Interpreting Video Engagement Prediction: A Deep Learning Framework

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*WITS 2021 Best Paper Award Winner
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Abstract: Predicting video engagement is a top priority for content creators and video-sharing platforms. Content creators feed on such predictions to maximize influences and minimize video budgets. Video-sharing platforms rely on this prediction to promote credible videos and curb violative videos. Although deep learning champions video engagement prediction, it lacks interpretability, which is fundamental to increase adoption of these prediction models and prescribe actionable advice to improve video engagement. Following the design science paradigm, we propose a novel interpretable deep learning framework, Precise Wide and Deep Learning (Prec-WD), to interpret video engagement prediction. Improving upon state-of-the-art interpretable frameworks, Prec-WD designs an unstructured component and offers precise total effects. Prec-WD’s prediction outperforms strong benchmarks on two case studies: health video engagement prediction and misinformation viewership prediction. A user study confirms the superior interpretability of Prec-WD. This study contributes to IS knowledge base with a novel and generalizable interpretable deep learning framework. Our findings provide implications to improve viewer engagement and video credibility.

Keywords: Deep learning, interpretability, design science, social media analytics, predictive analytics.

1. Introduction

Social media is increasingly taking up a greater share of consumers’ attention and time spent online, and hence becoming an effective and efficient channel to disseminate information and share knowledge. Among various social media platforms, video-sharing sites, such as YouTube and Vimeo, receive the most attention because of their easy-to-implement audio messages, visual presentations to spread information, and extensive viewer base. Video sharing technologies offer promising new venues to disseminate information to wider audiences and make the newest ideas accessible and easy to share.

How does a video become viral? This is a well-known open research question in social media analytics and the key profit driver for stakeholders of video-sharing sites. Viewership is a key measurement for viewer engagement and is the metric by which platforms pay their content creators (Liu
et al. 2020). In this paper, we propose an interpretable machine learning (ML) to predict viewer engagement and interpret the factors associated with engagement. We define viewer engagement as the average daily viewership of a video (Liu et al. 2020). The factors associated with engagement can be used to guide content design and effectively convey public messages in times needed.

Predicting viewer engagement is fundamental to “viralize” videos for these stakeholders. Content creators rely on viewership prediction to boost revenues. Our proposed method is of direct relevance to content creators to better understand and improve consumer engagement. Producing a video costs $1,500 to $50,000 per minute (Hinge Marketing 2021). Video production requires novel skills such as shooting and editing, as well as a considerably different communication mindset for elaborate audio-visual storytelling, which average content creators may find difficult to acquire. An interpretable ML viewership prediction helps identify approaches to improve viewer engagement and allocate budgets to potentially popular videos. Advertisers can also greatly benefit from such a prediction. For instance, YouTube adopts the cost-per-view (CPV) model to charge advertisers $0.06 for each video view (Hubspot 2021). Accurate prediction of video viewership lowers unnecessary advertising costs and optimizes marketing outcomes.

Besides content creators and advertisers, video-sharing sites can benefit from such a prediction. For instance, YouTube is keen to predict video viewership in order to manage video credibility, especially during the COVID-19 pandemic. YouTube hosts more than 100 million videos that provide information on pathogenesis, diagnosis, treatment, and prevention of various medical conditions (Liu et al. 2020). Although high engagement of credible videos benefits public health, widely shared misinformation undermines the global health response and jeopardizes public health education. Health misinformation is detrimental to viewers’ physical and mental health, elevates stigmatization and hate speech, threatens health gains, leads to poor health measures, and even costs lives (Liu et al. 2020). YouTube has revised its guidelines to address misinformation with a range of tools: removing content that violates its policies, raising up authoritative sources for news and information, and reducing recommendations of borderline content and misinformation. YouTube currently relies on the percentage of total views coming from misinformation videos to prevent them from spreading (NYTimes 2021). Predicting viewership helps the
platform increase views for legitimate videos and curb views for misinformation videos.

While ML and data-driven approaches present an incredibly potent resource to predict viewer engagement, several challenges have limited the uptake of ML tools. Among them, a lack of transparency and interpretability have been highlighted as significant challenges for wider ML adoption (Linardatos et al. 2021). Interpretability is essential to increase human trust and acceptance of ML models.

Interpretation in the data science life cycle largely occurs in the post-hoc analysis and modeling stages (Murdoch et al. 2019). The general principle of these interpretable methods is to estimate the total effect of the prediction, defined as the change of the outcome variable when a feature increases by one unit. Interpretability in the post-hoc analysis stage is called post-hoc interpretability. Post-hoc methods interpret the total effect after the prediction using standalone explaining models, such as regression, sensitivity analyses, SHAP, and LIME (Tsang et al. 2018). Although these methods could offer explanations to the prediction, the standalone explaining models could alter the total effect of the prediction model, since they possess different model specifications (Guo et al. 2020).

Interpretability in the modeling stage is called model-based interpretability. Model-based methods address the limitation of post-hoc models by embedding the interpretation component within the prediction model. The cutting-edge model-based interpretable methods include the Generalized Additive Model framework (GAM) and the Wide and Deep Learning framework (W&D). GAM is unable to model higher-order feature interactions and caters to small feature size, limiting its applicability in this study. Addressing that, W&D incorporates a linear model in the deep learning model (Cheng et al. 2016). We define the effect interpreted by the linear model (feature weights in the linear model) as the main effect. A few limitations persist for W&D. From the prediction perspective, the W&D framework is restricted to structured data, constrained by the linear part. In video analytics, only using structured data significantly hampers the prediction performance. From the interpretation perspective, W&D and its variants fall short in producing precise interpretations. They use the weights of the linear part (main effect) to approximate the total effect of the input on the prediction, even though the main effect and total effect largely differ.

To address the limitations of the existing interpretable methods, we propose a novel model-based
interpretable framework that leverages unstructured data and produces a precise interpretation. Our proposed method is called Precise Wide and Deep Learning (Prec-WD).

This study contributes to interpretable deep learning methodology and IS knowledge base. First, we develop Prec-WD that innovatively modifies the W&D framework with a precise interpretation component and an unstructured component. As our core contribution, the proposed interpretation component can capture the precise total effect of each feature. A generative adversarial network is leveraged within this component to approximate the data distribution to facilitate the interpretation process. Because of our interpretation component, we are able to add the unstructured component to extend the W&D framework to unstructured data analytics. Empirical evaluations from two case studies indicate that Prec-WD outperforms both blackbox and interpretable models in video engagement prediction. We design a user study to validate the contribution of our interpretation component. The result indicates Prec-WD provides better interpretability than state-of-the-art interpretable methods. Our feature interpretation enhances decisions and actions via improved trust and model usefulness.

Second, for design science research (Abbasi et al. 2010, 2012, Fang et al. 2013, Mai et al. 2018, Saboo 2016, Stieglitz and Dang-Xuan 2013), the successful design of our framework offers indispensable design principles. Our new interpretation component offers a generalizable approach to estimate precise and dynamic interpretation for prediction tasks in IS, such as user engagement prediction, product sales prediction, and project investment prediction. The user study serves as an exemplar for IS research to evaluate interpretable ML methods. The Prec-WD framework is also an deployable information system for social media platforms. This system is capable of predicting videos that are likely to go viral and interpreting the factors associated with this prediction. Social media platforms could leverage this system to actively monitor the predictors and manage viewer engagement and video credibility.

2. Literature Review

2.1. YouTube Viewer Engagement

Our empirical analysis is implemented with YouTube videos. YouTube has been one of the most successful video-sharing sites since its establishment in 2005 and constitutes the largest share of Internet
traffic (Liu et al. 2020). Viewership, defined as the number of views a video receives, is the key metric to measure viewer engagement and by which YouTube pays its content creators (Hoiles et al. 2017).

As YouTube relies on user-generated content, it is constantly bombarded with videos that run afoul of its guidelines, ranging from pornography, copyrighted material, violent extremism, to misinformation. The company has developed its AI system to prevent violative videos from spreading. YouTube recently revealed that this AI system’s effectiveness in finding and removing rule-breaking videos is evaluated with a metric called the violative view rate, which is the percentage of total views on YouTube coming from violative videos (NYTimes 2021). This disclosure shows that video view count is the most important measure that YouTube seeks to track to increase views for legitimate videos and at the same time to curb views for violative videos.

Understanding and predicting viewership is useful from the content creators’ perspective as well. On one hand, more popular content generates more traffic, so understanding viewership has a direct impact on caching and replication strategy that content creators should adopt. On the other hand, viewership has a direct economic impact, as content creators rely on viewership for payment and advertisement.

2.2. Interpretability Definition and Value Proposition

According to Breiman (2001), ML has two objectives: prediction (determine the value of the target for new inputs) and information (understand the relationship between the inputs and the target). Studies show that decision makers exhibit an inherent distrust of automated predictive models, even if they are proven to be more accurate than human forecasters (Dietvorst et al. 2015). When ML models are used to support decision-making on complex and important topics, understanding a model’s “reasoning” can increase trust in its predictions, expose hidden biases, and reduce vulnerability to adversarial attacks. To fully harness the power of AI and ML to support decision-making, interpretability is a much-needed milestone.

The definition of interpretability remains inconclusive, and domain-specific notions are left to the researchers and users to define (Lee et al. 2018). Related to ML and predictive analytics, two major definitions exist. One stream defines interpretability as the degree to which a human can trust and understand the cause of a decision (Miller 2019). In the context of ML, interpretability is described as the
degree to which a human can consistently predict the model’s result (Miller 2019). The interpretability of a model is higher if it is easier for a person to trust the model and trace back why a prediction was made by the model (Lee et al. 2018). Molnar (2019) notes that interpretable ML refers to models that make the behavior and predictions of ML understandable and trustworthy to humans. Consequently, interpretability is related to how well humans trust a model by looking and reasoning about it. The other stream suggests “AI is interpretable to the extent that the produced interpretation is able to maximize a user’s target performance” (Dhurandhar et al. 2017). Following this definition, Lee et al. (2018) uses usefulness to measure ML interpretability, as useful models lead to better decision-making performance.

Interpretability brings value to ML and the business world in many aspects. The most significant one is social acceptance, which is required to integrate algorithms into daily lives. Heider and Simmel (1944) show that people attribute beliefs and intentions to abstract objects, so they are more likely to accept ML if their decisions are interpretable. Ribeiro et al. (2016) argue that if users do not trust a model prediction, they will not use it. Interpretability is thus essential to increase human trust and acceptance of ML.

For human societies to embrace ML for decision support, ML must bring forth relevant information for the decision-making task and communicate in a way that allows a human recipient of the information to establish trust using intuition and reasoning. As our society is progressing toward the integration with ML and AI, new regulations have been imposed to require verifiability, accountability, and, more importantly, full transparency of algorithm decisions. A key example is the European General Data Protection Regulation (GDPR), which was enforced to provide data subjects the right to an explanation of algorithm decisions (Cichy et al. 2021).

In the case of viewership prediction for content moderation and production on social media, the transparency of algorithms is critical to avoid arbitrary decisions and backlash from the public about the violation of the Freedom of Speech. In the battle of misinformation, it is beneficial for YouTube and content creators to understand factors associated with popularity and build trust in certain systems so that patterns of misinformation spread can be learned, and that harmful content can be removed. For viewers, trust leads to better customer adherence on the platform and more content consumption. For credible
content creators, especially healthcare organizations and news sources that share valuable knowledge and evidence-based information, it takes significant time and effort to create such content. Interpretable predictions of viewer engagement can also guide them to create more high-quality and compelling content that may gain high viewer engagement.

2.3. Interpretable Machine Learning Methods

Recent video analytics studies heavily utilize deep learning models (Karahanna et al. 2020, Li et al. 2020, Liu et al. 2020, Shin et al. 2020). Although these models pioneer predictive analytics, their lack of interpretability fails to provide actionable insights for business decision-making. To remedy this gap, we propose an interpretable deep learning framework. We develop a taxonomy of the extant interpretable methods in Table 1 based on the data types that these methods deal with, the type of algorithms that could be applied (i.e., model-based and post-hoc), the scope of interpretation (i.e., instance level and model level), and how they attempt to address interpretability.

| Model                             | Scope         | Data Type | Interpretable Method | Usage       |
|-----------------------------------|---------------|-----------|----------------------|-------------|
| Deconvolutional Nets (Zeiler and Fergus 2014) | Instance-level | Image     | Backpropagation      | Post-hoc    |
| GAM (Caruana et al. 2015)         | Model-level   | Tabular   | GAM                  | Model-based |
| LIME (Ribetra et al. 2016)        | Both          | Any       | Perturbation         | Post-hoc    |
| W&D (Cheng et al. 2016)           | Model-level   | Tabular   | W&D                  | Model-based |
| SHAP (Lundberg et al. 2017)       | Both          | Any       | Perturbation         | Post-hoc    |
| Grad-CAM (Selvaraju et al. 2017)  | Instance-level| Image     | Backpropagation      | Post-hoc    |
| Focused Concept Miner (Lee et al. 2018) | Both        | Text      | Topic Model          | Model-based |
| W&D-CNN (Lee and Chan 2019)       | Model-level   | Tabular   | W&D                  | Model-based |
| W&D-BLSTM (Ye et al. 2019)        | Model-level   | Tabular   | W&D                  | Model-based |
| CaCE (Goyal et al. 2019)          | Model-level   | Image     | GAM                  | Post-hoc    |
| LRP (Montavon et al. 2019)        | Both          | Any       | Backpropagation      | Post-hoc    |
| W&D-LSTM (Tosun et al. 2020)      | Model-level   | Tabular   | GAM                  | Model-based |
| Piecewise W&D (Guo et al. 2020)   | Model-level   | Tabular   | W&D                  | Model-based |
| NAM (Agarwal et al. 2020)         | Model-level   | Any       | GAM                  | Model-based |
| Our proposed method               | Both          | Any       | Prec-WD              | Model-based |

Interpretable ML methods have been developed to discover, learn, and extract the hierarchical representations needed for prediction tasks. One crucial factor that should be considered is the data type to which these methods could be applied. Vast amounts of data in various forms have been used to train and develop such methods, including tabular (Guo et al. 2020, Tosun et al. 2020), image (Goyal et al. 2019, Selvaraju et al. 2017), and text (Agarwal et al. 2020, Lee et al. 2018).
The scope of an interpretable method depends on whether it interprets a local instance or understands the model as a whole. The scope of interpretations can be either instance- or model-level. Locally interpretable methods are designed to express the individual feature attributions of a single instance of input data (Selvaraju et al. 2017, Zeiler and Fergus 2014). Globally interpretable models provide insights into the decision as a whole – leading to an understanding of attributions for an array of input data (Agarwal et al. 2020, Tosun et al. 2020). Some methods can be extended to both (Lundberg et al. 2017).

An interpretable ML method with a specific scope and methodology can be either embedded in the neural network or applied as an external algorithm for interpretation. Post-hoc methods build on the predictions of an existing neural network and add ad-hoc explanations (Goyal et al. 2019, Selvaraju et al. 2017). Any interpretable ML algorithm that is dependent on the model architecture falls into the model-based category (Agarwal et al. 2020, Caruana et al. 2015, Guo et al. 2020). For most model-based algorithms, any change in the architecture needs alteration in the method itself or hyperparameters of the interpretable algorithm. However, model-based interpretable ML methods can better capture dynamic feature effects, higher-order relations of the features, or even interaction effects.

Post-hoc interpretable methods can be categorized into backpropagation- or perturbation-based. Interpretations generated by iteratively probing a trained ML model with different inputs fall under perturbation-based techniques. These perturbations can be on the feature level by replacing certain features by zero or random counterfactual instances, picking one or a group of pixels (superpixels) for explanation, blurring, shifting, masking operations, among others.

The Local Interpretable Model-agnostic Explanations (LIME) is one of the most popular perturbation-based post-hoc methods (Ribeiro et al. 2016). For any given instance and its corresponding prediction, simulated randomly sampled data around the neighborhood of the input instance, for which the prediction was produced, are generated. New predictions are made for generated instances and weighted by their proximity to the input instance. A simple, interpretable model, such as a decision tree, is trained on this newly created dataset of perturbed instances. By interpreting this local model, the initial black-box model is consequently interpreted.
Shapley Additive Explanations (SHAP) has a similar method of probing feature correlations by removing features in a game-theoretic framework (Lundberg et al. 2017). SHAP explains predictions of an input by computing individual feature contributions towards that output prediction. By formulating the data features as players in a coalition game, Shapley values can be computed to learn to distribute the payout fairly. SHAP can deduce the problem where the explanation is a linear function of features.

The other common approach among post-hoc interpretable methods is based on backpropagation. The core algorithmic logic is dependent on gradients that are backpropagated from the output layer back to the input layer. Deconvolutional Nets (Zeiler and Fergus 2014) uses backpropagation for activation visualizations and gives relative importance to gradient value during backpropagation. With Rectified Linear Unit (ReLU) activation, a backpropagation on traditional CNNs would result in zero values for negative gradients, while in Deconvolutional Nets, the gradient value is not clipped at zero. This allowed for accurate visualizations. The Layer-wise Relevance BackPropagation (LRP) technique in Bach et al. (2015) is used to find relevance scores for individual features in the input data by decomposing the output predictions of the DNN. The relevance score to the output class for each instance is calculated by backpropagating the class scores of an output class node towards the input layer.

While these post-hoc methods offer a form of explainability, they have pitfalls. Zafar and Khan (2019) reported that the random perturbation and feature selection methods that SHAP or LIME utilizes result in unstable generated interpretations. This is because, for the same prediction, different interpretations can be generated, which can be problematic for deployment. The post-hoc explaining model is also independent of the prediction model, each possessing unique training objectives and model specifications. The total effect of the prediction model – defined as the change of the outcome variable when a feature increases by one unit – could differ significantly from that learned from the explaining model (Guo et al. 2020). Therefore, the magnitude and direction of the total effect could be misinterpreted by the explaining model.

The model-based interpretable methods have a self-contained structure that not only makes accurate predictions but also characterizes the relationship between the input features and the outcome. The model-
based interpretable methods are usually based on two frameworks: Generalized Additive Model framework (GAM) and Wide and Deep Learning framework (W&D). Caruana et al. (2015) introduced GAMs with pairwise interactions (GA2Ms) to improve the accuracy while maintaining the interpretability of GAMs. However, for prediction tasks with many features, GAMs often require millions of decision trees to provide accurate results using additive algorithms. Also, depending on the model architecture, over-regularization reduces the accuracy of GAM. Numerous methods have improved GAMs. Neural Additive Models (NAM) learn a linear combination of neural networks where each attends to a single input feature: each feature is parametrized by a neural network (Agarwal et al. 2020). These networks are trained jointly and can learn arbitrarily complex shape functions. Interpreting NAMs is easy as the impact of a feature on the prediction does not rely on other features and can be understood by visualizing its corresponding shape function. However, this class of methods is limited in modeling any higher-order feature interactions and is constrained by the number of features, because every single feature is assumed independent and trained by a standalone model. When the feature size is large, and feature interactions and higher effects exist, GAMs and NAMs struggle to perform well (Agarwal et al. 2020).

The W&D framework is explicitly designed to address the low and high-order feature interactions in interpreting the importance of features (Cheng et al. 2016). Cheng et al. (2016) proposed W&D that trains an interpretable linear component jointly with a deep neural network. The wide component is a linear model with the input features. It produces a weight for each feature (main effect) to interpret the prediction. The second joint component is a deep neural network that models high-order relations in the hierarchical network to improve prediction accuracy.

Since the introduction of W&D, a range of its variants have emerged. They fall into two categories. The first category attempts to improve the predictive power of W&D. Since the deep component offers the core predictive capability in W&D, studies in this category design new networks to replace the deep network, such as CNN, CRF, and attention mechanisms. Burel et al. (2017) leveraged CNN in the deep component to identify information categories in crisis-related posts in social media. Instead of feeding separate inputs to the wide and deep components, Guo et al. (2018) developed a shared input layer so that
both wide and deep components can share inputs without feature engineering. Han et al. (2019) used a CRF layer to merge the wide and deep components and predict named entities of words.

The second category of variants aims to improve the interpretability of W&D. They attempt to tease out the influence of the deep component on the wide component so that the interpretation error from the wide component is mitigated. Guo et al. (2020) proposed piecewise W&D that divides the input features into smaller granularities for piecewise linear approximation. Multiple regularizations are introduced to the total loss function to reduce the influence of the deep component on the wide component so that the weights learned from the wide component are closer to the actual total effect.

The W&D and its variants still fall short in the following aspects. First, unstructured data are not compatible with the W&D framework. The existing W&D framework enforces the wide component and the deep component to share inputs and be trained jointly, so that the wide component can interpret the deep component. The wide component in W&D is a linear model: 

$$f^w(x) = w^T x + b.$$ 

$x = [x_1, x_2, ..., x_d]$ is a vector of $d$ features, including raw input features (continuous features and embeddings of categorical features) and product-transformed features (Cheng et al. 2016). The product transformation is 

$$\phi_k(x) = \prod_i x_i^{\xi_{ki}} (\xi_{ki} \in \{0,1\})$$ 

where $x$ is the raw input feature $[x_1, x_2, ..., x_d]$, and $\xi_{ki}$ indicates whether the $i$-th feature appears in the $k$-th transformation. Both raw input features (continuous or categorical) and product-transformed features are structured data. This is due to the structured nature of the linear model $f^w(x)$. Unstructured data, such as videos in this study, cannot be processed by $f^w(x)$, thus significantly limiting W&D’s predictive performance in unstructured data analytics.

Second, W&D uses the learned weights of the wide component $w^T$ (main effect) to interpret the prediction. When training the wide and deep components jointly, the deep component affects $w^T$. Consequently, $w^T$ is not the total effect. For instance, the weight $w_1$ for $x_1$ does not imply that if $x_1$ increases by one unit, the prediction would increase $w_1$. The real feature interpretation for $x_1$ cannot be precisely reflected in $w_1$. Even though a few studies (e.g., Guo et al. 2020) attempted to minimize such errors, their efforts still fail to interpret the precise total effect. In addition, $w^T$ is constant for all instances
of $\mathbf{x}$, which assumes the feature effect is insensitive to changes of feature value. This assumption does not hold in real settings. For instance, when a video is only a few minutes long, increasing one minute in duration would significantly impact its viewership. When a video is hours long, increasing one minute does not have a visible effect on its viewership.

2.4. Generative Models for Synthetic Sampling

The state-of-the-art interpretable methods, such as the W&D framework, cannot capture the precise total effect. In order to calculate the precise total effect, we develop a novel model-based interpretation framework, which we will detail in the Proposed Approach section. To facilitate such a framework, generating synthetic samples to learn the data distribution is essential.

Deep generative models define distributions over a set of variables organized in multiple layers. Early forms of such models dated back to works on Bayesian Networks and neural network models such as Helmholtz machines. Such models are trained via an EM framework, using either variational inference or data augmentation (Ebrahimi et al. 2022). Bayesian Networks require the knowledge of the dependency between every feature pair. It would be useful for cases with limited features that have domain knowledge. When the number of features increases, constructing the feature dependencies is infeasible and leads to poor performance.

Recent years have seen a resurgence of developments in deep generative models. The emerging approaches, including Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) have led to impressive results in various applications, such as image and text generation and disentangled representation learning (Ebrahimi et al. 2022). Unlike Bayesian Networks, deep generative models do not require the knowledge of feature dependencies. GANs and VAEs are two emerging families of generative model learning and have been largely considered as two distinct paradigms. VAE aims at maximizing the lower bound of the data log-likelihood, while GAN aims at achieving an equilibrium between Generator and Discriminator.

VAEs use the autoencoder architecture to learn a data distribution (Samtani et al. 2021). The encoder takes random samples and compresses them into a low-dimensional latent space. The decoder takes the
latent space representation and reproduces the original sample. VAE uses variational inferences to generate its approximation to a posterior distribution. Once the VAE is trained, it can generate unique samples with similar characteristics to those that the network was trained on.

GANs are a powerful class of deep generative models consisting of two networks: a generative network (generator) and a discriminative network (discriminator). These two networks form a contest where the generator produces high-quality synthetic data to fool the discriminator, and the discriminator distinguishes the generator’s output from the real data. Through recurrent learning from this contest, the generator is capable of approximating the distribution of the real data. Deep learning literature suggests that the generator could learn the precise real data distribution as long as those two networks are sufficiently powerful (Ebrahimi et al. 2022, Yu et al. 2022). The contest between the discriminator and the generator is achieved by training jointly. The resulting model is a generator that can closely approximate the real distribution. This generator can generate samples to compute the precise total effect.

Although both VAE and GANs are very exciting approaches to learn the underlying data distribution using unsupervised learning, GANs yield better results than VAEs empirically (Alqahtani et al. 2021). VAE optimizes the lower variational bound, whereas in GAN there is no such assumption. In fact, GANs do not deal with any explicit probability density estimation. The requirement of VAE to learn explicit density estimation hinders its ability to learn the true posterior distribution.

3. The Proposed Approach

3.1. Problem Definition

Let $V$ denote a set of videos $(v_1, \ldots, v_N)$. We design $M$ features $X = (X_1, \ldots, X_M)$ to represent each video. The feature values of a video $v_i$ are represented by a vector $x_i = (x_{i,1}, \ldots, x_{i,M})$. We also leverage the raw videos $(v_1, \ldots, v_N)$ as the unstructured input. The viewer engagement is operationalized as the average daily views of a video ($ADV$) (Liu et al. 2020), computed as the view counts to date divided by the number of days a video has been published. The average operation is the average daily views over the entire lifespan of a video. The $ADV$ value of video $v_i$ is denoted as $adv_i$. Our objective is to learn a
model \( F \) to predict \( adv_i \), where \( adv_i = F(x_i, v_i) \). In addition to predicting \( ADV \), this model is capable of interpreting how it makes such a prediction. Specifically, our second objective is to refine model \( F \), so that it can estimate the precise total effect of each feature \( X_j \) on the output \( adv (\Delta ADV/X_j) \).

### 3.2. The Prec-WD Framework for Video Engagement Prediction and Interpretation

The proposed framework builds upon the state-of-the-art W&D framework while addresses two of its challenges: 1) W&D can only process structured data; 2) W&D fails to offer the precise total effect and its dynamic changes. Our proposed framework is called Prec-WD, detailed in the following subsections.

#### 3.2.1. Piecewise Linear Component

Each feature \( X_j \) captures a different aspect of a video. Within each feature, heterogeneity between different values exists. For instance, video creator credibility is a feature in \( X \). Videos with low creator credibility not only influence the outcome variable, but these videos may have low quality as well, which indirectly influences the outcome variable. Therefore, it is essential to consider the homogeneity among similar feature values and the heterogeneity across different feature values. Specifically, we need to differentiate the varied feature effects when the feature is at different values. Consequently, we introduce a piecewise linear function in the linear component. For the \( j \)-th feature, let \( \beta_j = \max \{ x_{i,j} | i = 1, \ldots, N \} \) and \( \delta_j = \min \{ x_{i,j} | i = 1, \ldots, N \} \). We partition each feature into \( \gamma_j \) intervals: \( [\varphi_j^{0}, \varphi_j^{1}], \ldots, [\varphi_j^{\gamma_j-1}, \varphi_j^{\gamma_j}] \), where \( \varphi_j^{k} = \delta_j + \frac{k}{\gamma_j} (\beta_j - \delta_j) \). The piecewise feature vector for the \( i \)-th data point \( x_i \) is:

\[
\Phi_i = (\phi_{i,1}^{1}, \ldots, \phi_{i,1}^{\gamma_1}, \ldots, \phi_{i,j}^{1}, \ldots, \phi_{i,j}^{\gamma_j}, \ldots, \phi_{i,M}^{1}, \ldots, \phi_{i,M}^{\gamma_M})^T,
\]

where \( \phi_{i,j}^{k} = \begin{cases} 1, & x_{i,j} > \varphi_j^{k} \\ \frac{x_{i,j} - \varphi_j^{k-1}}{\varphi_j^{k} - \varphi_j^{k-1}}, & \varphi_j^{k-1} \leq x_{i,j} \leq \varphi_j^{k} \\ 0, & \text{otherwise}. \end{cases} \)

This piecewise vector \( \Phi_i \) is then fed into a linear model:

\[
y_i^{pw} = (w_i^{pw})^T \Phi_i + b_i^{pw},
\]

where \((w_i^{pw})^T\) is the weight in the linear component, \(b_i^{pw}\) is the bias, and \(y_i^{pw}\) is the output.

#### 3.2.2. Attention-based Second-Order Component

Lim and Benbasat (2002) suggest that multiple input modalities and their interactions could facilitate explanative processing information, such as information concerning relationships between or functions
underlying descriptive information. Our study aims to predict and interpret viewer engagement using multiple data modalities. Explicitly modeling data interactions needs to be an integral part of the framework. In parallel with the piecewise linear component, we devise an attention-based second-order component to model the interaction effects among the multi-modal features. The input to this component is $X$. For each video feature $x_t$, the interaction term of $x_{t,j}$ and $x_{t,j'}$ is denoted as $s_{t,(j,j')} = x_{t,j} \cdot x_{t,j'}$

Each interaction term has a parameter (Cheng et al. 2016). A set of $M$ features will generate $M^2$ interaction terms. This will cause the learnable parameters in the second-order component to grow quadratically as the feature set increases. To prevent such a quadratic growth and optimize computational complexity, we propose a self-attention mechanism in the second-order component where the number of parameters is fixed. The attention-based component could scale to large number of interactions while salient interaction terms still stand out. The attention mechanism assigns a score $a_{t,(j,j')}$ to each interaction term $s_{t,(j,j')}$. 

$$a_{t,(j,j')} = \frac{\exp(u_{t,(j,j')} \cdot h^A)}{\sum_{j=1}^{M} \sum_{j' = 1}^{M} \exp(u_{t,(j,j')} \cdot h^A)},$$

$$u_{t,(j,j')} = \tanh(w^A \cdot s_{t,(j,j')} + b^A),$$

where $w^A$, $b^A$ and $h^A$ are learnable parameters. The number of $w^A$, $b^A$ and $h^A$ are fixed, thus facilitating the analysis of a large scale of interaction terms. The attention score $a_{t,(j,j')}$ is used to weigh the interaction terms. The output of this component is as follows, where $w^{as}$ is a learnable weight and $\sum_j^M \sum_{j'}^M a_{t,(j,j')} s_{t,(j,j')}$ is the weighted sum of interaction terms.

$$y^{as}_t = w^{as} \sum_j^M \sum_{j'}^M a_{t,(j,j')} s_{t,(j,j')},$$

3.2.3. Nonlinear Higher-Order Component

The third parallel component is the nonlinear higher-order component. This component is a deep neural network that could capture higher-order effects. This network contains multiple fully connected layers. The number of hidden layers is determined using a grid search in the empirical analyses. The purpose of the higher-order component is to leverage the superior predictive power of deep learning to improve
predictability. Different from the dynamic total effect described above, the higher-order effect is a hidden component that is not interpretable, but only serves the predictive purpose. The dynamic total effect is able to delineate the magnitude of each feature’s total effect at each feature value. Without loss of generality, for the $i$-th video, each hidden layer computes:

$$a_{l,(l+1)} = f(W_{l}^{nh}a_{l,(l)} + b_{l}^{nh}),$$

where $l$ is the layer number. $f$ is the ReLU. $a_{l,(l)}$, $b_{l}^{nh}$, and $W_{l}^{nh}$ are the input, bias, and weight at the $l$-th layer. As no categorical features are involved in our study, no embedding layer is employed. Therefore, the input of the first layer is the feature vector (i.e., $a_{l,(1)} = x_i$). The output of this component is given by

$$y_{i}^{nh} = (w^{nh})^T a_{l,(l+1)},$$

where $(w^{nh})^T$ is the learnable weight and $L$ is the number of layers.

3.2.4. Unstructured Component

The W&D framework enforces the wide part and the deep part to share inputs so that the wide part can interpret the deep part. Since the wide part can only analyze structured data, the W&D framework is restricted to structured data as well. However, videos are in an unstructured format by nature. Although feature engineering can be deployed to extract structured features from videos, obtaining high predictive power in video analytics demands the capacity to process unstructured data. We relax the restraint of the subcomponents sharing inputs, because our proposed interpretation component could offer precise total effects without soliciting dependencies on the subcomponents. We extend the W&D framework with an unstructured component. Unlike W&D, this unstructured component does not share input with the other components. It directly takes the raw videos as the input. This component adopts the popular CNN-LSTM architecture for processing videos. We leverage the VGG-16 architecture to process the video frames, and an LSTM model is added on the top for frame-by-frame sequence processing. We denote the component parameter as $w^{uc}$, consisting of $w^{CNN}$ and $w^{LSTM}$. The last LSTM cell summarizes the video content information and is denoted as $y_{i}^{uc}$ for the $i$-th video $v_i$.

3.2.5. Interpretation Component
The fifth parallel component is our core contribution. Our primary focus is to estimate the precise total effect of video engagement prediction. Prec-WD predicts the outcome variable using

\[
\Delta \overline{ADV} = \text{ReLU}(\beta + \alpha_1 X_1 + \ldots + \alpha_M X_M + S(X_1, \ldots, X_M) + H(X_1, \ldots, X_M) + U(\nu)),
\]

where \(\beta + \alpha_1 X_1 + \ldots + \alpha_M X_M\) denotes the main effect, \(S(X_1, \ldots, X_M)\) denotes the interaction effect, \(H(x_1, \ldots, x_n)\) denotes the higher-order effect, and \(U(\nu)\) denotes the unstructured effect. We use ReLU because video views are non-negative. The total effect of \(X_1\) equals to the change of \(\Delta \overline{ADV}\) when \(X_1\) increases by one unit. In order to model the dynamic total effect of each feature, we predict the total effect of each feature at every value. Let \(\Delta \overline{ADV}(X_1 = c)\) denote the expected prediction conditioned on \(X_1 = c\).

The dynamic total effect of \(X_1\) under the condition of \(X_1 = c\) is given by

\[
\Delta \overline{ADV}(X_1 = c|X_2, \ldots, X_M) = \text{ReLU}(\beta + \alpha_1 (c + 1) + \ldots + \alpha_M X_M + S(X_1 = c + 1, \ldots, X_M) + H(X_1 = c + 1, \ldots, X_M) + U(\nu))
\]

\[
- \text{ReLU}(\beta + \alpha_1 c + \ldots + \alpha_M X_M + S(X_1 = c, \ldots, X_M) + H(X_1 = c, \ldots, X_M) + U(\nu)).
\]

The variable of interest is \(X_1\). \(U(\nu)\) utilizes ReLU as the internal activation, so it is always positive.

Therefore, the dynamic total effect of \(X_1\) is computed as

\[
\Delta \overline{ADV}(X_1 = c) = \Delta \mathbb{E}_{X_2, \ldots, X_M} \overline{ADV}(X_1 = c, X_2, \ldots, X_M)
\]

\[
= \Delta \int \ldots \int_{X_2, \ldots, X_M} \overline{ADV}(X_1 = c, X_2, \ldots, X_M)p(X_1 = c, X_2, \ldots, X_M) d(X_2) \ldots d(X_M).
\]

However, Equation 10 is intractable because of the integral computation. In order to facilitate the computation of Equation 10, we utilize the Monte Carlo method. Equation 10 can be transformed to:

\[
\Delta \overline{ADV}(X_1 = c) \approx \frac{1}{K} \sum_{k=1}^{K} \overline{ADV}(x_{k,1} = c, x_{k,2}, \ldots, x_{k,M}),
\]

where \((x_{k,1} = c, x_{k,2}, \ldots, x_{k,M})\) denotes the \(k\)-th sample drawn from the distribution \(p(X_1 = c, X_2, \ldots, X_M)\). In order to compute the precise total effect of \(X_1\), it is necessary to learn the distribution \(p(X_1 = c, X_2, \ldots, X_M)\), so that samples can be drawn from it. \(X_1, X_2, \ldots, X_M\) are numeric data that are sparse when using Monte Carlo method. In order to learn a smooth and accurate distribution, we integrate a generative adversarial network (GAN) to learn \(p(X_1 = c, X_2, \ldots, X_M)\). To overcome the learning instability issues of GANs, we introduce the Wasserstein GAN with gradient penalty (WGAN-GP) in this study. We cohesively integrate WGAN-GP in Prec-WD. The learning loss of the discriminator
(critic) in our proposed method is given by

\[ L_d = \mathbb{E}_{x \sim \mathbb{P}_r}[D(\tilde{x})] - \mathbb{E}_{x \sim \mathbb{P}_s}[D(x)] + \lambda \mathbb{E}_{x \sim \mathbb{P}_s}[\|\nabla x D(\tilde{x})\|_2^2 - 1]^2, \]  

(12)

where \( D(\cdot) \) is a score that measures the quality of the input sample. \( \mathbb{P}_r \) is the real distribution. \( \mathbb{P}_s \) is the learned distribution by the generator. \( \tilde{x} \) is sampled uniformly along the straight lines between pairs of points sampled from \( \mathbb{P}_r \) and \( \mathbb{P}_s \). The distribution of \( \tilde{x} \) is denoted as \( \mathbb{P}_{\tilde{x}} \). \( \mathbb{E}_{x \sim \mathbb{P}_s}[\|\nabla x D(\tilde{x})\|_2 - 1]^2 \) is the gradient penalty. \( \lambda \) is a positive scalar to control the degree of the penalty. The loss of the generator is:

\[ L_g = -\mathbb{E}_{x \sim \mathbb{P}_s}[D(\tilde{x})]. \]  

(13)

The contest between the discriminator and the generator is achieved by training Equations 12 and 13 jointly. The resulting model of this layer is a generator whose \( \mathbb{P}_s \) closely approximates the real distribution \( \mathbb{P}_r \). This generator can generate samples to compute the precise total effect and dynamic total effect according to Equations 8-11.

3.2.6. Joint Training of Prec-WD

The Prec-WD framework trains the previous components jointly based on mean squared error (MSE). The joint training is performed by backpropagating the gradients from the outputs of sub-components using mini-batch stochastic optimization. After the model is trained, the prediction will be made for an unseen sample and the total effect and the dynamic total effect of each input feature can be calculated.

Figure 1 shows the Prec-WD algorithm. Figure 2 shows the framework architecture.

---

**Input:** training data that include video features \( \mathbf{x}^{tr} = \{x_1^{tr}, x_2^{tr}, ..., x_{N_{tr}}^{tr}\} \) where \( N_{tr} \) is the number of videos in the training data and \( x_i^{tr} = (x_{i1}^{tr}, ..., x_{iM}^{tr}) \). \( \text{ADV}^{tr} = \{\text{adv}_1^{tr}, \text{adv}_2^{tr}, ..., \text{adv}_{N_{tr}}^{tr}\} \). Similarly, validation data \( \mathbf{x}^{val} = \{x_1^{val}, x_2^{val}, ..., x_{N_{val}}^{val}\} \) and \( \text{ADV}^{val} = \{\text{adv}_1^{val}, \text{adv}_2^{val}, ..., \text{adv}_{N_{val}}^{val}\} \). A small constant \( \epsilon \) (e.g., 0.1), \( n_s = 5 \). The number of synthetic samples \( N_{syn} \).

**Output:** model parameters and estimated total effects, dynamic total effects.

**Initialization:** \( \tilde{L}^{val} = 0, \Delta L^{val} = 10 \), initialize parameters \( \theta_{\text{Prec-WD}} \)

# Generative process

while \( \theta_{\text{gen}} \) not converge do

for \( i = 1, ..., n_s \) do

    Generate random vectors \( z \); Generator samples \( G_{\theta_{\text{gen}}}(z) \); Compute discriminator loss \( L_d \) according to Equation 9;

    Update discriminator weights \( \theta_{\text{disc}} \leftarrow \text{Adam}(L_d, \theta_{\text{disc}}) \).

end for

Compute generator loss \( L_g \) according to Equation 10.

Update generator weights \( \theta_{\text{gen}} \leftarrow \text{Adam}(L_g, \theta_{\text{gen}}) \)

end while

return generator weights \( \theta_{\text{gen}} \)

Generate random vectors \( z \)

Generator samples \( \mathbf{\tilde{x}} \leftarrow G_{\theta_{\text{gen}}}(z) \) where \( \mathbf{\tilde{x}} = \{\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_{N_{syn}}\} \)

# Training

19
while $\Delta L_{\text{val}} > \epsilon$ do:
  for $i = 1, \ldots, N_{\text{tr}}$ do
    Compute $y_i^{\text{pw}}$ according to Equations 1 and 2; Compute $y_i^{\text{as}}$ according to Equations 3-5; Compute $y_i^{\text{nh}}$ according to Equations 6 and 7; Compute $y_i^{\text{uc}}$; Compute $\hat{adv}_i$ according to Equation 8.
  end for
  Compute MSE loss $L_{\text{tr}}$ and update Prec-WD model weights $\theta_{\text{Prec-WD}} \leftarrow \text{Adam}(L_{\text{tr}}, \theta_{\text{Prec-WD}})$
  for $i = 1, \ldots, N_{\text{val}}$ do
    Compute $y_i^{\text{pw}}$ according to Equations 1 and 2; Compute $y_i^{\text{as}}$ according to Equations 3-5; Compute $y_i^{\text{nh}}$ according to Equations 6 and 7; Compute $y_i^{\text{uc}}$; Compute $\hat{adv}_i$ according to Equation 8.
  end for
  Compute MSE loss in validation set $L_{\text{val}}$
  Compute MSE loss change in validation set: $\Delta L_{\text{val}} = |L_{\text{val}} - \bar{L}_{\text{val}}|$
end while
return $\theta_{\text{Prec-WD}}$

for $j = 1, \ldots, M$ do
  for $c$ in all possible $X_j$ values:
    Compute dynamic total effect $\Delta \hat{ADV}(X_j = c)$ according to Equations 9-11.
    Compute total effect $\Delta \hat{ADV}(X_j)$ according to Equation 12.
  end for
end for
return $\Delta \hat{ADV}(X_j), \forall j; \Delta \hat{ADV}(X_j = c), \forall c, j$

**Figure 1. The Algorithm of Prec-WD**

**Figure 2. The Architecture of Prec-WD**

### 3.2.8. Novelty of Prec-WD

Compared to the W&D framework, Prec-WD has two novelties: 1) We propose a novel interpretation component that differentiates from W&D. W&D approximates the total effect using the main effect $w^T$, while our interpretation component is able to offer a precise total effect for the prediction using Equations 8-13. In order to capture the dynamic total effect for each feature, our model predicts the total effect at every feature value. The complex total effect when the feature varies can be modeled by our method. 2)
We extend the W&D framework by designing an unstructured component. This component extends the applicability of W&D to unstructured data analytics.

4. Empirical Analyses

4.1. Case Study 1: Health Video Engagement Prediction

4.1.1. Data Preparation

Due to the societal impact of healthcare and the timeliness of the COVID-19 pandemic, we first examine the utility of Prec-WD in health video prediction. We collected videos from the most well-known health organizations’ YouTube channels, including NIH, CDC, WHO, FDA, Mayo Clinic, Harvard Medicine, Johns Hopkins Medicine, MD Anderson, and Jama Network. In addition, we collected the third-party YouTube videos that share the same keywords as listed in the above nine channel’s playlists. In the end, we generated a dataset consisting of 6,528 videos and their webpages.

   Our features come from six sources: videos, audios, transcripts, video descriptions, webpages, and creators’ channels. The raw videos are directly fed into our model via the unstructured component. We also generate the commonly adopted video features using the BRISQUE measurement. In order to generate video features in a scalable and timely manner, we develop a python-based parallel processing method with 12 CPUs, which significantly reduced the expected computational time from 39 days to 7 days. To generate acoustic features, we separate the audio tracks from the videos. We utilize the Liborosa method to compute the acoustic features. In order to generate transcripts from audios, we develop a speech recognition model based on DeepSpeech. This model is trained on American English with synthetic noise augmentation that achieves a 7.06% word error rate on the LibriSpeech corpus. The trained speech recognition model is able to translate audios into transcripts. The description, webpage, and channel features are extracted directly from the webpage. A description of all the features and the methods to generate them are available in Appendix 1. In total, we generated 854 features.

4.1.2. Evaluation of Predictive Performance

We design two groups of baselines: blackbox methods (including machine learning and deep learning) (Ebrahimi et al. 2020, Xie et al. 2017, 2021, Xie and Zhang 2018, Zhang et al. 2016, Zhu et al. 2020,
2021) and interpretable methods (Cheng et al. 2016, Guo et al. 2020, Lee and Chan 2019, Tosun et al. 2020, Ye et al. 2019). These baseline models are detailed in Appendix 2. For all the following analyses, we adopt 10-fold cross validation where the dataset is divided into 10 folds. Each time we use one fold (10%) for test, one fold (10%) for validation, and eight folds (80%) for training. All the performances in the empirical analysis are the average performance of 10 times for each model. Table 2 shows the prediction comparison with blackbox methods.

### Table 2. Comparison of Prec-WD with Blackbox Methods

| Method               | MSE     | MSLE  | Method               | MSE     | MSLE  |
|----------------------|---------|-------|----------------------|---------|-------|
| Prec-WD (Ours)       | 165.442 | 0.992 | Gaussian Process-5   | 999.376 | 20.619|
| Linear regression    | 285.585 | **2.924** | MLP-1               | 364.064 | **3.094**|
| KNN-1                | 196.114 | **2.961** | MLP-2               | 351.437 | **2.852**|
| KNN-3                | 183.257 | **2.994** | MLP-3               | 281.090 | **2.728**|
| KNN-5                | 398.577 | **4.294** | MLP-4               | 279.648 | **2.550**|
| DT-MSE               | 382.407 | **3.624** | Gaussian Process-3   | 999.376 | 20.619|
| DT-MAE               | 374.503 | **4.065** | CNN-1               | 207.271 | **1.453**|
| DT-Fredmanmse        | 216.523 | **2.701** | CNN-2               | 193.240 | **1.333**|
| SVR-Linear           | 185.616 | **4.726** | CNN-3               | 199.997 | **1.414**|
| SVR-RBF              | 219.136 | **2.836** | CNN-4               | 196.158 | **1.326**|
| SVR-Poly             | 201.043 | **3.658** | LSTM-1              | 271.600 | **1.692**|
| SVR-Sigmoid          | 398.577 | **4.294** | LSTM-2              | 191.909 | **1.185**|
| Gaussian Process-1   | 999.376 | **20.619** | BLSTM-1             | 354.760 | **1.942**|
| Gaussian Process-3   | 999.376 | **20.619** | BLSTM-2             | 196.247 | **1.212**|

*: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

Compared with the best ML method KNN-3, Prec-WD reduces MSE by 17.815 ($p < 0.001$).

Compared with the best deep learning method LSTM-2, Prec-WD reduces MSE by 26.467 ($p < 0.001$).

Prec-WD remains the best when the hidden layers of the baseline models change. Although prediction is not the primary contribution of this study, our method still reached outperforming prediction results compared with state-of-the-art prediction benchmarks. The main downside of these blackbox methods is that they cannot offer feature-based interpretation. As we reiterated in the literature review, interpretability is critical in this study from the perspectives of trust, model adoption, regulatory enforcement, algorithm transparency, and practical implications and interventions for stakeholders.

Extending the line of interpretability, we compare Prec-WD with the state-of-the-art interpretable methods in Table 3. Compared with the best interpretable method W&D, Prec-WD reduces MSE by 35.072 ($p < 0.001$).

### Table 3. Comparison of Prec-WD with Interpretable Deep Learning
performance, suggesting optimal design choices. The left side of Prec-WD underwent the same parameter tuning process and reported the final fine-tuned results.

Table 4. Hyperparameter Fine-tuning

| Method-Network-Layer-Neuron | MSE  | MSLE | Method-Network-Layer-Neuron | MSE  | MSLE |
|-----------------------------|------|------|-----------------------------|------|------|
| Prec-WD-Dense-1-16          | 168.004 | 1.015 | Prec-WD-CNN-2-16            | 172.209 | 1.072 |
| Prec-WD-Dense-1-32          | 169.325 | 1.034 | Prec-WD-CNN-2-64            | 170.532 | 1.080 |
| Prec-WD-Dense-1-64          | 171.535 | 1.053 | Prec-WD-CNN-3-32            | 174.986 | 1.132 |
| Prec-WD-Dense-2-16          | 168.033 | 1.023 | Prec-WD-CNN-2-16            | 178.285 | 1.143 |
| Prec-WD-Dense-2-32          | 168.734 | 1.016 | Prec-WD-CNN-3-64            | 179.953 | 1.154 |
| Prec-WD-Dense-2-64          | 170.598 | 1.077 | Prec-WD-LSTM-1-16           | 175.494 | 1.015 |
| **Prec-WD-Dense-3-16**      | **165.442** | **0.992** | Prec-WD-LSTM-1-32           | 170.644 | 0.995 |
| Prec-WD-Dense-3-32          | 167.930 | 1.010 | Prec-WD-LSTM-2-16           | 168.650 | 0.984 |
| Prec-WD-Dense-3-64          | 166.352 | 1.040 | Prec-WD-LSTM-2-32           | 171.583 | 0.985 |
| Prec-WD-CNN-1-32            | 178.385 | 1.303 | Prec-WD-BLSTM-1-16          | 170.128 | 0.996 |
| Prec-WD-CNN-1-16            | 177.644 | 1.270 | Prec-WD-BLSTM-1-32          | 173.250 | 0.994 |
| Prec-WD-CNN-1-64            | 180.299 | 1.320 | Prec-WD-BLSTM-2-16          | 169.666 | 0.992 |
| Prec-WD-CNN-2-32            | 169.539 | 1.054 | Prec-WD-BLSTM-2-32          | 169.232 | 0.987 |

*: p < 0.05; **: p < 0.01; ***: p < 0.001

Note: Prec-WD-CNN-1-32 is the model that uses CNN to replace the deep part of Prec-WD. It has 1 hidden CNN layer with 32 neurons. Similar construction method applies to other architectures.

We further perform ablation studies to test the efficacy of the individual components of Prec-WD. The left side of Table 5 shows that removing any component of Prec-WD negatively impacts the performance, suggesting optimal design choices. In order to test the effectiveness of each feature group, we remove each feature group stepwise and test its contribution to the performance. The right side of Table 5 shows that removing any feature group will hamper the performance.

Table 5. Ablation Studies

| Method | MSE  | MSLE | Features | MSE  | MSLE |
|--------|------|------|----------|------|------|

We fine-tune the hyperparameters of Prec-WD to search for the best predictive performance. The hyperparameters include the number of hidden layers and the number of neurons in each layer. We replace the higher-order component in Prec-WD with other deep neural networks, including CNN, LSTM, and BLSTM, to evaluate the design choice. The fine-tuning results are shown in Table 4. The final model has 3 dense layers in the higher-order component and 16 neurons in each layer. To ensure fair comparison, all the baseline methods in Tables 2-3 underwent the same parameter tuning process and reported the final fine-tuned results.
| Prec-WD                      | 165.442  | 0.992  | All              | 165.442  | 0.992  |
|-----------------------------|----------|--------|------------------|----------|--------|
| Prec-WD without unstructured component | 181.056** | 1.060* | Without Webpage  | 189.535*** | 1.153** |
| Prec-WD without piecewise linear component | 213.434*** | 1.340*** | Without Unstructured | 182.847*** | 1.086** |
| Prec-WD without second-order component | 187.401*** | 1.107** | Without Acoustic | 177.610**  | 1.030  |
| Prec-WD without high-order component | 191.891*** | 1.152** | Without Description | 174.599*   | 1.018  |
| Prec-WD with simple linear encoding | 189.712*** | 1.063*  | Without Transcript | 170.482*   | 1.004  |
| Prec-WD with 10 ordinal one hot encoding | 190.224*** | 1.047*  | Without Channel  | 170.391*   | 1.006  |
| Prec-WD with 20 ordinal one hot encoding | 186.767*** | 0.994   |                  |            |        |
| Prec-WD with 10 ordinal encoding | 191.969*** | 1.149*** |                  |            |        |
| Prec-WD with 20 ordinal encoding | 195.750*** | 1.319*** |                  |            |        |
| Prec-WD without attention | 175.104*  | 1.053*  |                  |            |        |

*: p < 0.05; **: p < 0.01; ***: p < 0.001

4.1.3. Interpretation of Prec-WD

As the core contribution, Prec-WD can offer precise total effect using the proposed interpretation component. The WGAN-GP layer in the interpretation component estimates the data distribution to facilitate the computation of Equations 8-13. The training process contains a generator and a discriminator. The learning objective is to minimize the loss of these two. The loss of the generator (G_loss) and discriminator (D_loss) in Prec-WD are shown in Figure 3. The generator loss and discriminator loss converged after 8,000 iterations, indicating the training procedure is stable. To evaluate the synthetic samples, we visualize the distributions of the synthetic samples and the real samples in Figure 4. Since our feature space has 854 dimensions, we reduce the dimensions to two using t-SNE for visualization purposes (Van Der Maaten and Hinton 2008). The green circles are the real samples, and the red triangles are the synthetic samples. As shown in Figure 4, the real samples and the synthetic samples are inseparable, suggesting the synthetic samples can accurately mimic the distribution of the real samples. This result confirms the high quality of the synthetic samples.

We perform ablation studies to test alternative generative models, including VAE and Bayesian Network, reported in Table 6. We first use Principle Component Analysis to reduce the feature dimension, which resulted in 10 major dimensions. Table 6 suggests only WGAN-GP can generate samples that have statistically no difference from the real samples in means and variances. We plot the feature-based interpretations in Figure 5.

1 For visualization simplicity, we average over all the video features into one feature, as they all represent the video quality with the same scale. We also average over all the acoustic features into one feature, because they measure the audio quality with the same scale. In order to compare all the features in the same scale, we normalized the effect values.
The transcript and description features have a salient influence on the prediction. The transcript directly reflects the video content, and the description is a paragraph summarizing the content. These features include the number of medical terms, informativeness, readability, and complexity. The results
show that one unit of increase in transcript readability results in an increase of 757.402 average daily views. Medical knowledge, operationalized as the number of medical terms, has a sizable influence on the prediction as well. One unit of increase in the transcript medical terms will raise the average daily views by 440.649. These features measure how well the video can be perceived and how much medical information it contains. An easy-to-read and medically informative transcript or description leads to better engagement as the viewers attempt to seek medical information from the videos. Conveying the medical information that the viewers wanted to the largest extent could entertain the viewers and retain them to watch the rest of the video. If the medical information is easy to comprehend, the viewers have a better understanding of the video topic, which motivates them to watch the details from the video.

The transcript and description sentiments also significantly affect the prediction. A unit of increase in the transcript or description sentiment scores leads to an increase of 0.146-0.784 units in average daily views. These sentiments in the video bring in personal opinions and experience, which are relatable to viewers, thus enticing stronger viewer engagement.

The channel features have a critical influence on the prediction as well. In particular, if a channel is verified, the average daily views increase by 0.443 units. YouTube collects information from verified channels, such as phone numbers. Verified channels signal authenticity and credibility to viewers. Therefore, the viewers are more likely to watch the videos posted by these channels.

Figure 5 shows the average total effect of each feature. Prec-WD is also capable of estimating the dynamic total effect. Below, we randomly select three features and show how our method captures the dynamic total effect (Description complexity, description readability, and transcript negative sentiment). Figure 6.a. shows that the total effect of description complexity is positive when description complexity is low. Such a total effect turns negative when description complexity is high. This is because when description complexity is low, increasing complexity makes the description more formal and authoritative. Viewers watch it more because they trust it. As the complexity continues to increase, the description becomes too hard to comprehend and viewers lose interest in the video. Figure 6.b. shows that the total effect of description readability increases when the readability value increases. This could be
because when the description is readable, it is also easier for the viewers to understand the medical knowledge and other content in the video. Figure 6.c. indicates that the total effect of transcript negative sentiment increases when the value of transcript negative sentiment increases. When a video is enriched with negative sentiment, it usually contains opinions and commentaries, which may be relatable to the viewer’s personal experience or belief and even entice the viewers to write comments. Those interactions in the comment section further enhance video engagement.

Figure 6. Examples of the Dynamic Total Effect (Case Study 1)

4.1.4. Our Precise Interpretation v.s. Existing Approach

Our proposed framework offers the precise interpretation (total effect), while the existing frameworks could only approximate the interpretation using the main effect. The error correction of our framework has significant improvement on the feature interpretation. For instance, our framework interprets description readability to have a positive influence on video engagement. This is because readable descriptions are easy to comprehend, thus attracting viewers. However, the existing approach (main effect) interprets description readability to have a negative influence, contradicting common perception.

We also quantify the influence of the interpretation error correction in Table 7. We bolded the ones where the total effect and the main effect have an opposite direction. Such differences further validate the contribution of our precise interpretation component.

Table 7. Interpretation Error Correction (Normalized, Case Study 1)

| Feature             | Total Effect | Main Effect | Feature             | Total Effect | Main Effect |
|---------------------|--------------|-------------|---------------------|--------------|-------------|
| Use Cipher          | 0.000        | 0.053       | Description Compound Sentiment | 0.690        | 0.099       |
| Is Private          | 0.000        | 0.086       | Description Med Terms | 0.530        | 0.496       |
| Is Live Content     | 0.539        | 0.858       | Transcript Bigrams  | 0.109        | -0.816      |
| Video Duration      | 0.384        | 0.100       | Transcript Length   | 0.084        | 0.009       |
| Average Bitrate     | -0.135       | -0.151      | Transcript Complexity| 0.834        | 1.160       |
| Audio Sample Rate   | 0.000        | -0.459      | Transcript Readability| 0.390        | -2.959      |
| Audio Channels      | 0.539        | -0.053      | Transcript Informativeness| 0.105        | -0.200      |
| Description Bigrams | -0.020       | -0.853      | Transcript Stats    | 0.000        | 1.952       |
### 4.2. Case Study 2: Misinformation Viewership Prediction

Among all the YouTube videos, misinformation is the most concerning, as it leads viewers to institute ineffective, unsafe, costly, or inappropriate protective measures; undermine public trust in evidence-based health messages and interventions; and lead to a range of collateral negative consequences (Schillinger et al. 2020). Successful containment of misinformation hinges on accurate prediction of misinformation spread as well as the understanding of the factors. Case study 2 evaluates Prec-WD by predicting misinformation viewership. A number of trusted news outlets have identified a set of videos with health misinformation on YouTube (Appendix 4). We crawled all the videos reported by these sources, including 4,445 misinformation videos and their webpages.

We performed all the evaluations as we did in case study 1. Our method reached consistent leading performance. Compared to the best machine learning baseline model (KNN-3), Prec-WD drops MSE by 11.398. Compared with the best deep learning method (CNN-3), Prec-WD reduces MSE by 3.988. Compared with the best interpretable model (W&D), Prec-WD reduces the MSE by 29.206. Ablation study results excluding any component negatively impacts the performance. We also performed hyperparameter tuning, ablation analysis in feature group, and the ablation comparison with Bayesian Network and VAE. The conclusions are consistent with Study 1 and in favor of our method. Table 8 shows the comparison with baseline models. Table 9 shows the ablation studies. The other evaluations are reported in Appendix 3.

| Method          | MSE   | MSLE  | Method          | MSE   | MSLE  |
|-----------------|-------|-------|-----------------|-------|-------|
| Prec-WD (Ours)  | 140.202 | 0.728 | MLP-3           | 162.349*** | 0.950*** |
| Linear regression | 881.027*** | 3.184*** | CNN-1           | 245.382*** | 1.377*** |
| KNN-1           | 227.479*** | 2.421*** | CNN-2           | 158.040*** | 1.090*** |
| KNN-3           | 163.061*** | 2.327*** | CNN-3           | 155.651*  | 1.023*** |
| KNN-5           | 180.479*** | 2.264*** | CNN-4           | 169.584*** | 1.065*** |
| DT-MSE          | 284.387*** | 3.362*** | LSTM-1          | 341.301*** | 1.718*** |
| DT-MAE          | 288.223*** | 3.193*** | LSTM-2          | 182.828*** | 1.099*** |

Table 8. Comparison of Prec-WD with Baseline Models (Case Study 2)
SVR-Linear 185.644*** 4.924*** BLSTM-1 367.261*** 1.661***
SVR-RBF 185.989*** 4.901*** BLSTM-2 175.995*** 0.999***
SVR-Poly 192.951*** 4.913*** BLSTM-2 180.869*** 1.067***
SVR-Sigmoid 185.646*** 4.924*** W&D (Cheng et al. 2016) 186.773*** 1.866***
Gaussian Process-1 1291.331*** 8.508*** W&D-CNN (Lee and Chan 2019) 137.919*** 1.598***
Gaussian Process-3 1291.331*** 8.508*** W&D-LSTM (Ye et al. 2019) 206.321*** 2.454***
Gaussian Process-5 1291.331*** 8.508*** Piecewise W&D-10 (Guo et al. 2020) 227.633*** 3.116***
MLP-1 172.460*** 1.005*** W&D-10 (Guo et al. 2020) 206.792*** 3.016***
MLP-2 169.147*** 1.063***

*: p < 0.05; **: p < 0.01; ***: p < 0.001

### Table 9. Ablation Studies in Case Study 2

| Method                      | MSE  | MSLE | Data Sources | MSE  | MSLE |
|-----------------------------|------|------|--------------|------|------|
| Prec-WD                     | 140.202 | 0.728 | All (Ours)   | 140.202 | 0.728 |
| Prec-WD without unstructured component | 151.259* | 0.887* | Without Webpage | 194.553*** | 0.908** |
| Prec-WD without piecewise linear component | 175.136** | 0.915* | Without Unstructured | 164.936*** | 0.779 |
| Prec-WD without second-order component | 155.984* | 0.890* | Without Acoustic | 155.798*** | 0.817* |
| Prec-WD without high-order component | 159.354* | 0.848* | Without Description | 156.647*** | 0.832* |
| Prec-WD with simple linear encoding | 153.454* | 0.872** | Without Transcript | 149.663* | 0.770 |
| Prec-WD with 10 ordinal one-hot encoding | 167.449** | 0.938** | Without Channel | 147.250* | 0.737 |
| Prec-WD with 20 ordinal one-hot encoding | 166.821* | 0.968*** | Without Channel | 147.250* | 0.737 |
| Prec-WD with 10 ordinal encoding | 195.510*** | 2.862*** | Without Channel | 147.250* | 0.737 |
| Prec-WD with 20 ordinal encoding | 195.510*** | 2.862*** | Without Channel | 147.250* | 0.737 |
| Prec-WD without attention | 153.454* | 0.872** | Without Channel | 147.250* | 0.737 |

*: p < 0.05; **: p < 0.01; ***: p < 0.001

### Figure 7. Feature-based Interpretation (Normalized, Case Study 2)

As the primary contribution of our framework, we interpreted the prediction of case study 2, shown in Figure 7. The textual features and sentiments of transcript and description are critical features associated with misinformation video popularity. The interpretation of the prediction sheds light on the management of video credibility for video sharing platforms. These platforms could utilize our method to monitor the transcript and description features. Medical-related videos whose description is well perceived should be under scrutiny. When a video shows overwhelmingly negative content, it needs to be closely monitored as...
well to prevent misinformation spread widely. The detailed interpretation is included in Appendix 5.

4.3. Evaluation of Interpretation Component

Since our precise interpretation component is the core contribution, this section compares the Prec-WD’s interpretability with state-of-the-art interpretable frameworks. To quantify the interpretability, we design a user study. We devise five groups in Table 10. We recruited 174 students from two national universities in Asia. They were randomly assigned to one of these five groups. To ensure randomization, we selected nine control variables: age, gender, education, knowledge in CS, knowledge in ML, video watching frequency, video uploading experience, trust in AI and automation, and health literacy. The summary statistics of the control variables are shown in Appendix 7. We perform one-way ANOVA on the control variables and the outcome variable (interpretability) for randomization checks. Table 11 indicates the control variables do not affect interpretability. The full survey can be found in Appendix 6.

Table 10. Experiment Groups

| Group | Model                  | Rationale                                                                 |
|-------|------------------------|---------------------------------------------------------------------------|
| A     | Prec-WD                | Our model                                                                 |
| B     | W&D                    | Best-performing interpretable baseline model in Table 3                    |
| C     | Piecewise W&D          | State-of-the-art model-based interpretable model                          |
| D     | SHAP                   | State-of-the-art post-hoc interpretable model                             |
| E     | VAE-based model        | Best-performing generative baseline model in Table 5                      |

Table 11. Randomization Check in User Study

| Variable          | P-value of ANOVA (Trust) | P-value of ANOVA (Usefulness) |
|-------------------|--------------------------|-------------------------------|
| Age               | 0.281                    | 0.404                         |
| Education         | 0.265                    | 0.349                         |
| Gender            | 0.449                    | 0.133                         |
| CS Knowledge      | 0.884                    | 0.944                         |
| ML Knowledge      | 0.335                    | 0.410                         |
| Video Watching Frequency | 0.602          | 0.973                         |
| Upload Experience | 0.811                    | 0.589                         |
| Trust in AI       | 0.579                    | 0.560                         |
| Health Literacy   | 0.306                    | 0.213                         |

The participants were notified they would be assigned a ML model to predict the daily viewship of a YouTube video. We would show them the variables the model uses and the weights of the variables. We disclosed that the more reasonable these variables and weights are, the more accurate the prediction would be, and that their compensation is positively related to the prediction performance.

To ensure the participants understand what the variables and weights mean, we designed a training
session. We displayed a pseudo model, shown in Figure 9. We informed them the weight of a variable indicates the importance of the variable. We presented one example: “If the weight of a variable is 0.3, this means increasing this variable by 1 unit, the model’s prediction of this video's daily viewership will increase by 0.3 units.” After that, we designed the following two test questions to teach them how to read the model. If the participants choose an incorrect answer in the training, an error message and a hint will appear on the screen, shown in Figure 8. They need to find the correct answer before proceeding to the next page. This process ensures they can learn to understand the variables and weights of a model. The training session, test questions, and hint wording are the same across all groups.

1. **Question:** According to the above figure, when using the above model to predict the daily viewership of videos, what are the top two essential variables that have positive effects?  
   **Options:** Variable 1, Variable 2, Variable 3, Variable 4, Variable 5, Variable 6, Variable 7

2. **Question:** According to the weights in the figure, if variable 6 increases by 1 unit, how will the above model prediction of video viewership change?  
   **Options:** Increase by 0.3 unit, Increase by 0.6 unit, Decrease by 0.3 unit, Decrease by 0.6 unit

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**Figure 8. User Study Training Session Error Message**

**Figure 9. Pseudo Model in the Training Session**  **Figure 10. Model Displayed in the User Study**

In the experiment, we first ask the participants to watch the same YouTube video to familiarize the prediction target and context. We then show them a screenshot of the video webpage (Appendix 8), depicting the potential variables we can use for prediction. Then, we show them the variables and weights.
of their assigned model (Figure 10). We choose the seven most important variables by weight, because seven is considered the “Magical Number” in psychology and is the limit of our capacity to process short-term information (Miller 1956). To help the participants fully understand Figure 10, we design the following four test questions. If the participants choose an incorrect answer, an error message and a hint will appear on the screen, shown in Appendix 9. They need to find the correct answer before proceeding to the next page. This process ensures they can learn to understand the variables and weights of the given model. The test questions and hint wording are the same across all groups.

| Question | According to the above figure, when using the above model to predict video viewership, please rank the following variables from the most important to the least important used by the model. Please put the most important variable on the top and the least important on the bottom. You can drag the variables to reorder. Hint: The importance of a variable in a prediction can be measured by the weight of the variable.  
Options: The seven variables in a randomized order |
|-----------------|----------------------------------------------------------------------------------|
| 2. Question: | What are the top 2 most essential variables in the above model?  
Options: Description readability, Description negative sentiment, Transcript med terms, Transcript complexity |
| 3. Question: | If the creator of the above video would like to increase video viewership, which of the following option is more effective?  
Options: Increase "Is live content" by 1 unit, Increase "Transcript negative sentiment" by 1 unit |
| 4. Question: | According to the weights in the figure, if the "Description negative sentiment" increases by 1 unit, how will the above model prediction of video viewership change?  
Options: Increase by 1 unit, Increase by 0.6 unit, Decrease by 1 unit, Decrease by 0.6 unit |

After answering the previous questions correctly, the participants have a good understanding of the assigned model. We then ask them to rate the interpretability of this model. The literature review suggests that “interpretability is related to how well humans trust some information by looking and reasoning about it.” We adopt trust in automated systems as the first interpretability measurement (Chai et al. 2014). Dhurandhar et al. (2017) suggests “AI is interpretable to the extent that the produced interpretation is able to maximize a user’s target performance.” Our target is viewership prediction. Following Dhurandhar’s definition and similar designs in Lee et al. (2018), models that are more useful for viewership prediction decision is more interpretable. We adopt usefulness as the second interpretability measurement. The two measurement scales can be found in Appendix 6. The Cronbach’s Alpha is 0.963 for the trust in automated systems scale in our study, and 0.975 for the usefulness scale, suggesting excellent reliability. The factor loadings are shown in Appendix 10, showing great validity. We perform t-tests in Table 12 on our method and the other four groups to compare interpretability. We designed an attention check.
question in the scales (“Please just select neither agree or disagree”). After removing those who failed the attention check, we have 152 remaining participants.

Table 12: Comparison of Interpretability for Prec-WD and Interpretable Methods

| Group        | Mean of Interpretability: Trust | P-value of T-test with Prec-WD | Mean of Interpretability: Usefulness | P-value of T-test with Prec-WD |
|--------------|---------------------------------|---------------------------------|--------------------------------------|---------------------------------|
| Prec-WD      | 2.415                           | NA                              | 2.433                                | NA                              |
| W&D          | 1.559                           | 2.83E-05***                     | 1.500                                | 6.40E-06***                     |
| Piecewise W&D| 0.606                           | 1.06E-14***                     | 0.495                                | 3.83E-15***                     |
| SHAP         | 1.378                           | 4.20E-06***                     | 1.255                                | 5.77E-07***                     |
| VAE          | 1.202                           | 3.60E-06***                     | 1.160                                | 3.10E-06***                     |

Prec-WD has significant better interpretability than other methods. Compared with the best baseline method W&D, Prec-WD improves the user-rated interpretability by 55% (trust measurement) and 62% (usefulness measurement). Such improvement is attributed to Prec-WD’s ability to capture precise total effects which result in the most reasonable and trustworthy variables and ranking, while the baseline groups include many counter-intuitive variables and rankings. For instance, W&D shows the count of numbers in the description is the most important variable, which has little to do with the video content. Piecewise W&D suggests the number of bi-grams in the transcript is a top variable, while the readability is the least important. Such ranking is the inverse of common understanding. SHAP shows videos with more audio tracks reduce engagement, which contradicts common perception because more audio track options should add more foreign viewers. VAE suggests the number of bi-grams in the transcript is the most important variable. These examples significantly reduce participants’ trust in these models.

After the participants rated interpretability, as a supplementary step, we further investigate which model each participant would finally adopt. We tell the participants that they have a chance to decide whether to keep the current model. If they think the variables and weights of the previous model are not reasonable, they have a chance to change to a different model. Since we incentivized the participants to choose the most reasonable model in the beginning\(^2\), their final adoption indicates the model that they trust the most. Then we show them the variables and weights of all the five models, similar to Figure 7.

\(^2\) After the experiment, we disclosed how their model performed relative to the other four models. We compensated them with different-valued office supplies in the end, according to the model performance ranking.
The order of the five models is randomized. We ask which model they would like to finally adopt for the prediction, and the trust in automated systems and usefulness scales are displayed again to measure the interpretability of the adopted model. The results are reported in Tables 13 and 14.

### Table 13. Number of Participants in Each Original Model and Final Adopted Model

| Switch to Prec-WD | Original: Prec-WD | Original: Baseline |
|-------------------|-------------------|-------------------|
|                   | 23                | 92                |
| Switch to Baseline| 7                 | 30                |

### Table 14. Comparison of 1st Time and 2nd Time Interpretability

|                  | Mean of 1st Interpretability: Trust | Mean of 2nd Interpretability: Trust | T-test for Two Times | Mean of 1st Interpretability: Usefulness | Mean of 2nd Interpretability: Usefulness | T-test for Two Times |
|------------------|-------------------------------------|-------------------------------------|----------------------|------------------------------------------|------------------------------------------|----------------------|
| Prec-WD → Prec-WD| 2.700                               | 3.324                               | 0.0001***            | 2.717                                    | 3.348                                    | 0.000049***          |
| Prec-WD          |                                     |                                     |                      |                                          |                                          |                      |
| Baseline → Prec-WD| 0.924                               | 2.616                               | 2.20E-16***          | 0.868                                    | 2.583                                    | < 2.2e-16***         |

115 participants (75.66%) finally adopted our model regardless of what model they were originally assigned. Table 14 shows for those who finally adopted our model, the 2nd time interpretability is higher than the 1st time. This is because after the participants see the five models, the relative advantage of our model is even more obvious, causing them to rate the interpretability of our model higher the second time.

5. Discussion

5.1. Implications to Information Systems

In line with the design science research guidelines (Hevner et al. 2004), this study identifies an impactful social media analytics problem: video engagement prediction. We demonstrate that no adequate solutions exist in the prior literature and develop a novel information system that predicts video engagement while interpreting prediction factors. We conduct comprehensive evaluations and interpretations of the information system and design a user study to assess its utility. This study also fits in the computational genre of design science research (Rai 2017). The computational design science paradigm emphasizes an “interdisciplinary approach in developing novel data representations, computational algorithms, business intelligence, and analytics methods” (Rai 2017). Our study develops an interdisciplinary approach that involves a novel computational algorithm and an analytical solution to a major social problem, thus holding great potential for generating IS research with significant societal impact (Abbasi et al. 2018, Ebrahimi et al. 2020, Karahanna et al. 2018, Lin and Fang 2021, Yu et al. 2021).
5.2. Methodological Implications

We devise a novel Prec-WD framework to predict and interpret video engagement. Prec-WD innovatively models unstructured data and proposes an interpretation component to estimate precise total effect and dynamic total effect. The prediction performance of Prec-WD surpasses strong baselines. A user study confirms this approach significantly improves interpretability. Our feature interpretation enhances decisions and actions via improved trust and model usefulness. Prec-WD is not restricted to the video engagement prediction context. It can be generalized to understand the underlying factors of other human behaviors, including healthcare, cybersecurity, and technology acceptance, among others.

5.3. Practical Implications

This study offers many practical implications for the stakeholders. For the video-sharing platforms, Prec-WD is an implementable analytics tool that can predict video viewership. Our framework also offers the interpretation of this prediction. Since YouTube relies on the percentage of total views to manage video credibility, our framework provides YouTube insights to design intervention measures to promote legitimate videos’ viewership and curb violative videos’ viewership. For instance, negative videos from verified channels with easy-to-read descriptions need to be specially monitored. Content creators could leverage our framework to predict their viewership in order to decide where to allocate more budgets. Our interpretation also gives content creators directions to improve video engagement.

5.4. Limitations and Future Directions

This study has several limitations and areas for improvement. First, besides predicting video engagement, our method could also understand other human behaviors in healthcare, cybersecurity, and technology acceptance. However, new data types and representations need to be engineered to feed into the model. Future work could extend our method (data types, features, among others) to test its efficacy in other research contexts. Second, we focused our empirical analyses on YouTube videos. Other social media platforms, such as Facebook and Twitter, are also popular outlets for user engagement. More ground truth data could be collected from them to perform empirical analyses. Future work could adapt our framework with certain modifications to cater to text and audio analytics in Facebook and Twitter.
6. Conclusion

Understanding video engagement is fundamental for content creators and video-sharing sites. This study proposes Prec-WD for video engagement prediction and interpretation. To addresses the pitfalls of prior interpretable methods, our study incorporates an unstructured component and creates an innovative approach to estimate the precise total effect of as well as its dynamic changes. Empirical results indicate that Prec-WD outperforms strong baseline models. This method holds the potential to be generalized to understand other human behaviors. A user study confirms that the interpretability of Prec-WD is significantly better than other interpretable methods, particularly in improving trust and model usefulness. These findings offer implementable action plans for content creators and video sharing platforms to improve video engagement and manage video credibility.

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