Physiological and Socio-Behavioral Determinants of Viral Video User Engagement

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***Abstract* - The use of social media platforms like TikTok, Facebook, and YouTube to consume videos has seen significant growth in recent years. Some videos can generate high levels of engagement - views, likes, shares, or comments - at a rapid pace, making them "viral." However, understanding what causes these videos to become viral or predicting virality is still largely a mystery. This study aimed to uncover if biometrics-based emotion and arousal data, such as facial muscle and skin conductance data, could predict user engagement and contribute to video virality. The experiment used 64 participants, who watched 13 videos and had their facial expressions and galvanic skin response (GSR) data recorded throughout the viewing experience. The study then used an XGBoost classifier and 42 collected features, including physiological data and socio-behavioral responses, to predict user engagement (willingness to like, share, or comment) with over 80% accuracy. The results indicate that a combination of facial expression, GSR, and socio-behavioral data can accurately distinguish between high and low user engagement without needing to ask viewers anything about the videos or analyze video content. This study elevates the role of viewers' physiological and subconscious responses to video content across the viewing experience.**

Keywords - Video virality; Emotions; Facial expression; Galvanic skin response; XGBoost; Predictive modeling

I. INTRODUCTION

Video sharing has experienced tremendous growth over the previous decade [1]. Industry marketers and researchers alike have recognized that some videos garner high viewer engagement. Knowledge of how these videos become viral remains limited and elusive. Not surprisingly, the task of predicting which videos will become viral is even more challenging [2]. The present paper accepts this challenge by exploring the use of biometric-based user emotion data in conjunction with more advanced machine learning-based analytics to predict individuals' willingness to engage with videos on social media.

Social media platforms such as TikTok, Facebook, and YouTube offer social interaction, information, news, and entertainment via video modalities for large segments of the population [1]. Achieving 'viral' status has become the holy grail of digital marketing as well as a status sought by social video content creators. However, achieving virality is hard, rare, and valuable [3].

Researchers know emotions to be essential in the context of video virality and viewer engagement, but little progress has been made to convert emotional content-to-virality knowledge into actionable, predictive models. Recent advances in emotion detection across human-computer interaction research streams generally [4] and biometrics specifically based upon facial muscle movement, skin conductance, and other observations [5] offer new insights into users' affective states, including those of video viewers. New biometric methods, based upon Facial Action Coding System (FACS) [6-7] and skin conductance [8], assess emotions and emotion-related arousal at an instinctive and subconscious level during video consumption rather than in moments or metrics after video consumption thus increasing the likelihood video virality can be predicted.

The present study intends to generate a video virality predictive model based upon biometric data captured during the whole of the video viewing activity. To do so, the following research question is posed: Can users' physiological manifestation of emotions captured through facial expressions and skin conductance during video viewing be used to predict viewers' video engagement successfully?

II. BACKGROUND

A. Video Virality

A viral video is one viewed and shared expeditiously across popular social platforms. Common to all virality definitions is that a viral video takes advantage of the network effect [9], where the term 'viral' is a metaphoric reference to a contagious virus easily spreading quickly from one host to another. Emotion-focused research found that expressing emotional connection and emotional generosity in social media may prompt viral video sharing [10], while videos using emotion-eliciting strategies were more likely to be shared [3]. The relationship between video virality messages and emotions was also explored through the lens of consumers' emotional reactions to videos [11].

Video virality is of interest to computer science and information systems disciplines, especially in predictive modeling. For instance, Tik Tok dance video virality prediction was proposed using a multi-modal framework that integrates skeletal, holistic appearance, facial and scenic cues [12]. Others used models leveraging Support Vector Regression [13] and neural networks [14] to predict the future popularity of YouTube videos.

Problematic for virality studies however, previous research has relied upon two processes which may lead to incomplete data or incomplete analyses: non-subconscious data collection and self-reporting. To respond to both of these issues, the present study forges new paths for virality research by including subconscious data collected from video viewers during video viewing with no reliance upon self-reporting after the viewing experience.

B. *Biometric Sensors: Facial Muscle Movement and Galvanic Skin Response*

More recent advances in biometrics, based on Facial Action Coding System (FACS), provide new methods of assessing emotions at an instinctive and subconscious level. FACS, a method designed to help classify human fascial muscle movement, is used by facial expression researchers and human coders to identify and understand facial action units (AU) or basic facial movement building blocks from which more complex facial expressions can be understood [17]. More recently, tools automating facial expression analysis have emerged. Consequently, we have witnessed an increase in research and practical application of automated facial expression tools over the last three decades.

Galvanic Skin Response (GSR), also referred to as electrodermal activity (EDA), Skin Conductance Response (SCR), or Psychogalvanic Reflex (PGR), is a measure of the variation of conductivity of human skin due to sweat secretion [8]. GSR research has found that the increase in SCR (or "GSR peak") is linked to an increase in emotional arousal [8]. SCR, as a response to a stimulus extant usually within 1-5 seconds following the stimulus, is called Event-Related SCR [18], and it has been deployed by researchers to detect correlations between the arousal level of emotions [19], [20]. Although GSR data cannot provide the direction of the emotion it measures by itself, simultaneous use of a GSR sensor and automated FACS is a particularly effective way of understanding both the valance and the arousal associated with an emotional response [21].

Extant literature suggests that a viewer's emotions trigger participatory behavior as an essential element to video virality. Building on this notion, the present experiment was designed and deployed to collect rich facial expression consisting of over 20 emotional channels/AUs, seven basic emotions, valence, and visual engagement and attention variables, as well as GSR (peaks per minute) datasets to predict participatory behavior via users' willingness to like, share, and/or comment upon the videos they view.

III. Experiment And Data Collection

A. *Subjects*

Sixty-four undergraduate students from a public Midwestern university participated in data collection. About 34% (22) of participants identified as females. 97% (62) of subjects were between 19 and 22 with an average age of 20.2 years old, and most considered themselves dependents. About 72% (46) of participants were employed part-time (<40 hrs. per week). Virtually all participants identified as "white" (63) and never married (62). Most participants recently shared, commented, or liked video content on social media (during the day of the experiment or in the last seven days), with 'like' being the most frequent engagement activity.

B. *Experiment Set-up and Data Collection*

Subjects watched 13 videos in random order (See Appendix, Table 3 for a complete list). During video viewing, each participant's face and reactions were recorded using an HD camera and collected using the iMotions biometric platform through its Affectiva AFFDEX algorithm and iMotions' Facial Expression module. Similarly, GSR data was collected using the Shimmer GSR+ sensor and iMotions' GSR module. A Shimmer GSR+ device was placed on participants two fingers of one hand to monitor skin conductivity between two reusable electrodes (Figure 1).

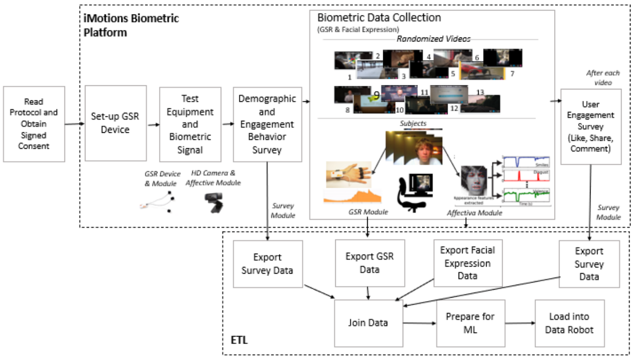

Figure 1: Experimental Setup & Data Collection

Before biometric data collection, each participant completed a survey to collect socio - demographic and past video engagement behavioral data. The answers were recorded and labeled as socio-behavioral features of 'Last Time Shared' (LAST_ENG1), 'Last Time Commented On' (LAST_ENG2), 'Last Time Liked' (LAST_ENG3) (for each question, the answer options were 'Today', 'Last 7 days', 'Last 30 Days', 'Last 360 Days', and 'Never), Income, Gender, Education & Employment status.

Each participant's video recording was post-processed using Affectiva's AI algorithm (AFFDEX) to capture twenty emotional channels, three valance categories (positive, neutral, and negative valance), two engagement metrics (engagement and attention time), and seven basic emotions (anger, contempt, disgust, fear, joy, surprise, and sadness) from participants' facials expressions. Counts for each biometric metric collected were excluded so that the input file only includes % of the time for each variable. This was done to eliminate bias due to differences in video lengths. Given the exploratory nature of the present research, and a relatively low number of features and data records (fast computation time), this study selected to leave all 42 features for model building (See Appendix, Table 2 for a complete list).

After each video, participants were asked to rate how likely they were to like, share, and comment on the video (1-7 scale). A prediction target feature was calculated (AVG_USER _ENGAGEMENT), using the average of Like, Share, Comment variable scores and then discretized into High (above mean) and Low (below mean) as the prediction target.

IV. Modeling

A. Predictive Algorithm and Model Selection

Once data was loaded into DataRabot, this study used a number of classifiers and 77 resulting models to find the best model. Cross-entropy loss, or Log Los, as a measure of the inaccuracy of predicted probabilities, was used to rank the models, an appropriate measure given the binary classification problem (High (1)/Low (0)). All models were created using 80% of data for training & validation and 20% as a holdout to test the model. K-folds (5 folds) were used in all models The initial list of models was ranked using validation results based on 64% of the data used in training the models (in training and validation folds, The top eight models were kept on the list and used in cross-validation (across five folds). The top model (again, based on Log loss performance), using eXtreme Gradient Boosted Trees (XGBoost) Classifier survived and was used against the hold-out or 20% of data (167 records) that our model was blind to when the best model was selected.

XGBoost is a very efficient, parallel version of the Gradient Boosting Machines (GBM) classifier [22] that has been heavily optimized for faster runtimes and higher predictive accuracy [23]. GBMs are an advanced algorithm (supervised) for fitting highly accurate predictive models. GBMs generalize Freund and Schapire's AdaBoost algorithm that handles arbitrary loss functions. XGBoost has been applied successfully across contexts and has become a widely popular tool among Kaggle competitors [24] and Data Scientists.

B. Model Evaluation

To assess the performance of the XGBoost-based model, this study followed standard performance measures: (i) True Positive (TP): The number of high user engagement videos correctly predicted as resulting in high user engagement. (ii) False Positive (FP): The number of low user engagement videos wrongly predicted as resulting in high user engagement, (iii) True Negative (TN): The number of low user engagement videos correctly predicted as resulting in low user engagement, and (iv) False Negative (FN): The number of high user engagement videos wrongly predicted as resulting in low user engagement (Figure 2).

n=167		Predicted Low (0)	Predicted High (1)	
Actual	Low (0)	TN 57	FP 28	85
Actual	High (1)	FN 12	TP 70	92
		69	98	

Figure 2: Confusion Matrix

Next, the study applied confusion matrix terms to calculate standard performance measures to evaluate the model (Table 1) using a specific threshold. The Accuracy measure suggests that the candidate model is correct 76.05% of the time or misclassification rate of 23.95% (Error Rate). Sensitivity (or Recall) indicates that when in actuality users indicated high engagement, the candidate model predicted it correctly 85.37% of the time, while incorrectly 14.63% (False Negative Rate). On the other hand, when users indicated low engagement, the candidate model predicted it correctly 67.06% (Specificity) and incorrectly 32.94% (Fallout) of time. Precision measure suggests that when the model predicts "high" user engagement, it is 71.43% correct, and incorrect 28.57% (False Discovery Rate). The F1 Score is an overall measure of a model's accuracy that combines precision and recall. In our case, our model reported the F1 Score of 77.78%.

TABLE 1: MODEL PERFORMANCE

AUC	0.8086	F1 Score	0.7778
Accuracy	0.7605	Error Rate	0.2395
Sensitivity	0.8537	False Neg. Rate	0.1463
Specificity	0.6706	Fallout	0.3294
Precision	0.7143	False Disc. Rate	0.2857

This study evaluated the model's ROC curve by focusing on Area Under Curve (AUC), or the area under the ROC curve (Figure 3). The candidate model's AUC of 0.8086 suggests an 80.9% chance that the model will correctly distinguish viewers' rating as a highly engaging video from a low engaging video. AUC of 0.5 suggests no discrimination, 0.7 to 0.8 is considered acceptable, 0.8 to 0.9 is considered excellent, and more than 0.9 is considered outstanding [25]. Based on this AUC heuristic, the candidate model is considered excellent.

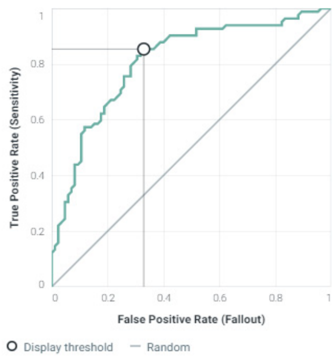

Figure 3: ROC

C. Model Interpretation

The present study used feature impact to interpret how each key feature is driving the model's decision.

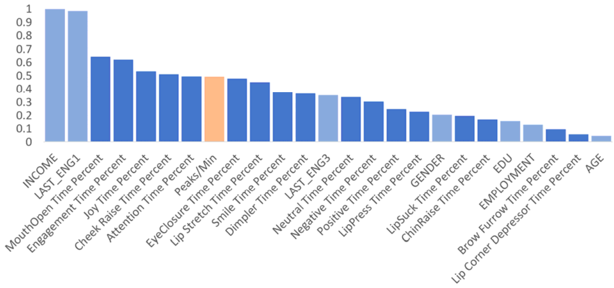

Figure 4: Feature Impact - Top 25 Features

Figure 4 displays the top 25 features, with 'INCOME' and 'LAST_ENG1' (Last Time Shared) 'having the largest impact from the group of socio-demographic and behavioral features. 'Mouth Open Time Percent', 'Cheek Raise Time Percent', and 'Eye Closure' features have the highest impact from the group of emotional channel or action unit features. 'Engagement Time Percent', 'Joy Time Percent', and 'Attention Time Percent' features have the highest impact from the group of features representing a group of combined action units based on FACS. 'Peaks/Min', the only GSR-collected feature, also appears to impact the model's classification decision substantially. Other features not included in Figure 3 have a normalized impact value of less than 0.04.

V. DISCUSSION

This study explored the possibility of using biometrics-based emotion and arousal data (fascial muscle and skin conductance data) to predict user engagement as an essential ingredient to video virality. The AUC evaluation of the candidate model suggests more than 80 % chance that a mix of facial expression, GSR, and socio-behavioral data will correctly distinguish between high and low user engagement.

This study's findings encourage the use of biometric data in predicting and understating factors influencing video virality. The present study finds that physiological measures offer nuance beyond basic emotions and valance by focusing on granular facial muscle movements to extract action units. Furthermore, the concept of arousal is not limited to the verbal description of emotion intensity but can be captured through a more objective measure of skin conductance.

Next, the present results emphasize the value of existing research investigating the emotional components of user experience relative to viewer engagement and virality [26]. In the process of interpreting the present model, our analysis confirmed the role of viewers' emotional responses such as joy, positive valance, and smile action unit. The predictive model also confirmed the role of arousal ('Peaks/Min') in user engagement, further validating the role of emotional arousal.

Focusing on analytics and systems, Information Systems, Computer Science, and Decision Science research communities can utilize the resulting data to continue improving video virality predictive models while further exploring video engagement from data and systems perspectives. Facial expression data, in particular, is valuable for modeling vis-a-vis machine learning as it provides information with various levels of granularity incorporating actions units and combinations of those units to capture emotions, valence, attention, and engagement. These information-rich features minimize the need for significant data engineering and further feature extractions that can add levels of complexity to interpret advanced algorithm results.

A. *Practical Implication*

From a practical perspective, the current paper is commercially contextualized, given that video strategy is an increasingly important component of marketing strategy and that companies and digital platforms are competing for the finite resource of viewers' attention. Video platforms offer significant entertainment and commercial value predicated upon eliciting user engagement. Given the ubiquity of videos and the potential value of viral videos in customer engagement, entertainment, marketing, and overall business strategy, improvements in (i) understanding factors that influence user engagement, (ii) ability to predict engagement, and (iii) ability to integrate physiological data into existing video creation and selection have the aforementioned clear and practical implications.

The present study edifies video creators' intent on virality-strategy as to what emotional responses to target (joy, positive valence, smile) when creating video content. Similarly, when multiple video versions are created, video makers can use a combination of social and behavioral-related and biometric features identified herein and use them with advanced classifiers to decide which video to be released. Combining this predictive model's accuracy with the known economic impact of video virality provides evidence that time and resources investment can yield a return on investment. However, investments should not completely replace existing processes inclusive of user engagement/video domain knowledge but, rather, should augment and enhance it.

B. *Limitations*

The present study has several limitations. First, the characteristics of the participants might have influenced the results. Second, the selection of videos and various video elements can provoke unique reactions from participants. Third, this study selected only two types of biometric data - facial expression and GSR – as the source of emotion and arousal data. Fourth, this study should be evaluated through the aforementioned research goal and exploratory analysis and predictive modeling scope.

VI. CONCLUSIONS

The present study's ability to create a predictive model represents the first attempt to explore the predictive use of this biometric data type in the context of video virality. In the process, the study (i) introduced the potential of facial expression and GSR data, (ii) confirmed the role of emotional response during video viewing as well as the resulting tendency of an audience to engage with viewed videos, (iii) elevated the need to integrate both socio-behavioral and physiological data, and (iv) provided evidence of the value of advanced analytics in the context of biometric data and video virality.

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APPENDIX

TABLE 2: FEATURE LIST

#	Feature	Feature Type	#	Feature	Feature Type
1	GENDER	Socio-Dem.	22	Brow Furrow Time Percent	AU/Em. Channel
2	AGE	Socio-Dem.	23	Brow Raise Time Percent	AU/Em. Channel
3	EDU	Socio-Dem.	24	Lip Corner Depressor T. %	AU/Em. Channel
4	MARITUAL_ST	Socio-Dem.	25	Smile Time Percent	AU/Em. Channel
5	EMPLOYMENT	Socio-Dem.	26	InnerBrowRaise T. Percent	AU/Em. Channel
6	INCOME	Socio-Dem.	27	EyeClosure Time Percent	AU/Em. Channel
7	LAST_ENG1	Behavioral	28	NoseWrinkle Time Percent	AU/Em. Channel
8	LAST_ENG2	Behavioral	29	UpperLipRaise Time %	AU/Em. Channel
9	LAST_ENG3	Behavioral	30	LipSuck Time Percent	AU/Em. Channel
10	Engagement Time %	Engagement	31	LipPress Time Percent	AU/Em. Channel
11	Attention Time Percent	Attention	32	MouthOpen Time Percent	AU/Em. Channel
12	Anger Time Percent	Basic Emotion	33	ChinRaise Time Percent	AU/Em. Channel
13	Sadness Time Percent	Basic Emotion	34	Smirk Time Percent	AU/Em. Channel
14	Disgust Time Percent	Basic Emotion	35	LipPucker Time Percent	AU/Em. Channel
15	Joy Time Percent	Basic Emotion	36	Cheek Raise Time Percent	AU/Em. Channel
16	Surprise Time Percent	Basic Emotion	37	Dimpler Time Percent	AU/Em. Channel
17	Fear Time Percent	Basic Emotion	38	Eye Widen Time Percent	AU/Em. Channel
18	Contempt Time %	Basic Emotion	39	Lid Tighten Time Percent	AU/Em. Channel
19	Positive Time Percent	Valence	40	Lip Stretch Time Percent	AU/Em. Channel
20	Negative Time Percent	Valence	41	Jaw Drop Time Percent	AU/Em. Channel
21	Neutral Time Percent	Valence	42	Peaks/Min	GSR/Arousal

TABLE 3: VIDEO SUMMARY

Video	Interesting/ Suprising	Amusing/ Funny	Annoying/ Boring	Emotional/ Intense	Length	Views
1 - 0.38 second rubric's cube solve https://youtu.be/nt00QzKuNVY	X				0:30	29,348,799
2-Amtrack snow-mo collision https://youtu.be/V-Cb9x70gYQ	X				0:43	31,102,210
3-Dogs favorite toy https://youtu.be/I7op92W7voE		X			0:59	53,855,299
4-Maddie waiting for the beat https://youtu.be/REmpPC9gPq0		X			1:11	13,152,888
5-My cat mumbles https://youtu.be/5ZRMV--H0AA			X		0:53	5,792,368
6-Robot beats - 1 am not a robot https://youtu.be/fsF7enQY8uI	X				0:30	29,296,624
7-Unreal rescue in baton https://youtu.be/UbiPT5VMo8E				X	1:46	4,416,589
8-Chimp at zoo throws poo https://youtu.be/0veiTgUQLKw		X			0:18	4,215,179
9-DISC profile theory https://youtu.be/0veiTgUQLKw			X		1:15	<100
10-The e-LEMON-ators https://youtu.be/M-D8DDjkcRk			X		1:46	<100
11-Accounting circle https://youtu.be/H9axyByA_rw			X		1:31	<100
12-Budweiser brewed by veterans https://www.ispot.tv/ad/wIao/budweiser-folds-of-honor-brewed-by-vets-for-vets				X	0:28	Not released
13-Budweiser 2017 super bowl https://youtu.be/7ZmlRtpzwos				X	1:01	1,863,872