The emotional pull of advertisements: How emotional reactions relate to purchase intent

The emotional pull of advertisements: How emotional reactions relate to purchase inte

The Question: Why is emotion important, and how do we assess it?
Noldus Consultants: Jason Rogers, PhD and Abbe Macbeth, PhD
Case study write up: Abbe Macbeth, PhD

Market researchers, advertisers, and consumer scientists have long been aware intense relationship between emotion and consumer behavior[1], and the interpl between emotion and advertising[2]. Advertisers make use of this knowledge by on our emotions: they employ cute animals and babies, remind us of when we w condition us to react to certain jingles, etc; all of these practices are designed to emotional bond between the consumer and the product.

How do consumer researchers, trying to harness consumers' emotions, actually emotionality? With technological advances over the past fifty years, researcher beyond self-report, and do more than simply asking the consumer "Tell me how

makes you feel". Instead, researchers began utilizing methods such as implicit r
time tests[3] and neuromarketing[4]. These methods both get at unconscious drive
decision making, yet neither looks at the one place where emotions are display
face.

Why is emotion important, and how do we assess it?

In the past fifteen years, technology has made it to market that automatically cl
facial expressions. Noldus provides our clients with FaceReader™
(http://www.noldus.com/human-behavior-research/products/facereader), an a
software platform providing automatic and objective assessment of facial emot
Based on the original "basic" emotions set forth by Paul Ekman[5], FaceReader
automatically determines the presence and intensity of Happy, Sad, Angry, Surp
Scared, and Disgusted, as well as Neutral. FaceReader has been validated again
coders[6], with degree of agreement ranging from 70% (Disgusted) to 99% (Happ
much of the previous work using FaceReader has focused in psychology[7,8] or fo
science research[9,10], recent work demonstrated the usefulness of FaceReader
consumer research field[11]. Specifically, the expression of Happy predicted an
advertisement's effectiveness: positive correlations were found between Happ
respondents' attitudes towards the advertisement (AAD) and attitude towards
(AB) for ads with high and medium levels of amusement, but not low[11].

A drawback to using the traditional FaceReader software for consumer researc
the software must be hosted on a local computer, with respondents present in t
laboratory in order to analyze their facial emotions. To address this, Noldus rec
debuted FaceReader Online (www.facereader-online.com), which provides the
researcher with a user-friendly, easily-accessible portal built around proven, re
FaceReader technology. By capturing respondents in their own homes, FaceRe
Online provides researchers with the option of gathering respondents from arc
globe.

A known metric of consumer behavior is purchase intent (PI), which has long be
upon by consumer researchers as an estimate of actual buying behavior[12]. Here
how does FaceReader's output compare to PI? Is it as good of a predictor as PI?
emotion assessments actually replace PI as a measure of purchasing desire? In t
current study, FaceReader Online was used to capture data from respondents a
United States as they watched a variety of advertisements. Afterwards, a PI me
taken and correlated to the expression of Happy, as it was hypothesized that a)
could predict and correlate with PI, and b) ads that performed better would also
higher PI and greater expressions of Happy.

The Journey: Using FaceReader Online

Respondents

Respondents were recruited via Survey Monkey. 22% of those invited responde
113 people total completing the study. Respondents varied in age from 21-65 a
split across gender. The only exclusionary criteria included were requiring that
respondents wear glasses and all must have a webcam attached to, or embedde
their computers.

Stimuli

After a few brief introduction slides requesting permission to use the webcam, age, and lack of glasses, respondents were shown one of eight ads. Each ad orig aired at a SuperBowl from 2009 to 2014, and ranged in category (consumer pa goods, household needs, food and beverage), as well as known market performa Each respondent saw one ad, with a final n=13-15 for each video. Ads were ran presented to respondents via FaceReader Online, randomized across age and g Videos were not taken of respondents; FaceReader Online used the responden webcams only to gather facial expression data and analyze it online. Immediate playing the advertisement, a Purchase Intent (PI) measure was taken. A short su appeared asking respondents if, based on the advertisement seen, they would b purchase that product within the month. The traditional 5-point Likert scale wa

FaceReader & FaceReader Online technology

FaceReader works in 3 simple steps, in both the original version[15] and subsequ releases[16]. The software detects the face and creates an accurate model of the based on the Active Appearance method[17]. The model describes over 500 key p the face, and facial texture is determined by how those points interact with eac The actual classification occurs by comparing the current facial expression of th respondent against an artificial neural network[18] that is trained with a databas 10,000 manually-annotated images. For each frame, FaceReader provides a val (not present at all) to 1 (maximally present) for all 7 emotions (Happy, Sad, Angr Surprised, Scared, Disgusted, and Neutral).

FaceReader Online uses FaceReader technology, but data is analyzed using Mic Windows Azure cloud platform instead of running on a local computer. Analysis carried out in the cloud using the same model and classification described abov

Data analysis

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

The Outcomes

FaceReader Online is a robust platform

Despite potential differences in lighting, web cameras, and camera placement i respondents' homes, there were no significant differences in number of frames across advertisements (average per person per ad was 415 +/- 11). All respond fewer than 11 % missed frames during analysis, with no ad having significantly missed frames than any other ad.

Ad performance predicted Purchase Intent

First, we wanted to compare the self-reported PI with each advertisement's kn performance[13], which split the ads into three categories: High-, Average-, and L performing ads. High-performing ads showed significantly greater PI compare Average- and Low-performing ads (Figure 1; $p < 0.05$); however, Average- and L performing ads did not significantly differ from one another.

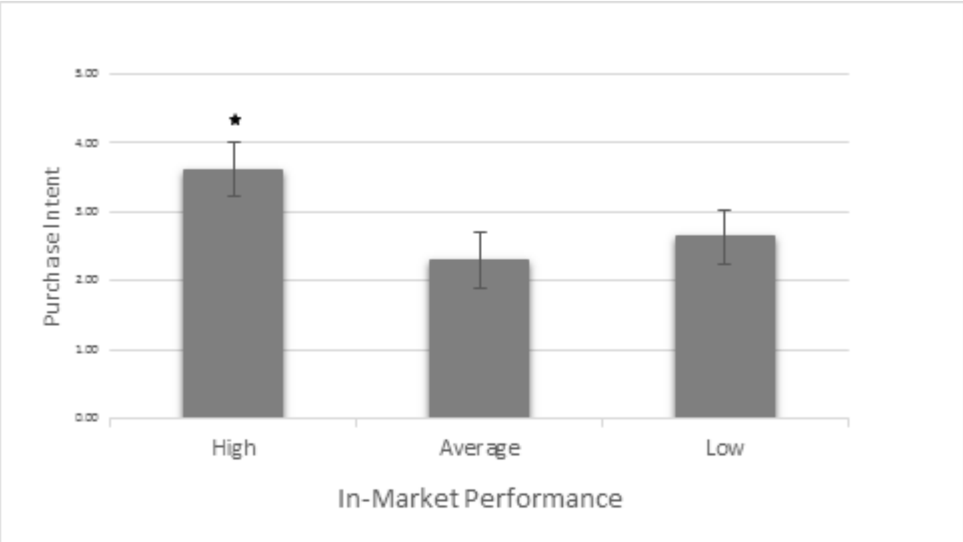

Figure 1. Ads that performed well showed significantly higher Purchase Intent Average- or Low-performing ads (*$p< 0.05$).

Ad performance predicted the amount of Happy

Based on earlier work[11], it was hypothesized that High-performing ads would greater Happy expressions. Just as we saw with PI, High-performing ads showe significantly greater outputs of Happy compared with Average- and Low-perfo

(Figure 2; p<.001); Average- and Low-performing ads did not significantly differ
another.

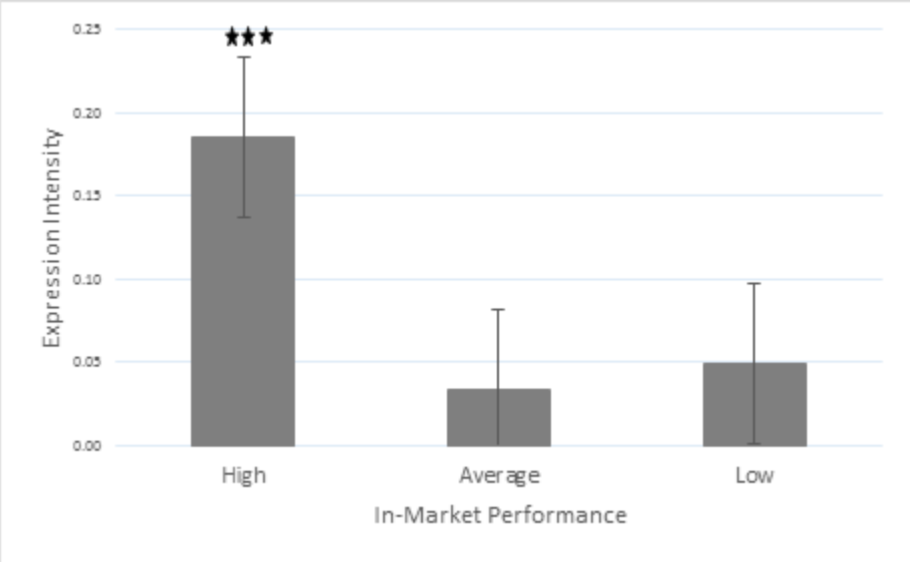

Figure 2: Ads that performed well showed significantly higher Happy expressio
Average- or Low-performing ads (***p< 0.001).

"Happy" correlated with Purchase Intent

Using a multiple regression analysis, we determined that Happy, unlike any oth
emotion, significantly predicted PI (β = .58, p<.001; data not shown). Furtherm
shown in Figure 3, Happy and Purchase Intent correlated in the same way with
Average-, and Low-performing ads.

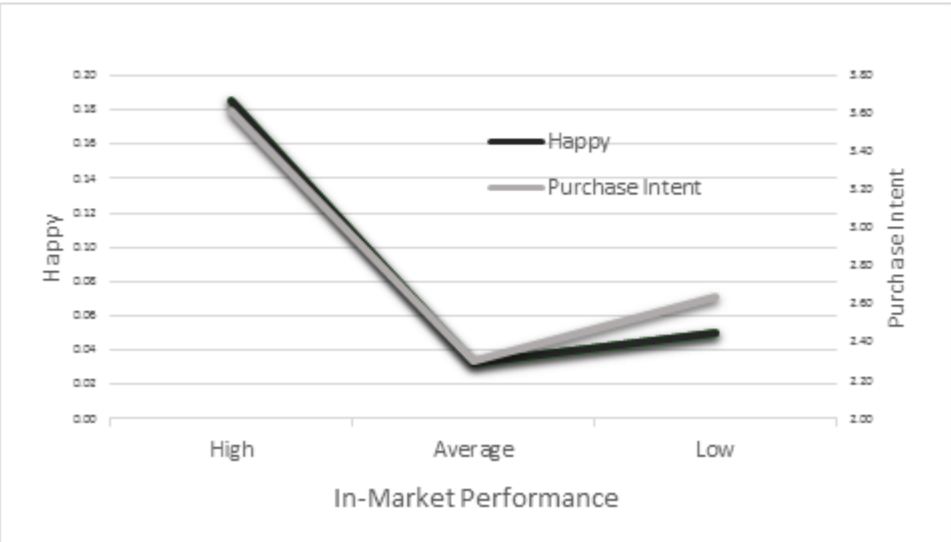

Figure 3: Ad performance as a function of Happy expression and Purchase Inte

Taken together, these data demonstrate that the Happy expression is a valid pr
PI and that an ad's performance can be defined by the amount of Happy expres
viewing.

Ad performance and general emotionality

In looking at overall emotion expression, we found that both High- *and* Low-per
ads resulted in similar emotionality: just over 30% of viewing time for both type
(Figure 4). In contrast, Average-performing ads elicited much lower emotionali
viewing – emotion expression dropped to approximately 20% of the viewing tir
Average-performing ads (Figure 4).

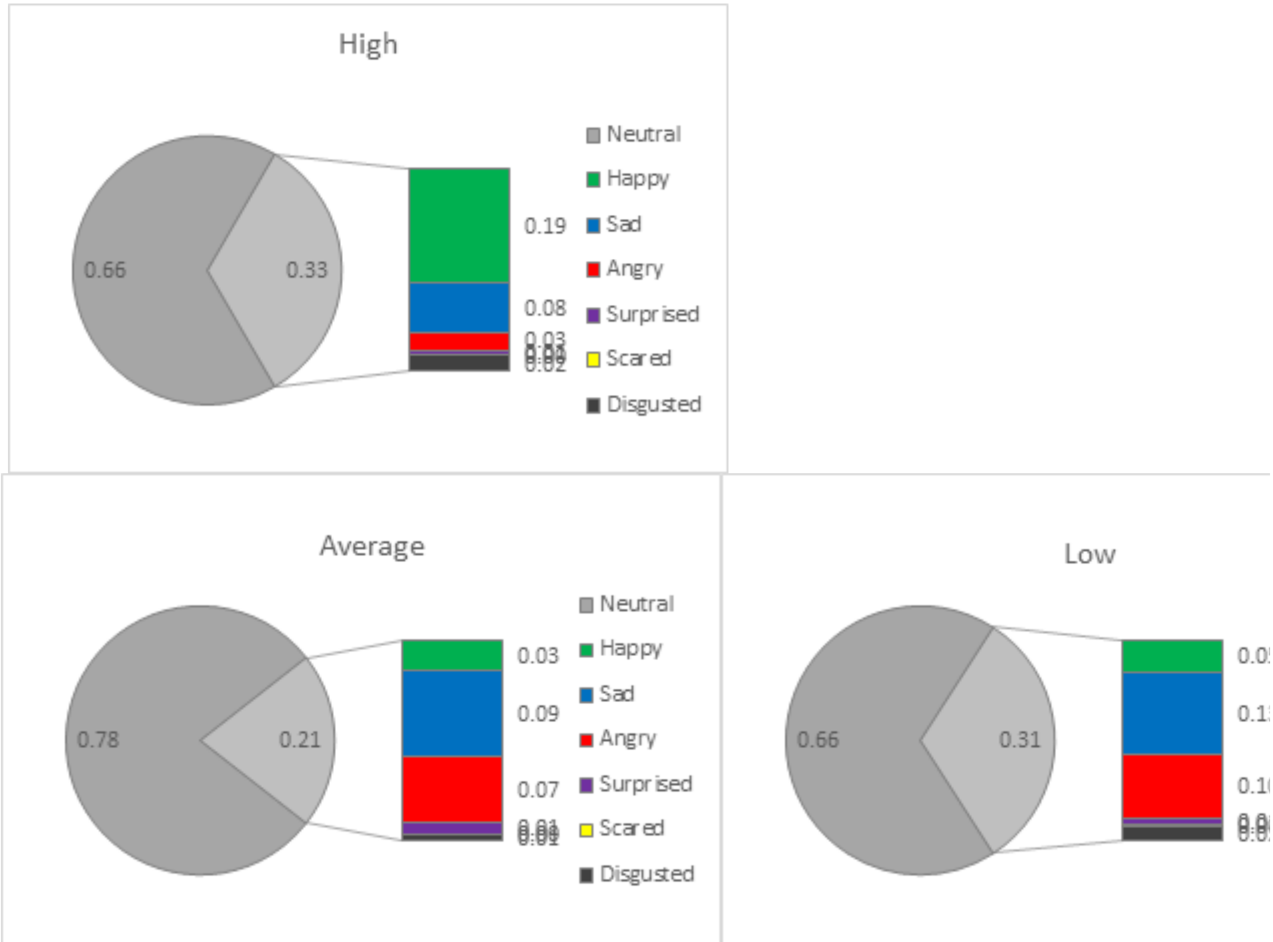

Figure 4: Overall emotional expression as a function of ad performance.

Despite eliciting similar overall levels of emotion during viewing, the types of er
elicited by High- and Low-performing ads differed. Viewers of High-performing

registered more Happy, whereas viewers of Low-performing ads displayed mor
Angry emotions. Although not significant, the data shown in Figure 4 are compe
the types of emotions that these ads elicit from viewers.

The Insights

Similar to what was found
by Lewinski et al11, FaceR
Online was able to accurat
predict PI. As anticipated,
High-performing ads displ
highest levels of PI (Figure
Happy (Figure 2). During th

of this experiment. Over ex
an ad can decrease ad effe
over time, which could influ
emotions expressed during
Finally, the halo effect, whe
consumer's overall impress
brand/market can influenc
thoughts and feelings towa
brand19 can result in an
immeasurable effect upon
effectiveness of any given
advertisement.

In addition to confirming th
usefulness of FaceReader i
predicting PI, this study als
determined that FaceRead
is a valuable tool for assess
advertisement effectivene

References

1Weinberg, P. & Gottwald, W. (1982). Impulsive consumer buying as a result of er
Journal of Business Research, 10, 43-57.

2Holbrook, M.B. & Batra, R. (1987). Assessing the role of emotions as mediators o
responses to advertising.

3http://gemmacalvert.com/everything-you-need-to-know-about-implicit-react...
(http://gemmacalvert.com/everything-you-need-to-know-about-implicit-reactio

4Sebastian, V. (2014). Neuromarketing and evaluation of cognitive and emotiona
of consumers to marketing stimuli. Procedia – Social and Behavioral Sciences, 12

5Ekman, P. Friesen, W.V. (1971). Constants across cultures in the face and emotio
of Personality and Social Psychology, 17, 124-129.

6Terzis, V.; Moridis, Ch. N.; Economides, A.A. (2010). Measuring instant emotions
self-assessment test: The use of FaceReader. Proceedings of Measuring Behavior
Eindhoven, The Netherlands, 192-193.

7Chentsova-Dutton, Y.E. & Tsai, J.L. (2010). Self-Focused attention and emotiona
the role of culture. Journal of Personality and Social Psychology, 98, 507-519.

8Ceccarini, F. & Caudek, C. (2013). Anger superiority effect: The importance of dy
emotional facial expressions. Visual Cognition, 21, 498-540.

9Garcia-Burgos, D. and Zamora, M.C. (2013). Facial affective reactions to bitter-t
foods and body mass index in adults. Appetite, 71, 178-186.

10de Wijk, R.A., Kooijman, V., Verhoeven, R.H.G., Holthuysen, N.T.E., & de Graaf, C
Autonomic nervous system responses on and facial expressions to the sight, sme
of liked and disliked foods. Food Quality and Preference, 26, 196-203.

11Lewinski, P., Fransen, M.L., and Tan E.S.H. (2014). Predicting advertising effecti
facial expressions in response to amusing persuasive stimuli. Journal of Neurosci
1-14.

12Fishbein, M. & Ajzen, I. (1975). Belief, Attitude, Intention, and Behavior. Readin
Addison-Wesley Publishing Company.

13www.acemetrix.com/spotlights/events (http://www.acemetrix.com/spotlights/

14Risen, E. & Risen, L. (2008). The Use of Intent Scale Translations to Predict Pur
Interest. Retrieved from http://www.biotrak.com/wp-content/uploads/2011/11/
Scale-White-Pap... (http://www.biotrak.com/wp-content/uploads/2011/11/Inter

type of emotion detected b
software, can be used by th
researcher to predict ad
effectiveness. With this to
has provided consumer re
with technology that rivals
measures, such as PI, in pre
advertisement effectivene

White-Paper.pdf).

15den Uyl, M.J. & van Kuilenberg, H. (2005). The FaceReader: Online facial expre
recognition. Proceedings of Measuring Behavior 2005, 5th International Confere
Methods and Techniques in Behavioral Research, Wagengingen, The Netherlands

16Van Kuilenberg, H, den Uyl, M.J., Israel, M.L., & Ivan, P. (2008). Advances in face
gesture analysis. Proceedings of Measuring Behavior 2008, Maastricht, The Neth
371-372.

17Cootes, T. & Taylor, C. (2000). Statistical models of appearance for computer vi
Technical report, University of Manchester, Wolfson Image Analysis Unit, Imagin
and Biomedical Engineering.

18Bishop, C.M. (1995). Neural Networks for Pattern Recognition. Oxford: Claren

19 Nisbet, R.E. & Wilson, T.D. (1977). The halo effect: Evidence for unconscious a
judgments. Journal of Personality and Social Psychology, 35, 250-256.

Contact us (/form/do-you-want-actionable-results)

About Noldus Consulting

Noldus Consulting provides services that help researchers uncover respondents' unique behavioral patterns, as naturally as possible.

Contact

International Headquarters
Phone: +31-317-473300
Email: info@noldus.nl (mailto:info@noldus.nl)

Asia Headquarte
Phone:
+86-10-621110
Email: info-
china@noldus.cc
(mailto:info-

North American Headquarters
Phone: +1-703-840-2454
Email: info@noldus.com (mailto:info@noldus.com)

All contact information (/contact)

china@noldus.cc
Website:
noldusconsulting
(http://www.nolc

Social media

(https://www.fac
/noldusconsultin

(https://twitter.c
/noldusco)

(https://www.linl
/company
/28105?trk=tyal