y., & Pan, J. (2022). The Pervasive Presence of Chinese Government Content on Douyin Trending Videos. In *Computational Communication Research* (Vol. 4, Issue 1). Amsterdam University Press. <https://doi.org/10.5117/CCR2022.2.002.LU>
- Lu, Y., & Shen, C. (2023). Unpacking Multimodal Fact-Checking: Features and Engagement of Fact-Checking Videos on Chinese TikTok (Douyin). *Social Media + Society*, 9(1), 20563051221150406. <https://doi.org/10.1177/20563051221150406>
- Maass, W., Parsons, J., Purao, S., Storey, V., & Woo, C. (2018). Data-Driven Meets Theory-Driven Research in the Era of Big Data: Opportunities and Challenges for Information Systems Research. *Journal of the Association for Information Systems*, 19(12). <https://doi.org/10.17705/1jais.00526>
- Matsa, K. E. (2023, November 15). More Americans are getting news on TikTok, bucking the trend seen on most other social media sites. *Pew Research Center*. <https://www.pewresearch.org/short-reads/2023/11/15/more-americans-are-getting-news-on-tiktok-bucking-the-trend-seen-on-most-other-social-media-sites/>
- Mayer, R. E., & Sims, V. K. (1994). For whom is a picture worth a thousand words? Extensions of a dual-coding theory of multimedia learning. *Journal of Educational Psychology*, 86(3), 389–401. <https://doi.org/10.1037/0022-0663.86.3.389>
- McCashin, D., & Murphy, C. M. (2023). Using TikTok for public and youth mental health – A systematic review and content analysis. *Clinical Child Psychology and Psychiatry*, 28(1), 279–306. <https://doi.org/10.1177/13591045221106608>

- McFee, B., Raffel, C., Liang, D., Ellis, D. P., McVicar, M., Battenberg, E., & Nieto, O. (2015). librosa: Audio and music signal analysis in python. *Proceedings of the 14th Python in Science Conference*, 8, 18–25.
- Mehta, I. (2023, February 3). Google says YouTube Shorts has crossed 50 billion daily views. *TechCrunch*. <https://techcrunch.com/2023/02/03/google-says-youtube-shorts-has-crossed-50-billion-daily-views/>
- Mejia, C. R., Rodriguez-Alarcon, J. F., Ticona, D., Flores-Lovon, K., Paredes-Obando, M., Avalos-Reyes, M. S., Ccasa-Valero, L., Carbajal, M., Esteban, R. F. C., Mamani-Benito, O., Rivera-Lozada, O., & Tovani-Palone, M. R. (2021). Validation of a Scale to Measure the Perception of SARS-CoV-2 Vaccines Acceptance: The VAC-COVID-19 Scale. *Electronic Journal of General Medicine*, 18(5), em303. <https://doi.org/10.29333/ejgm/11012>
- Mesulam, M. M. (1998). From sensation to cognition. *Brain*, 121(6), 1013–1052. <https://doi.org/10.1093/brain/121.6.1013>
- Miller, C. H., & Quick, B. L. (2010). Sensation Seeking and Psychological Reactance as Health Risk Predictors for an Emerging Adult Population. *Health Communication*, 25(3), 266–275. <https://doi.org/10.1080/10410231003698945>
- Morgan, S. E., Palmgreen, P., Stephenson, M. T., Hoyle, R. H., & Lorch, E. P. (2003). Associations Between Message Features and Subjective Evaluations of the Sensation Value of Antidrug Public Service Announcements. *Journal of Communication*, 53(3), 512–526. <https://doi.org/10.1111/j.1460-2466.2003.tb02605.x>
- Motoki, K., Saito, T., Nouchi, R., Kawashima, R., & Sugiura, M. (2019). Light colors and comfortable warmth: Crossmodal correspondences between thermal sensations and color

- lightness influence consumer behavior. *Food Quality and Preference*, 72, 45–55.
<https://doi.org/10.1016/j.foodqual.2018.09.004>
- Newman, N. (2022). *How publishers are learning to create and distribute news on TikTok*. Reuters Institute for the Study of Journalism.
<https://reutersinstitute.politics.ox.ac.uk/how-publishers-are-learning-create-and-distribute-news-tiktok>
- Niederdeppe, J. (2005). Syntactic Indeterminacy, Perceived Message Sensation Value-Enhancing Features, and Message Processing in the Context of Anti-Tobacco Advertisements An earlier version of this manuscript was presented at the 2004 National Communication Association Annual Convention in Chicago, IL, November 11–14, 2004. *Communication Monographs*, 72(3), 324–344. <https://doi.org/10.1080/03637750500206862>
- Niederdeppe, J., Davis, K. C., Farrelly, M. C., & Yarsevich, J. (2007). Stylistic Features, Need for Sensation, and Confirmed Recall of National Smoking Prevention Advertisements. *Journal of Communication*, 57(2), 272–292. <https://doi.org/10.1111/j.1460-2466.2007.00343.x>
- Noar, S. M., Palmgreen, P., Zimmerman, R. S., Lustria, M. L. A., & Lu, H.-Y. (2010). Assessing the Relationship Between Perceived Message Sensation Value and Perceived Message Effectiveness: Analysis of PSAs From an Effective Campaign. *Communication Studies*, 61(1), 21–45. <https://doi.org/10.1080/10510970903396477>
- O’Sullivan, N. J., Nason, G., Manecksha, R. P., & O’Kelly, F. (2022). The unintentional spread of misinformation on ‘TikTok’; A paediatric urological perspective. *Journal of Pediatric Urology*, 18(3), 371–375. <https://doi.org/10.1016/j.jpuro.2022.03.001>

- Paek, H.-J., Kim, K., & Hove, T. (2010). Content analysis of antismoking videos on YouTube: Message sensation value, message appeals, and their relationships with viewer responses. *Health Education Research*, 25(6), 1085–1099. <https://doi.org/10.1093/her/cyq063>
- Paivio, A. (1991). Dual coding theory: Retrospect and current status. *Canadian Journal of Psychology/Revue Canadienne de Psychologie*, 45(3), 255–287. APA PsycArticles®. <https://doi.org/10.1037/h0084295>
- Palmgreen, P., Donohew, L., Lorch, E. P., Rogus, M., Helm, D., & Grant, N. (1991). Sensation seeking, message sensation value, and drug use as mediators of PSA effectiveness. *Health Communication*, 3(4), 217–227. https://doi.org/10.1207/s15327027hc0304_4
- Palmgreen, P., Stephenson, M. T., Everett, M. W., Baseheart, J. R., & Francies, R. (2002). Perceived Message Sensation Value (PMSV) and the Dimensions and Validation of a PMSV Scale. *Health Communication*, 14(4), 403–428. https://doi.org/10.1207/S15327027HC1404_1
- Petrillo, S. (2021). What Makes TikTok so Addictive?: An Analysis of the Mechanisms Underlying the World's Latest Social Media Craze. *Brown Undergraduate Journal of Public Health*. <https://sites.brown.edu/publichealthjournal/2021/12/13/tiktok/>
- Petty, R. E., & Cacioppo, J. T. (1986). The Elaboration Likelihood Model of Persuasion. In R. E. Petty & J. T. Cacioppo (Eds.), *Communication and Persuasion: Central and Peripheral Routes to Attitude Change* (pp. 1–24). Springer New York. https://doi.org/10.1007/978-1-4612-4964-1_1
- Petty, R. E., Wells, G. L., & Brock, T. C. (1976). Distraction can enhance or reduce yielding to propaganda: Thought disruption versus effort justification. *Journal of Personality and Social Psychology*, 34(5), 874–884. <https://doi.org/10.1037/0022-3514.34.5.874>

- Plass, J. L., Heidig, S., Hayward, E. O., Homer, B. D., & Um, E. (2014). Emotional design in multimedia learning: Effects of shape and color on affect and learning. *Learning and Instruction*, 29, 128–140. <https://doi.org/10.1016/j.learninstruc.2013.02.006>
- Potter, R. F., & Callison, C. (2000). Sounds Exciting!!: The Effects of Auditory Complexity on Listeners' Attitudes and Memory for Radio Promotional Announcements. *Journal of Radio Studies*, 7(1), 29–51. https://doi.org/10.1207/s15506843jrs0701_5
- Prolific. (2023). *Prolific · Quickly find research participants you can trust*. Prolific. <https://www.prolific.co/>
- Qi, P., Cao, J., Li, X., Liu, H., Sheng, Q., Mi, X., He, Q., Lv, Y., Guo, C., & Yu, Y. (2021). Improving Fake News Detection by Using an Entity-Enhanced Framework to Fuse Diverse Multimodal Clues. *Proceedings of the 29th ACM International Conference on Multimedia*, 1212–1220. <https://doi.org/10.1145/3474085.3481548>
- Qian, S., Lu, Y., Peng, Y., Shen, C. (Cindy), & Xu, H. (2024). Convergence or divergence? A cross-platform analysis of climate change visual content categories, features, and social media engagement on Twitter and Instagram. *Public Relations Review*, 50(2), 102454. <https://doi.org/10.1016/j.pubrev.2024.102454>
- Qualtrics. (2022). *Qualtrics* (June 2021) [Computer software]. Qualtrics. <https://www.qualtrics.com>
- Quick, B. L. (2013). Perceived Message Sensation Value and Psychological Reactance: A Test of the Dominant Thought Disruption Hypothesis. *Journal of Health Communication*, 18(9), 1024–1038. <https://doi.org/10.1080/10810730.2013.768728>
- Reynolds, R. A. (1997). A validation test of a message elaboration measure. *Communication Research Reports*, 14(3), 269–278. <https://doi.org/10.1080/08824099709388670>

- Richards, A. (2022). *The Storm Is Coming: Climate Change and Conspiracy Theories on TikTok* [Wageningen University & Research]. <https://edepot.wur.nl/590388>
- Robinson, C. D., Tomek, S., & Schumacker, R. E. (2013). Tests of moderation effects: Difference in simple slopes versus the interaction term. *Multiple Linear Regression Viewpoints*, 39(1), 16–24.
- Rodriguez-Galiano, V., Sanchez-Castillo, M., Chica-Olmo, M., & Chica-Rivas, M. (2015). Machine learning predictive models for mineral prospectivity: An evaluation of neural networks, random forest, regression trees and support vector machines. *Ore Geology Reviews*, 71, 804–818. <https://doi.org/10.1016/j.oregeorev.2015.01.001>
- Romero-Vicente, A. (2023, February 6). Don't stop me now: The growing disinformation threat against climate change. *EU DisinfoLab*. <https://www.disinfo.eu/publications/dont-stop-me-now-the-growing-disinformation-threat-against-climate-change/>
- Rosenberg, B. D., & Siegel, J. T. (2018). A 50-year review of psychological reactance theory: Do not read this article. *Motivation Science*, 4(4), 281–300. APA PsycArticles®. <https://doi.org/10.1037/mot0000091>
- Rothman, A. J., & Salovey, P. (1997). Shaping perceptions to motivate healthy behavior: The role of message framing. *Psychological Bulletin*, 121(1), 3–19. <https://doi.org/10.1037/0033-2909.121.1.3>
- Ruby, D. (2023, July 27). 35 Instagram Reels Statistics In 2023 (Updated Data). *DemandSage*. <https://www.demandsage.com/instagram-reel-statistics/>
- Salthouse, T. A. (1996). The processing-speed theory of adult age differences in cognition. *Psychological Review*, 103(3), 403–428. <https://doi.org/10.1037/0033-295X.103.3.403>

- Schubert, E. (2004). Modeling Perceived Emotion With Continuous Musical Features. *Music Perception*, 21(4), 561–585. <https://doi.org/10.1525/mp.2004.21.4.561>
- Seelig, D., Wang, A.-L., Jaganathan, K., Loughhead, J. W., Blady, S. J., Childress, A. R., Romer, D., & Langleben, D. D. (2014). Low Message Sensation Health Promotion Videos Are Better Remembered and Activate Areas of the Brain Associated with Memory Encoding. *PLOS ONE*, 9(11), e113256. <https://doi.org/10.1371/journal.pone.0113256>
- Segal, M. R. (2004). Machine Learning Benchmarks and Random Forest Regression. *UCSF: Center for Bioinformatics and Molecular Biostatistics*.
<https://escholarship.org/uc/item/35x3v9t4>
- Shahani, N. M., Zheng, X., Liu, C., Hassan, F. U., & Li, P. (2021). Developing an XGBoost Regression Model for Predicting Young’s Modulus of Intact Sedimentary Rocks for the Stability of Surface and Subsurface Structures. *Frontiers in Earth Science*, 9.
<https://www.frontiersin.org/articles/10.3389/feart.2021.761990>
- Sharevski, F., Loop, J. V., Jachim, P., Devine, A., & Pieroni, E. (2023). *Abortion Misinformation on TikTok: Rampant Content, Lax Moderation, and Vivid User Experiences*. arXiv.
<https://doi.org/10.48550/arXiv.2301.05128>
- Shen, L., & Bigsby, E. (2013). The Effects of Message Features. In J. P. Dillard & L. Shen (Eds.), *The persuasion handbook: Developments in theory and practice* (pp. 20–35). Sage.
- Shen, Z., Tan, S., & Pritchard, M. J. (2022). Understanding the Effects of Visual Cueing on Social Media Engagement With YouTube Educational Videos. *IEEE Transactions on Professional Communication*, 65(2), 337–350.
<https://doi.org/10.1109/TPC.2022.3156225>

- Sherman, A. (2020, August 24). TikTok reveals detailed user numbers for the first time. *CNBC*.
<https://www.cnbc.com/2020/08/24/tiktok-reveals-us-global-user-growth-numbers-for-first-time.html>
- Siegler, K. (2023, December 21). 2023 was a tragic and bizarre year of wildfires. Will it mark a turning point? *NPR*. <https://www.npr.org/2023/12/21/1220594184/2023-was-a-tragic-and-bizarre-year-of-wildfires-will-it-mark-a-turning-point>
- Smith, D. P., Hillman, C. H., & Duley, A. R. (2005). Influences of Age on Emotional Reactivity During Picture Processing. *The Journals of Gerontology: Series B*, 60(1), P49–P56.
<https://doi.org/10.1093/geronb/60.1.P49>
- Southerton, C. (2021). Research Perspectives on TikTok & Its Legacy Apps| Lip-Syncing and Saving Lives: Healthcare Workers on TikTok. *International Journal of Communication*, 15(0). <https://ijoc.org/index.php/ijoc/article/view/16900>
- Southwick, L., Guntuku, S. C., Klinger, E. V., Seltzer, E., McCalpin, H. J., & Merchant, R. M. (2021). Characterizing COVID-19 Content Posted to TikTok: Public Sentiment and Response During the First Phase of the COVID-19 Pandemic. *Journal of Adolescent Health*, 69(2), 234–241. <https://doi.org/10.1016/j.jadohealth.2021.05.010>
- Stephenson, M. T. (1999). Message sensation value and sensation seeking as determinants of message processing [Ph.D., University of Kentucky]. In *ProQuest Dissertations and Theses* (304510892). ProQuest Dissertations & Theses A&I; ProQuest Dissertations & Theses Global. <https://www.proquest.com/dissertations-theses/message-sensation-value-seeking-as-determinants/docview/304510892/se-2?accountid=13607>

- Stephenson, M. T., & Palmgreen, P. (2001). Sensation seeking, perceived message sensation value, personal involvement, and processing of anti-marijuana PSAs. *Communication Monographs*, 68(1), 49–71. <https://doi.org/10.1080/03637750128051>
- Stephenson, M. T., & Southwell, B. G. (2006). Sensation Seeking, the Activation Model, and Mass Media Health Campaigns: Current Findings and Future Directions for Cancer Communication. *Journal of Communication*, 56(suppl_1), S38–S56. <https://doi.org/10.1111/j.1460-2466.2006.00282.x>
- Sun, Y., Jia, R., Razzaq, A., & Bao, Q. (2024). Social network platforms and climate change in China: Evidence from TikTok. *Technological Forecasting and Social Change*, 200, 123197. <https://doi.org/10.1016/j.techfore.2023.123197>
- Sundar, S. (2000). Multimedia Effects on Processing and Perception of Online News: A Study of Picture, Audio, and Video Downloads: *Journalism & Mass Communication Quarterly*, 77(3), 480–499. <https://doi.org/10.1177/107769900007700302>
- Sundar, S. (2008). The MAIN model: A heuristic approach to understanding technology effects on credibility. In *Digital Media, Youth, and Credibility*. (pp. 73–100). The MIT Press.
- TikTok. (2024). *Research API | TikTok for Developers*. Research API | TikTok for Developers. <https://developers.tiktok.com/products/research-api/>
- Trochidis, K., Delbé, C., & Bigand, E. (2011, July). Investigation of the relationships between audio features and induced emotions in Contemporary Western music. *8th Sound and Music Computing Conference 2011*. <https://u-bourgogne.hal.science/hal-01882061>
- Tyson, A., Funk, C., & Kennedy, B. (2023, August 9). What the data says about Americans' views of climate change. *Pew Research Center*. <https://www.pewresearch.org/short-reads/2023/08/09/what-the-data-says-about-americans-views-of-climate-change/>

- Tyson, A., & Pasquini, G. (2024, March 7). How Americans View the Coronavirus, COVID-19 Vaccines Amid Declining Levels of Concern. *Pew Research Center Science & Society*.
<https://www.pewresearch.org/science/2024/03/07/how-americans-view-the-coronavirus-covid-19-vaccines-amid-declining-levels-of-concern/>
- van der Linden, S. (2015). The social-psychological determinants of climate change risk perceptions: Towards a comprehensive model. *Journal of Environmental Psychology*, 41, 112–124. <https://doi.org/10.1016/j.jenvp.2014.11.012>
- van Kampen, K., Laski, J., Herman, G., & Chan, T. M. (2022). Investigating COVID-19 Vaccine Communication and Misinformation on TikTok: Cross-sectional Study. *JMIR Infodemiology*, 2(2), e38316. <https://doi.org/10.2196/38316>
- Van Poucke, M. (2023). COVID-19 vaccine hesitancy and shaming on TikTok: A multimodal appraisal analysis. *Multimodality & Society*, 3(2), 97–129.
<https://doi.org/10.1177/26349795231153955>
- Wagner, A. L., Sheinfeld Gorin, S., Boulton, M. L., Glover, B. A., & Morenoff, J. D. (2021). Effect of vaccine effectiveness and safety on COVID-19 vaccine acceptance in Detroit, Michigan, July 2020. *Human Vaccines & Immunotherapeutics*, 17(9), 2940–2945.
<https://doi.org/10.1080/21645515.2021.1917233>
- Wang, L., Xiong, Y., Wang, Z., Qiao, Y., Lin, D., Tang, X., & Van Gool, L. (2016). Temporal Segment Networks: Towards Good Practices for Deep Action Recognition. In B. Leibe, J. Matas, N. Sebe, & M. Welling (Eds.), *Computer Vision – ECCV 2016* (pp. 20–36). Springer International Publishing.

- Wang, Y. (2020). Humor and camera view on mobile short-form video apps influence user experience and technology-adoption intent, an example of TikTok (DouYin). *Computers in Human Behavior*, 110, 106373. <https://doi.org/10.1016/j.chb.2020.106373>
- Wang, Y., McKee, M., Torbica, A., & Stuckler, D. (2019). Systematic Literature Review on the Spread of Health-related Misinformation on Social Media. *Social Science & Medicine*, 240, 112552. <https://doi.org/10.1016/j.socscimed.2019.112552>
- Wang, Z., Vang, M., Lookadoo, K., Tchernev, J. M., & Cooper, C. (2015). Engaging High-Sensation Seekers: The Dynamic Interplay of Sensation Seeking, Message Visual-Auditory Complexity and Arousing Content. *Journal of Communication*, 65(1), 101–124. <https://doi.org/10.1111/jcom.12136>
- Wilms, L., & Oberfeld, D. (2018). Color and emotion: Effects of hue, saturation, and brightness. *Psychological Research*, 82(5), 896–914. <https://doi.org/10.1007/s00426-017-0880-8>
- Wyszecki, G., & Stiles, W. S. (2000). *Color science: Concepts and methods, quantitative data and formulae* (Vol. 40). John Wiley & sons.
- Xu, J. (2015a). Designing messages with high sensation value: When activation meets reactance. *Psychology & Health*, 30(4), 423–440. <https://doi.org/10.1080/08870446.2014.977280>
- Xu, J. (2015b). Message Sensation and Cognition Values: Factors of Competition or Integration? *Health Communication*, 30(6), 589–597. <https://doi.org/10.1080/10410236.2013.852460>
- Xu, J. (2017). Message Sensation Value in Health and Risk. *Oxford Research Encyclopedia of Communication*. <https://doi.org/10.1093/acrefore/9780190228613.013.305>
- Xue, H., & Taylor, L. (2022). When do people believe, check, and share health rumors on social media? Effects of evidence type, health literacy, and health knowledge. *Journal of Health Psychology*, 13591053221125992. <https://doi.org/10.1177/13591053221125992>

- Yang, X., Ram, N., Robinson, T., & Reeves, B. (2019). Using Screenshots to Predict Task Switching on Smartphones. *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–6. <https://doi.org/10.1145/3290607.3313089>
- Yu, J., & Egger, R. (2021). Color and engagement in touristic Instagram pictures: A machine learning approach. *Annals of Tourism Research*, 89, 103204. <https://doi.org/10.1016/j.annals.2021.103204>
- Zadrozny, B. (2021, July 14). How one man’s viral rant shows TikTok’s problem with misinformation. *NBC News*. <https://www.nbcnews.com/tech/tech-news/tiktok-audio-gives-new-virality-misinformation-rcna1393>
- Zeng, J., Schäfer, M. S., & Allgaier, J. (2020). Reposting “till Albert Einstein is TikTok famous”: The memetic construction of science on TikTok. *International Journal of Communication*, 15, 3216–3247.
- Zhang, F., & O’Donnell, L. J. (2020). Chapter 7—Support vector regression. In A. Mechelli & S. Vieira (Eds.), *Machine Learning* (pp. 123–140). Academic Press. <https://doi.org/10.1016/B978-0-12-815739-8.00007-9>
- Zhang, J., Xue, H., Calabrese, C., Chen, H., & Dang, J. H. T. (2021). Understanding Human Papillomavirus Vaccine Promotions and Hesitancy in Northern California Through Examining Public Facebook Pages and Groups. *Frontiers in Digital Health*, 3. <https://www.frontiersin.org/article/10.3389/fdgth.2021.683090>
- Zhang, W., Mei, J., Song, W., Evans, R., & Xiang, Y. (2021). Why Do Citizens Engage With the TikTok Accounts of Public Hospitals in China? *Sage Open*, 11(4), 21582440211061568. <https://doi.org/10.1177/21582440211061568>

- Zhang, W., Yuan, H., Zhu, C., Chen, Q., Evans, R. D., & Min, C. (2023). Factors influencing public engagement in government TikTok during the COVID-19 crisis. *The Electronic Library, ahead-of-print*(ahead-of-print). <https://doi.org/10.1108/EL-06-2023-0150>
- Zhi, Y., Tong, Z., Wang, L., & Wu, G. (2021). MGSampler: An Explainable Sampling Strategy for Video Action Recognition. *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, 1513–1522.
- Zuckerman, M. (1990). The Psychophysiology of Sensation Seeking. *Journal of Personality*, 58(1), 313–345. <https://doi.org/10.1111/j.1467-6494.1990.tb00918.x>
- Zuckerman, M. (1994). *Behavioral expressions and biosocial bases of sensation seeking*. Cambridge university press.
- Zuckerman, M. (2014). *Sensation seeking (psychology revivals): Beyond the optimal level of arousal*. Psychology Press.

Appendices

Appendix A: Measurements

Appendix Table A.1 The measure of Perceived Message Sensation Value (Palmgreen et al., 2002).

Dimensions	Items (1–7)
Emotional arousal	Emotional–unemotional Arousing–not arousing Involving–uninvolving Exciting–boring Powerful impact–weak impact Stimulating–not stimulating Strong visuals–weak visuals Strong sound effects–weak sound effects
Dramatic impact	Dramatic–undramatic Graphic–not graphic Creative–not creative Didn’t give me goosebumps–gave me goosebumps Intense–not intense Strong soundtrack–weak soundtrack
Novelty	Novel–ordinary Unique–common Unusual–usual

Appendix Table A.2 The brief sensation-seeking scale (Hoyle et al., 2002).

#	Question item	Response
1	I would like to explore strange places.	1 = Strongly disagree 7 = Strongly agree
2	I would like to take off on a trip with no pre-planned routes or timetables.	
3	I get restless when I spend too much time at home.	
4	I prefer friends who are excitingly unpredictable.	
5	I like to do frightening things.	
6	I would like to try bungee jumping.	
7	I like wild parties.	
8	I would love to have new and exciting experiences, even if they are illegal.	

Appendix Table A.3 Scripts for stimuli short videos about COVID-19 and climate change.

#scene	COVID-19	Climate change
1	In 2024, COVID-19 is still on the scene. There are millions of cases worldwide. In the United States, we're facing the second-largest COVID surge ever.	2023 witnessed the deadliest wildfire in modern U.S. history, killing 100 people in Maui, Hawaii, and destroying the historic tourist town of Lahaina. These fires are a direct consequence of climate change, fueled by higher temperatures, prolonged droughts, and ferocious winds.
2	We need to face the fact that the virus is floating around out there. The CDC tested the wastewater, and a large portion of the U.S. has a very high level of COVID-19 in the wastewater.	South of the equator, Australia's Great Barrier Reef is under threat. A mass bleaching event in 2022 affected 91% of reefs due to warming ocean temperatures.
3	The latest variant JN.1 accounts for about 93% of cases nationwide, according to the CDC. Although it's not as severe as the original strains, the JN.1 variant causes not just coughs or loss of taste but GI symptoms too.	In Africa, Lake Chad has shrunk by 90% in the last 60 years. It's a crisis affecting over 30 million people who rely on it for water, food, and their livelihoods. Climate change, along with overuse, is to blame.
4	It's pushing the major hospitals in the U.S. over the edge. A mass general hospital in Boston is out of beds and is in a full-blown crisis with COVID cases continuing to rise.	2022's Hurricane Ian is one of the most powerful hurricanes ever to hit the U.S.. It caused over \$112 billion in damages. Warmer ocean water is making hurricanes more intense and more destructive.
5	But we can still protect ourselves and our family with COVID vaccines. Studies show that COVID-19 vaccines still work against the new variant, preventing severe disease and hospitalization.	In the Arctic, polar bears are losing their habitat as sea ice reaches record lows. These majestic creatures could go extinct if the ice keeps melting like this.
6	Across communities, COVID vaccines have become our strongest ally. By protecting ourselves, we're safeguarding others. Get your shot today!	These examples are a wake-up call. They remind us that action is possible. Switching to renewable energy, saving wildlife, conserving water—we can all play a part. It's time to act, not just for the planet, but for all of us who call it home.

Appendix Table A.4 The measure of cognitive processing (Reynolds, 1997).

Please indicate whether you disagree or agree with each of the following statements on a 7-point scale from strongly disagree to strongly agree. While watching the video, were you:

#	Question item	Response
1	Attempting to analyze the issues in the video	1 = Strongly disagree 7 = Strongly agree
2	Not very attentive to the ideas in the video	
3	Deep in thought about the video	
4	Unconcerned with the ideas in the video	
5	Extending a good deal of cognitive effort	
6	Distracted by other thoughts not related to the video	
7	Not really exerting your mind	
8	Doing your best to think about the video	
9	Reflecting on the implications of the arguments in the video	
10	Resting your mind	
11	Searching your mind in response to the ideas in the video	
12	Taking it easy	

Appendix Table A.5 The measure of perceived credibility.

What do you think about this video using the scale below?

#	Question item (1-7)
1	Biased – unbiased
2	Unfair – fair
3	Cannot be trusted – can be trusted
4	Inaccurate – accurate
5	Tells the whole story – does not tell the whole story

Appendix Table A.6 The measure of the intention to engage with a short video.

Now think about how you would react to this video on your social media. Please indicate the extent to which you agree or disagree with the following statements.

#	Question item	Response
1	This short video is worth sharing with others on social media.	1 = Strongly disagree 5 = Strongly agree
2	I would 'Like' this short video.	
3	I would 'Comment' on this short video.	
4	I would share this short video on my social media.	
5	I would share this short video by directly messaging it to my close family or friends.	

Appendix Table A.7 The measure of attention with recognition tests. Correct answers are bolded.

Issue	#	Question	Options
COVID-19	1	What is the name of the latest COVID-19 variant mentioned in the video?	A. XM.2 B. JN.1 C. BV.3 D. KF.4
	2	According to the video, how does the CDC monitor the level of COVID-19 in the community?	A. Social media trends B. Hospital admission rates C. Wastewater testing D. International travel restrictions
	3	What new symptom is associated with the new COVID-19 variant, according to the CDC?	A. Skin rash B. GI symptoms C. Joint pain D. Hair loss
	4	According to the video, how is COVID-19 primarily affecting people in the United States as of 2024?	A. Cases are decreasing and becoming less severe. B. There's a surge causing the second-largest COVID outbreak. C. COVID-19 has been completely eradicated. D. Only a small number of cases are present in isolated regions.
	5	According to the video, how are COVID-19 vaccines effective against the new variant?	A. They completely prevent infection. B. They provide lifetime immunity against all COVID-19 variants. C. They prevent severe disease and hospitalization. D. They cure the infection in less than 24 hours.
Climate change	1	Which of the following places was mentioned in the video as being affected by a significant climate event?	A. Amazon Rainforest B. Maui, Hawaii C. Sahara Desert D. Tokyo, Japan
	2	What major environmental event affected the Great Barrier Reef according to the video?	A. Oil Spill B. Mass Bleaching C. Tsunami D. Plastic Pollution

	3	Which species is losing its habitat in the Arctic due to record lows in sea ice?	A. Polar Bears B. Emperor Penguins C. Arctic Foxes D. Seals
	4	Which of the following actions is NOT mentioned as a way to address climate change in the video?	A. Switching to renewable energy B. Saving wildlife C. Expanding urban areas D. Conserving water
	5	Which environmental issue is affecting over 30 million people living around Lake Chad?	A. Air pollution B. Deforestation C. Shrinking water levels D. Urban sprawl

Appendix Table A.8 The measure of risk perceptions of climate change (van der Linden, 2015).

In this section, we would like to know your thoughts on climate change. Please indicate your opinions using the scales below.

#	Question item	Response
1	How concerned are you about the impacts of climate change?	1 = Not concerned at all 7 = Very concerned
2	In your judgment, how likely are you, sometime during your life, to experience serious threats to your health or overall well-being, as a result of climate change?	1 = Very unlikely 7 = Very likely
3	In your judgment, how likely do you think it is that climate change will have very harmful, long-term impacts on our society?	1 = Very unlikely 7 = Very likely
4	How serious of a threat do you think climate change is to the natural environment?	1 = Not serious at all 7 = Very Serious
5	How serious would you rate the current impacts of climate change around the world?	1 = Not serious at all 7 = Very Serious
6	How serious of a threat do you believe climate change is, to you personally?	1 = Not serious at all 7 = Very Serious
7	How serious would you estimate the impacts of climate change for the United States?	1 = Not serious at all 7 = Very Serious
8	How often do you worry about the potentially negative consequences of climate change?	1 = Very Rarely 7 = Very Frequently

Appendix Table A.9 The measure of risk perceptions of COVID-19 (Mejia et al., 2021; Wagner et al., 2021).

In this section, we would like to know your thoughts on COVID-19. Please indicate your opinions using the scales below.

#	Question item	Response
1	Do you think you will be infected with COVID-19 over the next 12 months?	1 = Definitely not 5 = Definitely yes
2	How serious a problem would you say the COVID-19 pandemic is right now?	1 = Not serious at all 7 = Very serious
3	I think the pandemic has already ended.	1 = Strongly disagree 7 = Strongly agree
4	I do not think I belong to a risk group for COVID-19.	1 = Strongly disagree 7 = Strongly agree

Appendix Table A.10 The measure of conspiracy ideation (Brotherton et al., 2013).

There is often debate about whether or not the public is told the whole truth about various important issues. Please indicate the degree to which you believe each statement is likely to be true on the scale below.

#	Item	Response
1	The power held by heads of state is second to that of small unknown groups who really control world politics.	1–Definitely not true 2–Probably not true 3–Not sure/cannot decide 4–Probably true 5–Definitely true
2	The spread of certain viruses and/or diseases is the result of the deliberate, concealed efforts of some organization.	
3	Groups of scientists manipulate, fabricate, or suppress evidence in order to deceive the public.	
4	A small, secret group of people is responsible for making all world decisions, such as going to war.	
5	Technology with mind-control capacities is used on people without their knowledge.	
6	New and advanced technology which would harm current industry is being suppressed.	
7	Certain significant events have been the result of the activity of a small group who secretly manipulates world events.	
8	Experiments involving new drugs or technologies are routinely carried out on the public without their knowledge or consent.	
9	A lot of important information is deliberately concealed from the public out of self-interest.	

Appendix B: Descriptive and Summary Statistics

Appendix Table B.1 Demographics of participants ($N = 1007$) in the evaluation of Perceived Message Sensation Value of short videos ($N = 1200$).

Demographic Characteristics		Frequency	Percent
Gender	Female	510	50.6%
	Male	472	46.9%
	Non-binary	19	1.9%
Age, mean (SD)		41.0 (13.9)	-
Race	Asian	277	27.5%
	White	191	19.0%
	Black	36	3.6%
	Hispanic	184	18.3%
Education	Some high school or less	8	0.8%
	High School/GED	111	11.0%
	Some college no degree	235	23.3%
	Associates /technical degree	117	11.6%
	Bachelor's degree	374	37.1%
	Graduate/professional degree	158	15.7%
Income	<\$25,000	155	15.4%
	\$25,000–\$49,999	251	24.9%
	\$50,000–\$74,999	212	21.1%
	\$75,000–\$99,999	130	12.9%
	\$100,000–\$149,999	142	14.1%
	≥\$150,000	82	8.1%

Appendix Table B.2 The correlation between multimodal features and Perceived Message Sensation Value.

#	Multimodal feature		r	p
1		Brightness	-0.14	.000***
2		Color saturation	0.05	.065
3		Color warmness	0.01	.646
4		Visual complexity	0.01	.668
5		Shot count/s	0.11	.000***
6		Shot duration/s	-0.27	.000***
7		Loudness	0.09	.002**
8		Tempo	0.02	.497
9		Sound brightness	-0.07	.012*
10		Face count/s	0.08	.004**
11		Face duration/s	-0.43	.000***
12		Face age	0.08	.011*
13		Disgust	0.09	.006**
14		Anger	0.20	.000***
15	Facial expression	Fear	0.13	.000***
16		Happiness	-0.03	.276
17		Sadness	0.13	.000***
18		Surprise	0.05	.110

Appendix Table B.3 Factor loadings in Exploratory Factor Analysis (EFA) of 18 multimodal features. Selected features are bolded.

The Bartlett's test ($\chi^2 = 2056.82, p < .001$) was conducted to determine that the dataset is appropriate for factor analysis. The optimal number of factors emerged to be 7 by checking eigenvalues. These factors combined explained 38.1% of the variance in the factor analysis.

	factor 1	factor 2	factor 3	factor 4	factor 5	factor 6	factor 7
Brightness	0.13	-0.01	-0.10	0.06	0.05	-0.11	-0.08
Color saturation	-0.11	0.02	0.21	-0.05	-0.01	0.01	0.12
Color warmth	0.06	0.03	0.77	0.02	0.02	-0.01	0.01
Visual complexity	-0.05	0.01	0.58	0.04	0.03	0.00	0.02
Shot count/s	-0.18	0.97	0.08	-0.01	0.11	0.02	-0.04
Shot duration/s	0.52	-0.40	-0.13	-0.02	-0.04	0.05	-0.02
Loudness	-0.04	0.18	0.02	-0.01	-0.01	0.01	0.10
Tempo	-0.03	0.04	0.00	0.02	0.05	0.01	0.49
Sound brightness	-0.04	0.07	0.13	-0.02	-0.02	0.00	0.49
Face count/s	-0.25	0.10	-0.04	-0.03	-0.04	0.15	0.10
Face duration/s	0.95	-0.06	-0.04	-0.06	0.12	0.02	0.02
Face age	0.00	-0.11	-0.22	0.02	-0.09	0.11	0.00
Disgust	-0.03	-0.04	-0.04	-0.03	-0.22	0.06	0.00
Anger	-0.09	0.01	-0.08	-0.02	-0.33	0.12	0.04
Fear	0.02	0.00	0.05	-0.02	-0.17	-0.04	-0.13
Happiness	-0.02	-0.02	-0.03	-0.26	0.89	0.36	0.03
Sadness	-0.01	-0.02	-0.01	0.99	0.00	0.07	0.01
Surprise	0.04	-0.01	0.05	-0.07	0.01	-0.64	0.01

Appendix Table B.4 Demographics of participants in the experiment in Chapter 4.

Demographic Characteristics		Combined (N = 1467)		Prolific (n = 1003)		SONA (n = 464)	
		n	%	n	%	n	%
Gender	Female	952	64.9%	581	57.9%	75	16.2%
	Male	480	32.7%	405	40.4%	371	80.0%
	Non-binary	26	1.8%	12	1.2%	14	3.0%
Age, mean (SD)		36.6 (16.3)	-	44.3 (14.0)	-	19.7 (1.9)	-
Race	Asian	288	19.6%	69	6.9%	219	47.2%
	White	966	65.8%	791	78.9%	175	37.7%
	Black	146	10.0%	130	13.0%	16	3.4%
	Hispanic	111	7.6%	36	3.6%	75	16.2%
Education	Some high school or less	14	1.0%	12	1.2%	2	0.4%
	High School/GED	312	21.3%	151	15.1%	161	34.7%
	Some college no degree	468	31.9%	224	22.3%	244	52.6%
	Associates/technical degree	182	12.4%	148	14.8%	34	7.3%
	Bachelor's degree	351	23.9%	335	33.4%	16	3.4%
	Graduate/professional degree	130	8.9%	129	12.9%	1	0.2%
Income	<\$25,000	271	18.5%	146	14.6%	125	26.9%
	\$25,000–\$49,999	290	19.8%	249	24.8%	41	8.8%
	\$50,000–\$74,999	235	16.0%	210	20.9%	25	5.4%
	\$75,000–\$99,999	186	12.7%	159	15.9%	27	5.8%
	\$100,000–\$149,999	182	12.4%	136	13.6%	46	9.9%
	≥\$150,000	127	8.7%	79	7.9%	48	10.3%

Appendix Table B.5 Summary statistics of multimodal features and the predicted Message Sensation Value (MSV) across three quantiles of predicted MSV.

MSV	Low	Mid	High
Brightness	118.83	109.06	104.62
Color saturation	76.55	77.91	76.38
Color warmness	0.31	0.26	0.23
Visual complexity	6.90	6.67	6.53
Shot count/s	0.10	0.13	0.25
Shot duration/s	0.84	0.63	0.20
Loudness	0.06	0.06	0.06
Tempo	120.93	121.53	121.28
Sound brightness	2112.88	2006.36	1963.67
Face count/s	0.12	0.16	0.30
Face duration/s	0.76	0.28	0.10
Predicted MSV	3.05	3.44	3.92

Appendix C: Statistical Analysis Results

Appendix Table C.1 The variance inflation factor (VIF) of multimodal features in regression models. VIF above 2 represents moderate collinearity. The normal features include video length as an additional multimodal feature. The standardized features have shot count, shot duration, face count, and face duration standardized by video length.

Features (normal)	VIF	Features (standardized)	VIF
Video length	2.23	-	
Brightness	1.08	Brightness	1.08
Color saturation	1.10	Color saturation	1.11
Color warmth	1.36	Color warmth	1.36
Visual complexity	1.31	Visual complexity	1.32
Shot count	1.91	Shot count/s	1.46
Shot duration	2.17	Shot duration/s	1.83
Loudness	1.04	Loudness	1.06
Tempo	1.08	Tempo	1.08
Sound brightness	1.10	Sound brightness	1.10
Face count	1.45	Face count/s	1.12
Face duration	1.57	Face duration/s	1.54
Face age	1.09	Face age	1.07
Disgust	1.06	Disgust	1.06
Anger	1.12	Anger	1.13
Fear	1.06	Fear	1.06
Happiness	1.35	Happiness	1.36
Sadness	1.14	Sadness	1.14
Surprise	1.16	Surprise	1.15

Appendix Table C.2 Linear regression models predicting the Perceived Message Sensation Value of short videos.

	Model 1			Model 2		
	b (SE)	CI	p	b (SE)	CI	p
Intercept	-1.85 (0.16)	[-2.16, -1.53]	.000	-2.00 (0.67)	[-3.31, -0.69]	.003
Predicted MSV	1.53 (0.04)	[1.44, 1.62]	.000	1.50 (0.05)	[1.40, 1.59]	.000
Posting time				0.00 (0.00)	[0.00, 0.00]	.671
Unpopular account ^a				-0.10 (0.04)	[-0.18, -0.02]	.012
Video duration				0.00 (0.00)	[0.00, 0.00]	.000
Alternative medicine				0.09 (0.07)	[-0.05, 0.23]	.192
Climate change				0.14 (0.06)	[0.03, 0.26]	.016
COVID-19				-0.03 (0.05)	[-0.13, 0.07]	.569
Presidential election				0.00 (0.07)	[-0.14, 0.14]	.950
GMO				-0.18 (0.05)	[-0.28, -0.07]	.001
Health				0.04 (0.07)	[-0.10, 0.18]	.567
Russian-Ukraine conflict				0.16 (0.06)	[0.04, 0.28]	.009
Vaccination				0.12 (0.06)	[0.01, 0.23]	.037
Adjusted R2	0.490			0.516		
F-statistic	F (1, 1198) = 1152 (p < .001)			F (12, 1187) = 107.4 (p < .001)		

Note. ^a The popular account is used as the reference group.

Appendix Table C.3 Linear regression models predicting the Perceived Message Sensation Value of short videos among younger participants.

	Model 1			Model 2		
	b (SE)	CI	p	b (SE)	CI	p
Intercept	-1.77 (0.20)	[-2.17, -1.38]	.000	-0.54 (0.85)	[-2.20, 1.12]	.526
Predicted MSV	1.48 (0.06)	[1.37, 1.59]	.000	1.43 (0.06)	[1.31, 1.55]	.000
Posting time				0.00 (0.00)	[0.00, 0.00]	.232
Unpopular account ^a				-0.12 (0.05)	[-0.22, -0.02]	.024
Video duration				0.00 (0.00)	[0.00, 0.00]	.006
Alternative medicine				0.02 (0.09)	[-0.15, 0.20]	.778
Climate change				0.19 (0.07)	[0.04, 0.33]	.012
COVID-19				0.02 (0.06)	[-0.11, 0.14]	.783
Presidential election				-0.07 (0.09)	[-0.25, 0.10]	.416
GMO				-0.19 (0.07)	[-0.32, -0.05]	.008
Health				0.06 (0.09)	[-0.11, 0.24]	.477
Russian-Ukraine conflict				0.21 (0.08)	[0.06, 0.36]	.006
Vaccination				0.08 (0.07)	[-0.05, 0.22]	.229
Adjusted R2	0.364			0.388		
F-statistic	F (1, 1195) = 684 (p < .001)			F (12, 1184) = 64.29 (p < .001)		

Note. ^a The popular account is used as the reference group.

Appendix Table C.4 Linear regression models predicting the Perceived Message Sensation Value of short videos among older participants.

	Model 1			Model 2		
	b (SE)	CI	p	b (SE)	CI	p
Intercept	-1.81 (0.22)	[-2.24, -1.37]	.000	-3.51 (0.94)	[-5.35, -1.67]	.000
Predicted MSV	1.55 (0.06)	[1.43, 1.67]	.000	1.53 (0.07)	[1.39, 1.66]	.000
Posting time				0.00 (0.00)	[0.00, 0.00]	.054
Unpopular account ^a				-0.06 (0.06)	[-0.18, 0.05]	.269
Video duration				0.00 (0.00)	[0.00, 0.00]	.002
Alternative medicine				0.11 (0.10)	[-0.08, 0.30]	.265
Climate change				0.14 (0.08)	[-0.02, 0.31]	.078
COVID-19				-0.07 (0.07)	[-0.21, 0.07]	.310
Presidential election				0.04 (0.10)	[-0.16, 0.24]	.695
GMO				-0.19 (0.08)	[-0.34, -0.04]	.013
Health				0.01 (0.10)	[-0.18, 0.21]	.918
Russian-Ukraine conflict				0.12 (0.09)	[-0.05, 0.29]	.171
Vaccination				0.16 (0.08)	[0.00, 0.31]	.044
Adjusted R2	0.340			0.359		
F-statistic	F (1, 1193) = 615.2 (p < .001)			F (12, 1182) = 56.63 (p < .001)		

Note. ^a The popular account is used as the reference group.

Appendix Table C.5 Linear regression models predicting the Perceived Message Sensation Value of short videos among low sensation-seeking participants.

	Model 1			Model 2		
	b (SE)	CI	p	b (SE)	CI	p
Intercept	-1.88 (0.21)	[-2.29, -1.47]	.000	-2.75 (0.89)	[-4.51, -1.00]	.002
Predicted MSV	1.53 (0.06)	[1.41, 1.65]	.000	1.53 (0.06)	[1.40, 1.66]	.000
Posting time				0.00 (0.00)	[0.00, 0.00]	.315
Unpopular account ^a				-0.06 (0.06)	[-0.17, 0.05]	.284
Video duration				0.00 (0.00)	[0.00, 0.00]	.002
Alternative medicine				0.13 (0.09)	[-0.05, 0.31]	.166
Climate change				0.10 (0.08)	[-0.05, 0.26]	.185
COVID-19				-0.07 (0.07)	[-0.21, 0.06]	.272
Presidential election				0.00 (0.10)	[-0.19, 0.19]	.985
GMO				-0.13 (0.07)	[-0.27, 0.01]	.079
Health				-0.05 (0.09)	[-0.23, 0.14]	.635
Russian-Ukraine conflict				0.14 (0.08)	[-0.02, 0.30]	.088
Vaccination				0.15 (0.07)	[0.01, 0.30]	.042
Adjusted R2	0.356			0.371		
F-statistic	F (1, 1194) = 662.5 (p < .001)			F (12, 1183) = 59.81 (p < .001)		

Note. ^a The popular account is used as the reference group.

Appendix Table C.6 Linear regression models predicting the Perceived Message Sensation Value of short videos among high sensation-seeking participants.

	Model 1			Model 2		
	b (SE)	CI	p	b (SE)	CI	p
Intercept	-1.67 (0.21)	[-2.07, -1.26]	.000	-1.50 (0.88)	[-3.23, 0.23]	.090
Predicted MSV	1.49 (0.06)	[1.37, 1.60]	.000	1.46 (0.06)	[1.33, 1.58]	.000
Posting time				0.00 (0.00)	[0.00, 0.00]	.950
Unpopular account ^a				-0.10 (0.05)	[-0.21, 0.01]	.063
Video duration				0.00 (0.00)	[0.00, 0.00]	.013
Alternative medicine				0.09 (0.09)	[-0.09, 0.27]	.325
Climate change				0.19 (0.08)	[0.04, 0.35]	.011
COVID-19				0.06 (0.07)	[-0.07, 0.19]	.401
Presidential election				0.04 (0.09)	[-0.14, 0.22]	.670
GMO				-0.18 (0.07)	[-0.33, -0.04]	.011
Health				0.14 (0.09)	[-0.05, 0.32]	.143
Russian-Ukraine conflict				0.13 (0.08)	[-0.03, 0.28]	.111
Vaccination				0.07 (0.07)	[-0.08, 0.21]	.354
Adjusted R2	0.353			0.370		
F-statistic	F (1, 1189) = 651.5 (p < .001)			F (12, 1178) = 59.12 (p < .001)		

Note. ^a The popular account is used as the reference group.

Appendix Table C.7 Negative binomial models predicting short video engagement. Video engagement is adjusted by a factor of 10,000 for visual simplicity.

	Model 1			Model 2		
	b (SE)	CI	p	b (SE)	CI	p
Intercept	6.27 (0.57)	[4.95, 7.59]	0.000	3.56 (1.94)	[-0.95, 8.10]	0.067
Predicted MSV	-0.54 (0.16)	[-0.92, -0.17]	0.001	-0.12 (0.12)	[-0.39, 0.15]	0.289
Posting time				0.00 (0.00)	[0.00, 0.00]	0.689
Unpopular account ^a				-4.25 (0.12)	[-4.49, -4.01]	0.000
Video duration				-0.01 (0.00)	[-0.01, 0.00]	0.000
Alternative medicine				0.67 (0.16)	[0.35, 0.98]	0.000
Climate change				0.79 (0.13)	[0.53, 1.04]	0.000
COVID-19				2.85 (0.12)	[2.62, 3.09]	0.000
Presidential election				1.27 (0.17)	[0.94, 1.60]	0.000
GMO				-0.63 (0.14)	[-0.90, -0.36]	0.000
Health				1.19 (0.17)	[0.88, 1.51]	0.000
Russian-Ukraine conflict				1.73 (0.14)	[1.46, 2.00]	0.000
Vaccination				1.31 (0.13)	[1.06, 1.55]	0.000

Note. ^a The popular account is used as the reference group.

Appendix Table C.8 Negative binomial models predicting short video engagement. Video engagement is adjusted by a factor of 10,000 for visual simplicity.

	Model 1			Model 2		
	b (SE)	CI	p	b (SE)	CI	p
Intercept	-7.32 (3.31)	[-13.87, -0.22]	0.027	-8.79 (2.86)	[-15.01, -2.50]	0.002
Predicted MSV	7.21 (1.89)	[3.20, 10.91]	0.000	7.02 (1.18)	[4.49, 9.44]	0.000
Predicted MSV ²	-1.10 (0.27)	[-1.62, -0.53]	0.000	-1.02 (0.17)	[-1.36, -0.66]	0.000
Posting time				0.00 (0.00)	[0.00, 0.00]	0.643
Unpopular account ^a				-4.27 (0.12)	[-4.51, -4.04]	0.000
Video duration				0.00 (0.00)	[-0.01, 0.00]	0.000
Alternative medicine				0.73 (0.16)	[0.42, 1.04]	0.000
Climate change				0.85 (0.13)	[0.60, 1.11]	0.000
COVID-19				2.83 (0.12)	[2.60, 3.07]	0.000
Presidential election				1.34 (0.16)	[1.01, 1.67]	0.000
GMO				-0.67 (0.14)	[-0.94, -0.40]	0.000
Health				1.19 (0.16)	[0.87, 1.50]	0.000
Russian-Ukraine conflict				1.75 (0.14)	[1.48, 2.01]	0.000
Vaccination				1.39 (0.13)	[1.14, 1.63]	0.000

Note. ^a The popular account is used as the reference group.

Appendix Table C.9 Negative binomial models predicting short video engagement for the dataset of science-related short videos and the dataset of short videos recommended to children. Video engagement is adjusted by a factor of 10,000 for visual simplicity.

	Dataset 1: science-related videos			Dataset 2: kids videos		
	b (SE)	CI	p	b (SE)	CI	p
Intercept	36.19	[28.65, 43.80]	0.000	112.60	[95.85, 129.91]	0.000
Predicted MSV	10.99	[7.47, 14.48]	0.000	14.46	[10.00, 18.77]	0.000
Predicted MSV ²	-1.45	[-1.94, -0.96]	0.000	-2.13	[-2.77, -1.47]	0.000
Video duration	0.00	[0.00, 0.00]	0.731	0.00	[0.00, 0.00]	0.000
Posting time	0.00	[0.00, 0.00]	0.000	0.00	[0.00, 0.00]	0.000

Appendix Table C.10 Linear mixed effects models predicting the attention to short videos, measured by dwell time (2,575 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	1.40 (0.03)	[1.34, 1.45]	0.000	0.94 (0.11)	[0.73, 1.15]	0.000
Mid MSV ^a	0.01 (0.02)	[-0.04, 0.06]	0.734	0.01 (0.03)	[-0.05, 0.06]	0.822
High MSV ^a	-0.03 (0.02)	[-0.07, 0.02]	0.304	-0.03 (0.03)	[-0.09, 0.02]	0.204
Issue: COVID-19 ^b				0.16 (0.02)	[0.11, 0.20]	0.000
Pre-existing attitude				0.01 (0.01)	[-0.02, 0.04]	0.484
Sensation seeking				0.04 (0.02)	[0.01, 0.07]	0.023
Conspiracy ideation				0.04 (0.02)	[0.01, 0.07]	0.009
Age				0.00 (0.00)	[0.00, 0.00]	0.747
Education				0.03 (0.01)	[0.01, 0.05]	0.008
Income				0.01 (0.01)	[-0.01, 0.02]	0.452
Random Effects	Variance	SD		Variance	SD	
Participant	0.10	0.31		0.11	0.33	
Message order	0.00	0.02		0.00	0.03	
Residual	0.26	0.51		0.27	0.52	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.11 Linear mixed effects models predicting the attention to short videos, measured by message recognition (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	4.35 (0.04)	[4.26, 4.44]	0.000	4.51 (0.16)	[4.20, 4.82]	0.000
Mid MSV ^a	-0.02 (0.04)	[-0.08, 0.05]	0.640	0.00 (0.04)	[-0.07, 0.08]	0.916
High MSV ^a	-0.05 (0.03)	[-0.12, 0.01]	0.120	-0.04 (0.04)	[-0.11, 0.03]	0.247
Issue: COVID-19 ^b				0.08 (0.03)	[0.02, 0.14]	0.009
Pre-existing attitude				0.03 (0.02)	[-0.01, 0.07]	0.108
Sensation seeking				-0.07 (0.02)	[-0.12, -0.02]	0.003
Conspiracy ideation				-0.11 (0.02)	[-0.16, -0.07]	0.000
Age				0.00 (0.00)	[0.00, 0.01]	0.001
Education				0.01 (0.02)	[-0.02, 0.04]	0.592
Income				0.01 (0.01)	[-0.01, 0.04]	0.373
Random Effects	Variance	SD		Variance	SD	
Participant	0.35	0.59		0.33	0.57	
Message order	0.00	0.04		0.00	0.04	
Residual	0.51	0.72		0.49	0.70	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.12 Linear mixed effects models predicting the cognitive processing of short videos (2,578 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	3.34 (0.02)	[3.29, 3.38]	0.000	3.05 (0.14)	[2.78, 3.32]	0.000
Mid MSV ^a	0.07 (0.02)	[0.02, 0.12]	0.005	0.06 (0.02)	[0.01, 0.11]	0.019
High MSV ^a	0.16 (0.02)	[0.11, 0.21]	0.000	0.15 (0.02)	[0.11, 0.20]	0.000
Issue: COVID-19 ^b				-0.05 (0.02)	[-0.09, -0.01]	0.020
Pre-existing attitude				0.22 (0.02)	[0.19, 0.25]	0.000
Sensation seeking				-0.02 (0.02)	[-0.07, 0.02]	0.302
Conspiracy ideation				-0.11 (0.02)	[-0.15, -0.07]	0.000
Age				0.01 (0.00)	[0.00, 0.01]	0.000
Education				0.00 (0.02)	[-0.03, 0.03]	0.935
Income				-0.01 (0.01)	[-0.04, 0.01]	0.354
Random Effects	Variance	SD		Variance	SD	
Participant	0.46	0.67		0.38	0.61	
Message order	0.00	0.00		0.00	0.00	
Residual	0.23	0.48		0.21	0.46	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.13 Linear mixed effects models predicting the affective processing of short videos (2,579 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	1.83 (0.03)	[1.77, 1.89]	0.000	1.30 (0.09)	[1.14, 1.47]	0.000
Mid MSV ^a	0.02 (0.02)	[-0.02, 0.05]	0.410	0.01 (0.02)	[-0.02, 0.05]	0.544
High MSV ^a	0.06 (0.02)	[0.02, 0.09]	0.003	0.06 (0.02)	[0.03, 0.10]	0.001
Issue: COVID-19 ^b				-0.08 (0.01)	[-0.11, -0.05]	0.000
Pre-existing attitude				0.22 (0.01)	[0.20, 0.24]	0.000
Sensation seeking				0.02 (0.01)	[-0.01, 0.04]	0.152
Conspiracy ideation				-0.02 (0.01)	[-0.04, 0.01]	0.121
Age				0.00 (0.00)	[0.00, 0.00]	0.347
Education				0.00 (0.01)	[-0.01, 0.02]	0.704
Income				-0.01 (0.01)	[-0.02, 0.01]	0.460
Random Effects	Variance	SD		Variance	SD	
Participant	0.16	0.40		0.11	0.33	
Message order	0.00	0.03		0.00	0.03	
Residual	0.15	0.38		0.11	0.34	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.14 Linear mixed effects models predicting the perceived message credibility of short videos (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	3.53 (0.05)	[3.44, 3.63]	0.000	3.63 (0.19)	[3.24, 4.03]	0.000
Mid MSV ^a	0.09 (0.04)	[0.02, 0.17]	0.010	0.07 (0.04)	[-0.01, 0.14]	0.089
High MSV ^a	0.11 (0.04)	[0.04, 0.18]	0.002	0.13 (0.04)	[0.06, 0.21]	0.001
Issue: COVID-19 ^b				0.12 (0.03)	[0.06, 0.19]	0.000
Pre-existing attitude				0.57 (0.02)	[0.52, 0.62]	0.000
Sensation seeking				0.06 (0.03)	[0.00, 0.13]	0.038
Conspiracy ideation				-0.40 (0.03)	[-0.46, -0.34]	0.000
Age				-0.01 (0.00)	[-0.01, -0.01]	0.000
Education				-0.03 (0.02)	[-0.08, 0.01]	0.161
Income				-0.02 (0.02)	[-0.05, 0.02]	0.284
Random Effects	Variance	SD		Variance	SD	
Participant	1.60	1.27		0.67	0.82	
Message order	0.00	0.03		0.00	0.04	
Residual	0.51	0.71		0.53	0.73	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.15 Linear mixed effects models predicting the intention to engage with short videos (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	2.46 (0.04)	[2.39, 2.53]	0.000	1.75 (0.18)	[1.38, 2.12]	0.000
Mid MSV ^a	0.09 (0.03)	[0.03, 0.16]	0.004	0.07 (0.03)	[0.00, 0.14]	0.036
High MSV ^a	0.14 (0.03)	[0.08, 0.21]	0.000	0.15 (0.03)	[0.08, 0.22]	0.000
Issue: COVID-19 ^b				0.06 (0.03)	[0.00, 0.12]	0.041
Pre-existing attitude				0.45 (0.02)	[0.40, 0.49]	0.000
Sensation seeking				0.07 (0.03)	[0.01, 0.13]	0.015
Conspiracy ideation				-0.19 (0.03)	[-0.24, -0.13]	0.000
Age				0.00 (0.00)	[0.00, 0.00]	0.820
Education				0.01 (0.02)	[-0.03, 0.05]	0.668
Income				-0.02 (0.02)	[-0.05, 0.01]	0.226
Random Effects	Variance	SD		Variance	SD	
Participant	1.13	1.06		0.68	0.83	
Message order	0.00	0.00		0.00	0.00	
Residual	0.41	0.64		0.40	0.64	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.16 Linear mixed effects models predicting issue-relevant risk perceptions (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	3.97 (0.06)	[3.86, 4.09]	0.000	1.42 (0.17)	[1.09, 1.75]	0.000
Mid MSV ^a	0.03 (0.07)	[-0.11, 0.17]	0.659	0.00 (0.05)	[-0.10, 0.09]	0.928
High MSV ^a	0.05 (0.07)	[-0.09, 0.19]	0.515	0.07 (0.05)	[-0.03, 0.16]	0.171
Issue: COVID-19 ^b				-0.13 (0.04)	[-0.21, -0.04]	0.002
Pre-existing attitude				1.39 (0.02)	[1.35, 1.44]	0.000
Sensation seeking				0.03 (0.03)	[-0.02, 0.08]	0.284
Conspiracy ideation				-0.22 (0.02)	[-0.27, -0.18]	0.000
Age				0.00 (0.00)	[-0.01, 0.00]	0.168
Education				-0.02 (0.02)	[-0.06, 0.01]	0.197
Income				-0.01 (0.01)	[-0.03, 0.02]	0.569
Random Effects	Variance	SD		Variance	SD	
Participant	1.61	1.27		0.13	0.37	
Message order	0.00	0.00		0.00	0.00	
Residual	2.11	1.45		0.95	0.98	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.17 Mediation analyses of how (a) cognitive processing, (b) affective processing, (c) perceived credibility, and (d) engagement intention mediate the effect of Message Sensation Value (MSV) on issue-relevant risk perceptions.

	(a)			(b)		
	b	CI	p	b	CI	p
ACME ^a	0.02	[0.00, 0.03]	0.020	0.01	[-0.01, 0.03]	0.420
ADE ^b	-0.02	[-0.11, 0.07]	0.580	-0.02	[-0.11, 0.07]	0.730
Total effect ^c	-0.01	[-0.10, 0.08]	0.860	-0.01	[-0.10, 0.09]	0.860
Proportion mediated ^d	-0.13	[-4.84, 7.89]	0.870	0.01	[-3.91, 2.88]	0.990

	(c)			(d)		
	b	CI	p	b	CI	p
ACME ^a	0.03	[0.00, 0.06]	0.062	0.02	[0.00, 0.05]	0.028
ADE ^b	-0.01	[-0.11, 0.08]	0.772	-0.02	[-0.11, 0.07]	0.672
Total effect ^c	0.01	[-0.08, 0.10]	0.798	0.01	[-0.08, 0.09]	0.928
Proportion mediated ^d	0.36	[-7.87, 8.54]	0.772	0.21	[-6.25, 7.09]	0.920

Notes. ^a Average Causal Mediation Effect: the effect of MSV on mediators.

^b Average Direct Effect: direct effect of MSV on risk perception (mediator included).

^c Total Effect: the combined effects of ACME and ADE.

^d Proportion mediated: the proportion of the total effect mediated, with only statistically significant results indicating significant mediating effects.

Appendix Table C.18 Linear mixed effects models with the interaction between MSV and sensation-seeking predicting the attention to short videos, measured by dwell time (2,575 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	1.34 (0.06)	[1.23, 1.46]	0.000	0.96 (0.12)	[0.74, 1.19]	0.000
Mid MSV ^a	-0.03 (0.08)	[-0.18, 0.11]	0.655	-0.02 (0.08)	[-0.18, 0.14]	0.829
High MSV ^a	-0.06 (0.08)	[-0.21, 0.09]	0.404	-0.07 (0.08)	[-0.23, 0.08]	0.359
Sensation seeking	0.02 (0.02)	[-0.02, 0.06]	0.317	0.03 (0.02)	[-0.02, 0.07]	0.225
Mid MSV ^a × SS ^b	0.02 (0.03)	[-0.04, 0.07]	0.557	0.01 (0.03)	[-0.05, 0.07]	0.758
High MSV ^a × SS ^b	0.01 (0.03)	[-0.04, 0.07]	0.602	0.02 (0.03)	[-0.04, 0.07]	0.598
Issue: COVID-19 ^c				0.16 (0.02)	[0.11, 0.20]	0.000
Pre-existing attitude				0.01 (0.01)	[-0.02, 0.04]	0.486
Conspiracy ideation				0.04 (0.02)	[0.01, 0.07]	0.009
Age				0.00 (0.00)	[0.00, 0.00]	0.743
Education				0.03 (0.01)	[0.01, 0.05]	0.008
Income				0.01 (0.01)	[-0.01, 0.02]	0.457
Random Effects	Variance	SD		Variance	SD	
Participant	0.10	0.31		0.11	0.33	
Message order	0.00	0.02		0.00	0.03	
Residual	0.26	0.51		0.27	0.52	

Note. ^a Low MSV is used as the reference group.

^b SS: sensation-seeking.

^c The issue of climate change is used as the reference group.

Appendix Table C.19 Linear mixed effects models with the interaction between MSV and sensation-seeking predicting the attention to short videos, measured by message recognition (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	4.71 (0.09)	[4.53, 4.89]	0.000	4.60 (0.17)	[4.27, 4.93]	0.000
Mid MSV ^a	-0.09 (0.11)	[-0.30, 0.12]	0.402	-0.09 (0.11)	[-0.31, 0.13]	0.402
High MSV ^a	-0.19 (0.11)	[-0.40, 0.02]	0.072	-0.22 (0.11)	[-0.43, 0.00]	0.051
Sensation seeking	-0.14 (0.03)	[-0.20, -0.07]	0.000	-0.11 (0.03)	[-0.17, -0.04]	0.002
Mid MSV ^a × SS ^b	0.03 (0.04)	[-0.05, 0.10]	0.463	0.04 (0.04)	[-0.04, 0.12]	0.354
High MSV ^a × SS ^b	0.05 (0.04)	[-0.02, 0.13]	0.163	0.07 (0.04)	[-0.01, 0.14]	0.096
Issue: COVID-19 ^c				0.08 (0.03)	[0.02, 0.14]	0.010
Pre-existing attitude				0.03 (0.02)	[-0.01, 0.07]	0.110
Conspiracy ideation				-0.11 (0.02)	[-0.16, -0.07]	0.000
Age				0.00 (0.00)	[0.00, 0.01]	0.001
Education				0.01 (0.02)	[-0.02, 0.04]	0.581
Income				0.01 (0.01)	[-0.01, 0.04]	0.384
Random Effects	Variance	SD		Variance	SD	
Participant	0.34	0.58		0.33	0.57	
Message order	0.00	0.04		0.00	0.04	
Residual	0.51	0.71		0.49	0.70	

Note. ^a Low MSV is used as the reference group.

^b SS: sensation-seeking.

^c The issue of climate change is used as the reference group.

Appendix Table C.20 Linear mixed effects models with the interaction between MSV and sensation-seeking predicting the cognitive processing of short videos (2,578 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	3.40 (0.07)	[3.25, 3.54]	0.000	3.02 (0.14)	[2.74, 3.30]	0.000
Mid MSV ^a	0.17 (0.08)	[0.02, 0.32]	0.025	0.14 (0.08)	[-0.01, 0.29]	0.060
High MSV ^a	0.15 (0.07)	[0.00, 0.30]	0.045	0.15 (0.07)	[0.01, 0.30]	0.042
Sensation seeking	-0.02 (0.03)	[-0.08, 0.03]	0.388	-0.01 (0.03)	[-0.07, 0.04]	0.637
Mid MSV ^a × SS ^b	-0.04 (0.03)	[-0.09, 0.02]	0.161	-0.03 (0.03)	[-0.09, 0.02]	0.240
High MSV ^a × SS ^b	0.00 (0.03)	[-0.05, 0.05]	0.910	0.00 (0.03)	[-0.05, 0.05]	0.995
Issue: COVID-19 ^c				-0.05 (0.02)	[-0.09, -0.01]	0.023
Pre-existing attitude				0.22 (0.02)	[0.19, 0.25]	0.000
Conspiracy ideation				-0.11 (0.02)	[-0.15, -0.07]	0.000
Age				0.01 (0.00)	[0.00, 0.01]	0.000
Education				0.00 (0.02)	[-0.03, 0.03]	0.927
Income				-0.01 (0.01)	[-0.04, 0.01]	0.363
Random Effects	Variance	SD		Variance	SD	
Participant	0.45	0.67		0.38	0.61	
Message order	0.00	0.00		0.00	0.00	
Residual	0.23	0.48		0.21	0.46	

Note. ^a Low MSV is used as the reference group.

^b SS: sensation-seeking.

^c The issue of climate change is used as the reference group.

Appendix Table C.21 Linear mixed effects models with the interaction between MSV and sensation-seeking predicting the affective processing of short videos (2,579 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	1.69 (0.06)	[1.59, 1.80]	0.000	1.31 (0.09)	[1.13, 1.49]	0.000
Mid MSV ^a	0.07 (0.06)	[-0.04, 0.19]	0.207	0.05 (0.05)	[-0.05, 0.16]	0.323
High MSV ^a	0.02 (0.06)	[-0.09, 0.14]	0.703	0.00 (0.05)	[-0.11, 0.10]	0.958
Sensation seeking	0.05 (0.02)	[0.02, 0.09]	0.005	0.02 (0.02)	[-0.02, 0.05]	0.364
Mid MSV ^a × SS ^b	-0.02 (0.02)	[-0.06, 0.02]	0.292	-0.02 (0.02)	[-0.05, 0.02]	0.406
High MSV ^a × SS ^b	0.01 (0.02)	[-0.03, 0.05]	0.555	0.02 (0.02)	[-0.01, 0.06]	0.207
Issue: COVID-19 ^c				-0.08 (0.01)	[-0.11, -0.05]	0.000
Pre-existing attitude				0.22 (0.01)	[0.20, 0.25]	0.000
Conspiracy ideation				-0.02 (0.01)	[-0.04, 0.00]	0.121
Age				0.00 (0.00)	[0.00, 0.00]	0.354
Education				0.00 (0.01)	[-0.01, 0.02]	0.708
Income				-0.01 (0.01)	[-0.02, 0.01]	0.468
Random Effects	Variance	SD		Variance	SD	
Participant	0.15	0.39		0.11	0.33	
Message order	0.00	0.03		0.00	0.03	
Residual	0.15	0.38		0.11	0.34	

Note. ^a Low MSV is used as the reference group.

^b SS: sensation-seeking.

^c The issue of climate change is used as the reference group.

Appendix Table C.22 Linear mixed effects models with the interaction between MSV and sensation-seeking predicting the perceived message credibility of short videos (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	3.09 (0.13)	[2.84, 3.34]	0.000	3.66 (0.21)	[3.24, 4.07]	0.000
Mid MSV ^a	0.13 (0.11)	[-0.09, 0.36]	0.232	0.10 (0.12)	[-0.13, 0.34]	0.386
High MSV ^a	0.01 (0.11)	[-0.20, 0.23]	0.898	0.03 (0.12)	[-0.20, 0.26]	0.809
Sensation seeking	0.17 (0.05)	[0.08, 0.25]	0.000	0.06 (0.04)	[-0.02, 0.13]	0.161
Mid MSV ^a × SS ^b	-0.02 (0.04)	[-0.09, 0.06]	0.703	-0.01 (0.04)	[-0.10, 0.07]	0.746
High MSV ^a × SS ^b	0.04 (0.04)	[-0.04, 0.11]	0.359	0.04 (0.04)	[-0.04, 0.12]	0.352
Issue: COVID-19 ^c				0.12 (0.03)	[0.06, 0.19]	0.000
Pre-existing attitude				0.57 (0.02)	[0.52, 0.62]	0.000
Conspiracy ideation				-0.40 (0.03)	[-0.46, -0.34]	0.000
Age				-0.01 (0.00)	[-0.01, -0.01]	0.000
Education				-0.03 (0.02)	[-0.08, 0.01]	0.161
Income				-0.02 (0.02)	[-0.05, 0.02]	0.286
Random Effects	Variance	SD		Variance	SD	
Participant	1.58	1.26		0.67	0.82	
Message order	0.00	0.03		0.00	0.04	
Residual	0.51	0.71		0.53	0.73	

Note. ^a Low MSV is used as the reference group.

^b SS: sensation-seeking.

^c The issue of climate change is used as the reference group.

Appendix Table C.23 Linear mixed effects models with the interaction between MSV and sensation-seeking predicting the intention to engage with short videos (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	2.11 (0.11)	[1.90, 2.33]	0.000	1.76 (0.19)	[1.38, 2.15]	0.000
Mid MSV ^a	0.10 (0.10)	[-0.09, 0.30]	0.304	0.11 (0.10)	[-0.09, 0.32]	0.285
High MSV ^a	0.08 (0.10)	[-0.12, 0.28]	0.428	0.09 (0.10)	[-0.11, 0.29]	0.382
Sensation seeking	0.13 (0.04)	[0.05, 0.21]	0.001	0.07 (0.04)	[0.00, 0.14]	0.058
Mid MSV ^a × SS ^b	0.00 (0.04)	[-0.08, 0.07]	0.915	-0.02 (0.04)	[-0.09, 0.06]	0.687
High MSV ^a × SS ^b	0.02 (0.04)	[-0.05, 0.09]	0.517	0.02 (0.04)	[-0.05, 0.09]	0.532
Issue: COVID-19 ^c				0.06 (0.03)	[0.00, 0.12]	0.038
Pre-existing attitude				0.45 (0.02)	[0.40, 0.49]	0.000
Conspiracy ideation				-0.19 (0.03)	[-0.24, -0.13]	0.000
Age				0.00 (0.00)	[0.00, 0.00]	0.816
Education				0.01 (0.02)	[-0.03, 0.05]	0.670
Income				-0.02 (0.02)	[-0.05, 0.01]	0.228
Random Effects	Variance	SD		Variance	SD	
Participant	1.11	1.05		0.68	0.83	
Message order	0.00	0.00		0.00	0.00	
Residual	0.41	0.64		0.40	0.64	

Note. ^a Low MSV is used as the reference group.

^b SS: sensation-seeking.

^c The issue of climate change is used as the reference group.

Appendix Table C.24 Linear mixed effects models with the interaction between MSV and sensation-seeking predicting the issue-relevant risk perceptions (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	3.46 (0.18)	[3.10, 3.81]	0.000	1.57 (0.19)	[1.20, 1.94]	0.000
Mid MSV ^a	-0.03 (0.22)	[-0.46, 0.40]	0.890	-0.15 (0.15)	[-0.44, 0.14]	0.304
High MSV ^a	-0.12 (0.22)	[-0.55, 0.31]	0.572	-0.22 (0.15)	[-0.51, 0.06]	0.130
Sensation seeking	0.20 (0.07)	[0.07, 0.32]	0.003	-0.03 (0.04)	[-0.11, 0.05]	0.466
Mid MSV ^a × SS ^b	0.02 (0.08)	[-0.13, 0.18]	0.768	0.06 (0.05)	[-0.05, 0.16]	0.289
High MSV ^a × SS ^b	0.06 (0.08)	[-0.09, 0.21]	0.425	0.11 (0.05)	[0.01, 0.21]	0.037
Issue: COVID-19 ^c				-0.13 (0.04)	[-0.21, -0.04]	0.002
Pre-existing attitude				1.39 (0.02)	[1.35, 1.44]	0.000
Conspiracy ideation				-0.22 (0.02)	[-0.27, -0.18]	0.000
Age				0.00 (0.00)	[-0.01, 0.00]	0.174
Education				-0.02 (0.02)	[-0.06, 0.01]	0.205
Income				-0.01 (0.01)	[-0.04, 0.02]	0.548
Random Effects	Variance	SD		Variance	SD	
Participant	1.57	1.25		0.13	0.37	
Message order	0.00	0.00		0.00	0.00	
Residual	2.11	1.45		0.95	0.98	

Note. ^a Low MSV is used as the reference group.

^b SS: sensation-seeking.

^c The issue of climate change is used as the reference group.

Appendix Table C.25 Linear mixed effects models predicting the affective processing of short videos for low sensation-seeking (sensation-seeking ≤ 3 ; 1,738 observations from 869 participants) and high sensation-seeking (sensation-seeking > 3 ; 842 observations from 421 participants) participants.

Fixed Effects	Model 1: low sensation seeking			Model 2: high sensation seeking		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	1.31 (0.19)	[0.93, 1.68]	0.000	1.97 (0.27)	[1.43, 2.49]	0.000
Mid MSV ^a	-0.02 (0.06)	[-0.13, 0.09]	0.689	0.06 (0.09)	[-0.11, 0.23]	0.469
High MSV ^a	0.01 (0.06)	[-0.10, 0.13]	0.824	0.19 (0.09)	[0.02, 0.35]	0.029
Issue: COVID-19 ^b	0.02 (0.05)	[-0.07, 0.12]	0.656	-0.48 (0.08)	[-0.63, -0.33]	0.000
Pre-existing attitude	1.42 (0.03)	[1.37, 1.48]	0.000	1.29 (0.04)	[1.21, 1.37]	0.000
Conspiracy ideation	-0.23 (0.03)	[-0.28, -0.17]	0.000	-0.21 (0.04)	[-0.29, -0.12]	0.000
Age	0.00 (0.00)	[0.00, 0.00]	0.818	-0.01 (0.00)	[-0.01, 0.00]	0.016
Education	-0.03 (0.02)	[-0.07, 0.01]	0.165	0.00 (0.03)	[-0.06, 0.06]	0.975
Income	0.00 (0.02)	[-0.04, 0.03]	0.905	-0.02 (0.02)	[-0.06, 0.03]	0.508
Random Effects	Variance	SD		Variance	SD	
Participant	0.15	0.39		0.13	0.36	
Message order	0.00	0.02		0.00	0.03	
Residual	0.91	0.95		0.99	0.99	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.26 Linear mixed effects models with the interaction between MSV and age predicting attention to short videos, measured by dwell time (2,575 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	1.37 (0.05)	[1.28, 1.47]	0.000	0.96 (0.11)	[0.74, 1.18]	0.000
Mid MSV ^a	0.00 (0.06)	[-0.12, 0.12]	0.966	-0.02 (0.07)	[-0.15, 0.12]	0.780
High MSV ^a	-0.03 (0.06)	[-0.15, 0.09]	0.657	-0.07 (0.07)	[-0.20, 0.07]	0.337
Age	0.00 (0.00)	[0.00, 0.00]	0.562	0.00 (0.00)	[0.00, 0.00]	0.892
Mid MSV ^a × Age	0.00 (0.00)	[0.00, 0.00]	0.918	0.00 (0.00)	[0.00, 0.00]	0.689
High MSV ^a × Age	0.00 (0.00)	[0.00, 0.00]	0.970	0.00 (0.00)	[0.00, 0.00]	0.609
Issue: COVID-19 ^b				0.16 (0.02)	[0.11, 0.20]	0.000
Pre-existing attitude				0.01 (0.01)	[-0.02, 0.04]	0.490
Sensation seeking				0.04 (0.02)	[0.01, 0.07]	0.023
Conspiracy ideation				0.04 (0.02)	[0.01, 0.07]	0.009
Education				0.03 (0.01)	[0.01, 0.05]	0.008
Income				0.01 (0.01)	[-0.01, 0.02]	0.453
Random Effects	Variance	SD		Variance	SD	
Participant	0.10	0.31		0.11	0.33	
Message order	0.00	0.02		0.00	0.03	
Residual	0.26	0.51		0.27	0.52	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.27 Linear mixed effects models with the interaction between MSV and age predicting attention to short videos, measured by message recognition (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	4.22 (0.08)	[4.07, 4.36]	0.000	4.59 (0.17)	[4.26, 4.91]	0.000
Mid MSV ^a	-0.17 (0.09)	[-0.34, 0.00]	0.046	-0.15 (0.09)	[-0.34, 0.03]	0.104
High MSV ^a	-0.11 (0.09)	[-0.28, 0.05]	0.188	-0.09 (0.10)	[-0.28, 0.09]	0.330
Age	0.00 (0.00)	[0.00, 0.01]	0.039	0.00 (0.00)	[0.00, 0.01]	0.140
Mid MSV ^a × Age	0.00 (0.00)	[0.00, 0.01]	0.047	0.00 (0.00)	[0.00, 0.01]	0.071
High MSV ^a × Age	0.00 (0.00)	[0.00, 0.01]	0.454	0.00 (0.00)	[0.00, 0.01]	0.568
Issue: COVID-19 ^b				0.08 (0.03)	[0.02, 0.14]	0.009
Pre-existing attitude				0.03 (0.02)	[-0.01, 0.07]	0.128
Conspiracy ideation				-0.07 (0.02)	[-0.12, -0.02]	0.004
Age				-0.11 (0.02)	[-0.16, -0.07]	0.000
Education				0.01 (0.02)	[-0.02, 0.04]	0.580
Income				0.01 (0.01)	[-0.01, 0.04]	0.379
Random Effects	Variance	SD		Variance	SD	
Participant	0.34	0.58		0.33	0.57	
Message order	0.00	0.04		0.00	0.04	
Residual	0.51	0.71		0.49	0.70	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.28 Linear mixed effects models with the interaction between MSV and age predicting the cognitive processing of short videos (2,578 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	3.21 (0.06)	[3.09, 3.32]	0.000	2.99 (0.14)	[2.71, 3.27]	0.000
Mid MSV ^a	0.07 (0.06)	[-0.05, 0.18]	0.267	0.09 (0.06)	[-0.03, 0.22]	0.145
High MSV ^a	0.28 (0.06)	[0.16, 0.39]	0.000	0.30 (0.06)	[0.17, 0.42]	0.000
Age	0.00 (0.00)	[0.00, 0.01]	0.017	0.01 (0.00)	[0.00, 0.01]	0.000
Mid MSV ^a × Age	0.00 (0.00)	[0.00, 0.00]	0.980	0.00 (0.00)	[0.00, 0.00]	0.547
High MSV ^a × Age	0.00 (0.00)	[-0.01, 0.00]	0.034	0.00 (0.00)	[-0.01, 0.00]	0.016
Issue: COVID-19 ^b				-0.05 (0.02)	[-0.09, -0.01]	0.018
Pre-existing attitude				0.22 (0.02)	[0.19, 0.25]	0.000
Conspiracy ideation				-0.02 (0.02)	[-0.07, 0.02]	0.291
Age				-0.11 (0.02)	[-0.15, -0.07]	0.000
Education				0.00 (0.02)	[-0.03, 0.03]	0.946
Income				-0.01 (0.01)	[-0.04, 0.01]	0.352
Random Effects	Variance	SD		Variance	SD	
Participant	0.45	0.67		0.38	0.61	
Message order	0.00	0.00		0.00	0.00	
Residual	0.23	0.48		0.21	0.46	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.29 Linear mixed effects models with the interaction between MSV and age predicting the affective processing of short videos (2,579 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	1.94 (0.05)	[1.85, 2.02]	0.000	1.24 (0.09)	[1.07, 1.41]	0.000
Mid MSV ^a	0.02 (0.05)	[-0.07, 0.11]	0.717	0.07 (0.05)	[-0.02, 0.16]	0.150
High MSV ^a	0.14 (0.05)	[0.05, 0.23]	0.003	0.20 (0.05)	[0.11, 0.29]	0.000
Age	0.00 (0.00)	[0.00, 0.00]	0.005	0.00 (0.00)	[0.00, 0.00]	0.019
Mid MSV ^a × Age	0.00 (0.00)	[0.00, 0.00]	0.985	0.00 (0.00)	[0.00, 0.00]	0.186
High MSV ^a × Age	0.00 (0.00)	[0.00, 0.00]	0.053	0.00 (0.00)	[-0.01, 0.00]	0.001
Issue: COVID-19 ^b				-0.08 (0.01)	[-0.11, -0.05]	0.000
Pre-existing attitude				0.22 (0.01)	[0.20, 0.24]	0.000
Conspiracy ideation				0.02 (0.01)	[-0.01, 0.04]	0.166
Age				-0.02 (0.01)	[-0.04, 0.01]	0.125
Education				0.00 (0.01)	[-0.01, 0.02]	0.691
Income				-0.01 (0.01)	[-0.02, 0.01]	0.458
Random Effects	Variance	SD		Variance	SD	
Participant	0.15	0.39		0.11	0.33	
Message order	0.00	0.03		0.00	0.03	
Residual	0.15	0.38		0.11	0.33	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.30 Linear mixed effects models with the interaction between MSV and age predicting the perceived message credibility of short videos (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	4.37 (0.10)	[4.18, 4.57]	0.000	3.55 (0.20)	[3.14, 3.96]	0.000
Mid MSV ^a	0.03 (0.09)	[-0.14, 0.21]	0.717	0.14 (0.10)	[-0.05, 0.34]	0.155
High MSV ^a	0.21 (0.09)	[0.03, 0.38]	0.021	0.32 (0.10)	[0.12, 0.52]	0.002
Age	-0.02 (0.00)	[-0.03, -0.02]	0.000	-0.01 (0.00)	[-0.01, 0.00]	0.006
Mid MSV ^a × Age	0.00 (0.00)	[0.00, 0.01]	0.451	0.00 (0.00)	[-0.01, 0.00]	0.404
High MSV ^a × Age	0.00 (0.00)	[-0.01, 0.00]	0.256	0.00 (0.00)	[-0.01, 0.00]	0.044
Issue: COVID-19 ^b				0.12 (0.03)	[0.06, 0.19]	0.000
Pre-existing attitude				0.57 (0.02)	[0.52, 0.62]	0.000
Conspiracy ideation				0.06 (0.03)	[0.00, 0.12]	0.041
Age				-0.40 (0.03)	[-0.46, -0.34]	0.000
Education				-0.03 (0.02)	[-0.07, 0.01]	0.164
Income				-0.02 (0.02)	[-0.05, 0.02]	0.283
Random Effects	Variance	SD		Variance	SD	
Participant	1.46	1.21		0.67	0.82	
Message order	0.00	0.03		0.00	0.04	
Residual	0.50	0.71		0.53	0.73	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.31 Linear mixed effects models with the interaction between MSV and age predicting the intention to engage with short videos (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	2.80 (0.09)	[2.63, 2.97]	0.000	1.61 (0.19)	[1.22, 1.99]	0.000
Mid MSV ^a	0.14 (0.08)	[-0.02, 0.29]	0.085	0.22 (0.09)	[0.05, 0.39]	0.013
High MSV ^a	0.35 (0.08)	[0.19, 0.51]	0.000	0.46 (0.09)	[0.28, 0.63]	0.000
Age	-0.01 (0.00)	[-0.01, -0.01]	0.000	0.00 (0.00)	[0.00, 0.01]	0.118
Mid MSV ^a × Age	0.00 (0.00)	[-0.01, 0.00]	0.548	0.00 (0.00)	[-0.01, 0.00]	0.067
High MSV ^a × Age	-0.01 (0.00)	[-0.01, 0.00]	0.005	-0.01 (0.00)	[-0.01, 0.00]	0.000
Issue: COVID-19 ^b				0.06 (0.03)	[0.00, 0.11]	0.046
Pre-existing attitude				0.44 (0.02)	[0.40, 0.49]	0.000
Conspiracy ideation				0.07 (0.03)	[0.01, 0.13]	0.017
Age				-0.19 (0.03)	[-0.24, -0.13]	0.000
Education				0.01 (0.02)	[-0.03, 0.05]	0.657
Income				-0.02 (0.02)	[-0.05, 0.01]	0.225
Random Effects	Variance	SD		Variance	SD	
Participant	1.09	1.05		0.69	0.83	
Message order	0.00	0.00		0.00	0.01	
Residual	0.41	0.64		0.40	0.63	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.32 Linear mixed effects models with the interaction between MSV and age predicting the issue-relevant risk perceptions (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	5.21 (0.14)	[4.93, 5.49]	0.000	1.42 (0.18)	[1.06, 1.78]	0.000
Mid MSV ^a	-0.20 (0.17)	[-0.54, 0.14]	0.242	0.04 (0.13)	[-0.21, 0.28]	0.781
High MSV ^a	-0.14 (0.18)	[-0.49, 0.20]	0.417	0.01 (0.13)	[-0.24, 0.25]	0.967
Age	-0.03 (0.00)	[-0.04, -0.03]	0.000	0.00 (0.00)	[-0.01, 0.00]	0.327
Mid MSV ^a × Age	0.01 (0.00)	[0.00, 0.02]	0.124	0.00 (0.00)	[-0.01, 0.00]	0.736
High MSV ^a × Age	0.01 (0.00)	[0.00, 0.01]	0.243	0.00 (0.00)	[0.00, 0.01]	0.599
Issue: COVID-19 ^b				-0.13 (0.04)	[-0.21, -0.04]	0.003
Pre-existing attitude				1.39 (0.02)	[1.35, 1.44]	0.000
Conspiracy ideation				0.03 (0.03)	[-0.02, 0.08]	0.284
Age				-0.22 (0.02)	[-0.27, -0.17]	0.000
Education				-0.02 (0.02)	[-0.06, 0.01]	0.192
Income				-0.01 (0.01)	[-0.03, 0.02]	0.573
Random Effects	Variance	SD		Variance	SD	
Participant	1.38	1.18		0.13	0.37	
Message order	0.00	0.00		0.00	0.00	
Residual	2.11	1.45		0.96	0.98	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.33 Linear mixed effects models predicting the cognitive processing of short videos for participants younger (1,194 observations from 597 participants) and older (1,386 observations from 693 participants) than 35.

Fixed Effects	Model 1: under 35			Model 2: 35+		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	3.13 (0.18)	[2.77, 3.49]	0.000	3.45 (0.17)	[3.12, 3.79]	0.000
Low MSV ^a	0.08 (0.04)	[0.01, 0.16]	0.025	0.03 (0.03)	[-0.03, 0.10]	0.337
High MSV ^a	0.20 (0.04)	[0.13, 0.27]	0.000	0.11 (0.03)	[0.05, 0.18]	0.001
Issue: COVID-19 ^b	-0.07 (0.03)	[-0.13, 0.00]	0.055	-0.05 (0.03)	[-0.10, 0.00]	0.039
Pre-existing attitude	0.17 (0.02)	[0.12, 0.22]	0.000	0.26 (0.02)	[0.22, 0.30]	0.000
Sensation seeking	0.00 (0.03)	[-0.05, 0.06]	0.869	-0.07 (0.03)	[-0.13, 0.00]	0.040
Conspiracy ideation	-0.07 (0.03)	[-0.14, -0.01]	0.022	-0.12 (0.03)	[-0.18, -0.07]	0.000
Education	0.00 (0.02)	[-0.04, 0.05]	0.921	0.00 (0.02)	[-0.05, 0.04]	0.874
Income	-0.02 (0.02)	[-0.05, 0.01]	0.257	-0.01 (0.02)	[-0.05, 0.03]	0.593
Random Effects	Variance	SD		Variance	SD	
Participant	0.33	0.57		0.42	0.65	
Message order	0.00	0.00		0.00	0.00	
Residual	0.22	0.47		0.20	0.45	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.34 Linear mixed effects models predicting the affective processing of short videos for participants younger (1,194 observations from 597 participants) and older (1,385 observations from 693 participants) than 35 years old.

Fixed Effects	Model 1: under 35			Model 2: 35+		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	1.38 (0.12)	[1.14, 1.62]	0.000	1.35 (0.10)	[1.16, 1.54]	0.000
Mid MSV ^a	0.02 (0.03)	[-0.03, 0.08]	0.376	0.00 (0.02)	[-0.05, 0.04]	0.921
High MSV ^a	0.11 (0.03)	[0.06, 0.16]	0.000	0.02 (0.02)	[-0.02, 0.07]	0.332
Issue: COVID-19 ^b	-0.13 (0.02)	[-0.18, -0.08]	0.000	-0.06 (0.02)	[-0.09, -0.02]	0.002
Pre-existing attitude	0.19 (0.02)	[0.16, 0.23]	0.000	0.24 (0.01)	[0.22, 0.27]	0.000
Sensation seeking	0.04 (0.02)	[0.00, 0.08]	0.029	-0.01 (0.02)	[-0.04, 0.03]	0.642
Conspiracy ideation	-0.03 (0.02)	[-0.07, 0.01]	0.193	-0.01 (0.02)	[-0.04, 0.02]	0.373
Education	0.00 (0.01)	[-0.03, 0.03]	0.891	0.01 (0.01)	[-0.02, 0.03]	0.588
Income	-0.01 (0.01)	[-0.03, 0.01]	0.545	-0.01 (0.01)	[-0.03, 0.01]	0.511
Random Effects	Variance	SD		Variance	SD	
Participant	0.12	0.35		0.10	0.32	
Message order	0.00	0.04		0.00	0.02	
Residual	0.12	0.35		0.10	0.32	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.35 Linear mixed effects models predicting the perceived message credibility of short videos for participants younger (1,194 observations from 597 participants) and older (1,386 observations from 693 participants) than 35 years old.

Fixed Effects	Model 1: under 35			Model 2: 35+		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	3.78 (0.25)	[3.28, 4.27]	0.000	2.98 (0.24)	[2.49, 3.47]	0.000
Mid MSV ^a	0.08 (0.05)	[-0.02, 0.18]	0.111	0.04 (0.06)	[-0.08, 0.15]	0.530
High MSV ^a	0.19 (0.05)	[0.09, 0.29]	0.000	0.08 (0.06)	[-0.03, 0.20]	0.139
Issue: COVID-19 ^b	0.00 (0.05)	[-0.09, 0.10]	0.978	0.16 (0.04)	[0.07, 0.25]	0.000
Pre-existing attitude	0.39 (0.03)	[0.32, 0.46]	0.000	0.72 (0.03)	[0.65, 0.80]	0.000
Sensation seeking	0.06 (0.04)	[-0.01, 0.14]	0.107	0.08 (0.04)	[-0.01, 0.17]	0.069
Conspiracy ideation	-0.29 (0.04)	[-0.38, -0.21]	0.000	-0.44 (0.04)	[-0.52, -0.36]	0.000
Education	-0.07 (0.03)	[-0.13, -0.01]	0.027	-0.05 (0.03)	[-0.11, 0.01]	0.084
Income	-0.03 (0.02)	[-0.07, 0.02]	0.226	-0.01 (0.03)	[-0.06, 0.04]	0.821
Random Effects	Variance	SD		Variance	SD	
Participant	0.59	0.77		0.67	0.82	
Message order	0.00	0.00		0.00	0.06	
Residual	0.42	0.65		0.62	0.79	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.36 Linear mixed effects models predicting the intention to engage with short videos for participants younger (1,194 observations from 597 participants) and older (1,386 observations from 693 participants) than 35 years old.

Fixed Effects	Model 1: under 35			Model 2: 35+		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	2.00 (0.25)	[1.51, 2.50]	0.000	1.62 (0.23)	[1.16, 2.08]	0.000
Mid MSV ^a	0.12 (0.05)	[0.02, 0.21]	0.017	0.02 (0.05)	[-0.07, 0.11]	0.676
High MSV ^a	0.27 (0.05)	[0.17, 0.36]	0.000	0.05 (0.05)	[-0.05, 0.14]	0.334
Issue: COVID-19 ^b	0.00 (0.04)	[-0.09, 0.09]	0.936	0.06 (0.04)	[-0.01, 0.14]	0.115
Pre-existing attitude	0.33 (0.03)	[0.27, 0.40]	0.000	0.53 (0.03)	[0.47, 0.60]	0.000
Sensation seeking	0.05 (0.04)	[-0.03, 0.13]	0.213	0.09 (0.04)	[0.01, 0.18]	0.033
Conspiracy ideation	-0.13 (0.04)	[-0.21, -0.04]	0.004	-0.21 (0.04)	[-0.28, -0.14]	0.000
Education	-0.02 (0.03)	[-0.08, 0.04]	0.594	0.01 (0.03)	[-0.05, 0.07]	0.701
Income	-0.02 (0.02)	[-0.06, 0.02]	0.345	-0.02 (0.02)	[-0.07, 0.02]	0.339
Random Effects	Variance	SD		Variance	SD	
Participant	0.65	0.81		0.70	0.83	
Message order	0.00	0.01		0.00	0.06	
Residual	0.36	0.60		0.43	0.65	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.37 Linear mixed effects models with the interaction between MSV and belief congruence (BC) predicting attention to short videos, measured by dwell time (2,575 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	1.43 (0.03)	[1.37, 1.49]	0.000	0.97 (0.10)	[0.78, 1.15]	0.000
Mid MSV	0.02 (0.03)	[-0.05, 0.09]	0.543	0.02 (0.04)	[-0.05, 0.09]	0.583
High MSV	-0.02 (0.03)	[-0.09, 0.05]	0.564	-0.02 (0.04)	[-0.10, 0.05]	0.510
Belief congruence	-0.08 (0.04)	[-0.15, 0.00]	0.043	0.02 (0.04)	[-0.06, 0.11]	0.571
Mid MSV x BC	-0.02 (0.05)	[-0.13, 0.07]	0.626	-0.03 (0.06)	[-0.14, 0.08]	0.586
High MSV x BC	-0.01 (0.05)	[-0.11, 0.09]	0.816	-0.02 (0.06)	[-0.13, 0.09]	0.708
Issue: COVID-19				0.15 (0.02)	[0.11, 0.20]	0.000
Sensation seeking				0.04 (0.02)	[0.01, 0.07]	0.021
Conspiracy ideation				0.04 (0.01)	[0.01, 0.07]	0.013
Age				0.00 (0.00)	[0.00, 0.00]	0.811
Education				0.03 (0.01)	[0.01, 0.05]	0.008
Income				0.01 (0.01)	[-0.01, 0.02]	0.489
Random Effects	Variance	SD		Variance	SD	
Participant	0.10	0.32		0.11	0.33	
Message order	0.00	0.02		0.00	0.03	
Residual	0.26	0.51		0.27	0.52	

Appendix Table C.38 Linear mixed effects models with the interaction between MSV and belief congruence (BC) predicting attention to short videos, measured by message recognition (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	4.25 (0.07)	[4.11, 4.39]	0.000	4.45 (0.17)	[4.13, 4.78]	0.000
Mid MSV ^a	0.03 (0.09)	[-0.15, 0.21]	0.000	0.08 (0.09)	[-0.10, 0.26]	0.388
High MSV ^a	0.02 (0.09)	[-0.15, 0.20]	0.746	0.05 (0.09)	[-0.13, 0.23]	0.577
Belief congruence	0.04 (0.03)	[-0.01, 0.09]	0.799	0.06 (0.03)	[0.00, 0.11]	0.051
Mid MSV ^a x BC	-0.02 (0.03)	[-0.09, 0.05]	0.113	-0.03 (0.04)	[-0.10, 0.04]	0.369
High MSV ^a x BC	-0.03 (0.03)	[-0.10, 0.04]	0.576	-0.04 (0.04)	[-0.11, 0.03]	0.268
Issue: COVID-19 ^b				0.08 (0.03)	[0.02, 0.14]	0.010
Sensation seeking				-0.07 (0.02)	[-0.12, -0.02]	0.003
Conspiracy ideation				-0.11 (0.02)	[-0.16, -0.07]	0.000
Age				0.00 (0.00)	[0.00, 0.01]	0.001
Education				0.01 (0.02)	[-0.02, 0.04]	0.578
Income				0.01 (0.01)	[-0.01, 0.04]	0.382
Random Effects	Variance	SD		Variance	SD	
Participant	0.35	0.59		0.33	0.57	
Message order	0.00	0.04		0.00	0.04	
Residual	0.51	0.72		0.49	0.70	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.39 Linear mixed effects models with the interaction between MSV and belief congruence (BC) predicting the cognitive processing of short videos (2,578 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	2.80 (0.05)	[2.70, 2.89]	0.000	3.08 (0.14)	[2.80, 3.35]	0.000
Mid MSV ^a	0.02 (0.06)	[-0.10, 0.14]	0.778	0.02 (0.06)	[-0.11, 0.14]	0.805
High MSV ^a	0.12 (0.06)	[-0.01, 0.24]	0.062	0.11 (0.06)	[-0.02, 0.23]	0.089
Belief congruence	0.22 (0.02)	[0.19, 0.26]	0.000	0.21 (0.02)	[0.17, 0.25]	0.000
Mid MSV ^a x BC	0.02 (0.02)	[-0.03, 0.06]	0.441	0.02 (0.02)	[-0.03, 0.07]	0.468
High MSV ^a x BC	0.02 (0.02)	[-0.03, 0.07]	0.418	0.02 (0.02)	[-0.03, 0.07]	0.431
Issue: COVID-19 ^b				-0.05 (0.02)	[-0.09, -0.01]	0.020
Sensation seeking				-0.02 (0.02)	[-0.07, 0.02]	0.302
Conspiracy ideation				-0.11 (0.02)	[-0.15, -0.07]	0.000
Age				0.01 (0.00)	[0.00, 0.01]	0.000
Education				0.00 (0.02)	[-0.03, 0.03]	0.926
Income				-0.01 (0.01)	[-0.04, 0.01]	0.360
Random Effects	Variance	SD		Variance	SD	
Participant	0.38	0.62		0.38	0.61	
Message order	0.00	0.00		0.00	0.00	
Residual	0.21	0.46		0.21	0.46	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.40 Linear mixed effects models with the interaction between MSV and belief congruence (BC) predicting the affective processing of short videos (2,579 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	1.26 (0.04)	[1.18, 1.34]	0.000	1.34 (0.09)	[1.17, 1.51]	0.000
Mid MSV ^a	-0.03 (0.04)	[-0.11, 0.06]	0.518	-0.03 (0.05)	[-0.12, 0.06]	0.538
High MSV ^a	-0.01 (0.04)	[-0.10, 0.07]	0.744	-0.01 (0.04)	[-0.10, 0.07]	0.748
Belief congruence	0.23 (0.01)	[0.21, 0.26]	0.000	0.21 (0.01)	[0.18, 0.24]	0.000
Mid MSV ^a x BC	0.01 (0.02)	[-0.02, 0.05]	0.372	0.02 (0.02)	[-0.02, 0.05]	0.349
High MSV ^a x BC	0.03 (0.02)	[0.00, 0.06]	0.069	0.03 (0.02)	[0.00, 0.07]	0.066
Issue: COVID-19 ^b				-0.08 (0.01)	[-0.11, -0.05]	0.000
Sensation seeking				0.02 (0.01)	[-0.01, 0.04]	0.152
Conspiracy ideation				-0.02 (0.01)	[-0.04, 0.01]	0.127
Age				0.00 (0.00)	[0.00, 0.00]	0.341
Education				0.00 (0.01)	[-0.02, 0.02]	0.720
Income				-0.01 (0.01)	[-0.02, 0.01]	0.469
Random Effects	Variance	SD		Variance	SD	
Participant	0.11	0.33		0.11	0.33	
Message order	0.00	0.03		0.00	0.03	
Residual	0.11	0.34		0.11	0.34	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.41 Linear mixed effects models with the interaction between MSV and belief congruence (BC) predicting the perceived message credibility of short videos (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	2.09 (0.08)	[1.92, 2.25]	0.000	3.63 (0.20)	[3.23, 4.04]	0.000
Mid MSV ^a	0.10 (0.10)	[-0.09, 0.29]	0.325	0.09 (0.10)	[-0.11, 0.28]	0.390
High MSV ^a	0.13 (0.10)	[-0.06, 0.32]	0.192	0.10 (0.10)	[-0.10, 0.29]	0.325
Belief congruence	0.59 (0.03)	[0.53, 0.65]	0.000	0.57 (0.03)	[0.50, 0.64]	0.000
Mid MSV ^a x BC	-0.01 (0.04)	[-0.08, 0.06]	0.778	-0.01 (0.04)	[-0.08, 0.07]	0.834
High MSV ^a x BC	0.00 (0.04)	[-0.07, 0.07]	0.995	0.01 (0.04)	[-0.06, 0.09]	0.702
Issue: COVID-19 ^b				0.12 (0.03)	[0.06, 0.19]	0.000
Sensation seeking				0.06 (0.03)	[0.00, 0.13]	0.038
Conspiracy ideation				-0.40 (0.03)	[-0.46, -0.34]	0.000
Age				-0.01 (0.00)	[-0.01, -0.01]	0.000
Education				-0.03 (0.02)	[-0.08, 0.01]	0.161
Income				-0.02 (0.02)	[-0.05, 0.02]	0.282
Random Effects	Variance	SD		Variance	SD	
Participant	0.80	0.89		0.67	0.82	
Message order	0.00	0.04		0.00	0.04	
Residual	0.53	0.73		0.53	0.73	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.42 Linear mixed effects models with the interaction between MSV and belief congruence (BC) predicting the intention to engage with short videos (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	1.42 (0.07)	[1.28, 1.56]	0.000	1.80 (0.19)	[1.42, 2.18]	0.000
Mid MSV ^a	0.06 (0.09)	[-0.11, 0.22]	0.500	0.04 (0.09)	[-0.13, 0.22]	0.616
High MSV ^a	0.04 (0.08)	[-0.13, 0.20]	0.660	0.03 (0.09)	[-0.14, 0.20]	0.760
Belief congruence	0.43 (0.02)	[0.38, 0.48]	0.000	0.42 (0.03)	[0.36, 0.48]	0.000
Mid MSV ^a x BC	0.01 (0.03)	[-0.05, 0.07]	0.768	0.01 (0.03)	[-0.05, 0.08]	0.725
High MSV ^a x BC	0.05 (0.03)	[-0.02, 0.11]	0.144	0.05 (0.03)	[-0.01, 0.12]	0.121
Issue: COVID-19 ^b				0.06 (0.03)	[0.00, 0.12]	0.041
Sensation seeking				0.07 (0.03)	[0.01, 0.13]	0.015
Conspiracy ideation				-0.19 (0.03)	[-0.24, -0.13]	0.000
Age				0.00 (0.00)	[0.00, 0.00]	0.829
Education				0.01 (0.02)	[-0.03, 0.05]	0.675
Income				-0.02 (0.02)	[-0.05, 0.01]	0.226
Random Effects	Variance	SD		Variance	SD	
Participant	0.70	0.84		0.68	0.83	
Message order	0.00	0.00		0.00	0.00	
Residual	0.40	0.63		0.40	0.64	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.

Appendix Table C.43 Linear mixed effects models with the interaction between MSV and belief congruence (BC) predicting the issue-relevant risk perceptions (2,580 observations from 1,290 participants).

Fixed Effects	Model 1			Model 2		
	b (SE)	95% CI	p	b (SE)	95% CI	p
Intercept	0.29 (0.08)	[0.12, 0.45]	0.001	1.37 (0.18)	[1.01, 1.73]	0.000
Mid MSV ^a	0.04 (0.12)	[-0.20, 0.27]	0.765	0.06 (0.12)	[-0.17, 0.30]	0.611
High MSV ^a	0.14 (0.12)	[-0.09, 0.37]	0.231	0.16 (0.12)	[-0.08, 0.39]	0.188
Belief congruence	1.51 (0.03)	[1.45, 1.57]	0.000	1.41 (0.04)	[1.34, 1.48]	0.000
Mid MSV ^a x BC	-0.02 (0.04)	[-0.11, 0.07]	0.645	-0.03 (0.05)	[-0.12, 0.06]	0.549
High MSV ^a x BC	-0.03 (0.04)	[-0.12, 0.06]	0.481	-0.04 (0.05)	[-0.13, 0.05]	0.405
Issue: COVID-19 ^b				-0.13 (0.04)	[-0.21, -0.04]	0.002
Sensation seeking				0.03 (0.03)	[-0.02, 0.08]	0.283
Conspiracy ideation				-0.22 (0.02)	[-0.27, -0.18]	0.000
Age				0.00 (0.00)	[-0.01, 0.00]	0.168
Education				-0.02 (0.02)	[-0.06, 0.01]	0.203
Income				-0.01 (0.01)	[-0.04, 0.02]	0.560
Random Effects	Variance	SD		Variance	SD	
Participant	0.13	0.36		0.13	0.36	
Message order	0.00	0.00		0.00	0.00	
Residual	1.00	1.00		0.96	0.98	

Note. ^a Low MSV is used as the reference group.

^b The issue of climate change is used as the reference group.