The effect of voice emotion response on brand recall by gender

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Abstract
This research collaborates with researchers in the field of human-computer interaction and suggests an alternative method: the voice emotion response in Mandarin Chinese and analyse the effect of voice emotion responses on brand recall by gender in Taiwan. The bibliographic revision was submitted to a scientometric analysis through CiteSpace. Voice emotion software and an audio-recording equipment were conducted in a laboratory and field environment and the results were analysed through Optimal Data Analysis. Brand recall in Mandarin speech is positively associated with emotions and vary by products according to gender. Men have better recall scores when related to cars, whereas women scored higher when dealing with soft drinks and fast-food. This paper provides opportunities for companies to improve customer relationships. Marketers involved with advertising have this body of knowledge to capture consumers' emotions toward their products and services on which to base their marketing intelligence gathering and strategic planning.

Introduction

Emotions could be defined as expressions, embodiments, outcomes of cognitive appraisals, social constructs and products of neural circuitry (Calvo and D'Mello 2010). Darwin (1872) was the first to scientifically explore emotions as expressions, noticing that some facial and body expressions of humans were like those of other animals, and concluding that behavioural correlates of emotional experience were the result of evolutionary processes. James (1884) proposed a model of emotions as embodiments that combined expression with the interpretation of the perception of physiological changes as the emotion itself. Arnold (1960) is considered to be the pioneer of the cognitive approach to emotions, and believe that in order for a person to experience an emotion, an object or event must be appraised as directly affecting the person based on their experience, goals, and opportunity for action. Averill (1980) claimed that emotions are primarily social constructs.

Affective neuroscience is helping to understand the neural circuitry that underlies emotional experience, the ethology of certain mental health pathologies, and is offering new perspectives pertaining to the manner in which emotional states and their development influence our health and life outcomes (Damasio 2003; Davidson *et al.* 2003; Dalgleish *et al.* 2009). Affective neuroscience has also provided evidence that elements of emotional learning can occur without awareness (Ohman and Soares, 1998), do not require explicit processing (Clavo and Nummenmaa 2007), and also self-report of emotion might not reflect more subtle phenomena that do not make it to consciousness (Chamberlain and Broderick 2007). Wang, Chien and Moutinho (2015), show that emotions are better captured using voice emotion response than self-report measures. The relevance of voice emotion response can also be seen in Glenberg *et al.* (2005), which state that the relationship between emotion and language is a vital part of the experience of emotion as social construct.

In another study Lang (2010) shows the measurement of emotions is critical for commercial purposes, often conveyed by an advertising slogan, where an appealing campaign arouse positive consumer emotion toward the message being communicated, and Teixeira *et al.* (2012) state that it helps to deliver the desired image of brand position which could generate enormous profit.

According to Guimond *et al.* (2007) emotions vary with gender. Women tend to be more external in expressing their emotions (Gallois 1994; Brody 1997), more emotionally sensitive (Bradley *et al.* 2001; Becht and Vingerhoets 2002; Chentsova-Dutton and Tsai 2007), reporting greater impulse intensity and greater positive and negative expressivity whereas men used to mask their emotions (Kring and Gordon 1998; Chentsova-Dutton and Tsai 2007). Women were more emotional-sensitive and willing to communicate their internal emotional states verbally and non-verbally than males, who normally used more extreme ratings of arousal than females (Becht and Vingerhoests 2002; Burriss *et al*. 2007). For Sahay *et al.* (2012), younger women tend to have more emotional connection with brands while men have a more rational connection with brands, but as time passes, this difference between gender narrows.

The impact of automatic preferences (for instance, indulging in impulse purchase) is stronger when people focus on affect whereas cognition has greater impact when people focus on reason for choice (Scarabis *et al.* 2006). Men are, in general, selective information processors and focus on visual and tangible cues while shopping (Meyers-Levy 1988), whereas, women are more comprehensive and detailed processors helping them to have a finer distinction between the products (Laroche et al., 2003). In addition, females generally engage in a greater degree of elaborative processing of personal, real-life emotional experiences than males do (Davis 1999). Thus, women have in-depth knowledge structures about the products they use. In addition, the memories that women have comprise of greater emotional feelings and experiences which is very unlikely to be the case with men (Kring and Gordon 1998). Females directly recall actual experience when faced with an evaluation task, in addition to drawing upon subjective knowledge (Laroche et *al.* 2003, p. 256). Females recall more autobiographical memories of emotional events and are generally faster in doing so strongly suggesting that they engage in a greater degree of elaborative processing of personal, real-life emotional experiences than males do (Davis 1999). Meanwhile, a study exploring men's brand relationships stated in the findings that the relationships that men form are more oriented towards achieving certain goals; men do form relationships but are very functional in extracting benefits from a brand (Zayer and Neier 2011).

Following these findings, the current research goes deeper analyzing by gender the recall of emotions obtained by advertising slogans captured through voice emotion software, a tool included in Affective Computing. Due to the small size of the sample, it was also introduced the robust methodology of Optimal Data Analysis (Yarnold and Soltysik 2005), as well the bibliographical review was submitted to a scientometric analysis through CiteSpace, a free Java software.

Affective Computing aims to reduce the communication gap between the highly emotional human and the computer developing computer systems that respond to affective states user (Calvo and D'Mello 2010), allowing the detection of users' mental states, revealing which feature customers enjoy and excluding those that received negative feedback. It shows a great potential to enhance companies' capabilities of customer relationship management in order to increase their marketing strategies, constantly interested in collecting and predicting the attitudes of the general public toward their products and brands (Rukavina *et al.* 2016).
The basic principle behind most Affective Computing systems is that automatically recognizing and responding to a user's affective states with a computer can enhance the quality of the interaction, thereby making a computer interface more usable and effective by measuring multimodal signals, namely, speech, facial expressions and/or psychobiology. Affective Computing focus on extracting a set of emotion labels (Picard 1997, Zeng 2009, Calvo and D'Mello 2010, Schuller *et al*. 2011; Gunes and Shuller 2013) and polarity detection, usually a binary classification task with output such as positive versus negative, or like versus dislike (Pang and Lee 2008; Liu 2012; Cambria 2013).

Emotions play an important role not only in successful and effective human-human communication, as well as in humans' rational learning (Cambria 2016). Notable fallouts in marketing and financial market prediction have raised its interest by the scientific community and the business world in Affective Computing, which leverage human-computer interaction, information retrieval, and multimodal signal processing. Marketing intelligence gathering and strategic planning based on Affective Computing, provides opportunities for companies to enhance their capabilities of customer relationships, capturing general public emotions for their products and services, and reacting accordingly.

Literature review

Spoken language is between 200 thousand and 2 million years old (Gibson *et al.* 1993), and speech has become the indispensable means for sharing ideas, observations, and feelings (Furnas *et al.* 1987). Ambady and Rosenthal (1992) indicated that voice seem to be most important in the human judgment of behavioural cues. Many of the judgments we make about others in our everyday lives are based on cues from these expressive behaviors. We communicate our interpersonal expectancies and biases through very subtle, almost imperceptible, nonverbal cues. These cues are so subtle that they are neither encoded nor decoded at an intentional, conscious level of awareness (Christensen and Rosenthal 1982, Harris and Rosenthal 1985) Brief clips of behavior have been used to identify successfully the subtle expressive cues conveying interpersonal expectancies that are very influential in the interpersonal influence process (Chaikin *et al*. 1974, Rosenthal and Rubin 1978). For example, a series of studies conducted by Bugental and her colleagues revealed that parents' expectancies, identified from brief clips of their tone of voice, are related to their children's behavior (Bugental *et al.* 1980, Bugental *et al.* 1976, Bugental and Love 1975, Bugental *et al.* 1971).

Picard (1997) considered emotional states as generally associated with certain physiological features, which produce mechanical, and therefore, measurable properties in speech, particularly in pitch, timing, frequency, and voice quality. For example, in a state of fear, anger or joy, the sympathetic nervous system is aroused, blood pressure and heart rate increase, and the mouth becomes dry. Speech is then loud, fast, and voiced with strong high frequency energy (Breazeal 2003).

A connection exists between language processing and emotions, this would be most obvious with spoken language (Wurm *et al.* 2001). The accuracy of human emotion recognition as been improved by utilizing advanced analysis methods and techniques including voice recognition, natural language processing, image processing and electroencephalography devices (Cambria 2016). Picard et al. (2001) state that emotion modulates almost all modes of human communication (e.g. word choice, tone of voice), and can significantly change the message: sometimes it is not what was said that was most important, but how it was said. Cowie *et al.* (2001) analyse how emotions could be recognized in human-computer interactions, providing a comprehensive summary of qualitative acoustic correlations for prototypical emotions.

According to Picard (2003), comparing affect recognition to speech recognition is useful for highlighting how nascent and challenging the research is. Pantic and Rothkrantz (2003) discussed how to integrate into computers several components of human behaviour in the context-constrained analysis of multimodal behavioural signals toward a more naturalistic interaction and aimed at discrete emotion recognition from auditory features like pitch, intensity and speech rate.

Other researchers show some reliable correlates of emotion in the acoustic characteristics of the signal (Banse and Scherer 1996; Burkhardt *et al*. 2005). Ambady and Rosenthal (1992) indicated that voice and body correlates well with facial expression, and large number of studies in psychology and linguistic confirm the correlation between prototypical emotions, which include happiness, sadness, fear, anger, disgust, surprise, and specific audio and visual signals (e.g., Russell *et al*. 2003). Although many systems still focus on detecting the basic emotions, there are some marked efforts aimed at detecting other states, such as frustration (Kappor *et al*. 2007). Zeng *et al.* (2009), shows the advantage of the integration of multiple modalities like vocal and visual expression in human affect perception over single modalities, and when compared to vision-based detection, speech-based detection systems are more apt to meet the needs of real-world applications. According to Calvo and D'Mello (2010) speech transmits affective information through the explicit linguistic message (what is said) and the implicit paralinguistic features of the expression (how it is said), and pitch appears to be an index into arousal. Koelstra (2012) showed that recent advances in emotion recognition have motivated the creation of novel databases containing emotional expressions in different modalities, like speech.

The top ten more cited, innovative and central references about Affective Computing, commented above, are shown in Table 1.1, by title, authors, year and source, none of them in the field of marketing. These are the results of a scientometric review from CiteSpace (Chen 2013) on 5,078 bibliographical records published between 1991-2016 from Web-of-Science of Thomson Reuters records on Affective Computing.

(Take in Table 1.1 here.)

Since the 1980s, little research has related voice pitch analysis to marketing studies (Wang and Minor 2008). Compared to other psychophysiological techniques, voice pitch analysis has at least two notable advantages for marketing research: the experimental procedure only requires oral responses, and unobtrusive audio-recording equipment, which in controlled and unnatural experimental settings is less likely to influence individuals than bulky apparatus which is noticeable (Klebba 1985).

In pursuing these ideas, an investigation centred on slogans is helpful. Slogans are short phrases that communicate ideas with themed affective position, which are used to increase likeability and memorability for a brand (Boush 1993; O'Guinn *et al*. 2003). However, not all successful brands utilize slogans as positioning strategy to communicate brand attributes that are differentiated from competitors. For instance, Burberry, Zara, and Chanel devote efforts to designing the non-verbal marketing message using visual, textural, and atmosphere cues, instead of verbal speech. Nevertheless, as a verbal form of emotional expression that most consumers have no difficulty recognizing, slogans can deliver emotional messages more easily and proactively than non-verbal communication can.

Signal-based evaluation tools makes it possible to capture and analyse speech signals of advertising slogans and elicit emotions from the signal data, in a more natural way of measuring emotions than analysing the recalled data from self-report measures. Hence, this research proposes a different method for analysing voice expression and emotions so that marketing researchers can access an uncomplicated and easy-to-operate computer-based instrument for assessing emotions embedded in advertising slogans.

Example of use of methodology with a case study

Voice Emotion Response

The purpose of the Voice Emotion Response is to give computers affect recognition abilities, ideally at a level which enables researchers to label the emotional states of other people. However, researchers meet complex problems when they attempt to teach computers how to do this, and the complexities involved could be enormous. Hence, only partial solutions may be obtained, but nevertheless, such partial solutions can still be of value. Picard (2003) argues that infants recognize some kinds of affect in speech, obviously long before they recognize what is said. Researchers in the Department of Computer Science and Engineering at Tatung University, Taiwan, developed a user interface (also known as a human-computer interface) — the Voice Emotion Response—to classify emotion. Graphical user interface (GUI) is shown in Figure 1.1.

(Take in Figure 1.1. here)

This includes short utterances covering five full-blown emotions in Mandarin speech: happiness, anger, sadness, boredom, and neutrality (unemotional) (Murray and Arnott 1993). The term full-blown emotion is used to describe fully-developed emotional expression, which is typically impassioned, and has inherent factors considered relevant for emotional expressions. When emotion is used in this sense, a positive or negative orientation can be conveyed to others (Plutchik 1994). The core architecture of this interface was developed through four stages of computer engineering.

In the first stage, pre-processing, the interface locates the endpoints of the input speech signal and high-pass filters the speech signal, which is then partitioned into pieces of frame. The Hamming window is applied to each frame, minimizing the signal discontinuities at both the beginning and the end of each frame, and converting the frames into several types of parametric representations.

The second stage extracts possible candidates from speech features. Feature extraction methods include MFCC (mel-frequency cepstral coefficients) and LPCC (linear prediction cepstral coefficients).

The third stage is the feature vector quantization stage, which occurs when 20 MFCCs and 12 LPCCs of each speech frame extract the parameters of each utterance as a feature vector. A vector quantization method obtains the mean of the feature parameters corresponding to each frame in one utterance.

The fourth stage is a classification algorithm designed to evaluate the emotions in the speech data. A weighted D-KNN (distance K-Nearest Neighbor) is used to find a vector of real-valued weights that would optimize classification accuracy of the recognition system by assigning lower weights to less relevant features and higher weights to features that provide more reliable information.

In this study, the experiment required the author to record the voice of each participant as s/he spoke the slogan, then used the Voice Emotion Response to analyse the recorded emotions. In the Voice Emotion Response, each axis of the radar chart represents emotions in the designated key performance dimensions, and examines these five primary emotions. A radar chart visualizes the consumer's evaluated emotion results, analysing several factors at once and presenting them simultaneously. By analysing speech patterns, emotional speech processing recognizes the consumer's emotional state. Vocal properties and prosody features such as pitch variables and speech rate are analysed through pattern recognition. The source of the speech signals, whether the recorded utterances in the corpus or the real-time recorded utterances from the users, is the source frame. The interface then plots the evaluation results on the radar chart, from the least extent of the emotion at the central point to the greatest extent of the same emotion on the edges. The message frame indicates the progression of the evaluation or error messages. The resulting frame shows the recognition result (Figure 1.2).

(Take in Figure 1.2. here)

Voice Emotion Response can capture and analyse speech signals and their underlying emotions directly and can collect consumers 'emotional response more naturally than self-reported measures. Park and Thorson (1990) suggest that the consumer's emotional response toward the advertisement can greatly persuade post-exposure attitudes and recall. Additionally, Hazlett and Hazlett (1999) compare results of EMG (facial electromyography) and self-report on participants' emotional responses to TV commercials, finding that EMG measures are more connected to brand recall.

Optimal data analysis

Optimal Data Analysis (ODA) is a method developed by Yarnold and Soltysik (2005) which offers maximum predictive accuracy to data, even when the assumptions of the alternative statistical models are not applied. This method is used to identify patterns in the data that distinguish the effect of voice emotion response on brand recall by gender.

The accuracy of ODA is obtained by calculating the following measures: Sensitivity, the proportion of actual females who are correctly predicted by the model; Specificity, the proportion of actual males who are correctly predicted by the model; and Effect Size Sensitivity (ESS), an index of predictive accuracy relative to chance, where values less than 25% indicate a relative weak effect; 25% - 50% indicate a moderate effect, 50% - 75% indicate a relatively strong effect, and 75% or greater indicate a strong effect over chance.

To assess generalizability, ODA first estimates using the entire sample (training set), calculating accuracy measures as described previously. Next, the model is cross-validated, and the accuracy measures are recalculated. If the accuracy measures remain consistent with those of the original model using the entire sample, then it can be said that the model is generalizable. The current study applies the approach of 'leave-one-out' (LOO) cross-validation, which is simply an n-fold cross-validation, where n= 141 observations in the dataset. Each observation in turn is left out, and the model is estimated for all remaining observations. The predicted value is then calculated for the hold-out observation, and the accuracy is determined as female or male in predicting the outcome for that observation.

The results of all predictions are used to calculate the final accuracy estimates. Model accuracy measures are calculated using the average values across all hold-out models. All variables included in the ODA model were constrained to achieve identical classification accuracy in training (total sample), and LOO validity analysis. To ensure adequate statistical power, inhibit over-fitting, and increase the likelihood of cross-validation when the model is applied to classify a smaller independent sample, model endpoints were constrained to have N>= 10% of the total sample (Yearnold and Slotysik 2016).

Results

The study in Taiwan, involved a sample of 141 participants, from 18 to 55 years old, with 80 females and 61 males and a mix of salespeople, librarians, university staff, working professionals, and graduate students. Several studies indicate that gender is associated with brand commitment (Sigal and Ram 2012; Chiang and Chiou 2014), which explains the analysis of Voice Emotion Response and its effect on brand recall by gender, applying Optimal Data Analysis (ODA) due to its robustness with small samples (Yarnold and Soltysik 2016).

Participants were presented with eight slogans to be classified into five categories of emotion, registered by Voice Emotion Response, in order to determine the effect of the emotion on brand recall by gender.

With the exceptions of Family Mart and 7-Eleven, the other slogans have two patterns regarding recall by gender: males feel happier in cars (Suzuki and SYM) showing greater recall than females. In the remaining four slogans, Coca-Cola, Pepsi-Cola, KFC and Burger King, the opposite occurs, with females being happier, and showing better recall than males. The results are in line with those found by other researchers (Teixeira *et al*. 2012; Martensen *et al.* 2007; Faseur and Geuens 2006; Janssens and De Pelsmacker 2005; Vakratsas and Ambler 1999) who state that a significant relationship exists between advertising effectiveness and positive emotions.

The brand recall is higher when associated with positive emotions, as shown in Table 1.2, which reveals the ODA' performance indices to be better than chance for all brands: 8.38% for Burger King (exact $p = 0.02$); 8.77% for KFC (exact $p = 0.003$); 13.31% for Coca-Cola ($p < 0.00001$); 15.1% for Pepsi ($p < 0.00001$); 15.96% for Suzuki ($p < 0.00001$); and 26.57% for SYM ($p < 0.00001$).

(Take in Table 1.2 here)

The observed values of the relationship between brand recall by gender are shown in Table 1.3. Female recall is higher than man for Coca-Cola (98.75% vs 72.13%); KFC (92.94% vs 75.4%); Pepsi (92.50% vs 62.30%) and Burger King (72.50% vs 55.73%). Male recall is higher than female for SYM (86.89% vs 33.75%) and in Suzuki (60.66% vs 28.75%).

(Take in Table 1.3 here)

Except for Family Mart and 7-Eleven, where there is a high 95.74% of recall, almost equal between genders, all other brands have a statistically significant relationship with gender.

For Suzuki, males have at least 1.886 (=1/0.530) more chance of recall than females, while for Coca-Cola, females have at least 3.929 times more chance of recalling than males.

The magnitude of recall by substitute brands are: SYM (56.74%) higher than Suzuki (42.55%); Coca-Cola (87.23%) higher than Pepsi-Cola (79.43%); KFC (85.11%) higher than Burger King (65.25%); Family Mart and 7-Eleven are equal (both 95.74%). This can be explained by the fact that in the Taiwanese market, SYM motorcycles are more popular than Suzuki motorcycles (China Credit Information Service 2016), and Coca-Cola is still the leading soft drinks brand. KFC came to Taiwan in 1985 and Burger King in 1990, so KFC is much more well-known and loved by Taiwanese consumers (Daily View 2014). Finally, Family Mart and 7-Eleven are the top two popular brands of convenience store.

Conclusions

This study that analyse emotions associated with repeating a slogan in Mandarin Chinese, applies emotions as social constructs, and see their effects on brand recall. Man felt happier when referring their personalities to the use of automobiles, whereas female consumers felt happier when developing associations with both brands marketing soft drinks and fast-food products.

The eating of tasty food includes two factors that make the experience pleasurable. First, there is the sensation of eating the food, what it tastes like (e.g., salty, sweet), what it smells like, and how it feels in the mouth. This last quality -- known as "orosensation" -- can be particularly important. Food companies will spend millions of dollars to discover the most satisfying level of crunch in a potato chip. Their scientists will test for the perfect amount of fizzle in a soda. These factors all combine to create the sensation in the brain associates with a particular food or drink. The second factor is the actual macronutrient makeup of the food, the blend of proteins, fats, and carbohydrates that it contains. In the case of junk food, food manufacturers are looking for a perfect combination of salt, sugar, and fat that excites the brain and gets the need to coming back for more.

There has been always a clear association between the memorisation process of advertisements and the triggering of an emotional state towards brands. It has been confirmed using Optimal Data Analysis that a positive relationship between consumers recall and brand stimuli does exist.

Issues for further discussion

International marketers view Taiwan as an entry for other Asian markets, and the understanding of Taiwanese consumers is valuable not only in targeting China but also in gaining access to other Asian markets with high concentrations of ethnic Chinese people (Javalgi *et al.* 2013). This study offers international marketing managers practical suggestions for engaging in the Chinese consumer market which is growing in significance.

Given the preliminary nature of this study, the Voice Emotion Response can as yet only recognize five basic emotions, which critically constrains the effort. Hence, researchers at Tatung University are developing further techniques to recognize more emotions that better suit marketing research. Additionally, more research dedicated to translating the Mandarin Chinese Emotional Corpus into other languages, and replicating the voice recognition method of the WD-KNN algorithm, should provide more evidence of voice emotion. The scientometric analysis through CiteSpace identify the most relevant references in Affective Computing, which enabled see that little research related voice emotion responses with marketing studies, gap this paper gives its contribution to fill it.

The difficulty of measuring emotions should not, however, be overlooked (Ambler 2000), and diversity among methods improves the robustness of marketing research (Davis *et al.* 2013). Hence, future research should involve other psychophysiological measures to test the consistency of results with the aim of generating a deeper understanding of the construct of emotions.

Computer systems are now attempting to interact more naturally with the users as human beings. The application of recognizing affect in a context-specific response would form another level of work in Affective Computing.

The numerous perspectives on conceptualizing emotions are being further challenged by emerging neuroscience evidence. Some of this evidence challenges the common view that an organizing neural circuit in the brain is the reason that indicators of emotion covary. This evidence, together with progress in complex systems theory, has increased the interest in variable models where emotions do not cause, but rather are caused by the measured indicators of emotion (Calvo and D'Mello 2010).

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