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A Framework using Neurometrics, Machine Learning & Genetic Algorithms to Choose Optimal Advertisement Method

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Abstract* – *Neuromarketing is an emerging field and gaining rapid credibility and adoption among advertising and marketing professionals. Each year, over 400 billion dollars is invested in advertising campaigns. Yet, conventional methods for testing and predicting the effectiveness of those investments have generally failed because they depend on consumers' willingness and competency to describe how they feel when they are exposed to an advertisement. Neuromarketing offers cutting edge methods for directly probing minds without requiring demanding cognitive or conscious participation. This paper discusses the promise of neuromarketing and suggests it has the potential to significantly improve the effectiveness of both commercial and cause-related advertising messages around the world. Neuromarketing under the control of genetic algorithms and machine learning techniques result in a framework that can be used to evaluate the effectiveness of different advertisement strategies to figure out the best suitable channel of advertisement for business practices. This paper is divided into four sections. Section-I discusses brief introduction of neuromarketing, review of existing literature, gap analysis. Section-II discusses about problem formulation and objectives to be achieved. Section-III presents the methodology adapted and algorithm used in the research. Section-IV deals with results analysis and conclusion of the study. related to genetic algorithm, neurometrics, and machine learning. After reviewing the existing literature the researcher feels that Genetic algorithm, Neurometrics, and Machine learning can be clubbed together to provide a framework which can help in determining the impacts of different advertisement strategies to find out the best suitable mode of advertisement for business practices.

Keywords:* *Neurometrics, Genetic Algorithms (GAs), Machine Learning, Facial Analyser, Neuromarketing, SVM (Support Vector Machine)

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INTRODUCTION

Business is considered to be an extension of multichannel sales approach to augment the customer's shopping experience through a wide variety of digital channels like mobile and desktop applications, websites, virtual reality and email etc. The invent of internet has not only provided the limitless access to information but has also permanently changed the retail and marketing practices across the globe. The dominance of omnichannel business practices are considered disruptive by traditional business intermediates and functionaries[1]. The online players like Amazon, eBay, Expedia has caused a lasting impact on contemporary retail practices and marketing mix. Customers these days are very well informed about the potential purchases they are going to make; hence contemporary retail mix is required to be customized accordingly. Omnichannel marketing mix strategies have become indispensable for profit and sales maximization. The primary issue associated with the induction of marketing mix strategies lies with the choice of channels to be added to existing channel mix [2].The integration of mobile channel, online channel and social networking has resulted in drastic changes in retail practices [3]. The touch and feel options, which were earlier offered by brick and mortar retail stores for customer gratification has now been replaced by online virtual platforms [4].

According to Fortune from Times Inc. [5], business ventures fail because of reasons like failing to understand market need, not choosing the right team, poor marketing, ignoring consumers and limited liquid assets etc. In reference to aforesaid issues, it is hard to ascertain the existing challenges and opportunities associated with omnichannel business for evaluating established marketing and decision making practices. Traditional methods to review business strategies primarily include extensive and expensive surveys. Later, it was augmented by online social media platforms to get review about product performance, design and marketing mix strategies. Finding polarity of such product reviews is quite a challenging affair as a single review could include negative and positive opinions about different features of a single product [6]. Further, textual reviews could be biased and falsifying as there are professional reviews spamming organizations, which are hired by business houses to promote their product or to tarnish the image of their competitors [7]. Furthermore, the quality of data collected through surveys, interviews and questionnaires entirely depends upon the technical expertise of the investigator whereas nontraditional methods of collecting user response like eye tracking, electroencephalogram (EEG), speech, and facial action coding can not only provide quality data but can also lead to precise business conclusions and decisions. User sentiment analysis information is already being used by businesses, governments and individuals to make timely and profitable decisions. Neuromarketing make use of techniques like Neurometrics, Eye tracking, Biometrics, Implicit Response Testing and facial action coding to understand and record human reactions. Sentiment analysis, if infused with Neuromarketing techniques can further provide automated mining of attitudes, opinions, expressions and emotions from text, speech, emotion, neuron activity and other database sources for making profitable business decisions. Such information can also be used to design advertisements which could have a better impact on target audience which may ultimately lead to better sales and increased margins.

LITERATURE SURVEY

The literature reviewed has been structured in two parts. The first part consummated the trends in multichannel business and second part presents the scope of Neuromarketing metrics and machine learning in current business scenarios.

Neslin et. al. focused on the need of design, development and evaluation of channels for enhancing customer base and customer retention. It was opined that such channels facilitate firms to interact with their customers. This study typically focused on channels, which supported two-way communication. Single way mass communication channels like television advertisement were not considered. This study was a distinction as it did not consider traditional marketing channels like catalogs [8].

Verhoef, Neslin, and Vroomen in their study “research shopping” evaluated offline retail channels like stores, catalogs along with online e-commerce portals. They defined the term research shopping as a phenomenon where customers search and review product at one channel and purchase at another channel [9].

Ansari, Mela, and Neslin; Gensler, Leeflang and Skiera; Geyskens, Gielens, and Dekimpe; van Nierop et al. examined the effect of online channels on customer purchase habits, customer loyalty and their cumulative effect on sales [10]–[13].

Li and Kannan focused on the key points which customers would consider before they actually make any online purchase. The dependence on multiple online channels like displays, referral, custom search and emails too was discussed. This article presented a methodology to point the marginal value of online marketing channels [14].

Rigby had an opinion that the new digital mobile channels have caused a disruptive change in retail environment. As witnessed during the development of online channels, the research community is now focused on the impact of mobile apps on sales performance [15].

Xu et. al. found that omnichannel approach involves more channels in comparison to multichannel phase of retail management practices. Further the study concluded that with the expansion of digital world and omnichannel practices, the actual boundaries within marketing channels are fading away [16].

Brynjolfsson et. al. suggested retail strategies which could be used in omnichannel environment. Augmented reality was used to perform competitive analysis so as to remove barriers in retail marketing due to geography and customer negligence among retailers [4].

Choudhury and Karahanna provided the adoption of electronic channels to study the relative advantage at various stages of purchase process. The authors calculated the confirmatory factor analysis (CFA) through linear structural relations (LISREL) and partial least squares (PLS) to calculate the relative advantage in the purchase process. The authors suggested the use of artificial intelligence and Web techniques to ensure a multichannel business environment [17].

Wallace et. al. provided a five-phase model for promotion of multiple channel retailing strategies and customer loyalty [18].

Baird and Kilcourse in a report by Retail System Research Company used a build, own, operate, transfer (BOOT) model to study the behavior of omnichannel customers. The report considered various aspects of Retail business marketing over two years from various demographic domains to study the business challenges in Retail marketing [19].

Wallace summarizes that for a majority of manufacturer, the e-commerce strategists will eventually be dependent on an omnichannel approach which may include investments in 3 core elements: Content, data and targeted media. The collection and mining of online data and analytics is a key to understand buyer and seller mindset [20].

William et. al. in the eBay report on omnichannel opportunities stated the benefits of omnichannel retailing environment in UK and European markets through the use of economic model. With the advent of IT enabled techniques, it was expected that the demand for omnichannel retailing will become thrice till 2018 in comparison to last 10 years [21].

Solnais et. al. discussed the popularity of neuroimaging and psycho-physiological techniques such as functional magnetic resonance imaging and eye tracking within the marketing discipline. This study examines the state of art approach adopted by neuromarketing and consumer neuroscience researchers to measure benefits and uncertainty within the domain of Neuromarketing and compared it with traditional methods to propose future research challenges [22].

Boxtel considered human source as the richest source of information for revealing someone's affective state. The use of scientific methods was proposed for quantitative analysis of affective facial expressions, or by automated systems recognizing facial expressions through visual analysis of facial movements. A concise overview of electromyography (EMG) signals of specific facial muscles was discussed. Both visual and EMG methods have their strengths and weaknesses [23].

Fugate explained that Neuromarketing enumerated some of the findings in anecdotal form, and suggests future consumer behavior research directions based on these findings [24].

Kulkarni et. al. used Facial image based mood detection techniques for non-invasive mood detection. The authors in his research developed an intelligent system for facial image based expression classification using neural networks. The method used to extract facial image was based on several generalized and specialized neural networks for detecting facial expression [25].

Granero et. al. focused on finding the most inequitable features that allowed commercials to be classified as negative, neutral and positive effectiveness based on the Ace Score index. The experiment made use electroencephalography (EEG), electrocardiography (ECG), Galvanic Skin Response (GSR) and respiration data for an audio-visual subject shown for 30- minutes. An average of 89.76% was classified according to the Ace Score through GSR and Heart Rate Variability signals [26].

Hilderbrand focused on various factors to improve advertising and other branding in industries like sensory branding, emotional appeal, correct message being perceived by customers and correct message being delivered by companies. The use of smaller and cheaper eye-tracking and galvanic readings instead of costly research methods of fMRI and EEG was suggested to be used for the purpose of understanding brain responses for study of marketing trends [27].

Chaturvedi and Tripathi proposed a fuzzy rule - based algorithm to detect 6 facial expressions of still images. The author discussed about various feature - extraction methods used for facial emotion detection and proposed an algorithm based on fuzzy rule based system to detect 6 different facial emotions. The graph based algorithm used Euclidean distance and triangular membership functions for input detection and output. The accuracy of the proposed algorithm varies from 80-100% for various set of emotions [28].

Eser et. al. reviewed the perception and attitude of professionals, neurologists and academics towards neuromarketing studies and how it can play a vital role in the marketing industry [29]

Ayata et. al. after experimentation proposed that emotions play a significant and powerful role in everyday life of human beings. Developing algorithms for computers to recognize emotional expression is a widely studied area. In their study, emotion recognition from Galvanic signals was performed using time domain and wavelet based features [30].

Bakardjieva et. al. As a new addition to the marketing research toolbox, neuromarketing science has given rise to a variety of questions relevant to consumer perceptions of this nascent area of investigation. Neuromarketing researchers are dependent on consumer involvement as research participants and finding means to educate the public about neuromarketing is a priority for professionals working in the field.[31]

Dellaert and Benedict proposed a model that digs deep into consumers' media channel consideration as a function of the media channels whether TV, billboards or social media advertising perceived benefits. In addition, they hypothesize that the usage situation affects consumers' media channel consideration and that situation-based benefit requirements moderate the effect of the benefits on their channel consideration [32].

GAP ANALYSIS

From the literature studied, it was concluded that contemporary literature never focused upon theoretical concepts associated with

Neuromarketing, machine learning and genetic algorithms. The published research lacks empirical studies to evaluate the scope of Neuromarketing techniques with respect to business advertisement strategies. In reference to the identified research gaps, there is need to implement an framework to determine the effectiveness of advertisements with respect to business.

Though Neuromarketing techniques are considered effective in recording user responses yet it is faced with a number of teething problems, including the costliness and complexity of its state-of-the-art techniques like EEG or fMRI. Such techniques require laboratory set-ups and do not lend themselves to day-to-day market research processes. In response to this, a third Neuromarketing wave is under way as innovative enterprises are developing ways to use low cost devices or even mobile phones to carry out in-home Neuromarketing measurements. From the literature review, it came into light that there is need to evaluate the performance of low-cost devices for recording customer Neurometrics against any given marketing stimulus. The business being most dynamic and ever demanding environment, require customized marketing efforts for product promotion, sales optimization and customer retention. Advertisements being the most tried and tested technique for sales optimization, cannot be ignored from multichannel business prospective. There is a need to evaluate the effectiveness of various advertisement strategies, so as to find the most suitable advertisement channel for promoting business practices.

PROBLEM DEFINITION

The biggest gap for the retailers that are aiming to increase their profits via retailing, as it turns out, is the Customers. Each customer has its own mindset while purchasing and it's a clear challenge for businesses to evaluate each customer's profile uniquely.

Frameworks for real time emotion recognition are not cost effective due to the fact that equipment used for emotion recognition like EEG(Electroencephalogram) and fMRI(Functional magnetic resonance imaging) are very costly hence they cannot be applied into Micro, Small & Medium Enterprises (M/o MSME) for building their cost effective and efficient ad campaigns and moreover using all channels (offline and online) for advertising is not affordable for industries setup in lower tier cities which can lead to failure of most new products. The pace at which data is being generated in retailing has a huge influence on merchants on how they handle business strategy. The variety and volume of data challenges merchants to shape their unique path in commerce. Merchants are being forced to manage multiple options which include email marketing, social media, mobile experiences -- including apps and web browsing -- as well as traditional storefronts, catalogs and of course, websites. Collectively, this provides a vast range of both opportunities and challenges for merchants -- making multichannel one of the most difficult yet important journeys to perfect as a merchant. "Brands have been steadily increasing their digital ad spend as they get increasingly comfortable with digital advertising and measurement, but TV formats still deliver the highest unduplicated reach (i.e., the ad reaches each audience member only once) of 85%-90%," said Beard. "While digital ads can offer considerable benefits—such as precision-focused campaigns, in-flight adjustments and more creative options—moving from TV to an all-display digital plan is a bold move for any marketer. Consider a mix of both offline and online channels for the best ROI.

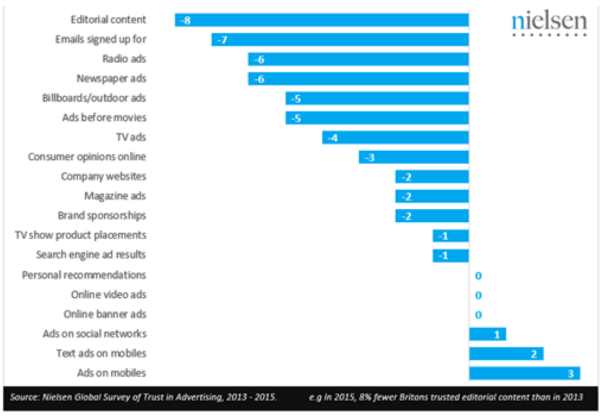

Figure 1: How consumer trust in advertising formats has changed over the years [34]

Figure 1 is a survey done by the Nielsen group and it clearly shows the variations in consumer trust in different advertising formats over the years and to summarize, as quoted by Randall Beard, president, Nielsen Expanded Verticals "while advertisers have started to follow consumers online, about a third of online advertising campaigns don't work—they don't generate awareness or drive any lift in purchase intent"

As consumers are in control of how they consume content and interact with brands more than ever, understanding ad resonance across screens is the only way to successfully drive memorability and brand lift today.

OBJECTIVES

The main objective of the study is to use the algorithms of neurometric, genetic and machine learning to figure out the best suitable channel of advertisement for business practices. The specific objectives are as below:

- To record neurometric information of prospective customers against given marketing stimulus like product advertisement.

- To transform and use the recorded neurometric information for proposing business rules.

- To evaluate the performance of business rules for identifying most suitable advertisement method for business.

METHODOLOGY

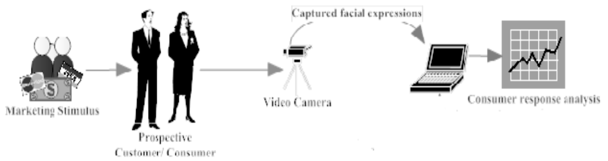

Figure 2: Experiment design to record consumer response for business

Figure 2 corresponds to the proposed experimentation for recording consumer response with respect to any marketing stimulus. Experiment will be divided into three phases namely data collection, analysis and reporting phase. Data collection phase will require a marketing stimulus and a few volunteers, so as to record their natural reactions against the given marketing stimulus. Marketing stimulus could be anything like a product, advertisement, catalog, online channel or could even be a product review. In this experiment, video renowned cosmetic brands will be used as stimulus. The volunteers need to sit in front of a video camera while they will be made to watch the commercials as marketing stimulus. The computer will be trained to identify different facial expressions like happy, sad, angry, neutral and surprise.

The experiment will be performed under controlled environment with the following parameters:

- A well-lighted room will be used to setup the necessary equipment.

- An IP Camera (Hikvision) will be used to record high resolution images of the respondents.

- Mix of 3 cosmetic advertisements will be shown to them in 3 different formats namely videos, social media/web ads and pamphlet.

Algorithm for identifying facial expressions recorded using camera

Vi[] = Reaction sequences of viewers from DEAP dataset.

Step 1: For each video in Vi[] repeat steps 2 - .

Step 2: Slice the video into frames and for each frame repeat steps 3 & 4 - .

Training data will be cropped images of dimensions 50 x 30 of eyes and mouth of each emotion for a variety of persons, as shown in table.

Table 1: Size of training data used to detect emotions

Emotion	Cropped Object	No. of Samples
Happy	Eyes	10045
Sad	Eyes	10156
Surprised	Eyes	10945
Anger	Eyes	10515
Neutral	Eyes	10087
Happy	Mouth	10113
Sad	Mouth	10145
Surprised	Mouth	10033
Anger	Mouth	10098
Neutral	Mouth	10104

Step 3. Read each training data file and vectorize it i.e. converts the 2d matrix of 50 x 30 into array of 1 row and 1500 (50x 30) columns.

Step 4: Crop eyes and mouth using HAAR-cascading as shown in figure 3 & 4.

Figure 3: Captured data

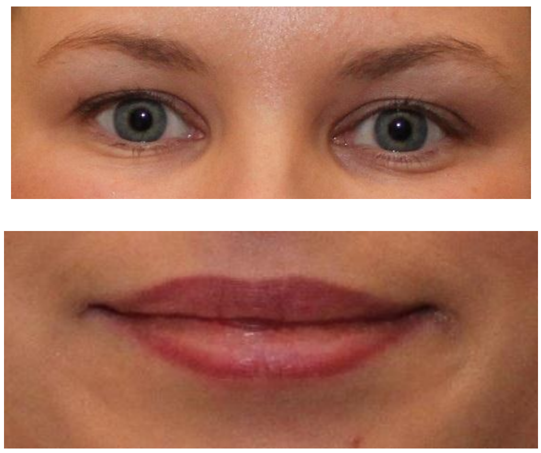

Figure 4: Cropped eyes and mouth

Step 4. Train an SVM classifier using genetic algorithm inspired parameter tuning using parameter tuning on labelled data.

Step 5. Run the pre trained SVM classifier on T and for each frame (total = 180) of the test data {1...k} store the probabilities of classification of each emotion as {Ha , An , Sa, Su ,Ne}.

RESULTS

In order to test the model, videos having facial expressions of 20 male as well as 20 female were recorded and fed to the computer for analysis. SVM technique used to do analysis of videos frame by frames thenafter results are represented to the outer world. The training was performed to identify different expressions related to face viz. happy, sad, surprised, anger and neutral.

These facial expressions are used in order to check response of different respondents against the different methods of advertisement. Only popular brands are used in order to minimize the bias, as respondents have already seen these advertisements so it minimizes the biasness that is impulsive in nature. The videos were given to the logic engine to find out the inferences in order to know the effectiveness of the various advertisement methods.

FE_{mn} denotes Probability for a certain set of emotions calculated during analysis of face against each recorded video frame. Following business rules represented as interpretations are drawn from the experiment results as:

Interpretation 4.1:

$$\underset{1\leq m\leq 180,\quad n=3}{[FE_{mn}]} > 0.7 \text{ then set value } [FE_{mn=1}]$$

Explanation: *P*redicts “Happy” as an output if the value of happy emotion for m[th] frame is more than 0.72.

Interpretation 4.2:

$$\underset{1\leq m\leq 180,\quad n=4}{[FE_{mn}]} > 0.72 \text{ then set the value } [FE_{mn=2}]$$

Explanation: *P*redicts “Sad” as an output if the value of sad emotion for m[th] frame is more than 0.72.

Interpretation 4.3:

$$\underset{1\leq m\leq 180,\quad n=4}{[FE_{mn}]} > 0.72 \text{ then set the value } [FE_{mn=3}]$$

Explanation: *P*redicts “Angry” as an output if the value of angry emotion for m[th] frame is more than 0.72.

Interpretation 4.4:

$$\underset{1\leq m\leq 180,\quad n=4}{[FE_{mn}]} > 0.72 \text{ then set the value } [FE_{mn=4}]$$

Explanation: *P*redicts “Surprised” as an output if the value of surprised emotion for m[th] frame is more than 0.72.

Interpretation 4.5:

$$\underset{1\leq m\leq 180,\quad n=4}{[FE_{mn}]} > 0.72 \text{ then set the value } [FE_{mn=5}]$$

Explanation: *P*redicts “Neutral” as an output if the value of neutral emotion for m[th] frame is more than 0.72.

DEAP datasets were used for training the logical model on facial expressions. The dataset consists of videos as well as images data. The software facial analyzer was coded in a manner to identify various face expressions like happy, angry, sad, surprise, neutral. Different marketing stimuli of different popular cosmetic brands were analyzed and the mean score of responses were calculated for each marketing method. Figures shown below represent probability scores of different emotions for different respondents.

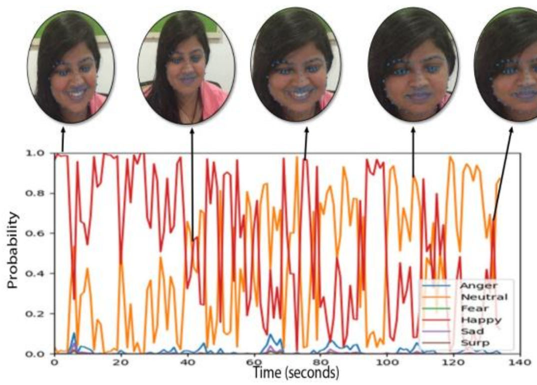

Figure 5: Respondent A emotions probability scores

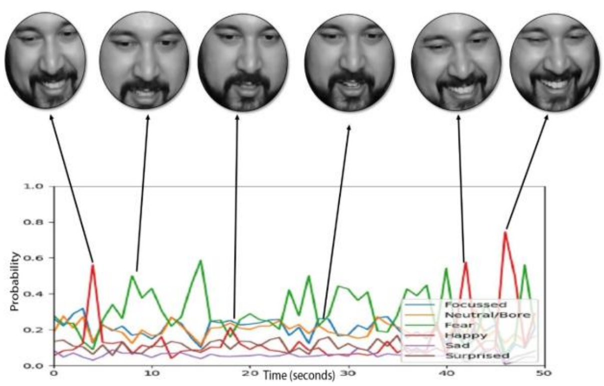

Figure 6: Respondent B emotions probability scores

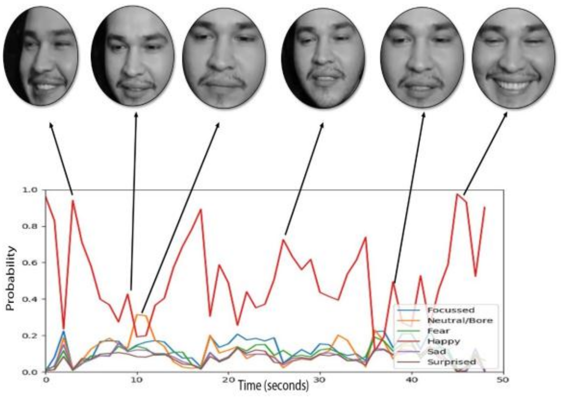

Figure 7: Respondent C emotions probability scores

After performing tests by providing face expressions as inputs, the below mentioned confusion matrix was created by the software facial analyzer to know the precision of the model:

Table 2: Confusion Matrix

Emotion	Angry	Surprised	Sad	Happy	Neutral	Total
Angry	85	3	7	1	1	97
Surprised	3	70	2	2	3	80
Sad	5	4	72	3	5	89
Happy	3	2	2	170	6	183
Neutral	2	2	1	8	130	143

The total number of images used=592

Calculation of precision

The formula used is

$$Precision = True\ Positive / True\ Positive + False\ Positive \text{ --- (1)}$$

With the help of table 2, the precision for all emotions is calculated by using equation (1):

a) Precision of "Happy" Emotion = 170/183 = 0.928

b) Precision of "Sad" Emotion = 72/89 = 0.808

c) Precision of "Angry" Emotion = 85/97 = 0.876

d) Precision of "Surprise" Emotion = 70/80 = 0.875

e) Precision of "Neutral" Emotion = 130/143 = 0.909

Average precision = 0.879

Impact of different advertisement stimulus on behavior of customer

This section explains the impact of different marketing stimuli viz video advertisements, flyers/catalogs/billboards/pamphlets and social networking sites on the customer. To know the impact, facial analyzer is used that works on 180 frames and duration is 180 seconds; the average probability score has been calculated by the formula as mentioned in equation (2).

Probability score (PS) =

Frames classified for particular emotion by facial analyzer (E_f) / Total frames analyzed by facial analyzer (T_f) --(2)

Business Rules

To know the optimal advertisement methods, the advertisement methods used are videos (VI), Flyers/catalogs/billboards (FL) and social networking sites (SI).

Basic Terms Used:

E_f = Frames classified for particular emotion by facial analyzer

T_f = Total Frames Analyzed i.e. 180

Probability Score for each particular emotion (PSPE) = E_f / T_f

The rules are:

This whole process is done to know the effectiveness of different marketing stimulus on the marketing channels and how they effectively help in the growth of the sales. After performing calculations, the effectiveness of video advertisement, online social networking web pages and static promotional efforts like Story Boards/Text/pamphlets/Flyers/billboards were recorded.

I. If (PSPE of [VI] > PSPE of [SI]) and If(PSPE of [VI] > PSPE of [FL]) The optimal advertisement method is videos

II. If(PSPE of [SI] > PSPE of [VI]) and If(PSPE of [SI] > PSPE of [FL]) The optimal advertisement method is social networking sites

III. If(PSPE of [FL] > PSPE of [SI]) and If(PSPE of [FL] > PSPE of [VI]) The optimal advertisement method is flyers/catalogs/billboards/pamphlet

Table 3: Expressions' Probability Score for Video Advertisement

Stimulus: Video Advertisements of different cosmetic products Sample Duration: 180 seconds Total Frames Analyzed by facial analyzer: F=180		
Expressions	**E_f**	**Average Probability Score**
Surprised	7	0.038889
Happy	69	0.383333
Angry	18	0.1
Sad	26	0.144444
Neutral	60	0.333333

Table 4: Expressions' Probability Score for Billboards/ Flyers

Stimulus: Flyers/ billboard pictures and pamphlet Sample Duration: 180 seconds Total Frames Analyzed by facial analyzer: F=180		
Expressions	**E_f**	**Average Probability Score**
Surprised	7	0.038889
Happy	37	0.205556
Angry	20	0.111111
Sad	33	0.183333
Neutral	73	0.405556

Table 5: Expressions' Probability Score for Product Page of Social Networking Site

Stimulus: Social Networking Site Product Page Sample Duration: 180 seconds Total Frames Analyzed by facial analyzer: F=180		
Expressions	**E_f**	**Average Probability Score**
Surprised	8	0.044444
Happy	84	0.466667
Angry	7	0.038889
Sad	5	0.027778
Neutral	76	0.422222

Figures shown below represent bar-charts showing impact of stimulus on business practices based on values of tables 3, 4 and 5.

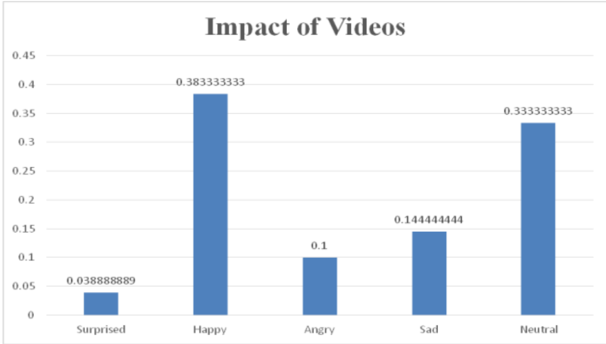

Figure 8: Probability v/s Emotion Graph for Impact of video Advertisement

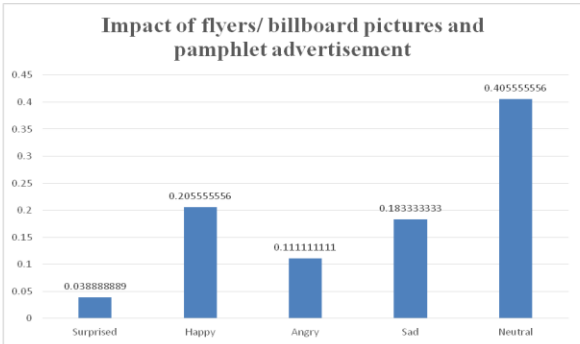

Figure 9: Probability v/s Emotion graph for impact of flyers/ billboard pictures

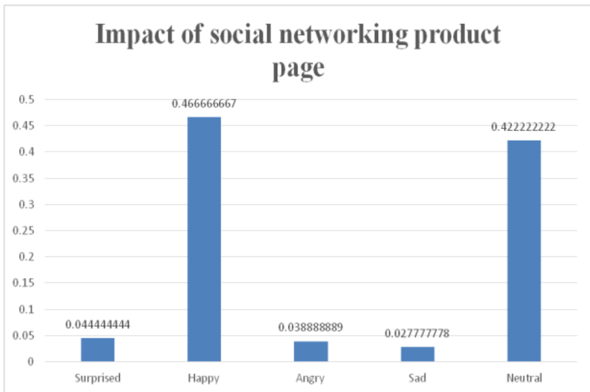

Figure 10: Probability v/s Emotion Graph Impact of social networking product page

To evaluate the performance of individual advertisement channels for varying omnichannel options with respect to average cumulative probable score for cosmetic product advertisements, a comparative analysis was made and the output is shown in Figure 11.

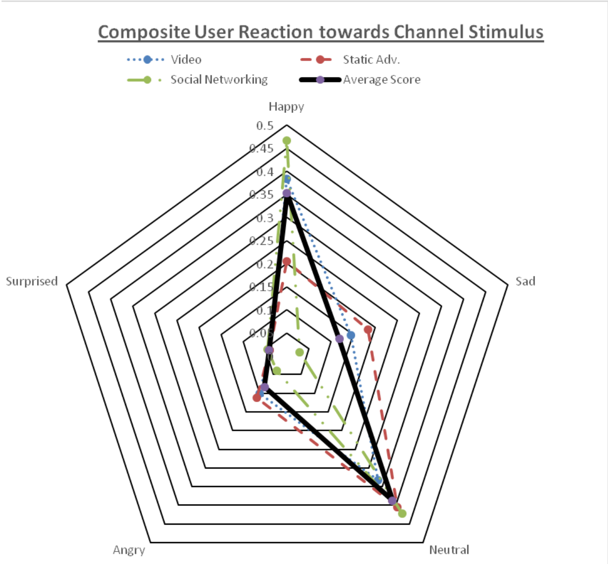

Figure 11: Combined comparison of Advertisement Stimulus

CONCLUSION

After finding out the average probability score for each particular emotion it is revealed that most positive impact for "Happy" emotion is created by social website pages followed by videos and further followed by flyers respectively. The probability for "Happy emotion" is respectively 0.46, 0.38 and 0.20 approximately.

The result showed that social networking product page have highest impact on the product promotions and the expressions that are recorded are closest to the expected average probability score. The second highest impact is of video advertisements followed by the impact of catalogs/flyers/pamphlets.

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