Noldus
Information Technology

FaceReader In-Market

Validation

Automated recognition of facial expressions has recently become a popular tool for market researchers. One such tool, FaceReader by Noldus, is an advanced software platform providing automatic and objective assessment of facial emotion. FaceReader automatically determines the presence and intensity of the six 'basic' expressions: happy, sad, angry, surprised, scared, disgusted, as well as neutral/no emotion. Recent studies have demonstrated FaceReader's efficacy in predicting advertisement effectiveness. To further expand to meet the needs and demands of the industry, Noldus created FaceReader Online, which provides a user-friendly, easily-accessible web portal built around FaceReader's proven, reliable technology, and allows for reaching respondents around the globe. The current study focuses on how FaceReader Online compares to current known in-market metrics, such as purchase intent. Using an online forum to recruit a random sample of adults from across the US, we tested the effectiveness of eight video advertisements, ranging in year produced, in-market performance, and category. FaceReader Online assessed emotion expressions while watching the ads, and afterwards a Purchase Intent measure was taken. Quantitative analysis determined that levels of Happy and Sad were both significant predictors of high or low Purchase Intent (respectively). Furthermore, FaceReader detected significantly higher levels of Happy during high-performing ads compared to average or low-performing ads. Qualitative analysis revealed that higher overall emotion expression during ads is further indicative of advertisement effectiveness. Overall, the data verify the usefulness of FaceReader Online as an automated tool for determining market performance for advertisements.

INTRODUCTION

Over the past fifty years, technological advances have made it possible to automatically classify facial expressions. One example is FaceReader, by Noldus: an advanced software platform providing automatic and objective assessment of facial emotion. Based on the original "basic" emotions set forth by Paul Ekman [1], FaceReader automatically determines the presence and intensity of the following emotions: Happy, Sad, Angry, Surprised, Scared, and Disgusted, as well as Neutral (no emotion). FaceReader has been validated against human coders [2], with degree of agreement ranging from 70% (Disgusted) to 99% (Happy). Many academic publications using FaceReader have focused in the realm of psychology [3,4] or food science research [5,6], but a recent scientific publication [7] demonstrated the usefulness of FaceReader in the consumer research field. With many researchers aware of the intense relationship between emotion and consumer behavior [8], as well as the interplay between emotion and advertising [9], applying a tool such as FaceReader to this market is a natural next step. Indeed, researchers present evidence that expression of Happy could predict an advertisement's effectiveness. Specifically, positive correlations were found between Happy and the respondents' attitudes towards the advertisement (AAD) and attitude towards the brand (AB) for ads with high and medium levels of amusement, but not low [7]. Unsurprisingly, the other basic emotions (Sad, Anger, Surprise, Disgust, and Fear) did not predict advertisement effectiveness regardless of level of amusement present in the ad.

A drawback to using the traditional FaceReader software for consumer research is that the software must be hosted on a local computer, with respondents present in the laboratory in order to analyze their facial emotions. To address this, Human Insight Services B.V. (an initiative of Noldus and VicarVision) recently debuted FaceReader Online, which provides the researcher with a user-friendly, easily-accessible portal built around proven, reliable technology (FaceReader). By being able to capture respondents in their own homes, FaceReader Online provides researchers with access to consumers around the world. Consumer researchers have previously relied on tried-and-true methods such as purchase intent (PI, 10); how does FaceReader's output compare to these known in-market metrics? In the current study, FaceReader Online was used to capture data from respondents around the United States, as they watched a variety of advertisements. Afterwards, a PI measure was taken. It was hypothesized that the expression of Happy would predict PI and that ads that performed better would also have higher PI and greater expressions of Happy.

METHODS

Respondents
Respondents were recruited via Survey Monkey. In all, 518 invitations were sent out, with 113 people completing the study. Respondents varied in age from 21-65 and were split across gender. The only exclusionary criteria included were requiring that no respondents wear corrective lenses (i.e., glasses), and all must have a webcam attached to, or embedded within, their computers. Total experiment duration for each participant was less than five minutes.

Stimuli
After a few brief introduction slides requesting permission to use the webcam, and verifying age and lack of glasses, respondents were shown one of eight ads. Each ad ranged in year (2009 to 2014), category (consumer package goods, household needs, food and beverage), as well as known market performance [12]. Each respondent saw one ad, recorded and presented to the respondents via FaceReader Online. Each ad was presented randomly; 13-15 respondents saw each video, with video presentation randomized across age and gender Videos were not taken of the respondent; FaceReader Online used the respondents' webcams to gather facial expression data and analyze it online. Immediately after playing the advertisement, a Purchase Intent (PI) measure was taken.

Purchase Intent
Intent scale translations provide market researchers with an estimate of actual buying behavior. Respondents were asked to report if, based on the advertisement seen, they would be likely to purchase that product within the month. The traditional 5-point Likert scale was used [13].

FaceReader
FaceReader works in 3 simple steps, in both the original version [14], and subsequent releases [15]. The software detects the face using the Viola-Jones algorithm [16] and creates an accurate model of the face based on the Active Appearance method [17]. The model describes over 500 key points on the face, and facial texture is determined by how those points interact with each other. The actual classification occurs by comparing the current facial expression of the respondent against an artificial neural network [18]. The network is trained with a database of over 10,000 manually-annotated images.

FaceReader Online
FaceReader Online uses the FaceReader technology, but data is analyzed using Microsoft Windows Azure cloud platform, instead of running on a local computer. This provides researchers with the option of gathering respondents from around the globe, simply by collecting video with respondents' own webcams. Analysis is then carried out online using the same FaceReader technology described above.

RESULTS

Data analysis
All data were exported from FaceReader and analyzed in SPSS (Version 22, IBM, Armonk, NY), and Microsoft Excel (Microsoft, Redmond, WA) using the Data Analysis plug-in.

All respondents were equally analyzed
The average number of frames tested per person per ad was 415 +/- 11, with no significant difference in number of frames analyzed across advertisements. For each frame, FaceReader provides a value from 0 (not present at all) to 1 (maximally present) for all seven emotions (Happy, Sad, Angry, Surprised, Scared, Disgusted, and Neutral). All respondents had fewer than 11 % missed frames during analysis, with no ad having significantly more missed frames than any other ad.

Ad performance predicted Purchase Intent
To determine the validity of the PI measure, ads were compared based on their known performance [12]. A one-way between subjects ANOVA was conducted to compare the effect of ad performance on PI in High-, Average-, and Low- performing ads. High-performing ads showed significantly greater PI compared with Average- and Low-performing ads (Figure 1). There was a significant effect of performance on PI for three types of ads ($F_{2, 74} = 6.23$, $p<.01$). Post hoc comparisons using the Tukey HSD test indicated that the High-performing ads were significantly different than the Average- ($p<.05$) and Low- ($p<.05$) performing ads; however, Average- and Low- performing ads did not significantly differ (n.s.).

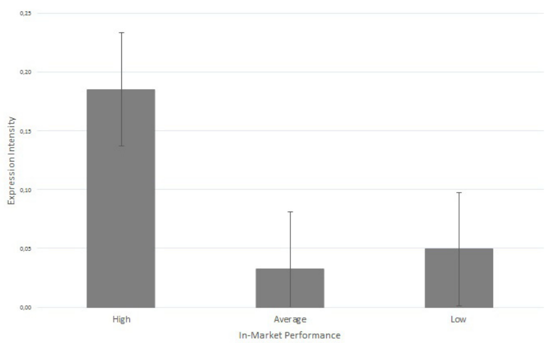

Figure 1. *Ads that performed well showed significantly higher Purchase Intent than Average- or Low-performing ads (*p< 0.05).*

Happy was a significant predictor of Purchase Intent
It was hypothesized that the expression of Happy would predict PI scores. Multiple regression analysis was performed with PI as the outcome variable and the six emotional expressions as the predictor variables (Figure 2). The results of the regression indicated that all facial expressions explained 61% of the variance (R^2=.37, $F_{6,70}$=6.96, p<.001). Furthermore, Happy significantly predicted PI (β = .58, p<.001).

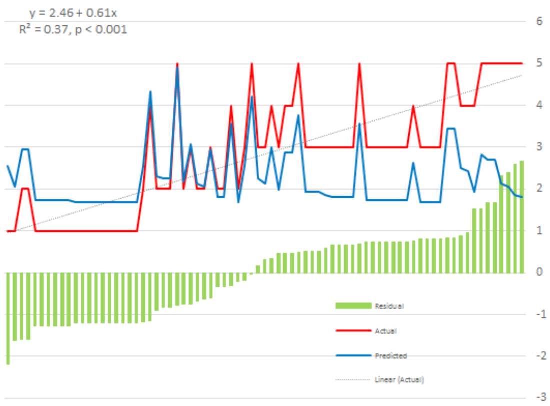

Figure 2. *Purchase Intent as a function of the Happy expression, showing the actual scores, predicted values, residual plots, and linear trend line.*

High-performing ads result in significantly more Happy expressions than either Average or Low ads
It was also hypothesized that High-performing ads would result in greater Happy expressions. A one-way between subjects ANOVA was conducted to compare the effect of ad performance on the Happy expression in High-, Average-, and Low-performing ads. As anticipated, High-performing ads showed significantly greater outputs of Happy compared with Average- and Low-performing ads ($F_{2,74}$ = 16.70, p<.001; Figure 3). Post hoc comparisons using the Tukey HSD test indicated that the High-performing ads were significantly different than both Average- (p<.05) and Low- (p<.05) performing ads; however, Average- and Low-performing ads did not significantly differ (n.s.).

Overall, High- and Low-performing ads resulted in similar amounts of emotional expression: 33% of time emoting during High- performing ads, and 31% of time emoting during Low-performing ads (Figure 4). However, viewers of High-performing ads registered more Happy, whereas viewers of Low-performing ads displayed more Sad and Angry emotions. Although not significant, the data shown in Figure 4 are compelling in the types of emotions that these ads elicit from viewers. One further item to note is that Average-performing ads brought forth fewer emotional expressions overall (21% of time emoting).

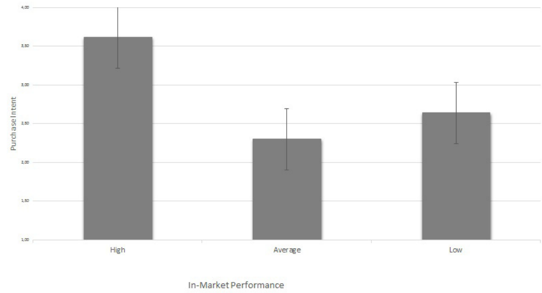

Figure 3. *Ads that performed well showed significantly higher Happy expressions than Average- or Low-performing ads (***p< 0.001).*

Taken together, these data demonstrate that the Happy expression is a valid predictor of PI and that an ad's performance can be defined by the amount of expression of Happy (Figure 5).

DISCUSSION

Similar to what was found previously by Lewinski *et al* [7], FaceReader was able to accurately predict PI. During the 8 advertisements presented, regardless of the performance of the ads, Happy was the only measured emotion that could predict PI, based upon a linear regression analysis. As anticipated, PI was highest for those ads that measured as "High-performing" ads.

When looked at separately, High-, Medium-, and Low-performing ads saw very different responses in emotions as measured by FaceReader. Viewers of High-performing ads displayed significantly higher levels of Happy than viewers of Medium- or Low-performing ads (Figure 3).

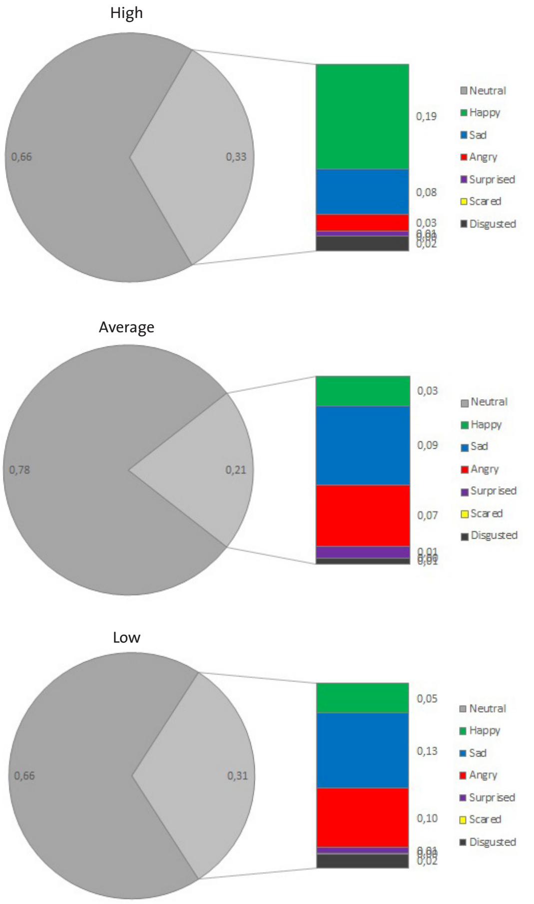

Figure 4. *Overall emotional expression as a function of ad performance.*

It should be noted, however, that the Happy expression, although a significant predictor, is not the only factor in determining an ad's performance, as seen by the R^2 value. For example, not every advertisement is meant to be humorous; many are meant to be taken seriously, and thus would not evoke a response of "Happy". Over exposure to an ad can also decrease the effectiveness of the ad over time. Finally, the halo effect, wherein the consumer's overall impression of a brand/market can influence his/her thoughts and feelings towards that brand [19] can result in an immeasurable effect upon the effectiveness of any given advertisement.

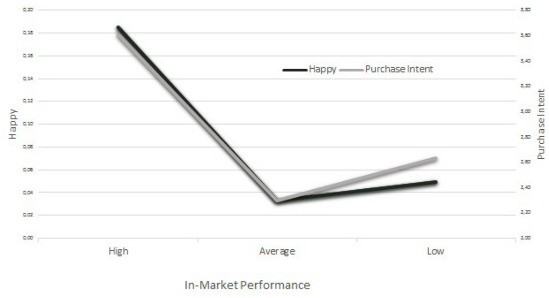

Figure 5. *Ad performance as a function of Happy expression and Purchase Intent.*

In this study, a large number of participants had to be recruited in order to reach a satisfying sample size. This was mainly a technological constraint inherent to Survey Monkey. The original design of the study was for respondents to view three ads, then take a brand recall measure, followed by a purchase intent questionnaire. However, due to the need for a platform with Flash compatibility, this was not possible, and each respondent was only shown one ad. Finally, it was not possible to control the lighting or the angle of the webcam in these studies, which accounts for the missing 12% of samples reported. Future studies are under way to test a broader range of ads.

Even given the technical constraints within this study, the data clearly show that FaceReader is a tool that is well-placed in the market as an automated, non-intrusive measure of engagement with an advertisement. Furthermore, data obtained from the software can be used to accurately predict PI by the viewer. Both the overall amount of emotions displayed, as well as the type of emotion detected by the software, can be used by the researcher to predict ad effectiveness. With this tool, Noldus has provided consumer researchers with technology that rivals older measures, such as PI, in predicting advertisement effectiveness.

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