Unboxing Engagement in YouTube Influencer Videos: An Attention-Based Approach

Prashant Rajaram
Puneet Manchanda

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* Rajaram (prajaram@ivey.ca) is Assistant Professor of Marketing at the Ivey Business School, Western University, and Manchanda (pmanchan@umich.edu) is Isadore and Leon Winkelman Professor and Professor of Marketing, at the Stephen M. Ross School of Business, University of Michigan. The authors would like to thank David Jurgens, Mengxia Zhang, Eric Schwartz, Zhenling Jiang, Hortense Fong, Jun Li, Yiqi Li, Yu Song, the Marketing faculty and doctoral students at the Ross School of Business, seminar participants at Ivey Business School, University of Wisconsin-Madison, Singapore Management University, Bocconi University, National University of Singapore, University of Manitoba, Bank of Canada, Bass FORMS Conference 2021, AIM Conference 2021, ISMS Marketing Science Conference 2021, Joint Statistical Meeting 2021, KDD 2021, ISMS Doctoral Consortium 2022, MSI Webinar 2022, Workshop by Global Institute for AI and Business Analytics 2023, JSM 2023 and Symposium on AI in Marketing 2024 for their valuable comments and feedback. The authors also acknowledge the use of chatGPT for copy editing.
Abstract

Influencer marketing videos have surged in popularity, yet significant gaps remain in understanding the relationships between video features and engagement. This challenge is intensified by the complexities of interpreting unstructured data. While deep learning models effectively leverage raw unstructured data to predict engagement, they often function as black boxes with limited interpretability, particularly when human validation is hindered by the absence of a known ground truth. To address this issue, we develop an ‘interpretable deep learning framework’ that provides insights into the relationships captured by the models. Inspired by visual attention in print advertising, our interpretation approach uses measures of model attention to video features, eliminating spurious associations through a two-step process and identifying a subset of relationships for formal causal testing. This approach is versatile, as it applies across well-known attention mechanisms—additive attention, scaled dot-product attention, and gradient-based attention—when analyzing text, audio, or video image data. We apply our framework to YouTube influencer videos, linking video features to measures of shallow and deep engagement developed based on the dual-system framework of thinking. Our findings guide influencers in prioritizing the design of video features associated with deep engagement sentiment.

Keywords: Influencer Videos, Interpretable Deep Learning, Social Media Engagement, Unstructured Data Analysis, Model Attention
1. Introduction

Influencers have the capacity to shape the opinion of others in their network. A vast majority of the influencers or “social media stars” today are individuals who have cultivated an audience over time by making professional videos that demonstrate authority and credibility (Digital Marketing Institute, 2024). The increasing popularity of social media stars has resulted in an exponential growth of the influencer marketing industry which is expected to reach a global valuation of $22.2B in 2025 from $9.7B in 2020 (Statista, 2023).

Despite the rapid emergence and growth of influencer videos, there remain two main gaps in the analysis and understanding of the relationship between video features and video engagement measures. First, while there are plenty of machine learning methods that can be used to predict engagement well with unstructured video data, they often provide little explanation on model reasoning. There is a lack of approaches in the literature that isolate video features which can causally impact video engagement, particularly when the ground truth linking influencer video features to engagement is unknown. Second, engagement measures studied in social media are often a linear combination of comments, likes, shares, etc. and differences between these measures have not been adequately investigated, possibly due to their high correlation (Hartmann et al., 2021; Hughes et al., 2019; Lee et al., 2018). This has led to an inadequate understanding of how video features are differentially associated with distinct engagement measures.

In this paper, we address these gaps by developing an “interpretable deep leaning framework,” and supplying it with measures of shallow engagement (System I) and deep engagement (System II) motivated by Kahneman’s work on frames of intuitive and deliberate thinking respectively (Kahneman, 2003). We apply our framework to publicly available influencer videos on YouTube, one of the most popular platforms for long-form videos. There are several challenges in implementing our framework. First, past approaches in the business literature using deep learning methods have documented a tradeoff between predictive ability and interpretability (Dzyabura et al., 2023; Liu et al., 2020; Liu et al., 2019). Specifically, deep learning models that use raw unstructured data as input, predict business outcomes well
out-of-sample but suffer from poor interpretability. This is because deep learning models are good at capturing all the latent constructs in a modality (text, audio or video images) using raw unstructured data allowing for good prediction but are often opaque when it comes to understanding the mechanics of the model. Second, the analysis of unstructured data is computationally very demanding (in terms of both resources and time) to get good prediction performance, requiring large datasets to prevent overfitting. Hence, any proposed framework needs to carry out analyses using feasible resources on an adequately sized dataset in a reasonable amount of time. Third, while the typical approach in the machine learning literature for validating model reasoning involves human judges (e.g., validating sentiment analysis results based on human interpretation of word meanings), this approach is not feasible when dealing with business outcomes such as engagement, views, or sales, where no ground truth links these outcomes to specific video features. Furthermore, since video features may not be uniformly present across all parts of a video, the potential relationships among the triad of video features, video parts and business outcomes of interest are vast, making it costly and challenging to experimentally examine all possible combinations.

We overcome the aforementioned challenges as follows. Our “interpretable deep leaning framework” uses raw unstructured data across different modalities as input to deep learning models, thereby achieving strong predictive performance. It then “looks inside” the framework to interpret the deep learning models’ inner workings using a novel interpretation approach. Note that we use individual deep learning models designed for each modality, and do not employ a multimodal approach, because simultaneously analyzing multiple sources of raw unstructured data (without handcrafted features) is not computationally feasible without access to large scale commercial computing resources. While a multimodal approach using raw data may enhance predictive performance as a consequence of capturing interactions between modalities during training, achieving optimal predictive performance is not the primary objective of the paper. Instead, our goal is to present an effective approach to interpret the inner workings of deep learning models that demonstrate strong out-of-sample predictive performance. This

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1 On the other hand, deep learning models that use ex-ante handcrafted features as input obtain high interpretability of the captured relationships but suffer from poor predictive ability. This is because handcrafted features allow easy interpretation between a change in the feature and a change in the outcome, but fail to capture all latent constructs in the modality, leading to poor predictive ability.
can be efficiently achieved using individual models designed for each modality (text, audio and video images). A potential concern with analyzing all features in a modality separately from other modalities is the risk of endogeneity due to correlations between observable features across modalities. To address this, we control for features across all modalities in the second step of our interpretation approach, thereby mitigating these concerns.

To tackle the computational demands, we employ transfer learning on each modality of data (text, audio and video images) (Liu et al., 2020; Yang et al., 2023) that benefits from using models pretrained on millions of observations. Hence, when fine-tuning these models on our data, we are able to work with a moderate sized sample of 1620 videos, using feasible computational resources (48GB GPU and 128GB RAM) employed for a feasible amount of time (less than 700 hours). Transfer learning also prevents overfitting and enhances interpretation by leveraging insights from the millions of observations in the pre-trained data.

We address the challenges posed by the impracticality of using human judges to validate model reasoning and the burden of examining numerous potential relationships, through two steps of our novel interpretation approach. Our approach adapts the theoretical framework of (visual) attention capture and transfer from the print advertising literature (Pieters & Wedel, 2004) to our context where we capture model attention (not visual attention) in each modality. In the first step, we find significant correlations between features of interest (to researchers and influencers) and the attention measures attributed by the models to these features. In the second step, we find significant correlations between the features and engagement measures predicted by our model. This process allows us to prune spurious relationships that are not correlated across both steps, (Draelos & Carin, 2020; Vashishth et al., 2019) thus shortlisting a subset of features likely to be causal for (further) formal experimental testing. The versatility of our interpretation approach is reflected in its applicability across three popular attention mechanisms—additive attention, scaled dot-product attention and gradient-based attention—used in models for different modalities of unstructured data. Furthermore, using simulated data, we validate the efficacy of our
interpretation approach and demonstrate its superiority over commonly used benchmark feature selection methods.

Our interpretation approach uncovers interesting findings regarding the sentiment of engagement. For example, we find that mentioning brand names, in captions/transcript in the beginning or middle of a video is associated with a decrease in the sentiment of deep engagement (System II) but not sentiment of shallow engagement (System I). In addition, we find that an increase in duration of music in the beginning of a video is associated with an increase in the sentiment of deep engagement (System II) but not sentiment of shallow engagement (System I). We also find that an increase in size of human images (packaged goods) displayed in video images in the beginning of a video is associated with an increase (decrease) in the sentiment of shallow engagement (System I) but not sentiment of deep engagement (System II). Overall, we identify a greater number of associations for the beginning of the video compared to the middle or end, likely due to the higher salience of stimuli at the video’s onset. During this critical initial period, the text and audio features we study are associated with sentiment of deep engagement (System II), whereas the video image features we study are associated with sentiment of shallow engagement (System I). We elaborate on how these findings can be explained by theory in the manuscript.

In summary, this paper makes the following contributions. First, it enables interpretation of deep learning models trained on raw unstructured (video) data that make strong out-of-sample predictions but are typically regarded as a black box. By adapting the visual attention transfer and capture framework from the print advertising literature to model attention in an unstructured data setting, our novel ex-post interpretation approach identifies “likely causal” video features that influence engagement. We eliminate 72% of significant associations that are spurious, thus shortlisting a smaller subset of relationships for rigorous causal testing. Second, the paper reveals new associations between influencer video features and measures of shallow and deep engagement, enhancing understanding of how YouTube influencer videos align with the dual-system framework of human thinking.
Our methodological approach and findings are relevant for multiple audiences. First, academics and marketing agencies across various fields (e.g., advertising, education and politics) can apply our methodological approach to examine any local video feature of interest, while pruning spurious associations, for formal causal testing (details in Section 3.2). By focusing on a smaller set of associations in targeted (field) experiments, they can achieve more cost effective and efficient results compared to testing a broader set of hypotheses. Second, brands who want to partner with YouTube influencers often struggle to identify the right engagement metrics to use to evaluate influencer performance (Alain, 2023). Influencers are also often uncertain about how particular video features are linked with engagement (Influencer Marketing Hub, 2022). Our findings offer valuable insights for optimizing video design to promote desired engagement outcomes.

2. Related Literature

In this section, we review the literature on influencer marketing and unstructured data analysis (using deep learning) and describe how our work builds on it.

2.1 Influencer Marketing

The growing body of literature on influencer marketing has examined its effectiveness across text, audio and video data. Research on textual data reveals that high influencer expertise increases engagement when the advertising intent is to raise awareness (Hughes et al., 2019). Likewise, Weibo posts with more brand mentions are associated with an increase in informativeness, leading to more reposts (Leung et al., 2022).

Recent studies have focused on audio and video data in influencer marketing. Findings suggest softer voice tones in sponsored Instagram videos increase positive sentiment (Hwang et al., 2022), while sponsored videos on YouTube can lead to a loss in subscribers (Cheng & Zhang, 2024). Similarly early brand disclosure in videos on Bilibili can reduce engagement (Chen et al., 2022). On TikTok, products advertised in engaging video segments lead to higher sales, and an increase in follower counts increases impressions (Tian et al., 2023; Yang et al., 2023). However, simultaneously employing large and small
influencers has been shown to decrease sales (Gu et al., 2024). Sponsored streams on Twitch have been found unprofitable for most game publishers (Huang & Morozov, 2024). On audio platforms, unknown music creators can increase their follower base by seeding creators with less followers than established influencers (Lanz et al., 2019), and a novel framework has been developed to increase profit potential by buying future endorsements from prospective influencers (Lanz et al., 2024).

While most of the past literature considers engagement as a linear combination of shares, comments and likes, our work extends this by developing distinct measures of shallow and deep engagement motivated by Kahneman’s dual-system framework. These are further divided into the sentiment and level of engagement, creating four unique engagement constructs whose differential association with video features has not been studied in prior work.

2.2 Unstructured Data Analysis via Deep Learning

Deep learning’s application in business literature has risen due to its capacity to capture complex, non-linear relationships which help improve predictions. Studies on textual data have employed Convolutional Neural Nets (CNNs), Long Short-Term Memory Cells (LSTMs) and Transformer-based architectures to study various outcomes including sales conversion (Liu et al., 2019), sentiment in reviews (Chakraborty et al., 2022), company survival (Zhang & Luo, 2023), instructor performance (Wang et al., 2023) and consumer perception of service (Puranam et al., 2021). Image and audio data have been analyzed using CNN-based architectures to classify and label images (Hartmann et al., 2021; Zhang et al., 2021), to obtain lower dimensional embeddings (Malik et al., 2023) and to predict brand personality, product return rates or emotional response to music (Dzyabura et al., 2023; Fong et al., 2024; Liu et al., 2020).

Video data analysis has also utilized deep learning, extracting engineered features to study their relationship with various outcomes, such as product preference while shopping (Lu et al., 2016), project success on Kickstarter (Li et al., 2019), consumer sentiment on Instagram (Hwang et al., 2022), video completion of educational courseware (Zhou et al., 2021), number of subscribers on YouTube (Cheng & Zhang, 2024) and real-time purchase (Li et al., 2023). Transfer learning has also been applied to identify engaging video segments on TikTok (Yang et al., 2023). There is also research embedding multimodal
data to predict business outcomes (Lee et al., 2024), to suggest logo features for a new brand (Dew et al., 2022) and to use as a control variable (Tian et al., 2023).

We contribute to this stream of literature by applying distinct transfer learning methods tailored to each unstructured data modality in videos across text, audio and video images. Our approach not only predicts well but also interprets model reasoning through attention mechanisms. Furthermore, unlike past studies that adapted causal inference methods from econometrics to analyze unstructured data, we introduce a novel two-step interpretation approach grounded in model attention theory from the deep learning literature. This method helps identify relationships that are likely to have external validity for formal causal testing.

3. Interpretation Approach: Frameworks and Theory

3.1 Interpretable Deep Learning Framework

Our interpretable deep learning framework, depicted in Figure 1, uses unstructured video data as input to individual deep learning models to predict engagement. To avoid the computational demands associated with training millions of videos, we use a transfer learning approach. We begin with base models for each data type (text, audio and images) that have been pre-trained in prior research on millions of observations at a high computational cost. By virtue of being pre-trained, these models have already learned basic patterns in unstructured data, making it easier for the model to identify patterns in our data sample. We customize these models with additional architectures, including attention mechanisms, that enable interpretation of inner workings of the models. Finetuning these models on our sample allows us to capture the relationship between our unstructured video data and our engagement measures.

Using raw unstructured video data as input, rather than handcrafted features, enables our models to achieve strong predictive performance (Dzyabura et al., 2023; Liu et al., 2020; Liu et al., 2019). After predictions are made, we implement ex-post interpretation by analyzing the trained models to uncover the captured relationships. We accomplish this by engineering features ex-post from the unstructured data which were supplied as input to the deep learning models, and then study the attention (importance)
attributed by the model to these features (stimuli) while originally predicting engagement. We explain the theory behind interpretation in 3.2.

![Figure 1: Interpretable Deep Learning](image)

3.2 Ex-Post Interpretation Framework

We propose a framework adapted from the visual attention theory in print advertising by Pieters and Wedel (2004), tailored to the context of influencer videos. On entertainment platforms like YouTube and TikTok, bottom-up (saliency-based) attention is more common than top-down (volitional) attention (Yang et al., 2023). This type of attention where salient features in text, audio or video images capture viewer focus is particularly relevant for our setting.

The top of Figure 2 illustrates the relevant part of the framework of Pieters and Wedel (2004), while the bottom of the figure shows our adaptation. In print ads, a stimulus such as the size of a brand logo affects the reach of the ad through the mediating effect of visual attention to the stimulus. In our context, the stimuli comprise of features that can be locally identified within unstructured data (presence of text features, duration of audio features or size of image features) (Box I) so that we can measure attention attributed to those features. We capture model attention (or importance) to these features (Box II) and not viewer visual attention. These attention measures are more salient for those features that explain more variation in engagement (Box III)² (Selvaraju et al., 2017; Vashisht et al., 2019). The effect of a feature on engagement is thus mediated by model attention to the feature, making it a theoretically

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² The framework in Pieters and Wedel (2004) uses eye-tracking studies to measure visual attention. We complement this stream of work by analyzing secondary data and introduce the concept of model attention from the machine learning literature to the business literature. Our approach can be applied on public videos that potentially engage millions of viewers over many minutes of viewing, as opposed to the small number of viewers in conventional lab or field studies. It is also important to note that model attention is not independent of eye tracking attention, and extant research in machine learning has found that they have a statistically significant correlation (Selvaraju et al., 2017).
necessary condition for the feature to impact predicted engagement. This parallels the role of visual attention in print ads where attention to brand features is necessary for effective brand communication (Pieters & Wedel, 2004). However, an increase in model attention alone does not guarantee a significant effect on engagement. Deep learning models can sometimes attribute attention to features spuriously. We discuss the theory behind this in the subsequent section.

![Bottom-Up Attention Capture Conceptual Model](image)

**Figure 2: Ex-Post Interpretation Framework**

### 3.3 Theory of Model Attention

Three popular attention mechanisms introduced in seminal papers in the deep learning literature are additive attention, scaled dot-product attention and gradient-based attention. We explain how spurious associations can emerge in each attention mechanism and our approach to prune such associations.

#### 3.3.1 Additive Attention

Introduced by Bahdanau et al. (2014), additive attention improves neural machine translation by allowing models to focus on different parts of the input, thereby enhancing performance over fixed-size context vectors. It functions similarly to a gating-unit that either allows or blocks the passage of information (see Vashishth et al. (2019) for details) by adding hidden state vectors and passing them through a feedforward neural network to generate attention scores. The mechanism has since been widely adopted in sequence-to-sequence models.

While Jain and Wallace (2019) and Wiegrefe and Pinter (2019) present contrasting views on whether attention weights are interpretable, Vashishth et al. (2019) reconcile their differences and investigate the behavior of this attention mechanism on single-sequence tasks such as sentiment analysis.
on the IMDb dataset. They find that the originally learned model attention weights are both meaningful (i.e., correspond to words that are truly linked with sentiment) and associated with the correct prediction 79.5% of the time (see Figure 3).

![Figure 3: Additive Attention: Results of Sentiment Analysis on IMDb dataset (Vashishth et al., 2019)](image)

However, there are instances when the model learns meaningful attention weights but still makes incorrect predictions (4.5% of the time). Additionally, there are cases when the model learns meaningless attention weights but the predictions are correct (11.5% of the time). These are spurious associations which we highlight in grey in Figure 3. The remaining instances (4.5% of the time) involve both meaningless attention weights and incorrect predictions.

Thus, Figure 3 demonstrates that models using the additive attention mechanism on single-sequence tasks most often identify relationships that align with both meaningfulness and correctness (corresponding to the ground truth underlying the data) but can also pick up spurious associations. The approach to test for meaningfulness in Vashishth et al. (2019) rely on human validation of whether the words (with high attention weights) in sentences convey sentiment, a common approach in the machine learning literature. Such an approach is not easily replicable in business settings such as ours where the ground truth linking influencer video features and engagement measures is often unknown. To address this challenge, we investigate whether deep learning models attribute attention to the focal feature of interest and also whether that focal feature is correlated with the predicted outcome (see Figure 4).

As shown in Figure 4, there can be situations where the focal feature is attributed attention but the feature is not correlated with the predicted outcome, resulting in Type A spuriousness. This can occur when (a) the focal feature is meaningless (but is attributed attention) leading to incorrect predictions.
(Category IV in Figure 3), or (b) the focal feature is meaningful (and is attributed attention), yet the predictions are incorrect (Category I in Figure 3). Similarly, there can be situations when the focal feature is *not* attributed attention but the feature is correlated with the predicted outcome, resulting in Type B spuriousness. This can happen when (a) the presence of the focal feature is correlated with the presence of other meaningless features (to which attention is attributed) that are associated with correct predictions (Category III in Figure 3), or (iv) the presence of the focal feature is correlated with the presence of other meaningful features (to which attention is attributed) that are associated with correct predictions (Category II in Figure 3). Thus, theoretically, both Type A and Type B spuriousness are possible.

![Figure 4: Types of spurious associations](image)

### 3.3.2 Scaled Dot-Product Attention

Scaled Dot-Product attention, introduced by Vaswani et al. (2017), has become the core component of self-attention and cross-attention mechanisms in modern architectures like transformers. It takes the dot product of hidden state vectors followed by scaling, simultaneously computing attention scores for all tokens (word-pieces) relative to a given token. This method is better suited than additive attention for capturing long range dependencies, improving computational efficiency and enabling parallel processing.³

When attention weights in encoder-based transformer models (e.g., BERT, RoBERTa, etc.) are randomly permuted (giving rise to meaningless features), the rate of decrease in prediction ability is slower (see Figure 4b in Vashisht et al. (2019)) compared to encoder-decoder-based transformer models used for generation of unstructured data (e.g., GPT). This can be problematic for encoder-based

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³ Additive attention can capture more complexity (than scaled dot-product attention) due to its use of a non-linear feedforward neural network, making it preferable when capturing complexity is more important.
transformer models when used for single sequence tasks such as classification or regression (see Figure 4a in Vashishth et al. (2019)). In such cases, the model might produce correct predictions while attributing attention to meaningless features. As discussed earlier, if the presence of the focal feature is correlated with the presence of other (meaningless or meaningful) features that are both given attention and associated with the predicted outcome, this can result in Type B spurious associations. While Type A spurious associations may also occur, the likelihood of Type B spurious associations using scaled dot-product attention on single sequence tasks is higher as it has been documented in prior work.

3.3.3 Gradient-based Attention

A generalized approach for gradient-based attention named Grad-CAM (Gradient-weighted Class Activation Mapping) was introduced by Selvaraju et al. (2017) to interpret CNNs (Convolutional Neural Networks) by highlighting image regions that influence predictions. Despite the rise of transformer-based methods, CNNs remain popular for image analysis due to their established effectiveness and relatively lower computational demands. Grad-CAM computes gradients with respect to the last convolutional layer, averages them over each feature map channel to determine importance, and uses these values as weights to produce saliency scores that highlight image regions influencing the outcome. While the averaging process in Grad-CAM helps reduce noise in the gradients (Selvaraju et al., 2017), it also has a downside: it can expand the attention map to include areas not actually used by the model for prediction (see Figure 1 in Draelos and Carin (2020)). However, it better identifies pixels associated with the focal object as compared to other approaches such as HiResCAM (Draelos & Carin, 2020).

Since Grad-CAM can expand the attention map, it may attribute spurious attention to features not actually used by the model for prediction, leading to Type A spurious associations. While Type B

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4 Draelos and Carin (2020) propose a modified framework, HiResCAM, that does not do averaging like Grad-CAM but instead multiplies the gradients element-wise with the feature map. This approach better discriminates the pixels used for prediction (e.g., using a nearby car to predict presence of a bus in an image), but does a poorer job of identifying all pixels associated with the focal object. In other words, HiResCAM excels at pinpointing the pixels used for predicting an object even if those pixels lie outside the object. However, this is not ideal for our setting as our framework (shown earlier in Figure 2) aims to investigate whether a focal image feature, rather than other correlated features, is associated with the outcome (engagement). Hence, we use Grad-CAM and not HiResCAM.
spurious associations may also occur, the likelihood of Type A spurious associations using gradient-based attention is higher as it has been documented in prior work.

### 3.4 Two-Step Approach

To address spurious associations in deep learning models, we employ a two-step approach (see Figure 5).

![Figure 5: Two-step approach](image)

In the first step, we assess whether attention is attributed to a feature by analyzing the correlation between the feature (Box I, Fig. 5) and the attention it receives (Box II, Fig. 5) during model training. This helps determine if features of interest are important in predicting engagement. However, spurious attention can occur if a feature is not genuinely correlated with predicted engagement, leading to Type A spuriousness. In order to identify and remove such spurious associations, we implement Step 2 of the analysis where we analyze the correlation between features (Box I, Fig. 5) and the predicted engagement measures returned by the models (Box III, Fig 5). We use predicted (estimated) engagement (and not observed engagement) as the dependent variable since it is theoretically influenced by the attention measures, making the Step 2 analysis directly comparable with the Step 1 analysis that uses (estimated) attention measures as the dependent variable. As discussed earlier, some of the features can also be spuriously correlated with predicted engagement without the necessary mediating effect of an increase in attention, resulting in Type B spuriousness. Hence, we find relationships at the intersection of Step 1 & 2 which is visually illustrated using a Venn diagram at the bottom-half of Figure 5. Analogously, our two-
step approach can be understood through the lens of visual attention in print advertising where, at a minimum, the feature (stimulus) must be correlated with both the mediator (visual attention to the stimulus) and the outcome (reach of print ads), as a necessary condition for establishing causality.

We remove Type A spurious features from the left and Type B spurious features from the right of the Venn diagram, identifying features (Box I) that cause both a change in attention (Box II) and predicted engagement (Box III). To address the "brittleness" of deep learning models, which may converge to local optima, we implement a form of bootstrapping, by running each model multiple times and find the average across iterations (details in Section 6). This ensures that we do not erroneously discard a causal association. While the two-step approach removes spurious associations, it is not a definitive method for identifying only causal features. Some relationships at the intersection may still be coincidentally correlated across both steps and remain confounded due to endogeneity arising from correlation with unobservables. Nonetheless, by narrowing down to features likely to be causal, we reduce the effort required for future causal research. The number of spurious associations removed will increase as more local features are tested in Box I or more engagement measures are evaluated in Box III.

4. Data

We focus on influencer videos on YouTube, one of the most popular platforms for long-form content (Shaikh, 2024). To create our sample, we first shortlist 110 influencers identified by Forbes in February 2017 (O'Connor, 2017) across 11 product categories (Beauty, Entertainment, Fashion, Fitness, Food, Gaming, Home, Parenting, Pets, Tech & Business, Travel) with 10 influencers in each category. These influencers are top performers, earning revenue from brand endorsements and primarily posting in English across Facebook, YouTube, Instagram, and Twitter. We refine our sample by excluding influencers not active on YouTube and those with fewer than 1,000 followers or more than 100 million followers. Additionally, we focus on influencers who post at least 50 videos to ensure sufficient variation in their content, narrowing our pool to 73 influencers.

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5 The criteria used by Forbes to identify these influencers include total reach, propensity for virality and level of engagement (across all social media channels) including endorsements and related offline business.
We thus have a sample of YouTube influencers who primarily create content for adults, post only pre-recorded videos, and have between 1000 and 100M subscribers reflecting the typical range of YouTube subscribership. From this group, we randomly select 3 influencers per category, totaling 33 influencers who can be categorized by their subscriber count: 1000 to 10K (2), 10K to 100K (6), 100K to 1M (7), 1M to 10M (13), and 10M+ (5). Using the YouTube Data API v3, we scrape the titles and posting times of all videos posted by these 33 influencers until October 2019, resulting in a master list of 32,246 videos. We then randomly select 50 public videos per influencer, creating a balanced sample of 1650 videos whose unstructured data (text, audio and images) is computationally feasible to analyze. After excluding videos with disabled likes, dislikes or comments, we are left with 1620 videos, from which we scrape all publicly available data in November 2019. Since we use transfer learning methods that benefit from using models pretrained on millions of observations (details in Section 5.1), we are able to work with a moderate sized sample of 1620 videos, thus allowing us to use feasible computational resources employed for a reasonable amount of time (details in Section 6).

We assess whether the influencers in our sample comply with the U.S. Federal Trade Commission (FTC) guidelines, which mandate that sponsorships be disclosed early in a video using terms like ‘ad’ or ‘sponsor’ (FTC, 2020). By examining the captions/transcript in the beginning (and middle) of each video, we find that only 1% of videos include such disclosures. For instance, despite reports in the media indicating a partnership between a specific parenting influencer and a brand, related videos lack sponsorship disclosures. This overall low compliance suggests that our sample contains both paid and organic videos, often without clear indicators of whether a video is paid. Next, we detail the outcome measures used for analysis.

4.1 Outcome Variables

In the industry, the most important criteria used by brands to evaluate influencers to partner with are engagement/clicks, followed by content type/category, impressions and sales (Influencer Marketing Hub,

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6 Our usage of this data falls within the ambit of YouTube’s fair use policy.
In making these decisions, brands generally consider overall engagement—rather than differentiating between paid and organic posts—since it better reflects an influencer's capacity to generate high-performing content (Alain, 2023). Consequently, influencers are motivated to build engagement across all their videos to increase their chances of securing brand sponsorships. Given that our sample includes both paid and organic videos (with incomplete indicators of paid content as discussed earlier), focusing on engagement across both types of videos is appropriate for our analysis.

We construct engagement measures using Kahneman’s dual-system theory of human thinking—System I and System II (Kahneman, 2003). System I, which involves automatic and intuitive reactions, is captured by "shallow engagement" measures such as likes and dislikes on YouTube. These actions require little effort—completed with a simple click—and have no social consequences as they neither reveal the user’s name or push the post onto their YouTube timeline (Dwoskin, 2021). System II, involving more conscious and deliberate reactions, is captured by "deep engagement" measures such as comments on YouTube, which on average require more thought and effort, and get posted with your profile name below the video, resulting in potential social consequences (Dwoskin, 2021).

Traditional metrics often do not distinguish between shallow and deep engagement, likely due to their high correlation (Hartmann et al., 2021; Hughes et al., 2019; Lee et al., 2018). For example, in our sample of 1620 videos there is a high correlation between log views and log (comments+1) at 0.91, between log views and log (likes+1) at 0.95 and between log views and log (dislikes+1) at 0.92.

Additionally, YouTube’s algorithm, which recommends videos based on expected watch time, can confound these engagement measures (Covington et al., 2016). To address these issues, we construct engagement measures that control for views, resulting in unique constructs (see Section 4.1.3) that are not highly correlated with each other or with views, minimizing the algorithm's influence.

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7 These frames of thinking have also been introduced in prior research in related contexts such as peripheral and central routes of persuasion (Petty & Cacioppo, 1986) and heuristic and systematic modes of information processing (Chen & Chaiken, 1999).
4.1.1 Engagement Level

We develop measures for shallow and deep engagement levels: “Thumbsability,” calculated as (#likes + #dislikes) / (#views), which captures shallow engagement, and “Commentability,” calculated as (#comments) / (#views), which captures deep engagement. Thumbsability reflects automatic, intuitive reactions that require minimal effort, while commentability reflects more deliberate responses on average. As both measures are exponentially distributed, they are transformed using their natural log, with 1 added to avoid log (0): log thumbsability = log ((#likes + #dislikes + 1) / #views) and log commentability = log ((#comments + 1) / views). Log thumbsability ranges from −8.41 to −1.97, and has a median of −3.78 (or approximately 228 likes and dislikes per 10K views)\(^8\) and log commentability ranges from −11.42 to −2.14 and has a median of −6.21 (or approximately 20 comments per 10K views).

4.1.2 Sentiment of Engagement

Past research shows that the sentiment expressed in visual and verbal components of advertising can influence attitude towards the ad which in turn affects brand attitude including purchasing behavior (Mitchell, 1986). Moreover, the sentiment of user generated content on brand managed social media communities has been linked with sales (Goh et al., 2013). Therefore, understanding viewer sentiment towards videos can serve as a proxy for sales. We develop measures for the sentiment of shallow and deep engagement: "Likeability," calculated as (#likes) / (#dislikes), measures shallow engagement sentiment, while "Loveability" captures deep engagement sentiment by analyzing the sentiment in comments using Google’s Natural Language API (Li & Xie, 2020).

Likeability measures the likelihood of a viewer liking rather than disliking a video, with higher values indicating more positive sentiment. This measure is also transformed using log likeability = log ((#likes + 1) / (#dislikes + 1)), ranging from −0.92 to 6.83, and has a median of 3.99 (or 54 likes per dislike). Loveability is determined by the average sentiment of the top 25 comments below a video, with sentiment scores ranging from -1 (very negative) to +1 (very positive).\(^9\) For comments made in a

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\(^8\) Note that from Nov 2021 YouTube has made thumbs down (dislike) counts private (https://blog.youtube/news-and-events/update-to-youtube/).

\(^9\) A tabulation shows that 99% of comments in our data are made by viewers and not the influencer and hence we do not separate the two.
language not supported by the Google Natural Language API, we use the Google Translation API to translate them into English before analyzing sentiment. The distribution of average sentiment scores ranges from $-0.90$ to $0.90$, and we use the median value ($0.34$) to categorize loveability into "positive" and "not positive" (neutral or negative). This binary approach helps create a more objective measure of sentiment, consistent with previous research (Goh et al., 2013; Li & Xie, 2020). We assume that if viewers do not comment on a video, and comments are not disabled, the sentiment is neutral. As a robustness check, we scrape the top 50 or 100 comments from a random sample of 66 videos (2 videos per influencer) and explore use of decreasing weights. We find that sentiment from these measures is highly correlated with a simple average of the top 25 comments ($\rho \geq 0.88$).

### 4.1.3 Summary of outcome variables

We have three continuous outcomes and one binary outcome, as summarized in Table 1a. The average magnitude of the Pearson correlation coefficient among the four outcomes is 0.28, indicating that these measures are not highly correlated with each other (individual values for the four measures and views is shown in Table 1b). A Principal Component Analysis (PCA) on these outcomes (including views) reveals that each measure loads heavily ($\geq 0.83$) on a distinct construct. This provides further evidence that each outcome variable captures unique information: \{deep or shallow\} x \{engagement level or sentiment\}.

| Engagement Level | Deep Engagement | Shallow Engagement |
|------------------|-----------------|--------------------|
|                  | Commentability: | Thumbsability:     |
|                  | $\frac{\#\text{comments}}{\#\text{views}}$ | $\frac{\#\text{likes} + \#\text{dislikes}}{\#\text{views}}$ |
| Sentiment of Engagement | Loveability: Positive or Not Positive | Likeability: $\frac{\#\text{likes}}{\#\text{dislikes}}$ |

Table 1a: Summary of outcome variables

|                      | Log thumbsability | Log commentability | Log likeability | Loveability | Log views |
|----------------------|-------------------|--------------------|-----------------|-------------|-----------|
| Log thumbsability    | 1                 |                    |                 |             |           |
| Log commentability   | 0.67              | 1                  |                 |             |           |
| Log likeability      | 0.53              | 0.14               | 1               |             |           |
| Loveability          | 0.01              | -0.15              | 0.15            | 1           |           |
| Log views            | 0.18              | 0.04               | 0.43            | -0.21       | 1         |

Table 1b: Correlation between variables
4.2 Unstructured Data

We now describe the unstructured data modalities which serve as inputs to our deep learning models. These modalities are present within videos and, therefore, can influence engagement conditional on video viewing, as captured by our four outcome variables. Text data consists of the captions or transcript of the video. Captions are present in 74% of the videos in our sample; for videos without captions, we use Google’s Cloud Speech-to-Text API to transcribe the audio to English. We also utilize the raw audio data alongside captions/transcript to capture acoustic information (e.g., music). Video image data are comprised of frames captured at the standard sampling rate of one frame per second (fps) (Yang et al., 2023; Yue-Hei Ng et al., 2015). These frames have a resolution of 135x240 pixels, which is both visually clear and feasible for analysis.

We focus on the beginning, middle and end 30 seconds of each video (extracting 30 frames per clip at one fps) for three reasons. First, the minimum duration of video content that must be viewed to register an impression is 30 seconds (Parsons, 2017) making this an adequate threshold. Second, to manage computational costs, we limit data analysis to 30-second segments, which is feasible using a 48GB GPU with 128GB RAM (further details are provided when we discuss results in Section 6). Third, we aim to study whether effects differ across various parts of the video, considering many viewers do not watch YouTube videos in their entirety (Bump, 2021).

5. Interpretation Approach: Implementation

In this section, we outline our models for estimating attention weights while predicting engagement, followed by identification of theory-based features for ex-post interpretation, our list of control variables and finally details of the two steps of the interpretation approach (referenced in Figure 5).

5.1 Models

We employ three individual (transfer learned) deep learning models for text, audio and video images, which are popular in the machine learning literature for their efficiency and effectiveness in analyzing unstructured data. These models use the popular attention mechanisms discussed earlier: scaled dot-
product attention, additive attention and gradient based attention, demonstrating the versatility of our interpretation approach across different data modalities.

5.1.1 Text model

For text data, we use Bidirectional Encoder Representation from Transformers (BERT Base), a high performing NLP model (Devlin et al., 2018). This seminal model has been widely used in the machine learning literature for single sequence tasks like classification and regression, and its use is also emerging in business research (Puranam et al., 2021; Wang et al., 2023). BERT is pre-trained on Book Corpus (800M words) and English Wikipedia (2,500M words) to predict words and sentences over four days using four Tensor Processing Units. It employs a self-attention mechanism with scaled dot-product attention as its core computation method that generates relative attention weights for each word-piece. We fine-tune BERT on our data sample for each engagement measure, and provide details on how we operationalize the model and obtain attention weights in Online Appendix A.

5.1.2 Audio model

For audio data, we use the pre-trained YAMNet model which converts raw audio signals into Mel spectrograms (capturing acoustic characteristics) and processes them through a MobileNet v1 architecture (Pilakal & Ellis, 2020). YAMNet is well-regarded in the machine learning community for its ability to identify sound classes, as it is pre-trained on the AudioSet data which contains over two million 10-sec YouTube audio segments (Gemmeke et al., 2017). We customize YAMNet by adding a Bidirectional LSTM (Bi-LSTM) layer to capture the sequential relationship between sound moments. Additionally, we incorporate the additive attention mechanism from neural machine translation literature (Bahdanau et al., 2014) to help the Bi-LSTM layer capture relative attention weights between sound moments. We fine-tune the Audio model on our data sample for each engagement measure and provide details on how we operationalize the model and obtain attention weights in Online Appendix B.

5.1.3 Video Image model

For video images, we use a combination of VGG-16 and Bi-LSTM. VGG-16 is a high-performing, seminal image model pre-trained on 1.2M images from the ImageNet dataset (Simonyan & Zisserman,
that has also gained popularity in business research (Hartmann et al., 2021; Zhang et al., 2021). In our approach, each model processes a single video frame as input, and we then combine the outputs using a Bi-LSTM, an architecture known for its effectiveness at capturing sequential information from video frames (cf. Yue-Hei Ng et al. (2015)). We fine-tune the Video Image Model on our data sample for each engagement measure and identify salient areas in images using Grad-CAM (Gradient weighted Class Activation Mapping) (cf. Selvaraju et al., 2017), which employs gradient-based attention. We slightly modify the approach to allow the generation of both positive and negative gradients. Positive (negative) gradients correspond to regions that are positively (negatively) associated with continuous outcomes and the predicted class of the binary outcome. Details on the operationalization of the Video Image Model and gradient generation are in Online Appendix C.

While negative gradients in the Video Image Model identify areas that are negatively associated with an outcome, negative attention weights in the Text and Audio models identify areas with no association. We avoid using approaches like additive or scaled dot-product attention in the Video Image Model to find salient areas because it would be computationally expensive over a 135x240 pixel frame for 30 frames. The gradient-based approach achieves the same objective more efficiently.

5.2 Theory-based Features

Having outlined our models for estimating attention weights, we turn to our process for identifying features to use within our framework (Box I in Figure 2 and 5). Now, existing literature in social media, advertising and influencers has not differentiated between features linked to shallow versus deep engagement sentiment. As our goal is to uncover this distinction in the context of YouTube influencers, we need a systematic approach to identify the set of features to investigate from the vast pool of features in video data.

First, we focus only on features that can be identified locally within text, audio, or video images, so that they can be used within our interpretation framework (as discussed in Section 3.2). For example, a person present in an image is a locally identifiable feature, whereas overall image brightness, which affects the entire frame, is not (Dzyabura et al., 2023; Li et al., 2019; Zhang et al., 2021). Second, we
consulted with executives at Google/YouTube and two prominent influencers to discuss local features of interest for these stakeholders. Third, we used theory from relevant literature including influencer marketing, social media, news media and advertising, to identify local features that have been linked with the sentiment of engagement, as it can act as a proxy for sales (as discussed in Section 4.2.1). Through this systematic approach, we identify a broad set of features with theory-based expectations for their impact on sentiment of engagement, summarized in Table 2.

| Unstructured data | Features in unstructured data | Theory | Representative Source | Expected change in sentiment of engagement |
|-------------------|-----------------------------|--------|-----------------------|-------------------------------------------|
| Text: Captions/ Transcript | Presence of brand names (1) | Brand mentions may lower entertainment value and decrease persuasiveness of message. Brand mentions may increase informational value and increase viewers’ trust in the brand. | Tellis et al. 2019; Teixeira et al. 2010; Leung et al. 2022 | Ambiguous |
| | Presence of emotional words (2) | Emotional words are tied to a brand’s personality, evoke high arousal and increase message persuasiveness. Emotional words are associated with disingenuous persuasion or insincerity and signal fakeness. | Lee et al. 2018; Berger & Milkman 2012; Bakir & McStay 2018; Guo et al. 2019 | Ambiguous |
| Audio | Duration of music (3) | Music in ad videos reduces irritation towards the ad. | Pelsmacker & Van den Bergh 1999 | Positive |
| | Rapid speech (4) | Rapid speech is associated with being more knowledgeable and an increase in watch time. Change in pace of voice grabs viewer attention. | Peterson et al. 1995; Guo et. al. 2014; Beck 2015; Jennings 2021 | Ambiguous |
| Video Images | Size of humans (5) | Human images increase desire to socialize, engage and communicate. | Xiao and Ding 2014; Hartmann et al. 2021; To & Patrick 2021 | Positive |
| | Size of packaged goods (6) | Packshots (which focus on a product and not humans) decrease desire to socialize, engage and communicate. | Hartmann et al. 2021 | Negative |
| | Size of animals (7) | Ads featuring animals are more likeable. | Biel & Bridgwater 1990; Pelsmacker & Van den Bergh 1999 | Positive |
| | Emotional expressions of joy (8) and surprise (9) | Joy and surprise in internet videos ads concentrate attention and retain viewers for longer time periods. Joyous faces are associated with decrease in retweets but are not associated with likes on Twitter or Instagram. Surprise exhibited by instructors in educational videos has no dominant directional effect on video watch time, as it depends on contextual factors and topics discussed | Teixeira et al. 2012; Li & Xie 2020; Zhou et al. 2021 | Ambiguous |

Table 2: Theory-based features and expectations
5.2.1 Presence of text features

Viewers generally prefer ads with high entertainment value and low informational content (Woltman Elpers et al., 2003), and similarly, influencer videos are watched for entertainment (Landsberg, 2021). Brand mentions (in captions/transcript) may lower entertainment value and increase informational content, which could reduce the persuasiveness of the message and decrease (positive) sentiment (Teixeira et al., 2010; Tellis et al., 2019). However, an alternate view suggests that increase in informational value may complement entertainment, educate viewers and build trust, potentially increasing (positive) sentiment (Leung et al., 2022).

The use of emotional words has been associated with higher engagement, such as shares, comments, and likes, due to their connection to brand personality and their ability to evoke high arousal (Berger & Milkman, 2012; Lee et al., 2018). However, emotional language can also be perceived as insincere, particularly in fake news (Bakir & McStay, 2018; Guo et al., 2019). Given these contrasting set of findings in prior literature on the effect of brand mentions and emotional words, their association with the sentiment for influencer videos on YouTube remains unclear.

5.2.2 Duration of audio features

Music in ads can reduce irritation and enhance brand memory, especially when used without voiceovers (Alexomanolaki et al., 2007; Pelsmacker & Van den Bergh, 1999). Thus, longer durations of music without voiceover may be associated with increased (positive) sentiment.

Fast speakers are often perceived as more knowledgeable and effective (Peterson et al., 1995), and faster speech rates in educational videos have been linked to increased watch time (Guo et al., 2014). However, anecdotal evidence from linguists suggests that changes in pace, rather than rapid speech, are what typically capture attention (Beck, 2015; Jennings, 2021). The effect of speech rate on sentiment for influencer videos on YouTube is therefore uncertain.

5.2.3 Size of image features

Human faces are generally preferred in print ads and are linked to increased engagement on social media (Li & Xie, 2020; Xiao & Ding, 2014; Yang et al., 2023), possible due to human desire for social
interaction (To & Patrick, 2021). In influencer videos, the influencer is often demonstrating something to a viewer with the help of their hands which can further aid in engaging the viewer. Hence, we can expect the presence and size of the whole human (influencer) in the video, including their hands, to enhance (positive) sentiment. Conversely, images of brand packaging, unlike human faces, tend to decrease engagement, as they are less likely to elicit a desire to interact (Hartmann et al., 2021). Thus, larger images of packaged goods in videos may lead to reduced (positive) sentiment. However, like humans, animals in ads are often more likable and have lower irritation scores, suggesting that larger images of animals may increase (positive) sentiment (Biel & Bridgwater, 1990; Pelsmacker & Van den Bergh, 1999).

Facial expressions like joy and surprise in ads can hold attention and retain viewers (Teixeira et al., 2012). However, their impact on social media engagement is mixed, with happy faces sometimes linked to fewer retweets and no effect on likes (Li & Xie, 2020). Similarly, surprise in educational videos shows mixed effects on watch time depending on context (Zhou et al., 2021), making the impact of facial expressions on sentiment in influencer videos on YouTube ambiguous.

As summarized in Table 2, existing literature in influencer marketing, social media, news media and advertising, provide either ambiguous or deterministic expectations for the relationship between video features and sentiment of engagement on YouTube. Furthermore, since the differential association of these features with sentiment of shallow and deep engagement on YouTube has not been explored in prior work, uncovering these distinctions becomes important. We generate the aforementioned features using our models and other APIs, with details and descriptive statistics provided in Online Appendix D.

5.3 Control Variables

Having identified the features of interest, we now list the wide set of structured features that are used as control variables in our interpretation approach (see Table 3). These include fixed effects for the influencer (channel) that control time invariants effects associated with the influencer. In addition, we have features for video length, number of tags, features for playlist information, time-based features and whether video captions are available. Additionally, we include controls for total number of URLs in the
Next, we discuss our two-step approach for shortlisting video features in different parts of the video that can causally affect our engagement measures.

### 5.4 Interpreting Relationship with Attention (Step 1)

After estimating attention weights from the Text model for each word-piece in captions/transcript, we implement Step 1 of the interpretation approach by analyzing the following equation 12 times—across 4 outcomes and 3 video parts (beginning, middle and end):\(^{10}\)

\[
\log(\text{AttentionWeight}_{itk}) = \alpha_i + \gamma X_{it} + \sum_{k=1}^{n_b} \beta_{1k}(BIT_{itk}) + \sum_{k=1}^{n_e} \beta_{2k}(EIT_{itk}) + \beta_3(TP_{itk}) + \beta_4(\text{NOT}_{it}) + \epsilon_{itk}
\]

(1)

where \(\text{AttentionWeight}_{itk}\) is the estimated weight for each token \(k\) (word-piece created from raw text by the model) in video \(t\) made by influencer \(i\). Since it is exponentially distributed, we take its log. \(\alpha_i\) is influencer fixed effects and \(X_{it}\) is the vector of structured features listed earlier in Table 3. \(BIT_{itk}\) is ‘brand indicator in token’ indicating whether token \(k\) is a brand name, \(EIT_{itk}\) is ‘emotion indicator in token’ indicating whether token \(k\) is an emotional word, \(TP_{itk}\) controls for token position, \(\text{NOT}_{it}\) controls

\(^{10}\) Note that we cannot simultaneously control for presence of features in all parts of the video in the same equation in Step 1 because the number of observations (e.g., tokens \(k\)) in each part of the video may be different (see Table 4 & 6 in Results for difference in number of observations).
for number of tokens in the text, \( n_b \) is total number of brand names, \( n_e \) is total number of emotional words, and \( \epsilon_{itk} \) is the error. We use a unique coefficient for each brand and emotional word to model potential heterogeneity in effects. We use a covariate for the token position (\( TP_{itk} \)) to control for any potential influence of the position of the word-piece in the text, and we control for the number of tokens (\( NOT_{it} \)) because attention weights in text are relative to each other and sum up to one, i.e. more the number of tokens, lower will be the attention directed to it.

For audio data, after estimating attention weights for each sound moment, we implement Step 1 using a similar approach for each outcome and video part:

\[
\log(\text{AttentionWeight}_{itk}) = \alpha_i + \gamma X_{it} + \beta_1 (\text{CI}(\text{Human})_{itk}) + \beta_2 (\text{CI}(\text{Music})_{itk}) + \\
\beta_3 (\text{CI}(\text{Human})_{itk} \times \text{CI}(\text{Music})_{itk}) + \beta_4 (\text{CI}(\text{Animal})_{itk}) + \beta_5 (\text{CI}(\text{Other})_{itk}) + \beta_6 (\text{Location}_{itk}) + \\
\epsilon_{itk} \tag{2}
\]

where \( \text{AttentionWeight}_{itk} \) is the estimated weight for sound moment \( k \) in video \( t \) made by influencer \( i \), \( \text{CI}(\text{Human}) \) is the Category Indicator for human sounds in moment \( k \), and \( \text{CI}(\text{Human}) \times \text{CI}(\text{Music}) \) corresponds to moments when both human and music sounds occur together, \( \text{Location}_{itk} \) controls for location of the moment within the 30 second audio clip and other terms are similar to those in Equation 1. We use a covariate for location so that we can control for any potential influence of the position of the moment. Note that we do not include a covariate for number of audio moments, as each clip has the same length of 30 seconds.

For video image data, after estimating gradient values, we implement Step 1 using a similar approach for each outcome and video part:

\[
\text{MeanGradientValues}_{itk} = \alpha_i + \gamma X_{it} + \sum_{k=1}^{8} \beta_{1k} \text{SizeObject}(k)_{it} + \beta_{21} \text{Joy}(\text{Face})_{itk} + \\
\beta_{22} \text{Surprise}(\text{Face})_{it} + \beta_{23} \text{Joy}(\text{Face})_{it} \times \text{SizeObject}(\text{Face})_{itk} + \\
\beta_{24} \text{Surprise}(\text{Face})_{it} \times \text{SizeObject}(\text{Face})_{it} + \epsilon_{itk} \tag{3}
\]

where \( \text{MeanGradientValues}_{itk} \) is the mean gradient values across the area (pixels) occupied by all items of object category \( k \) across 30 frames in video \( t \) made by influencer \( i \), and \( k = 1 \) to 8 corresponds to each object category: \{humans, faces, animals, brand logos, packaged goods, clothes & accessories, home & kitchen and other objects\}. \( \text{SizeObject}(k)_{it} \) is the mean across 30 frames of the percentage of the
image occupied by all objects of category $k$ in video $t$ made by influencer $i$. Hence, the coefficient $\beta_{tk}$ can be interpreted as the effect of a one percent increase in size of the object of category $k$ on average across 30 seconds of the video. Note that features for size of humans and size of faces are not highly correlated (variance inflation factor $\leq 2.5$ across each video part). $Joy(Face)_{it}$ and $Surprise(Face)_{it}$ indicate the mean (across 30 frames) of the level of surprise or joy in each face $\{-2: \text{very unlikely}, \ -1: \text{unlikely}, \ 0: \text{possible}, \ 1: \text{likely}, \ 2: \text{very likely}\}$. The two interaction terms capture the interaction between the emotion registered and the size of faces, and other terms are similar to those in Equation 1.

5.5 Interpreting Relationship with Outcome (Step 2)

After obtaining predicted outcomes from all models, we implement Step 2 of the interpretation approach, where information from all modalities (text, audio, and video images) is combined into a single equation. This allows us to examine the effect of a feature from each modality while controlling for the effects of features from the other modalities. We analyze the following equation 36 times—across 3 models, 4 outcomes and 3 video parts (beginning, middle and end):

$$\text{PredictedOutcome}_{it} = \alpha_t + \gamma X_{it} + \sum_{p \text{ in part}} \left( \sum_{k=1}^{n_b} \beta_{1pk} (BITX_{it}) + \sum_{k=1}^{n_e} \beta_{2pk} (EITX_{it}) + \beta_{3p} (NOT_{it}) + \beta_{4p} (\text{Sum of CI(Human)}_{it}) + \beta_{5p} (\text{Sum of CI(Music)}_{it}) + \beta_{6p} (\text{Sum of CI(Other)}_{it}) + \sum_{k=1}^{n} \beta_{7pk} \text{SizeObject}(k)_{it} + \beta_{10p} \text{Joy}(Face)_{it} + \beta_{11p} \text{Surprise}(Face)_{it} + \beta_{12p} \text{Joy}(Face)_{it} \times \text{SizeObject}(Face)_{it} + \beta_{13p} \text{Surprise}(Face)_{it} \times \text{SizeObject}(Face)_{it} \right) + \epsilon_{it}$$

(4)

where $\text{PredictedOutcome}_{it}$ is the predicted outcome from a model for a part of video $t$ made by influencer $i$, $\alpha_t$ is influencer fixed effects and $X_{it}$ is the same vector of structured features used earlier in Equation 1. $BITX_{it}$ is a ‘brand indicator in text’ indicating whether the text (captions/transcript) in video $t$ by influencer $i$ has a brand, $EITX_{it}$ is ‘emotion indicator in text’ indicating whether the text has an emotional word, and $NOT_{it}$ controls for number of tokens in text. As done in Equation 1, we use a unique coefficient for each brand and emotional word to model potential heterogeneity in effects.

$\text{Sum of CI(Human)}_{it}$ corresponds to the duration of human sounds (or sum of the Category Indicator for human sounds) across the 30 seconds (60 moments) in video $t$ made by influencer $i$, and
Sum of \( CI(\text{Human})_{it} \times CI(\text{Music})_{it} \) finds the total duration when human and music sounds overlap. The other variables mirror those used in Equation 3. Thus, we control for features across all sources of unstructured data (that were used in the three equations of Step 1). We also sum over the parts = \{beginning, middle, end\} in Equation 4 to control for the presence of words, sounds and objects in different parts of the video.

The coefficients from Step 1 (Equation 1-3) and Step 2 (Equation 4) help identify whether a feature is attributed attention (Step 1) and associated with the predicted outcome (Step 2).

6. Results

Our “interpretable deep learning framework” does not compromise on predictive ability since it uses raw unstructured data and not hand-crafted features for prediction, consistent with prior research (Dzyabura et al., 2023; Liu et al., 2020; Liu et al., 2019). However, deep learning models can be sensitive to starting values of hyperparameter weights randomly chosen by the model, leading to potential variability in results. Hence, we discuss our approach to generate stable results.

We divide our sample of 1620 videos into a random 60% training set (972 videos), 20% validation set (324 videos) and 20% holdout set (324 videos). We fine-tune the pre-trained models (discussed in Section 5.1) using the training set, adjusting Adam gradient descent steps based on the validation set, and evaluate performance on the holdout set. We follow standard parameter values for the BERT, YAMNet, and VGG-16 models to produce stable estimates. Additionally, we implement a form of bootstrapping, by repeating the training, validation and prediction processes 50 times (25 times) for every covariate-outcome pair in the Text and Audio models (Video Image Model). This approach mitigates concerns about model brittleness due to random convergence to a local optima. The analysis is performed using an NVIDIA RTX A6000 GPU (48GB RAM) and 128GB CPU RAM that takes the maximum time to analyze the Video Image model. For 25 bootstrap iterations, it takes around 36 hours to run the model and complete the gradient analysis for each covariate-outcome pair, and a total of 432 hours across all
outcomes and video parts. For computational ease, we limit to 25 bootstrap iterations for the Video Image model but extend to 50 iterations for the Text and Audio models.

Our models show strong predictive performance where all the continuous outcomes (commentability, thumbsability and likeability) are predicted with a low RMSE ranging from 0.75 to 1.03, and the binary outcome (loveability) shows moderately high accuracy, ranging from 63% to 71% (details in Online Appendix E). More importantly, the sample standard deviation of error and accuracy values across iterations ranges from 0.01 to 0.03, indicating stable model performance, enhancing the reliability of interpreting the models’ inner workings.

For interpretation, we use our fine-tuned deep learning models to predict each outcome on the entire sample of 1620 videos (leveraging complete data) for a single bootstrap iteration. This process is repeated 50 times (25 times) for every covariate-outcome pair in the Text and Audio models (Video Image Model), following the same bootstrapping logic to mitigate brittleness. We then interpret the results across all iterations using the two-step interpretation approach.

6.1 Interpretation Results for Text Model

We estimate Equation 1 (Step 1) and Equation 4 (Step 2) using Ridge Regression to capture heterogeneity in effects across brand names and emotional words (and present additional reasons in Online Appendix F.1). The ridge parameter is chosen from a wide array of values with the help of the validation sample, and is then applied to estimate Equation 1 over the full video sample.

Table 4 presents the analysis results for brand and emotion mentions, showing the percentage of total brand names and emotional words whose median coefficient value (across 50 bootstrap iterations) has a positive effect (+) on predicted attention weights (Equation 1) and a positive (+) and/or negative effect (−) on predicted outcome (Equation 4). When calculating this percentage, we ignore brand/emotional words whose value is less than 5% of the magnitude of the maximum predictive effect on the respective outcome in Equation 1 or 4. This 5% bar (with robustness discussed ahead) allows us to ignore non-important predictors whose coefficients have been shrunk toward 0 by the Ridge Regression model.
We highlight in grey the cells representing the dominant directional effect of brand/emotional words on predicted outcome. For these cells, we also show (in the row below) the average across all brand/emotional words of the average frequency (over 50 bootstrap iterations) with which a brand/emotional word (that meets the 5% bar) consistently has a positive effect on attention weight and maintains the dominant directional effect on predicted outcome. We highlight in green (orange) the cells where the effect on attention weight (Step 1) and predicted outcome (Step 2) is in the same direction (+/-) at least 80% of the time. Our choice of the 80% threshold (as compared to a less conservative 50% even chance threshold) lends more confidence that these results are less likely to be spurious. We validate this threshold in our simulations (Section 7.1). Conversely, we highlight in orange the cells where the effect is the same direction in only one of the steps (Step 1 or Step 2) at least 80% of the time, indicating spurious relationships.

Our findings indicate that most brand mentions in the beginning or middle of the video are often assigned high importance (Step 1) and often have a negative association with predicted loveability (deep engagement) (Step 2). A graphical visualization of these key results is shown in Online Appendix F.2.

### Table 4: Interpretation results of the Text model

|          | (Eq 1) Attention Weights (AW) (Step 1) | (Eq 4) Predicted Outcome (PO) (Step 2) | Sentiment of Engagement |
|----------|---------------------------------------|----------------------------------------|-------------------------|
|          |                                       |                                        | Brand names             |
|          |                                       |                                        | Loveability | Likeability |
|          |                                       |                                        | Deep       | Shallow     |
|          |                                       |                                        | Deep       | Shallow     |
| **Beginning** |                                        |                                        |                  |         |
|           | +                                    | +                                      | 21.6%       | 38.6%       | 8.3%       | 29.0%       |
|           | % of time AW+, PO+                    |                                        | 76%, 92%    | 77%, 90%    |
|           | +                                    | -                                      | 42.5%       | 29.4%       | 23.3%       | 19.5%       |
|           | % of time AW+, PO-                    |                                        | 85%, 93%    | 79.5%, 93%  |
| **Middle** |                                        |                                        |                  |         |
|           | +                                    | +                                      | 20.0%       | 26.4%       | 11.4%       | 22.1%       |
|           | % of time AW+, PO+                    |                                        | 77%, 86%    | 76%, 86%    |
|           | +                                    | -                                      | 36.4%       | 21.8%       | 20.3%       | 16.5%       |
|           | % of time AW+, PO-                    |                                        | 82%, 93%    | 78%, 95%    |
| **End**   |                                        |                                        |                  |         |
|           | +                                    | +                                      | 18.4%       | 33.3%       | 9.4%        | 20.3%       |
|           | % of time AW+, PO+                    |                                        | 76%, 86%    | 77%, 87%    |
|           | +                                    | -                                      | 40.2%       | 26.4%       | 20.5%       | 16.9%       |
|           | % of time AW+, PO-                    |                                        | 79%, 94%    | 79%, 94%    |

Sample Size: N = 114,536 tokens in beginning 30s, 107,411 tokens in middle 30s, 83,607 tokens in end 30s (Step 1); N = 1620 videos (Step 2).
Bar: 5% (% of max coefficient value used to ignore non-important predictors that have been shrunk towards 0 by Ridge Regression)
Highlighted grey cells: Dominant directional effect of brand/emotional words on predicted outcome.
Highlighted green (orange) cells: Average across all brand/emotional words of the average frequency with which a brand/emotional word has the same directional effect is at least 80% across 50 iterations in both (only one of) Step 1 and Step 2.
Robustness checks confirm that the associations highlighted in green hold true across a range of values of the bar used in Table 4 (details in Online Appendix F.2). This demonstrates how our findings are robust to brand mentions that have a small or a large negative association with loveability. Additionally, we find no robust association between use of brand names or emotional words and measures of commentability and thumbsability.

Our findings for brand mentions suggest that a decrease in entertainment value resulting from a discussion of commercial content in the beginning or middle may trigger deliberate System II thinking in more viewers, leading them to respond unfavorably or neutrally in their comments, thus decreasing loveability (Teixeira et al., 2010; Tellis et al., 2019). This aligns with previous research showing a decrease in the sharing of commercial content on YouTube (Tellis et al., 2019). This supports one of the competing hypotheses discussed earlier in Table 2. Notably, the negative association with loveability is dominated by brands in the electronics and digital categories, where related ads are typically more informative and less entertaining, as the products are generally more functional and less hedonic. This is consistent with the theoretical mechanism of reduced entertainment driving the observed effect. We find no strong evidence of a relationship between emotional words and sentiment of shallow or deep engagement.

Overall, we identify two robust relationships (green cells) at the intersection of Steps 1 and 2 that are less likely to be spurious and exclude 10 Type B spurious relationships (orange cells) from Step 2. The presence of Type B but not Type A spurious relationships above the 80% threshold aligns with the theoretical discussion on scaled dot-product attention in Section 3.3.2.

### 6.2 Interpretation Results for Audio Model

We estimate Equation 2 (Step 1) and Equation 4 (Step 2) using OLS for continuous outcomes and logistic regression for the binary outcome across the entire video sample (details in Online Appendix F.3). Table 5 presents the results, showing the median value of estimated coefficients, $\hat{\beta}$, across 50 bootstrap iterations. The coefficients indicate the percent change in the (non-log-transformed) outcome when a sound moment is present (Equation 2) or when sound duration increases by one moment (Equation 4).
The rows below each coefficient show the percentage of time (across 50 iterations) the corresponding p value is statistically significant. As before, we highlight in green (orange) the cells that are significant at least 80% of the time in both (only one of) Step 1 and Step 2 (and we validate the 80% threshold in Section 7.2).

| Eq (2) Attention Weights (Step 1) | Eq (4) Predicted Outcome (Step 2) |
|----------------------------------|-----------------------------------|
| Loveability                      | Commentability                    | Shallow Engagement              |
| Begin                            | Middle                           | End                              | Begin               | Middle | End                              | Begin               | Middle | End                              |
| Human $\hat{\beta}_1$            | -3.9%                            | 17.8%                           | -0.4%                           | 2.6% | 9.5%                            | 0%                  | 24.7% | 1.0%                            |
| $p \leq 0.05$                     | 49%                              | 55%                             | 58%                             | 60% | 86%                             | 50%                  | 56% | 82%                             |
| Music $\hat{\beta}_2$            | 248.3%                           | 78.8%                           | -0.6%                           | 13.9% | 4.7%                            | 0.0%                  | 0.0% | 15.9%                           | 0.1%              |
| $p \leq 0.05$                     | 96%                              | 63%                             | 52%                             | 92% | 54%                             | 74%                  | 82% | 60%                             | 80%               |
| H x M $\hat{\beta}_3$            | -54.4%                           | -46.0%                          | 3.9%                            | -5.3% | -7.1%                            | 0.0%                  | 0.0% | -5.8%                            | 0.0%              | -1.1% |
| $p \leq 0.05$                     | 90%                              | 65%                             | 64%                             | 78% | 82%                             | 62%                  | 68% | 60%                             | 72%               | 60% | 58%                             |
| Animal $\hat{\beta}_4$           | 354.3%                           | 1325.2%                         | 111.7%                          | 0.0% | 0.0%                            | 0.0%                  | 0.0% | 52.5%                            | 0.0% | 0.0% | 1.1%                             | 10.1%             |
| $p \leq 0.05$                     | 90%                              | 80%                             | 92%                             | 46% | 20%                             | 78%                  | 52% | 68%                             | 72% | 38% | 44%                             | 68%               |
| Human $\hat{\beta}_1$            | -2.5%                            | -6.5%                           | -4.6%                           | -0.2% | 0.1%                            | -0.4%                 | 0.2% | 0.3%                            | 0.3% | -0.1% | -0.1%                           | -0.4%             |
| $p \leq 0.05$                     | 29%                              | 69%                             | 46%                             | 38% | 48%                             | 82%                  | 78% | 90%                             | 74% | -40% | 52%                             | 90%               |
| Music $\hat{\beta}_2$            | 30.6%                            | 20.5%                           | 16.4%                           | -2.0% | -1.4%                            | -1.5%                 | -0.3% | 0.0%                            | -0.2% | -0.9% | -0.7%                           | -1.1%             |
| $p \leq 0.05$                     | 100%                             | 96%                             | 96%                             | 100% | 100%                            | 100%                  | 78% | 50%                             | 70%               | 100% | 100%                            | 100%              |
| H x M $\hat{\beta}_3$            | -18.0%                           | -7.6%                           | -15.1%                          | -0.4% | 0.2%                            | 0.7%                  | 0.1% | 0.1%                            | 0.0% | -0.1% | 0.1%                            | 0.4%              |
| $p \leq 0.05$                     | 82%                              | 61%                             | 64%                             | 52% | 52%                             | 82%                  | 58% | 54%                             | 24%               | 34% | 66%                             | 54%               |
| Animal $\hat{\beta}_4$           | 51.5%                            | 72.6%                           | 98.0%                           | -0.1% | 0.6%                            | 1.6%                  | 0.8% | 1.2%                            | 1.2% | -0.5% | 0.7%                            | 4.3%              |
| $p \leq 0.05$                     | 59%                              | 57%                             | 84%                             | 2%  | 38%                             | 82%                  | 90% | 96%                             | 76% | 20% | 74%                             | 94%               |

Sample Size: N = 97,200 moments in beginning 30s, middle 30s or end 30s (Step 1); N= 1620 videos (Step 2)
Highlighted green (orange) cells: p value is significant $\leq 0.05$ at least 80% of the time across 50 iterations in both (only one of) Step 1 and Step 2 and coefficient in Step 1 is positive (because negative attention weight indicates non-important coefficient).

Table 5: Interpretation results of the Audio Model

We summarize a few key results corresponding to the cells in green. As can be seen in Table 5, an increase in the duration of music (without simultaneous speech) by one moment (about half a second) within the beginning 30 seconds is associated with an increase in the odds ratio of loveability by 30.6% (Equation 4) but a 2.0% decrease in commentability (Equation 4). These associations are significant 100% of the time across our 50 iterations (Equation 4) and are supported by a significant increase in attention at least 90% of the time (Equation 2). These effects are particularly dominant in the beginning compared to the middle or end, as evidenced by more frequent significant positive effects on attention (>90%) in the beginning (Equation 2) when the feature is new and more salient. However, the association between music in the first 30 seconds and measures of shallow engagement is weaker or less frequently
significant, suggesting that music has a stronger association with deep engagement than shallow engagement.

The positive association between music duration and the sentiment of deep engagement aligns with our general expectation, as discussed in Table 2, where we highlighted the positive affective influence of music in advertising literature (Pelsmacker & Van den Bergh, 1999). Additionally, the reduction in commentability suggests a decrease in negative comments, which can contribute to the increase in loveability. Overall, the strong link between music at the beginning of the video and our measures of deep engagement suggests that music can strongly influence deliberate viewer reactions (System II thinking).

We also find no instance where the coefficient for the duration of human sounds is negative in Step 2 and significant more than 80% of the time in both steps. This suggests there is no strong association between rapid speech in any part of the video and our engagement measures, consistent with the expectation of linguists (Beck, 2015; Jennings, 2021). Note that a decrease in duration of human sounds can be interpreted as rapid speech because we control for the number of word-pieces in Equation 4. However, we do observe a positive association between slower speech (positive coefficient for duration of human sounds) in the middle 30 seconds and likeability, suggesting that the middle of the video maybe an important time to slow down.

In summary, we identify a subset of 5 robust relationships (green cells) at the intersection of Steps 1 and 2 that are less likely to be spurious. We exclude 18 spurious relationships (orange cells): 4 Type A relationships from Step 1 and 14 Type B relationships from Step 2. The presence of both Type A and Type B spurious relationships above the 80% threshold aligns with the theoretical discussion on additive attention in Section 3.3.1.

6.3 Interpretation Results for Video Image Model
We estimate Equation 3 (Step 1) and Equation 4 (Step 2) using OLS for continuous outcomes and logistic regression for the binary outcome on the entire video sample (details in Online Appendix F.3). The results are presented in Table 6, which shows the median value of estimated coefficients, $\hat{\beta}$, across 25 bootstrap
iterations. The coefficients reflect the percent change in the (non-log-transformed) outcome when size of an object increases by one percent on average across 30 video frames. The rows below each coefficient show the percentage of time (across 25 iterations) the corresponding p value is statistically significant. As before, we highlight in green (orange) the cells that are significant at least 80% of the time in both (only one of the) steps (and we validate the 80% threshold in Section 7.2).

![Table 6: Interpretation results of the Video Image Model](image)

We summarize a few key results corresponding to the cells in green. An increase in size of human images by 1% in the beginning, middle or end of a video is associated with a 0.4%, 0.2% or 0.4% increase in likeability (sentiment of shallow engagement), respectively, which aligns with our expectations in Table 2. These associations are significant at least 90% of the time across our 25 iterations (Equation 4) and are also supported by a significant increase in attention 100% of the time (Equation 3).

However, we do not find a corresponding positive association with the sentiment of deep engagement that is frequently significant across both Steps 1 and 2. This suggests that human images may trigger
automatic, intuitive reactions from viewers, leading to likes for the video. Furthermore, the association between size of faces and sentiment of shallow or deep engagement is not frequently significant, indicating that the image of the entire human is more important when controlling for face size. This is reasonable because the size of the whole person is likely correlated with the area of the screen where they are demonstrating something to the viewer using their hands.

We also find that a 1% increase in the size of packaged goods in the beginning 30 seconds is associated with a 0.7% decrease in likeability (sentiment of shallow engagement). These findings for human images and packaged goods are consistent with Hartmann et al. (2021) who found that consumer selfies (human images) receive more likes than brand selfies and packshots (packaged goods) on Instagram. The desire to socialize with other humans likely drives these effects (Hartmann et al., 2021; To & Patrick, 2021; Xiao & Ding, 2014). Notably, our results apply to sentiment of shallow engagement but not deep engagement, suggesting that the desire for social interaction manifests more readily in quick reactions.

We also find that a 1% increase in the size of animals at the beginning, middle or end of a video is associated with a 1.0%, 0.6% or 1.7% increase in likeability respectively. This is consistent with prior research in advertising where ads featuring animals have been found to be more likeable and have a low irritation score (Biel & Bridgwater, 1990; Pelsmacker & Van den Bergh, 1999). We do not find frequent significant associations between facial expressions of joy or surprise and our engagement measures, which aligns with results in related domains (Li & Xie, 2020; Zhou et al., 2021). It is important to note that inferences of emotion, whether made by humans or AI, based on facial expressions in images rely on common heuristics and may not reflect the true emotion being experienced (Barrett et al., 2019). This could be a key reason for not observing significant effects. We also do not find frequent significant associations for everyday objects such as clothes & accessories and home & kitchen items, so their coefficient values are not reported in Table 6.

Overall, we identify 14 robust relationships (green cells) at the intersection of Steps 1 and 2 that are less likely to be spurious and exclude 25 Type A spurious relationships (orange cells) from Step 1.
The presence of Type A but not Type B spurious relationships above the 80% threshold aligns with the theoretical discussion on gradient-based attention in Section 3.3.3.

### 6.4 Summarizing Insights

We examined the association between 9 features of interest across text, audio and images present in 3 parts of long-form videos (beginning, middle and end) and 4 engagement measures, resulting in 108 possible hypotheses (9 x 3 x 4). To address concerns about brittleness, we repeated model training over multiple bootstrap iterations and applied a two-step process with an 80% threshold (validated in Section 7) across iterations to filter out spurious relationships. We identified a subset of 21 robust relationships (green cells) between features of interest in text, audio and video images and distinct measures of engagement, and pruned 53 spurious associations (orange cells). This is summarized in Table 7. The remaining 34 associations (108 – 21 – 53) were not (frequently) significant in either Step 1 or 2, indicating null effects.

|          | Robust | Spurious | % Spurious |
|----------|--------|----------|------------|
|          | Begin  | Middle   | End | Total | Begin | Middle | End | Total |          |
| Text     | 1      | 1        | 2   | 10    | 3     | 3      | 4   | 10    | 83%      |
| Audio    | 3      | 1        | 1   | 5     | 3     | 6      | 9   | 18    | 78%      |
| Video Images | 6     | 4        | 4   | 14    | 8     | 10     | 7   | 25    | 64%      |
| Total    | 10     | 5        | 5   | 20    | 14    | 19     | 20  | 53    | 72%      |

*Table 7: Tabulation of robust and spurious associations*

These relationships were obtained while controlling for various features across unstructured and structured data sources. However, our approach does not guarantee causality of the 21 relationships because of potential endogeneity arising out of correlation with unobservables. Despite this limitation, our method substantially reduces the effort needed for future causal work (e.g., field experiments) by eliminating 72% of (frequently) significant associations that are spurious and shortlisting 28% of relationships with a likelihood of having external validity. Of the 21 relationships identified, 10 correspond to beginning 30 seconds of the video, 6 to the middle 30 seconds and 5 to the end 30 seconds. This reduction in identified relationships at the middle and end of the video as compared to the beginning,
suggests that features at a video’s onset are more salient and effective in prompting viewer engagement. This finding aligns with evidence that many viewers do not watch YouTube videos in their entirety (Bump, 2021). We summarize the results for the beginning 30 seconds, capturing the association of salient features at the onset of a video, in Table 8. The highlighted cells in grey are linked to theory (discussed earlier in Table 2). The direction of association between features and outcomes is indicated by a + or – sign.

| Unstructured Data | Features         | Deep Engagement Sentiment | Deep Engagement Engagement Level | Shallow Engagement Sentiment | Shallow Engagement Engagement Level | Expected change in sentiment before interpreting model (Table 2) |
|-------------------|------------------|---------------------------|---------------------------------|------------------------------|-----------------------------------|---------------------------------------------------------------|
| Text: Captions/ Transcript | Brand names        | –                          |                                  | –                             | –                                 | Ambiguous                                                   |
| Audio             | Music             | +                          | –                               | –                             | –                                 | Positive                                                      |
| Video Images      | Human             | +                          |                                  | +                             | +                                 | Positive                                                      |
|                   | Animal            | +                          |                                  | +                             | +                                 | Positive                                                      |
|                   | Packaged goods    | –                          |                                  | –                             | –                                 | Negative                                                      |

Table 8: Summary of key interpretation results for the beginning 30 seconds

We clarify the previously ambiguous relationship between brand mentions and sentiment (discussed earlier in Table 2), finding a negative association with deep engagement sentiment for YouTube influencers. Importantly, our key results show distinct associations with shallow versus deep engagement, a difference not pinpointed in prior research. For the beginning 30 seconds, our *text and audio* features are linked to *deep engagement* sentiment, while our *video image* features are linked to *shallow engagement* sentiment. Our models also allow us to visualize the level of salience attributed to these features in text, audio and video images, providing a valuable tool for agencies and influencers to identify potential areas for improvement (details in Online Appendix G).

7. **Validation**

We validate our ex-post interpretation approach through three systematic analyses. First, simulations show that our method accurately recovers the true data-generating process while eliminating spurious relationships using an 80% threshold in both Step 1 and Step 2. Second, we apply benchmark feature selection methods, such as LASSO and Elastic Net, to the simulated data and demonstrate that our approach yields better results. Finally, we re-estimate Equation 4 on a random 80% sample of the 1,620
videos and find that all key findings from Table 8 remain consistent, with similar effect sizes and significance, confirming that our results are robust and that our transfer learning methods are effective with moderate-sized samples.

For the simulations, we create outcomes that vary based on specific features in text, audio or video images, followed by model training and ex-post interpretation using our approach. We then compare this with benchmark methods, testing whether LASSO and Elastic Net (0.5L1,0.5L2) can identify the data generating process without the need for a two-step process. Bootstrap iterations are conducted 50 times for the Text and Audio models and 25 times for the Video Image model across all approaches.

7.1 Text Model – Simulation and Benchmarks

To simulate the outcome for the Text Model, we pick a covariate-outcome pair, say “brand mentions in beginning 30 seconds of captions/transcript – likeability”. We then generate a random normal distribution of log-likeability such that the mean and standard deviation across the observations where a brand name is present is twice the mean and half the standard deviation of the observations where a brand name is absent (details in Online Appendix H). The ex-post interpretation results are shown in Table 9 (analogous to Table 4).

We find that 66.7% of brand names meeting the 5% bar (same as that in Table 4) are more often associated with an increase in predicted likeability, while only 0.7% of brand names show a decrease. Furthermore, (the average across all brands of) the average frequency with which a brand name (that meets the 5% bar) is associated with an increase in attention weights (Step 1) and predicted outcome (Step 2) is 91% and 97% respectively, both exceeding our 80% threshold. These results are robust to changes in the value of the bar (details in Online Appendix H). Thus, our interpretation approach using text data is able to recover the true data generating process for brand mentions. For emotion mentions, 25.6% are more often associated with an increase in predicted likeability, while 21.5% show a decrease. However, the average frequency of an increase in attention weights and predicted outcome is 78% and 90% respectively, with the former falling below the 80% threshold. Thus, our two-step approach
effectively eliminates the Type B spurious association between emotional words and predicted likeability when using an 80% threshold.

Benchmark methods, LASSO and Elastic Net, also show that brand names are more often associated with an increase (16.3% brands in LASSO, 19.6% brands in Elastic Net) than a decrease in predicted likeability (0.7% brands in both). However, both methods also associate emotional words with an increase in predicted likeability (5.7% emotional words in LASSO and 8% emotional words in Elastic Net) more than a decrease (1.8% emotional words in LASSO and 2% emotional words in Elastic Net). The average across all brand/emotion words of the average frequency (over 50 bootstrap iterations) with which selected emotional words have a positive effect on predicted outcome is higher (69% in LASSO and 70% in Elastic Net) than for selected brand names (67% in LASSO and 69% in Elastic Net), which does not align with the true data generating process (since brand names and not emotional words affect the simulated outcome). This indicates that benchmark methods are not as reliable in eliminating spurious associations with emotional words.

| Text Outcome: Likeability | Brand names | Emotional words |
|---------------------------|-------------|-----------------|
| Step 1 AW+, Step 2 PO+    | 66.7%       | 25.6%           |
| % of time AW+, PO+        | 91%, 97%    | 78%, 90%        |
| Step 1 AW+, Step 2 PO-    | 0.7%        | 21.5%           |
| PO+                       | 16.3%       | 5.7%            |
| % of time PO+             | 67%         | 69%             |
| PO-                       | 0.7%        | 1.8%            |
| PO+                       | 19.6%       | 8.0%            |
| % of time PO+             | 69%         | 70%             |
| PO-                       | 0.7%        | 2.0%            |

Table 9: Simulation and Benchmarks – Text model

7.2 Audio and Video Image Model – Simulation and Benchmarks

To simulate the outcome for the Audio model, we pick a covariate-outcome pair, say “music duration in beginning 30 sec – commentability.” We then generate a random normal distribution of log-commentability whose value decreases by 0.5 for a unit increase in music duration (details in Online
Appendix H). The ex-post interpretation results, shown in Table 10 (analogous to Tables 5 & 6), include median values of estimated coefficients across 50 bootstrap iterations.

The median estimated coefficient for music duration in Step 2 is $-0.47$, close to the true value of $-0.5$, and is significant in $100\%$ of iterations for Step 2 and $92\%$ for Step 1. We also eliminate a Type B spurious association with animal sounds, frequently significant in Step 2 but not Step 1. This demonstrates that our interpretation approach using audio data can recover the true data generating process and remove spurious associations using an $80\%$ threshold.

| Feature                  | Audio Outcome: Comment-ability | Video Image Outcome: Likeability |
|--------------------------|--------------------------------|----------------------------------|
| Human                    | +, 100%                         | +, 100%                          |
| Music                    | -, 92%                          | -, 84%                           |
| Human x Music            | -, 74%                          | -, 84%                           |
| Animal                   | -, 72%                          | -, 72%                           |
| Brand Logo               | -                              |                                 |
| Packaged Goods           | +, 100%                         | +, 100%                          |
| Clothes & Acc            | +, 100%                         | +, 100%                          |
| Home & Kitchen           | +, 100%                         | +, 100%                          |
| Other Objects            | +, 100%                         | +, 100%                          |
| Joy                      | -, 4%                           | -, 4%                            |
| Surprise                 | -                               | -                                |
| Joy x Face               | -                               | -                                |
| Surprise x Face          | +, 100%                         | +, 100%                          |

| Two-Step Approach | LASSO | Elastic Net (0.5L1, 0.5L2) |
|-------------------|-------|---------------------------|
| Step 1 Sign of coefficient, % of time $p<0.05$ | Coefficient | Coefficient |
| Step 2 Coefficient, % of time $p<0.05$ | Coefficient | Coefficient |

Highlighted feature name in grey: True data generating process;
Highlighted green (orange) cells: $p$ value is significant $\leq 0.05$ at least $80\%$ of the time across all bootstrap iterations in both (only one of) Step 1 and Step 2 and coefficient in Step 1 (for Audio Model) is positive (because negative attention weight indicates non-important coefficient).

Table 10: Simulation and Benchmarks – Audio and Video Image model

For the Video Image model, we simulate the outcome using “size of human images in beginning 30 sec – likeability.” We then generate a random normal distribution of log-likeability whose value increases by $0.25$ units for a unit increase in the mean size of human images across the first 30 frames of a video (details in Online Appendix H). The results, shown in Table 10, indicate that the median estimated coefficient for size of human images in Step 2 is $0.13$, close to the true value of $0.25$, and significant in $100\%$ of the iterations for both Steps 1 and 2. Our estimation process also shortlists two
spurious associations related to the size of animals and the size of clothes & accessories (highlighted green). However, we are able to remove seven Type A spurious associations that are frequently significant in Step 1 but not in Step 2 (highlighted orange). Thus, our interpretation approach using image data recovers the true data generating process while eliminating many spurious associations using an 80% threshold.

Table 10 also presents median estimated coefficients obtained from LASSO and Elastic Net for the Audio and Video Image models. LASSO recovers the true feature in the Audio model, but with a highly biased coefficient (-198.82), and fails to recover the true feature in the Video Image model. Elastic Net performs better, recovering the true features in both models with reduced bias, but the coefficient values are not closer to the ground truth as compared to those obtained from our two-step approach. Elastic Net also selects additional spurious features—one in the Audio model and six in the Video Image model—whereas our two-step approach selects no spurious features in the Audio model and only two in the Video Image model. Overall, our two-step approach is more effective in selecting the true feature (with smaller bias) and fewer spurious associations compared to benchmark methods.

8. Conclusion

This paper advances the limited body of work explaining the “black-box” nature of deep learning models that predict business outcomes. While deep learning models leveraging unstructured data excel in out-of-sample predictions, they often struggle with interpretability, particularly in business settings where human validation is difficult because true drivers of business outcomes are not well understood. We address this challenge by developing an “interpretable deep learning framework” that not only predicts effectively but also helps interpret the captured relationships.

Our interpretation approach is inspired by the bottom-up (visual) attention capture and transfer framework from print advertising literature. A crucial aspect of our approach is the necessary condition that model attention must be attributed to a feature for it to affect the predicted outcome. This insight allows us to eliminate spurious associations through a two-step process: first, by removing spurious
relationships where attention is attributed to features not correlated with the predicted outcome, and second, by eliminating spurious relationships with the predicted outcome without the necessary attention attributed to the feature. We are thus left with a subset of relationships that can be causal. Thus, our approach reduces the effort required for future causal work by pruning definite spurious associations. Our approach is applicable across three common attention mechanisms in deep learning—additive attention, scaled dot-product attention and gradient based attention—and can be used to examine any local feature within text, audio or video image data. This makes our approach extremely versatile and applicable across various types of videos including advertising, education and politics. We validate our approach using simulations and demonstrate its superiority over benchmark feature selection methods.

We apply our framework to unstructured data from long-form YouTube influencer videos, a growing but understudied area in influencer marketing. Our study develops measures of shallow engagement (System I) and deep engagement (System II), inspired by Kahneman’s framework of intuitive and deliberate thinking. Our results show that brand mentions and music in the beginning of a video are associated with deep engagement sentiment (in comments) but not with shallow engagement sentiment (like/dislike ratio). Conversely, human faces, packaged goods and animals in video images in the beginning are linked to shallow engagement sentiment but not deep engagement sentiment. These findings can help influencers design video features and agencies can test for improvements in deep engagement sentiment which has been linked with sales in prior research on brand-managed social media communities. In summary, our study extends the understanding of how influencer videos on YouTube relate to the dual-system framework of human thinking.

This work has some limitations. First, our sample includes only top-performing influencers (on at least one popular platform) who use brand endorsements, so findings may not generalize to other influencers. Second, while YouTube is a major platform for long-form videos, our findings may not apply to other platforms where long-form videos are not as common or newer formats like YouTube Shorts. Third, while we use individual models designed for each modality of data, with information combined in
the second step of our interpretation approach, future research leveraging richer computational resources can explore the role of attention mechanisms in multi-modal models. Fourth, while our two-step process eliminates many spurious relationships, it does not guarantee causality of all the identified relationships. However, by narrowing down to 21 “feature - video part - outcome” triads of interest (from all 108 possibilities), it substantially reduces the effort needed to test hypotheses in future causal research such as field experiments.

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Online Appendix A – Operationalization of Text Model

We provide an overview of the implementation of our Text Model – the BERT Framework (Devlin et al., 2018) and explain the architecture of the encoders and attention mechanism (used in the BERT framework).

A.1 BERT Framework

The BERT model converts a sentence into word-piece tokens¹ as done by state-of-the-art machine translation models (Wu et al., 2016). Furthermore, the beginning of each sentence is appended by the ‘CLS’ (classification) token and the end of each sentence is appended by the ‘SEP’ (separation token). For example, the sentence ‘Good Morning! I am a YouTuber.’ will be converted into the (word-pieces or) tokens ['[CLS]', 'good', 'morning', '!', 'i', 'am', 'a', 'youtube', '##r', '.', '[SEP]']. A 768-dimensional initial embedding learnt for each token during the pre-training phase is passed as input to the model, and is represented by the vector $x_m$ in Figure A1, where m is the number of tokens in the longest sentence. This vector $x_m$ has pre-learned contextual embeddings that will aid the model in capturing relationships with our four outcome variables.

The token embedding is combined with a positional encoder $t_m$ that codes the position of the token in the sentence using sine and cosine functions (see Devlin et al. (2018) for details). This is passed through a set of 12 encoders arranged sequentially. The output of the ‘CLS’ token is passed through the feed forward 1 layer that is initialized with pre-trained weights from the next sentence prediction task, and has a $tanh$ activation function. We follow this up with an output layer that connects with either of our three continuous outcomes or binary outcome. We then fine-tune the entire model with all hierarchical layers over our data sample.

¹ We use the BERT-base-uncased model (that converts all words to lower case and removes accent markers) as compared to the cased model, because the uncased model is known to typically perform better unless the goal is to study case specific contexts such as 'named entity recognition' and 'part-of-speech tagging.'
The Encoders contain the self-attention heads (explained further ahead) which help the model capture the relative importance between word-pieces while forming an association with the outcome of interest. By virtue of being pre-trained to capture contextual usage of words, the model is able to make better decisions on assigning relative attention (importance) weights to different word-pieces (tokens) in our sample. Word-pieces that receive more attention play a more important role (in either a positive or negative direction) in predicting the outcome of interest. We analyze these attention weights during ex-post interpretation.

A.2 BERT Encoders

BERT Encoders comprise a set of 12 sequentially arranged identical encoders, and we illustrate the architecture of one encoder in Figure A2.²

We use an example with a sentence that has only two tokens, and this can be extended to any example that has a maximum of 512 tokens, which is the maximum limit of the pre-trained BERT model. The combined vector of the initial token embedding \((x_1, x_2)\) and positional encoding \((t_1, t_2)\) results in the vectors \((x'_1, x'_2)\) that are passed through self-attention heads which incorporate information of other

² Our figures are inspired by the work of Jay Alammar (see Alammar (2018) for more details).
relevant tokens into the focal tokens. The architecture of the self-attention head is explained further ahead. The outputs of the self-attention head \((z_1, z_2)\) are then added with the original input \((x_1', x_2')\) using a residual connection (shown with a curved arrow) and normalized (using mean and variance). The outputs \((z_1', z_2')\) are passed through identical feed forward networks that have a GELU (Gaussian Error Linear Unit) activation function, i.e. \(gelu(x) = 0.5x \left(1 + \text{erf} \left(\frac{x}{\sqrt{2}}\right)\right)\). The gelu activation combines the advantages of the ReLU (Rectified Linear Unit) non-linearity (i.e., \(relu(x) = \max(0, x)\)) with dropout regularization. The outputs of the feed forward network are added with the inputs \((z_1', z_2')\) using a residual connection and normalized again before being fed to the next encoder in sequence. In addition, each sub-layer is first followed by a dropout probability of 0.1 before being added and normalized.

![Figure A2: Encoders](image)

### A.3 BERT Attention Mechanism: Scaled Dot-Product Attention

Next, we explain the scaled dot-product attention mechanism within the self-attention heads illustrated in Figure A3. There are 12 self-attention heads that capture the contextual information of each token in relation to all other tokens used in the text. In other words, the self-attention heads allow the model to identify and weigh all other tokens in the text that are important when learning the vector representation.
of the focal token. We use them to measure the importance (strength) of association between the tokens in the text and the outcome of interest.

The inputs \((x'_1, x'_2)\) are concatenated and multiplied with three weight matrices, \(W^q, W^k\) and \(W^v\) (that are fine-tuned during model training) to get three vectors – \(Q\) (Query), \(K\) (Key) and \(V\) (Value). These three vectors are combined by taking a dot product using an attention function \((A)\):

\[
A(Q, K, V) = z''_0 = \text{softmax} \left(\frac{Q^T K}{\sqrt{d_k}}\right) V
\]

where, \(d_k\), the dimension of the Key vector, is 64 and is equal to the dimensions of the other two vectors \(d_q\) and \(d_v\); and \(\text{softmax}(x) = \frac{e^{x_i}}{\sum_{i=1}^{m} e^{x_i}}\). The scaling (division) by \(\sqrt{d_k}\) is performed to ensure stable gradients. The computation of \(z''_0\) is for one attention head, and this is carried out in parallel for 11 additional attention heads to give us 12 vectors, \(z''_0 \ldots z''_{12}\), which are concatenated to produce \(z''\). This is multiplied with a weight vector \(W^o\) (which is fine-tuned during model training) to produce output \((z_1, z_2)\). The use of 11 additional attention heads allows the model to capture more complex contextual information.

*Figure A3: Self-Attention Heads*
In order to capture the estimated attention weights, we average the output across all the attention heads in the last encoder of the BERT model, which results in an attention vector of dimension \( <n, k, k> \) where \( n \) is the number of videos used in the analysis, and \( <k,k> \) corresponds to \( k \) weights for \( k \) tokens, where \( k \) equals the maximum number of tokens (word-pieces) for a covariate type – title, description (first 160 characters) or captions/transcript (beginning, middle or end). As mentioned earlier, the first token for each example is the ‘CLS’ or classification token. We are interested in the attention weights corresponding to this token because the output from this token goes to the output layer (as shown earlier in Figure A1). Thus, we get at an attention weight vector of dimension \( <n, k> \), where each observation has \( k \) weights corresponding to the ‘CLS’ token. We exclude ‘CLS’, ‘SEP’ and any token used for padding short sentences, during ex-post interpretation.
Online Appendix B – Operationalization of Audio Model

We provide an overview of the implementation of our Audio Model – YAMNet +Bi-LSTM+ Attention Mechanism, and explain the architecture of MobileNet v1 and Bi-LSTM with attention mechanism.

B.1 YAMNet +Bi-LSTM+ Additive Attention Mechanism

We analyze audio data using the pre-trained YAMNet model (Pilakal & Ellis, 2020), and customize it with an additional Bidirectional LSTM (Bi-LSTM) layer and an attention mechanism as shown in the framework in Figure B1.

![Figure B1: Audio Model Framework](image)

Each audio signal is a 30 second clip, which we resample at 16,000 Hz and mono sound (for consistency), and this results in 480,000 data points for each clip. Note that for a few influencer videos that are shorter than 30 seconds, we append it with moments of silence to make the audio length consistent across our sample. To summarize the large number of data points, the YAMNet model first generates a Mel spectrogram that spans the frequency range of 125 to 7500Hz (note that the 2000-5000 Hz range is most sensitive to human hearing (Widex, 2016)) over which the YAMNet model has been pre-trained. The spectrogram uses the pre-trained Short-Term Fourier Transform window length of 25ms with a hop size of 10ms that results in a 2998 x 64 (time steps x frequency) vector corresponding to 30 seconds of each audio clip. This corresponds to 64 equally spaced Mel bins on the log scale, such that sounds of equal distance on the scale also sound equally spaced to the human ear. The model then passes each segment of 960ms from the spectrogram output, i.e., 96 frames of 10ms each with overlapping patches (to avoid losing information at the edges of each patch) as input to the MobileNet v1 architecture.
The size of the overlap or hop size is 490ms, which results in a total of 60 moments for each 30 second audio clip.

The MobileNet v1 processes the spectrogram through multiple mobile convolutions and returns audio class predictions for each of the 60 moments in the clip. This comprise a total of 521 different audio classes such as speech, music, animal, etc. (corresponding to each 960 ms segment) over which the model has been pre-trained. Pilakal and Ellis (2020) remove 6 audio classes (viz. gendered versions of speech and singing; battle cry; and funny music) from the original set of 527 audio classes to avoid potentially offensive mislabeling.

We then pass the <521x60 > dimensional vector as input to the Bi-Directional LSTM layer with an attention mechanism. We make this layer bidirectional to allow it to capture the interdependence between sequential audio moments from both directions. For example, the interdependence between the sound of a musical instrument at 5 seconds and the beginning of human speech at 15 seconds can be captured by the model bidirectionally. We adapt the attention mechanism used for neural machine translation by Bahdanau et al. (2014) (explained further ahead) to help the Bi-LSTM layer capture the relative importance between sound moments in order to form an association with an outcome. These measures of relative importance (attention) can be understood similarly as the attention weights in the Text model, and are analyzed during ex-post interpretation. We pass the output of the Bi-LSTM (with attention mechanism) through an output layer which connects with either of our three continuous outcomes or binary outcome. We then fine-tune the Bi-LSTM with attention mechanism over our data sample.

B.2 MobileNet v1 architecture

The MobileNet v1 architecture is illustrated in detail in Table B1 (Howard et al., 2017). Each row describes Stage $i$ with input dimension $[H_i, W_i]$ (resolution), output channels $C_i$ and $L_i$ layers (depth). Stage 1 has a regular convolution operation, whereas Stage 2 to 10 have the Mobile Convolution which is the main building block of the architecture. It is represented as “MConv, $k \times k$, $s$” where $k \times k = 3 \times 3$ is the size of the kernel and $s = \{1,2\}$ is the stride. MConv divides the regular convolution operation into
two steps – depth wise separable convolutions and point wise convolution, thus increasing the speed of computation (see Howard et al. (2017) for details). Stage 11 has a Global Average Pooling Layer that averages the inputs along its height and width and passes its output to Stage 12 which is a Dense output layer with 521 logistic functions that give the per class probability score corresponding to the 960 ms input segment. As mentioned earlier, we use a hop size of 490 ms so that we get an even number of 60 time step predictions corresponding to the 30 seconds of input. The resulting output vector has a dimension of 521x60 (audio classes x time steps) for each 30 second clip.

| Stage $i$ | Operator $\mathcal{F}_i$ | Input Resolution $(\tilde{H}_i \times \tilde{W}_i)$ | Output Channels $\tilde{C}_i$ | Depth $\tilde{L}_i$ (Layers) | Pre-trained Weights |
|-----------|-----------------|-----------------|-----------------|-----------------|---------------------|
| 1         | Conv, k3x3, s2  | 96 x 64         | 32              | 1               |                     |
| 2         | MConv, k3x3, s1 | 48 x 32         | 64              | 1               |                     |
| 3         | MConv, k3x3, s2 | 48 x 32         | 64              | 1               |                     |
| 4         | MConv, k3x3, s1 | 24 x 16         | 128             | 1               |                     |
| 5         | MConv, k3x3, s2 | 24 x 16         | 128             | 1               |                     |
| 6         | MConv, k3x3, s1 | 12 x 8          | 256             | 1               |                     |
| 7         | MConv, k3x3, s2 | 12 x 8          | 256             | 1               |                     |
| 8         | MConv, k3x3, s1 | 6 x 4           | 512             | 5               |                     |
| 9         | MConv, k3x3, s2 | 6 x 4           | 512             | 1               |                     |
| 10        | MConv, k3x3, s2 | 3 x 2           | 1024            | 1               |                     |
| 11        | Global Average Pooling | 3 x 2 | 1024            | 1               |                     |
| 12        | Dense           | 1 x 1           | 521             | 1               |                     |

*Table B1: MobileNet-v1 architecture*

**B.3 Bi-LSTM with Additive Attention**

The output from MobileNet v1 is passed as input to the Bi-LSTM with (additive) attention mechanism, shown in Figure B2.

We use two layers of LSTM cells – the first layer is a 32-unit Bidirectional LSTM layer and the second layer is a 64-unit (unidirectional) LSTM layer. They are separated by an additive attention mechanism as shown in the figure. Each audio segment $x_m <521,1>$, where $m$ is the total number of moments (time steps), is passed as input to each cell of the Bidirectional LSTM layer. This layer is made bidirectional to allow it to capture the interdependence between sequential audio segments from both
directions. The sequential nature of LSTM cells in a layer allow the model to capture dependencies between audio segments that are separated from each other (see the LSTM paper by Gers et al. (1999) for more details). We adopt the additive attention mechanism used for neural machine translation by Bahdanau et al. (2014) to help the Bi-LSTM model focus on more important parts of the input. The mechanism weighs the output activations \(a^{<t>} = [\tilde{a}^{<t>}, \tilde{a}^{<t>}], t = 1 \text{ to } m\) from each cell of the pre-attention Bi-LSTM layer before passing the contextual output, \(c^{<t>}\), to the post-attention LSTM layer above it. In addition, each cell of the attention mechanism takes as input the output activation \(s(t - 1)\) from each preceding cell of the post-attention LSTM layer which allows it to factor in the cumulative information learnt by the model till that time step (see Bahdanau et al. (2014) for more details on the attention mechanism). The output of the last cell in the post-attention LSTM layer is passed to an output layer which has a linear activation function for the three continuous outcomes and a sigmoid activation function for the binary outcome. The context vector \(c^{<m>}\) from the last cell of the attention mechanism allows measurement of the relative weights placed by the model along the time dimension of the input in order to form an association with the outcome of interest. Audio moments that have higher weight are more important while forming an association between the audio clip and the outcome.

*Figure B2: Bi-LSTM with Additive Attention*
Online Appendix C – Operationalization of Video Image Model

We provide an overview of the implementation of our Video Image Model – VGG-16 +Bi-LSTM. We then explain the architecture of VGG-16, the architecture to combine information from all video frames, and our approach to find gradient-based attention (saliency).

C.1 VGG-16 + Bi-LSTM

We use a combination of VGG-16 and Bi-LSTM to analyze video frames and illustrate its framework in Figure C1. We pass each image frame $i = 1$ to $m$, where $m$ has a value of 30 frames, through a VGG-16 architecture. Note that for a few influencer videos that are shorter than 30 seconds, we append it with black frames to make the video image length consistent across our sample. Our sampling rate of one frame per second (30 frames in 30 seconds) in conjunction with the size of our data sample (1620 videos) ensures that our model is feasible to analyze.

![Figure C1: Framework to analyze Video Frames](image)

In the last step, we combine the outputs from each VGG-16 model. Our combination architecture comprises the Bi-LSTM, known to be one of the best performing architectures at capturing sequential information from video frames (c.f. Yue-Hei Ng et al. (2015)). The output of the combination architecture is passed through an output layer which connects with either of our three continuous outcomes or binary outcome.
C.2 VGG-16 Architecture

VGG-16 has 16 layers whose parameters can be learned (Simonyan & Zisserman, 2014). The architecture of VGG-16, customized to our input dimension of 135 x 240 x 3 (where 3 corresponds to pixel intensities for Red, Green and Blue channels), is shown in Table C1. Each row describes Stage $i$ with input dimension $[\tilde{H}_i, \tilde{W}_i]$ (resolution), output channels $\hat{C}_i$ and $\hat{L}_i$ layers (depth).

| Stage $i$ | Operator $\hat{F}_i$ | Input Resolution $(\tilde{H}_i \times \tilde{W}_i)$ | Output Channels $\hat{C}_i$ | Depth $\hat{L}_i$ (Layers) | Pre-trained ImageNet weights |
|-----------|----------------------|-----------------------------------------------|----------------------------|-----------------------------|-----------------------------|
| 1         | Conv, k3x3, s1       | 135 x 240                                    | 64                         | 2                           | Yes                         |
| 2         | Max Pooling, k2x2, s2| 135 x 240                                    | 64                         | 1                           |                             |
| 3         | Conv, k3x3, s1       | 67 x 120                                     | 128                        | 2                           |                             |
| 4         | Max Pooling, k2x2, s2| 67 x 120                                     | 128                        | 1                           |                             |
| 5         | Conv, k3x3, s1       | 33 x 60                                      | 256                        | 3                           |                             |
| 6         | Max Pooling, k2x2, s2| 33 x 60                                      | 256                        | 1                           |                             |
| 7         | Conv, k3x3, s1       | 16 x 30                                      | 512                        | 3                           |                             |
| 8         | Max Pooling, k2x2, s2| 16 x 30                                      | 512                        | 1                           |                             |
| 9         | Conv, k3x3, s1       | 8 x 15                                       | 512                        | 3                           |                             |
| 10        | Max Pooling, k2x2, s2| 8 x 15                                       | 512                        | 1                           |                             |
| 11        | Global Average Pooling| 4 x 7                                   | 512                        | 1                           | No                          |
| 12        | Dense                | 1 x 1                                        | 1                          | 1                           |                             |

Table C1: VGG-16 architecture

Stages 1, 3, 5, 7 and 9 have convolution operations, whereas Stages 2, 4, 6, 8 and 10 have the max pooling operation, where $k \times k = 3 \times 3$ is the size of the kernel and $s = \{1,2\}$ is the stride. Stage 11 has a Global Average Pooling Layer that averages the inputs along its height and width and passes its output to Stage 12 which is a Dense layer.

C.3 Combination Architecture

To analyze video frames ($i = 1$ to $m$, where $m$ has a maximum value of 30) we use the Bi-LSTM architecture that captures sequential information across different video frames. This is illustrated in Figure C2. Each VGG-16 architecture takes a unique video frame as input and provides the output from Stage 10 to the Global Average Pooling (GAP) Layer. This is followed by Dense Middle Layers (that use ReLU activation for continuous outcomes and sigmoid activation for the binary outcome), which is followed by a single Bi-LSTM layer with 256 memory cells, and finally a Dense output layer (that uses linear
activation for continuous outcomes and softmax activation for the binary outcome). We use the pre-trained ImageNet weights (Krizhevsky et al., 2012) from Stage 1 to 10 in each VGG-16 architecture and then we finetune the weights of the top layers.

C.4 Gradient-based attention (saliency)

As our VGG-16 model uses pretrained weights from the ImageNet classification task, the lower layers of the model are well trained to detect basic attributes of objects in images. This helps the model differentiate between various objects in the images of our video sample during the process of finetuning. After the end of model training, we ex-post identify the salient parts of images that are associated with an outcome through gradient-based activation maps (cf. Selvaraju et al., 2017). We find gradients by taking the derivative between the predicted continuous outcome (or class of predicted binary outcome) and the output of the activation layer after the last convolution layer in each VGG-16 architecture that processes one video frame. However, unlike Selvaraju et al. (2017), we do not apply the ReLU (Rectified Linear Unit) activation on the gradient values as we would like to retain negative gradient values for interpretation. Hence our approach is a modified gradient-based activation map that is suitable for our setting. Areas of the image with positive (negative) gradients correspond to regions that are positively (negatively) associated with continuous outcomes and the predicted class of loveability.

Figure C2: Bi-LSTM
Online Appendix D – Feature Generation of Theory-based Features

We generate theory-based features with the help of trusted databases, reliable transfer learned models and accurate APIs, which is more efficient compared to employing human coders.

For text data, we focus on the following features: presence of brand names and emotional words in captions/transcript in 30 seconds of the beginning, middle and end of a video. We identify these features by applying regular expressions on textual data while relying on a master list of words. The master list of brand names comprise the Top 100 Global brands in 2019 that were obtained from BrandZ, Fortune100 and Interbrand. We then add more than 32,000 brands (with US offices) from the Winmo database to this list. This is further combined with brand names identified by applying Google’s Vision API – Brand Logo Detection on video frames (one fps in 30 seconds of beginning, middle and end) in our sample. From this combined list, we remove more than 800 generic brand names such as ‘Slice,’ ‘Basic,’ ‘Promise,’ etc. that are likely to be used in non-brand related contexts. The master list of emotional words is obtained from the list of 2,469 emotional words identified in the LIWC dictionary (Berger & Milkman, 2012; Pennebaker et al., 2015). We identify brand and emotion mentions within 305,554 word-pieces (that are generated by the BERT model) in captions/transcript across all parts (beginning, middle and end) of the 1620 videos in our sample. We find that 28% (80%) of videos have a brand (emotion) mentioned at least once (in any part of the video).

For audio data, we mainly focus on the following features: music and human speech in 30 seconds of the beginning, middle and end of a video. The YAMNet model (Mel Spectrogram + MobileNet v1) finds the predicted probability of each moment\(^3\) of a 30 second audio clip (which has 60 moments) belonging to a sound class. Our model can efficiently accomplish this identification for 291,600 moments (1620 videos x 3 parts x 60 moments in a part). We combine the identified sound classes into different categories based on the AudioSet ontology (Gemmeke et al., 2017) – Human (86%), Music (83%), Animal (17%), and Others which include sounds of silence, things, ambiguous sounds,

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\(^3\) Each moment is 960ms long, and the subsequent moment begins after a hop of 490ms. Hence, each 30 second audio clip encompasses 60 moments (details in Web Appendix B).
background sounds and natural sounds. The percentage in brackets indicates the percentage of videos that contain a sound of that category (with probability > 0.5) in any part of the video. Note that a moment of sound can be classified into multiple categories if sounds from more than one category occur together.

For image data, we focus on the following features: size of humans, size of face of humans, size of packaged goods, size of animals, and human facial expressions of joy and surprise. In addition, we also study the role of brand logos, and control for the size of everyday objects such as clothes & accessories and home & kitchen items. We study these features in 30 frames that lie in 30 seconds of the beginning, middle and end of a video. We identify these features using the Cloud Vision API from Google, that has been pre-trained on millions of images and whose high accuracy has been validated in prior academic and industry research (FileStack, 2019; Li & Xie, 2020; Szegedy et al., 2016). We can efficiently implement this API over 145,800 frames (1620 video x 3 parts of video x 30 frames per part). The API returns the vertices of the identified object which allows us to create a rectangular bounding box to define its area. We divide the identified objects into eight different categories – Humans (91%), Faces (86%), Animals (27%), Brand Logos (16%), Packaged Goods (28%), Clothes & Accessories (86%), Home & Kitchen (58%), and Other Objects. The percentage in brackets indicate the percentage of videos that contain an object of that category (in any part of the video). The API also returns the level of surprise or joy in each face that was detected: {-2: very unlikely, -1: unlikely, 0: possible, 1: likely, 2: very likely}
Online Appendix E – Prediction Results

We summarize the prediction errors from our models for each engagement measure using each component of unstructured data from different video parts (in Table E1). For instance, captions/transcript in the beginning 30s predict commentability within a RMSE of $\pm e^{0.92} = \pm 2.5$ ($\text{#comments} + 1)/(\text{#views})$.

| Model                        | Unstructured data            | Deep Engagement | Shallow Engagement |
|------------------------------|------------------------------|-----------------|--------------------|
| Text Model (BERT)            | Captions/transcript (begin 30s) | 0.71 (0.03)     | 0.92 (0.02)       | 0.98 (0.02)       | 0.75 (0.02)       |
|                              | Captions/transcript (middle 30s) | 0.69 (0.02)     | 0.98 (0.02)       | 1.03 (0.02)       | 0.79 (0.02)       |
|                              | Captions/transcript (end 30s)  | 0.67 (0.02)     | 0.98 (0.02)       | 1.03 (0.02)       | 0.78 (0.02)       |
| Audio Model (YAMNet + Bi-LSTM + Attention) | Audio (begin 30s)             | 0.64 (0.01)     | 0.92 (0.02)       | 1.01 (0.01)       | 0.80 (0.01)       |
|                              | Audio (middle 30s)            | 0.63 (0.01)     | 0.95 (0.01)       | 1.02 (0.01)       | 0.80 (0.01)       |
|                              | Audio (end 30s)               | 0.65 (0.01)     | 0.96 (0.01)       | 1.01 (0.01)       | 0.79 (0.01)       |
| Video Image Model (VGG-16 + Bi-LSTM) | Video Frames (begin 30s @1fps) | 0.66 (0.02)     | 0.92 (0.02)       | 0.99 (0.02)       | 0.77 (0.02)       |
|                              | Video Frames (middle 30s @1fps) | 0.66 (0.01)     | 0.96 (0.02)       | 0.99 (0.01)       | 0.77 (0.01)       |
|                              | Video Frames (end 30s @1fps)  | 0.67 (0.02)     | 0.94 (0.03)       | 0.98 (0.03)       | 0.75 (0.02)       |

Note: RMSE for Commentability, Thumbsability and Likeability; Accuracy for Loveability. The number in brackets is the standard deviation in prediction error across all bootstrap iterations.

Table E1: Model performance for each component of unstructured data in holdout sample
Online Appendix F – Details of Interpreting Text Model Results

F.1 Modelling Choice of Ridge Regression

We use Ridge Regression to interpret the relationships captured in the Text Model so that we can capture heterogeneity in effects across brands and emotional words. Additional reasons for our choice of Ridge Regression are as follows: (a) Some brands or emotional words may only be used once in our data and hence OLS cannot be used, (b) number of predictors \( n_p > n \) for Equation 4 while interpreting the Text model which makes Ridge Regression suitable, and (c) a limitation of other penalized regression methods such as LASSO is that it will cap variable selection at \( n \) variables (and not \( n_p \)) and hence we may miss out on capturing important predictors, (d) LASSO or Elastic Net may miss out on selecting some brands or emotional words if their effect is collinear with other brands or emotional words, (e) Ridge Regression shrinks the non-important predictors towards 0, thus allowing us to identify the relatively more important predictors.

F.2 Graphical Illustration and Robustness of Interpretation Results of Text Model

We show a graphical illustration of the findings highlighted in green in Table 4 in Figure F1. The X axis shows the median value of brand coefficients (across 50 bootstrap iterations) from Step 1 of the analysis that correspond to a change in the attention weights. The Y axis shows the median value of brand coefficients (across 50 bootstrap iterations) from Step 2 of the analysis that correspond to a change in the predicted outcome. Our quadrants of interest are Quadrant 1 and 4 that have a positive X axis corresponding to an increase in attention directed to the brand/emotion. The brands/emotions in Quadrant 1 have a positive Y axis corresponding to an increase in the predicted outcome variable, whereas those in Quadrant 4 have a negative Y axis corresponding to a decrease in the predicted outcome variable. We label the data points for the brands/emotions in these quadrants whose coefficient value is at least 30% (\( bar \) value) of the magnitude of the maximum coefficient value on each axis to avoid cluttering the figures with labels (Note that the results in Table 4 used a \( bar \) of 5%). The values in brackets below the name of a brand in Q1 (Q4) correspond to the % of time (across 50 bootstrap iterations) the brand
coefficient is positive (positive) on the X axis and positive (negative) on the Y axis. As can be seen in the graph, brands are more often present in Q4 as compared to Q1.

![Graph showing the distribution of brands across Q1 and Q4.]

*Figure F1: Interpretation results of Text Model for brand mentions*

The results for the Text model corresponding to the highlighted cells in green in Table 4 are robust to changes in the values of the *bar*. This is because the difference between the percentage of brands that have a negative effect (Quadrant 4) versus a positive effect (Quadrant 1) on predicted loveability continue to hold true across a range of values of the *bar*. We show this in Figure F2. As can be seen, the green and brown lines do not intersect which demonstrates that the differential effect is in the same direction as we move along the respective X and Y axis of Figure F1. In other words, we demonstrate how our findings for the beginning 30s and middle 30s are robust to brands that have a small or a large effect on predicted loveability.

![Graphs showing the robustness of interpretation results for text model in beginning 30s and middle 30s.]

*Figure F2: Robustness of interpretation results of Text Model for brand mentions in beginning 30 seconds and middle 30 seconds*
F.3 Modelling Choice of OLS

We are able to estimate Equation 4 using OLS while modeling the predicted outcomes from the Audio or Video Image models because in these instances we do not model the heterogeneity across brands or emotional words. Instead, we use covariates for ‘number of brand mentions’ and ‘number of emotional word mentions’ because textual features in this case are not features of interest and are only used as controls. More concretely, we replace $\sum_{k=1}^{n_b} \beta_{1p} (BITX_{it}) + \sum_{k=1}^{n_e} \beta_{2p} (EITX_{it})$ in Equation 4 with $\beta_{1p} (\text{Number of brand mentions}_{it}) + \beta_{2p} (\text{Number of emotion mentions}_{it})$. 
Online Appendix G – Visual Illustration of Salient Regions in Text, Audio and Images

We provide illustrations of how measures of attention returned by our deep learning models can be visualized to help influencers identify areas for improvement.

First, we show an example of how text data can be visually interpreted. In Figure G1, we visualize the attentions weights on the captions/transcript (beginning 30s) from a video of a technology & business influencer. The words are tokenized into word-pieces in the figure as done by the model, and a darker background color indicates relatively higher attention weights. As can be seen in the figure, on average more attention is paid to the word ‘iphone’ than other words in the text. Note that the model assigns different attention weights to the word ‘the’ based on the context in which it is used (lower attention in the first line, but higher attention in the last line). While the model also assigns more attention to punctuation marks, such as the apostrophe, these associations may be spurious (as discussed in the manuscript) or may be confounded by word usage unique to the influencer which we control for during ex-post interpretation using influencer fixed effects ($\alpha_i$) in Equation 1. Our model predicts ‘not positive’ loveability for this clip (consistent with the findings in Table 4) and this matches the observed value.

Next, we illustrate an example of how attention paid to audio moments in a video can be visually interpreted. We focus on the relationship between music and loveability. In Figure G2, we show the beginning 30 seconds of the audio clip of a travel influencer using four sub plots. The first plot shows the variations in the amplitude of the 30 second audio wave (sampled at 16 KHz) followed by the spectrogram of the wave where brighter regions correspond to stronger (or louder) amplitudes. Next, we show the interim output of the Audio model with the top 10 sound classes at each moment in the audio,
where the darker squares indicate higher probability of observing a sound of that class at that moment. The last plot displays the attention weights corresponding to each moment in the audio clip, where the darker squares indicate higher relative attention placed on that moment while forming an association with loveability. As can be seen in the figure, relatively more attention is directed to moments where there is music but no simultaneous speech. The model predicts positive loveability for this clip (consistent with the findings in Table 5) and this matches the observed value.

![Image of attention weights in an audio clip](image)

*Figure G2: Attention weights in an audio clip (beginning 30 sec) of a video*

Next, we illustrate how attention paid to image pixels on the video frames of a video can be visually interpreted. We show the first 15 frames @1fps for a video of a parenting influencer in Figure G3. The bottom of the figure shows the heat map (gradient values), where brighter (redder) regions are positively associated with likeability. We find that pixels associated with images of persons have brighter heat maps, and more attention is often paid to the whole image of the person than just the face of the person (e.g., Frame 3, 5, 6 and 7). This is correlated with the area below the face of the person where the influencer is gesturing with their hands. We can also note the attention paid to images of packaged goods in Frame 14 and 15. Also note that the model assigns high attention to all the pixels in Frames 1, 9 and 13, and hence they appear completely red. The predicted likeability for this example is 40 likes per dislike.
which is less than the median likeability of 54 likes per dislike. This can be expected given that the person is present in only around half the frames and the large size of packaged goods in the frames (which is consistent with the conclusions from Table 6).

These visual illustrations for text, audio and images can help influencers, agencies and brands understand the potential influence of individual words, sound elements and objects in images. It can help them experiment with usage of different words, sounds and objects to improve engagement with the video.
Online Appendix H – Simulations to Recover the True Data Generating Process

We explain in detail our simulation process for the Text Model, Audio Model and Video Image Model.

H.1 Simulations – Text Model

We first pick a covariate-outcome pair of interest, say “brand mentions in beginning 30 seconds of captions/transcript – likeability”. For those observations (of video \( t \) and influencer \( i \)) where a brand is not mentioned in the beginning 30 seconds, we generate a random normal distribution of log-likeability as follows:

\[
brand_{\text{absent}}_{it} \sim N(3.79,1.11)
\]

For those observations (of video \( t \) and influencer \( i \)) where a brand is mentioned in the beginning 30 seconds, we generate a random normal distribution of log-likeability whose mean is twice the mean and standard deviation is half the standard deviation of the above equation:

\[
brand_{\text{present}}_{it} \sim N \left( 2 \times 3.79, \frac{1.11}{2} \right)
\]

We can summarize our simulated outcome of log likeability, \( Y_{\text{simulated}}_{it} \), for video \( t \) by influencer \( i \), as follows:

\[
Y_{\text{simulated}}_{it} = \begin{cases} 
N(3.79,1.11) \text{ when brand is absent} \\
N \left( 2 \times 3.79, \frac{1.11}{2} \right) \text{ when brand is present}
\end{cases}
\]

We visually illustrate the results of ex-post interpretation in Figure H1. As can be seen in the figure, brands are more often present in Quadrant 1 (increase in attention and an increase in predicted likeability). The results for the Text model are also robust to changes in the value of the \( bar \) used in Table 9. This is because the difference between the percentage of brands that have a positive effect (Quadrant 1) versus a negative effect (Quadrant 4) on predicted likeability continues to hold true across a range of values of the \( bar \). We show this in Figure H2. As can be seen, the green and brown lines do not intersect which demonstrates that the differential effect is in the same direction as we move along the respective X and Y axis of Figure H1. Hence, our findings are robust to brands that have a small or a large effect on predicted likeability.
H.2 Simulations – Audio Model

As done above, we first pick a covariate-outcome pair of interest, say “music duration in beginning 30 seconds – commentability”. We generate a random normal distribution for video $t$ by influencer $i$ as follows:

$$v_{it} \sim Uniform(-11.42, -2.18)$$

We then generate the simulated outcome of log commentability, $Y_{simulatedit}$, for video $t$ by influencer $i$ as follows:

$$Y_{simulatedit} = v_{it} - 0.5 \times \text{Sum of CI(Music)$_{it}$}$$

where, $\text{Sum of CI(Music)$_{it}$}$ is the duration of music sounds in the beginning 30 seconds in video $t$ by influencer $i$.

H.3 Simulations – Video Image Model

As done above, we first pick a covariate-outcome pair of interest, say “size of human images in beginning 30 seconds – likeability”. We generate a random normal distribution for video $t$ by influencer $i$ as follows:

$$w_{it} \sim Uniform(-0.92, 6.83)$$

Figure H1: Interpretation Results of Simulation – Text Model

Figure H2: Robustness of Interpretation Results of Simulation – Text Model
We then generate the simulated outcome of log likeability, $Y_{\text{simulated}_{it}}$, for video $t$ by influencer $i$ as follows:

$$Y_{\text{simulated}_{it}} = w_{it} + 0.25 \times \text{SizeObject(Human)}_{it}$$

where, $\text{SizeObject(Human)}_{it}$ is the mean across 30 frames of the percentage of the image occupied by all objects that are humans in video $t$ made by influencer $i$. 
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