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Don't Look Blank, Happy, or Sad: Patterns of Facial Expressions of Speakers in Banks' YouTube Videos Predict Video's Popularity Over Time

Peter Lewinski
University of Amsterdam

There has been little focus on nonverbal communication in social media advertising campaigns. We propose that specific patterns of facial expressions predict the popularity of YouTube videos among users of social media. To test that proposition, we used a neuromarketing tool—FaceReader—to code facial videos of professional speakers who participated in the YouTube social media campaigns of 2 large commercial banks. We analyzed more than 25,000 video frames of 16 speakers' 6 basic facial expressions. We found that less incidence of affiliative facial emotions (happiness and sadness) and more incidence of nonemotional expressions (surprise) explained an additional 25% of variance (from 61% to 86%) in the video's popularity (number of YouTube views) after 8 months in t2 (July 14, 2015), in comparison to t1 (October 31, 2014) as the only baseline predictor. We further showed that the disaffiliative facial emotions of the speakers (anger, fear, and disgust) did not contribute as an indicator of the future performance of social media content. We hope that these findings will open new lines of research in corporate communication by incorporating neuromarketing and nonverbal communication to understand not only what content is effective but how it should be presented.

Keywords: social media, YouTube, nonverbal communication, facial expression, emotions

Nonverbal communication is a pertinent aspect of presenting a message and transmitting information (Jones & LeBaron, 2002). A specific type of social media that seems especially relevant for nonverbal communication is video-sharing websites such as YouTube. This is because video communication allows social media users to see the source presenting the message. When users can see people talking, they evaluate not only what is being said but also how people are saying it, which arguably constitutes what Singh and Sonnenburg (2012) referred to as an *improvisation theater metaphor*. In this paper, we literally (and exclusively) focus on the how element of social media communication because, arguably, research into this aspect within the context of corporate communication in social media is lacking, although it still constitutes an essential part of brand storytelling in social media (Singh & Sonnenburg, 2012, p. 17; the content vs. process).

We believe that by studying facial expressions of speakers who do not expect to have their expressions judged by an objective neuromarketing software, we tap more easily into what Buck and VanLear (2002) call *spontaneous communication*. This is "the nonintentional communication of motivational-emotional states based upon biologically shared nonpropositional signal systems" (p. 522). Spontaneous communication is an especially important aspect of nonverbal communication as compared to pseudospontaneous displays, which involve strategic and intentional manipulation of one's nonverbal behavior, which may be an attempt to "control the receiver's response in accordance with the intended message or other social goals" (p. 526).

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Peter Lewinski, Department of Communication Science, University of Amsterdam.
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Correspondence concerning this article should be addressed to Peter Lewinski, who is now at Faculty of Economics, Université de Neuchâtel. Rue A.-L. Breguet 2 - 2000 Neuchâtel, Switzerland. E-mail: peter.lewinski@unine.ch

Importantly for the study of nonverbal communication, facial expressions are difficult to spontaneously control (see Gosselin, Perron, & Beaupré, 2010 on the voluntary control of facial action units in adults). Therefore, this renders them a more truthful source of information (Ekman, 2003; Ekman & O'Sullivan, 1991). We propose that, paradoxically, such a spontaneous nonverbal communication as facial expression is especially informative with respect to today's ever-cautious social media users. For example, Labrecque, vor dem Esche, Mathwick, Novak, and Hofacker (2013) show that social media users have considerable power in the digital age. Consider the number of views on YouTube for a particular company's video message. We argue that the quantity of video views is a reflection of social media users' interest and hence the video's popularity. Therefore, the popularity of the firm's message is directly related to how many times people chose to watch it.

Another reason to focus on facial expression is that human faces are the richest source of nonverbal behavior. People can make up to 10,000 combinations of facial movements (Ekman & Rosenberg, 1997), and the face is easily accessible for others to look at it (e.g., Carroll & Russell, 1996). The face is often studied in the context of facial emotions, which are not random expressions but distinct expressions conveying affective, emotional, and nonemotional meaning (Ekman & Cordaro, 2011; Ekman, Sorenson, & Friesen, 1969). Facial expressions are assumed to reflect the six basic emotions (happiness, sadness, anger, fear, disgust, and surprise; Ekman & Friensen, 1986).

Happiness is clearly a positive emotion, and sadness is clearly a negative emotion (Russell, 1980). Surprise is ambiguous in terms of emotional valence (Russell, 1980); however, it is the most cognitive of all basic emotions (Lorini & Castelfranchi, 2007) and is often considered not to be a (basic) emotion (Ortony & Turner, 1990) but more of a cognitive appraisal tendency (Frijda, Kuipers, & Ter Schure, 1989), also indicating heightened attention (Smith & Ellsworth, 1985). Thus, in this paper, we assume that surprise is not an emotion. Furthermore, happiness and sadness are affiliative emotions, generating approach tendencies toward the person expressing them by the person who is watching them (Frijda, 2010; Frijda & Tcherkassof, 1997). For example, when people smile or are sad, they invite an approach to either share the joy or be consoled. Expressions of happiness and sadness are defined to correspond mainly to Facial Action Coding System (FACS's; Ekman, Friesen, & Hager, 2002) Action Unit 12 (lip corner puller) and Action Unit 15 (lip corner depressor), which are two antagonistic muscle movements, as the names indicate (Emotional Facial Action Coding System-7 [EMFACS-7] Friesen & Ekman, 1983). This means that it is extremely difficult to show the two emotions at the same time because the muscles are working in opposite directions. This adds further support that happiness and sadness, although affiliative emotions, can explain unique variance in other behavioral measures (e.g., popularity, as in this study). Anger, fear, and disgust are clearly negative emotions (Russell, 1980) with disaffiliative tendencies (Frijda & Tcherkassof, 1997; Frijda, 2010). Surprise is regarded as ambiguous as to properties of affiliation because it can indicate either approach or avoidance, depending on the context.

In nonverbal behavior, not only is the presence and intensity of a facial emotion important, but equally the lack of emotion is informative and even expected (see Fernández-Dols, Carrera, Barchard, & Gacitua, 2008); that is, sometimes less emotion can be more. However, the face should also not be simply blank because neutral faces can look threatening (e.g., see Lee, Kang, Park, Kim, & An, 2008), and people have problems recognizing neutral faces as neutral (as compared to an objective judge; Lewinski, 2015). Therefore, in certain contexts (e.g., in corporate communication in the banking industry), a certain "tension" might be created in which people who communicate the company's message should likely not show emotions in their faces but they also should not have a blank face. We test this proposition in this paper. We make a critical distinction among specific facial expressions that indicate antagonistic emotions yet are similar in terms of affiliation (happiness and sadness), nonemotional facial expression (surprise), and disaffiliative emotional expressions (anger, fear, and disgust) as previously explained.

We believe this proposition might be especially important for corporate communication. Social media users likely do not expect certain facial expressions (especially emotional expressions) to be present in professional actors (or speakers) who present a firm's informative message. We also assume that certain professional groups such as bankers are not expected to show happiness or sadness while presenting a firm's message or information (Percy, 2014). The banking industry is assumed to cultivate a "serious" image (at least the two banks we selected in this study, see *Video Selection*; Percy, 2014). There is no reason to show emotions while talking in a professional, informative context (by contrast, consider an advertising or sales context), but there is also no reason not to show anything in the face, and the only nonemotional expression left is surprise. Therefore, we hypothesize and test in this study if less expression of happiness and sadness in the facial emotions of bankers leads to higher popularity of a video message. We also test whether more nonemotional facial expression has this positive effect. In other words, we suggest that the more emotional facial expressions (happiness and fear) and the fewer nonemotional facial expressions (surprise), the less popular the video is. We further predict that no relationship exists between disaffiliative emotions (anger, fear, and disgust) and video's popularity.

Method

Video Selection

First, the author perused a YouTube channel playlist featuring the campaigns of large banks with front-up, forward-facing, talking speakers and with good lighting in the video. The author used 10 of 28 available videos from the same campaign, "ING Private Banking," and 6 videos from the ABN AMRO campaign targeted at English-speaking expats living in the Netherlands, all of which met the previously mentioned criteria. These criteria were necessary to use the automatic facial coding software. In the ING campaign, the speakers were talking in Dutch about topics related to private banking, such as purchasing power, testaments, or spending patterns. In the ABN AMRO campaign, the speakers were talking in English about banking issues especially important to expatriates living in the Netherlands (e.g., opening a bank account, applying for a mortgage, or using a credit card). On average, the video lasted 91.25 s (SD = 9.20), or 2,281.18 frames (SD = 221.89). In total, the videos contained 36,499 frames. The ethical committee of the author's first affiliation institution has approved this study under code 2014-CW-115.

Facial Expressions

To measure the facial expressions of the speakers, we used FaceReader version 6.0 (Noldus, 2014), which is a software that automatically codes six basic facial emotions. For each emotion, the software assigns a value from 0 to 1 that indicates the intensity and probability of that emotion. FaceReader works in three steps. First, it detects the face. Second, through the Active Appearance Model it creates a three-dimensional superimposed model of a face with 500 hyperconnected tracking points. As the last and most important stage, FaceReader uses a three-layer feed-forward hidden neural network trained on more than 10,000 facial images depicting basic emotions (e.g., similar to ones reported in Olszanowski et al., 2015). It uses that neural network to recognize an emotional expression. For a detailed algorithmic description of the software analysis process, see van Kuilenburg, Wiering, and den Uyl (2005). Importantly, accuracy rates for recognizing basic emotions of 89% for FaceReader 1.0 (den Uyl & van Kuilenberg, 2005) and 88% for FaceReader 6.0 have been reported (Lewinski, den Uyl, & Butler, 2014a). This neuromarketing tool has been successfully used in consumer research (de Wijk, He, Mensink, Verhoeven, & de Graaf, 2014), marketing research (Lewinski, Fransen, & Tan, 2014b), and psychology research (He, Boesveldt, de Graaf, & de Wijk, 2014).

We used a measure of facial expressions that took into account the most intense periods of showing an expression. The most intense periods of facial expressions were defined as an average of 10% of the highest values of probability and intensity of facial expressions per frame. This measure has been validated by Lewinski et al. (2014b). The software was not able to analyze 10,074 of 36,499 frames (27.6%). This was due to different technical reasons—mostly because the software could not detect the face or properly model it. In these cases, the actors were moving their heads or the face was shown from an angle higher than 45°. See Figure 1 for the visualization of the FaceReader analysis of a facial emotion of a speaker.

Figure 1. Visualization of the FaceReader analysis of a facial emotion of three speakers. The videos (and therefore the frames from the videos captured in this Figure, which are presented here) were available at open (at least in time of publication of those videos and of this paper). They have been accessed from a publicly available database of videos at video-sharing platform YouTube at the following links: ING Nederland (2014a, 2014b, 2014c). See the online article for the color version of this figure.

Number of Video Views

On YouTube channels, the number of video views is reported for each video. We accessed this number at two points: first on October 31, 2014 (t1) and then on July 14, 2015 (t2). The number of video views is assumed to be an objective and behavioral measure of a video's popularity and possibly virality. Furthermore, Google, Inc. (owner of YouTube, LLC) explains on their support page that ". . . just active views will be counted . . ." (YouTube, 2015) into this metric, which highlights consideration of the behavioral intentionality to engage with the video by a viewer. Eight months separating t1 and t2 was judged as a sufficiently lengthy period to predict popularity of the video from a baseline at t1. There was a high positive correlation between the t1 and t2, $r(10) = .82$, $p < .01$, indicating that the number of views is a stable measure of popularity. (This and all following significance testing are two-tailed.)

Results

Table 1 provides mean, standard deviations, and minimum and maximum values of all dependent (video views in t2) and independent variables (video views in t1, happiness, sadness, surprise, anger, fear, and disgust).

A linear regression was run to predict the number of video views in t2 from the number of video views in t1. This variable statistically and significantly predicted the number of video views in t2, $F(1, 14) = 24.50$, $p < .0005$, adj. $R^2 = .61$. The number of video views in t1 accounted for 61% of the explained variability in the number of video views in t2. We assume this to be a baseline prediction.

Table 1
Descriptive Statistics

Variable	*N*	*M*	*SD*	Minimum	Maximum
Video views-t2	16	362.25	179.14	128.00	716.00
Video views-t1	16	157.31	115.53	53.00	479.00
Happiness	16	0.44	0.20	0.06	0.74
Sadness	16	0.06	0.15	0.00	0.51
Surprise	16	0.65	0.30	0.13	0.99
Anger	16	0.38	0.23	0.05	0.87
Fear	16	0.04	0.06	0.00	0.17
Disgust	16	0.47	0.20	0.20	0.86

Note. Valid cases = 16; cases with missing value(s) = 0.

A multiple linear regression was run to predict the number of video views in t2 from the number of video views in t1 and facial expressions of happiness, sadness, and surprise. These variables statistically and significantly predicted the number of video views in t2, $F(4, 11) = 24.46$, $p < .0005$, adj. $R^2 = .86$. All four variables added statistical significance to the prediction, $p < .05$. The number of video views in t1 and facial expression of happiness, sadness, and surprise accounted for 86% of the explained variability in the number of video views in t2. Therefore, we explained an additional 25% of variance from the baseline prediction.

Regression coefficients and standard errors can be found in Table 2. The values from Table 2 indicate that for each unit of decrease in happiness, there is an increase in video views in t2 by 252.52. Likewise, for sadness, a decrease of a single unit equates to a 742.65 increase in video views in t2. However, for each unit increase in surprise, there is an increase in video views in t2 by 198.75.

As a check, a multiple regression was run to predict the number of video views in t2 from the number of video views in t1, and facial expressions of happiness, sadness, and surprise as well as anger, fear, and disgust (i.e., all basic emotions). These variables statistically and significantly predicted the number of video views in t2, $F(4, 11) = 24.46$, $p < .0005$, adj. $R^2 = .84$. However, only the first four variables (i.e., the same variables as in the previous regression) added statistical significance to the prediction, $p < .06$. Therefore, anger, fear, and disgust did not explain any additional variance (all $ps > .32$). Regression coefficients and standard errors for this additional analysis can be found in Table 3.

Table 2
Summary of Multiple Regression Analysis With Hypothesized Predictors

Variable	Unstandardized coefficients *B*	*SE*	Standardized coefficients β	*t*	*p*
(Constant)	87.19	72.84	0.00	1.20	.254
Video Views-t1	1.92	0.21	1.24	9.18	.000
Happiness	−252.52	90.88	−0.29	−2.78	.018
Sadness	−742.65	170.06	−0.61	−4.37	.001
Surprise	198.74	62.94	0.34	3.16	.009

Note. Coefficients (video views-t2).

Table 3
Summary of Multiple Regression Analysis With All Basic Emotions

Variable	Unstandardized coefficients *B*	*SE*	Standardized coefficients β	*t*	*p*
(Constant)	46.94	142.04	0.00	0.33	.749
Video Views-t1	2.06	0.25	1.33	8.14	.000
Happiness	−316.88	150.21	−0.36	−2.11	.068
Sadness	−1043.57	315.51	−0.85	−3.31	.011
Surprise	265.60	95.89	0.45	2.77	.024
Anger	−152.56	145.19	−0.19	−1.05	.324
Fear	553.86	665.42	0.19	0.83	.429
Disgust	114.99	109.68	0.13	1.05	.325

Note. Coefficients (video views-t2).

Discussion

We found that the lack of facial emotions and the presence of facial nonemotions were important indicators of a video's popularity. The fewer affiliative emotions (happiness and sadness) that were present, the more popular the video was. More nonemotions (surprise) also predicted a more popular video. We performed this study in a novel way. We used two objective measures of behavior: automatically coded facial expressions and the number of video views on YouTube. We strategically did not use any self-reported measures, thereby demonstrating an automatic and unobtrusive method of predicting a video's popularity. We successfully showed how a neuromarketing approach might be integrated into research on corporate communication.

We found that fewer affiliative facial emotions (happiness and sadness) and more nonemotional expressions (surprise) explained an additional 25% of variance (from 61% to 86%) in the video's popularity (number of views on YouTube) after 8 months in t2 in comparison to t1 as the only baseline predictor. We further showed that the disaffiliative facial emotions of the speakers (anger, fear, and disgust) did not contribute as an indicator of the future performance of social media content. As a speculation on possible mechanism, we note that this could be because people do not expect bankers to show affiliative emotions. On the other hand, disaffiliative emotions are simply not acceptable in any company-consumer interaction and are simply ignored by social media users as atypical instances or simple artifacts of spontaneous facial behavior. This plausible process needs further testing.

Theoretical Implications

In theory, our findings are novel because they show that fewer of certain emotional expressions is an important indicator of the performance of social media videos. Similar to how Singh and Sonnenburg (2012) highlighted the difference between the content (what) and process (how) in performance of brand in social media, we successfully predicted most of the variance, but only from how the content was shown. From this study, we cannot yet conclude what is the precise mechanism behind this finding. We may only speculate about this further, as we partially did in the introduction.

However, one important theoretical insight is that facial expressions lead to lower popularity and not that lower popularity changes facial expressions. Because the facial videos were recorded before, we can now prove a causal link of facial expressions leading to a change in video popularity in time t2. Our finding relates to similar findings in advertising research in which facial expression also predicted liking for a video stimuli and not liking predicting the facial expression (Lewinski et al., 2014b). This all adds further support to the idea of Buck and VanLear (2002) that people's spontaneous nonverbal communication (such as facial expressions) is often close to a true indicator of their internal emotional-cognitive states. This is why their facial expressions are predictive of other people's motivational responses, such as popularity or liking. This is presumably because such expressions do not try to "control the receiver's response" (p. 526); hence, they may resonate with people easier than controlled forms of nonverbal expressions.

Indeed, FaceReader (and likely most automated facial coding software for that matter) cannot yet assess if the expression is spontaneous or not. However, an implicit assumption, in bringing up this issue, is that (a) people can easily control their facial expressions and (b) a naïve observer can recognize such attempts. Actually, studies show that both of those tasks are often difficult to perform. For example, Mehu, Mortillaro, Bänziger, and Scherer (2012) showed that most people cannot control some facial muscles related to expressions of basic emotions, although for other facial muscles of the same emotions, it is easier to control them (for an overview, see Mehu et al. 2002, Table 1, p. 702). Furthermore, as studies show, only a trained observer can reliably recognize rehearsed/controlled expressions; therefore, it is very likely that FaceReader is as well equipped to judge facial expressions as a typical social media user would be. As such, asking untrained human judges to rate those expressions would be fruitless. This is because "untrained observers [are] unable to discriminate real and false expressions above the level of chance" (Porter, Ten Brinke, & Wallace, 2012, p. 23). Furthermore, recent evidence suggests that software such as FaceReader (arguably an objective observer) can outperform untrained human judges—under certain circumstances—in emotion recognition tasks (Lewinski, 2015).

Nonetheless, to investigate that issue further, a FACS-certified coder (Ekman et al., 2002) from our laboratory watched the videos in an open-ended way to determine if the expressions could have been controlled by the speakers. This can be done by looking at onset and offset as well as durations of expressions. Although no systematical coding was undertaken, the patterns of facial expressions have been judged to be spontaneous and not controlled or strategically produced. With these additional arguments already presented in the introduction, we judge the nonverbal communication channel of facial expressions less likely to be strategically controlled, especially in comparison to other communication channels (e.g., verbal content).

Furthermore, we hypothesized that speakers should show as little as possible of affiliative emotions (happiness and sadness) while still being expressive (surprise) because we assumed that this is what the social media users expected. Another possible explanation is the assumptions made by social media users who watched the videos. Some of the users may have assumed the speakers to be employees of the bank whereas others thought they were just actors. However, these proposed explanations, although reasonable, were not tested in this paper and should be tested in the future.

Limitations

One of the limitations of our findings lays in the small sample size of YouTube videos because only 16 videos were available and eligible for this analysis. However, what must be taken into account is that appropriate facial videos for analysis with facial coding software are scarce because the videos must meet specific criteria (see *Method*). This limitation has been mitigated by the relatively large number of data points analyzed in the data set (more than 25,000 frames successfully analyzed). Worth noting is that this method saves considerable time when compared with manual coding. Assuming that a human coder would take 1 min to code six basic emotions for each frame, it would take more than 300 hr of manual coding to code our material and therefore a substantial money and time investment.

Furthermore, only videos from the banking industry were analyzed, and the hypotheses were matched to that context. Thus, the possibility of generalization beyond this specific context might be limited. Therefore, we suggest replicating our findings with a larger sample of videos in more diverse settings (e.g., different banks, markets, and countries).

Another limitation is that several factors, for which we did not control, could have influenced the number of video views. The videos differed in terms of content, their order in the playlist, release date, and different actors present. Any of these factors could have influenced the results. For example, Gorn, Jiang, and Johar (2008) showed that "babyfaces" of actors lead to inference of different traits of the speakers and hence change people's response to public relations communications. Finally, even with ignoring the verbal content (what) of the messages, we managed to achieve a high explanatory power by using the facial expressions of the speakers. Although we did not control for those and many other possible explanatory factors, we successfully demonstrated a model that explained up to 86% of variance in a video's future popularity, leaving only 14% of variance unexplained, which we judge to be a relatively small value.

Practical Implications

Importantly, to our knowledge this is the first time that this technique has been applied to YouTube videos on corporate channels of big firms. This method opens up a new and exciting avenue of studying nonverbal communication in corporate communication. Furthermore, it is easy to imagine analyzing nonverbal behavior in different contexts (e.g., presidential debates or news presenters). With our method, we show the first proof-of-concept at work, alongside its possible applications and interpretations. Such analysis of the emotional face behavior of actors in company's messages or advertisements could be used to build and measure brand value and added to social media metrics guidelines (e.g., Peters, Chen, Kaplan, Ognibeni, & Pauwels, 2013). In fact, the first steps have been taken in that direction by a startup called Media Distillery (see http://www.mediadistillery.tv). In principle, such analysis could be automated and applied to all video material everywhere on the Internet (e.g., on YouTube, Facebook, Twitter, etc.) but also to the monitoring of TV channels 24 hr a day, 7 days a week. The basic applied idea stemming from this study would be to combine such analysis with a system that would automatically detect the appearance of specific people on TV (politician, celebrities, experts, etc.), emotional expression (basic emotions, arousal, valence, confusion, etc.) of the speakers (both specific people but also everyone appearing on TV), and statistics on the demographics of people appearing on TV (age, gender, ethnicity, etc.). The follow-up step would be to correlate such statistics with other metrics (e.g., popularity, awareness, likability, etc.), such as those we report in this study, or create emotional "content heatmaps."

Furthermore, we contribute significantly to the current and future practice of corporate communication. Firms must pay attention to not only what is verbally expressed in video communication but also how the speakers behave with their body. To our understanding, the practice of teaching "proper" nonverbal behavior to key representatives is rather rudimentary. We show convincing evidence that patterns of facial expressions are important to consider during social media campaigns and when company speakers are "out in the public"; indeed, these patterns matter as much as what they say (Riff, Lacy, & Fico, 2014) and what clothes they are wearing (Shao, Baker, & Wagner, 2004). To sum up, our findings are intuitively easy to understand. In the case of professional institutions such as banks, a simple and nonemotional nonverbal message is what viewers and potential customers (e.g., social media users) find most compelling.

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