Towards Evaluating e-Commerce Sites Purchase Intention using Affective Computing, a Preliminary Study

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Abstract: The evaluation of an e-commerce website usability and effectiveness is traditionally measured through surveys. These tools provide subjective information about the user perception of the website, and their use is expensive and involve some drawbacks, since it requires the user to collaborate in the study and to control the sample. In this work, we explore the relation between what the users perceives and shares when they are asked about their experience, and the emotion they show while using the system under study. We use Affective Computing algorithms to analyse user expressions, and we compare the results with the information provided by means of a TAM based survey.

1 INTRODUCTION

The success of any e-commerce website is strongly determined by the usability of its user interface, and thus, by the satisfaction of the user that access the site (Sahi, 2015). The most popular and traditional way to measure the satisfaction of the user is applying Technology Acceptance Models (TAMs) (Marangunić & Granić, 2015), that is, using surveys that the subject must fulfil after using the product. Although this method is well tested and accepted, it has many drawbacks that make it difficult and expensive to use, especially in frequently updated web sites, since it requires the subject collaboration and a controlled sample. Moreover, the results of the evaluation are based on the subjective perception from the user, who can be influenced by many factors (familiarity, learning effect, sympathy for the website, reluctance to changes, etc.) that could bias the results, and favour a website over others with better design and usability.

In order to remove the subjective component, there are other strategies like, for example, the use of eye-tracking technologies, which measure the performance of the user with objective parameters (Cooke, 2004; Lasa et al., 2015; Rakoczi & Pohl, 2012). However, they usually require onsite evaluation and technological infrastructure.

On the other hand, one of the emerging and most active lines of research in Human Computer Interaction is the one related to the perception of user emotions though artificial vision algorithms. This is part of what we know as Affective Computing (AC) (Ma & Yarosh, 2021). AC algorithms can process the picture of a subject and classify their emotions analysing their facial expression. The relation between emotions, usability and purchase intentions has been already demonstrated by previous research works (Eroglu et al., 2001).

In this paper, we try to explore whether the user emotion captured by AC algorithms while using an e-commerce site is consistent with the user subjective perception of usability according to responses to a

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TAM based survey. We designed a prototype that simulates the purchase process in an e-commerce website, gathering pictures of the subject and evaluating them with three different AC algorithms, and at the same time, we asked users to fulfil the survey at the end of the process. The results we obtained, despite the reduced size of the sample, point out that there is a significant correlation between the output of the AC algorithms and some questions of the survey.

2 RELATED WORK

Results from earlier studies demonstrate a strong and consistent association between user emotions and purchase behaviour. The most important factor affecting user emotion on an e-commerce website is undoubtedly the user interface and user experience (Eroglu et al., 2001). These authors developed an exemplary e-commerce site in their study and conducted a survey with 328 people who tried the site. They concluded that the environment of the online shopping site will affect the emotion and attitude of the user, which in turn will affect the shopping results (Eroglu et al., 2001). Makkonen et al. emphasized that, in cases of successful sales, users are generally in a positive mood. Moreover, they found that positive emotions are more effective than negative ones in situations such as satisfaction, repurchase and recommendation (Makkonen et al., 2020). In addition, Kemppainen et al. found that the user interface is a critical factor that can cause negative emotions (Kemppainen et al., 2020).

Numerous studies have been conducted to evaluate interface performance based on user feelings. Although the selected methods are different from each other, the main idea is to detect the emotions of the user with the help of sensors while trying a product, and then to direct a survey to the users and analyse the data obtained to measure the performance of the user interface.

2.1 Emotion Detection

Several different dimensions can be used to represent emotions. For example, the *Pleasure, Arousal and Dominance* (PAD) emotion model developed by Mehrabian et al. uses 3 dimensions to detect all emotions (Mehrabian & Russell, 1974). In contrast, Fontaine and Plutchick examined emotions using more than two dimensions (Fontaine et al., 2007; Plutchick, 1980). Bhandari et al. used arousal and valence dimensions to analyse user emotions in their study examining the effects of design factors (Bhandari et al., 2017). Johanssen et al., on the other hand, developed a framework to define usage issues in mobile applications based on user sentiment, and tended to divide sentiment into 7 different dimensions (Johanssen et al., 2019). In their study, Eroglu et al. experienced that the PAD scheme could not capture most of the effects of the site atmosphere and suggested the use of a more inclusive scheme in nature that includes reactions such as interest, anger, surprise and disgust (Eroglu et al., 2003). In our study, similar to such suggestion, we examined emotions in 7 different dimensions.

Furthermore, many methods such as Galvanic Skin Response (GSR), Electrodermal Activity (EDA), Electroencephalogram (EEG), Electromyography (EMG) and Facial Expression Recognition (FER) have been used to detect emotions in research. Gasah et al. used an EEG device to detect emotions in their study, which was aimed to determine whether a user interface would create positive emotions in students (Gasah et al., 2019). Bhandari et al. used more than one method: Facial-EMG for valence and EDA for arousal in their study (Bhandari et al., 2017). Lasa et al. developed a UX evaluation tool using FER and an eye tracker (Lasa et al., 2015). Psychophysiological sensors (GSR/EDA, EEG, EMG etc.) can give the user's emotional state in real time, but there are some disadvantages associated with the use of such sensors. Firstly, measurements made with them can be expensive. Moreover, the use of these sensors is so intrusive that can disrupt human nature by distracting the user and hence change the results of the experiment (Maia & Furtado, 2016). In our study, we used the facial expression detection method to detect emotions. No physical contact was made with the participants, the user carried out the experiment in his own personal environment, and only the user's own computer and camera were used to collect data.

2.2 Measuring Satisfaction with Surveys

The Technology Acceptance Model (TAM) pretends to understand how users accept and use a technology (Marangunić & Granić, 2015). TAM has been used in many studies covering the subject of Human Computer Interaction (Tang & Hsiao, 2016). It was developed by Fred Davis in his study, “What causes people to accept or reject information technology?” (Davis, 1989). In response to the question, he proposed the following bivariate approach.

Perceived Usefulness: The degree to which a user believes that a new technology will improve business performance.

Perceived Ease of Use: The degree to which users believe that they will not have difficulty using a new technology.

We used a questionnaire survey method based on the Technology Acceptance Model in our work. Questionnaires are useful tools for collecting subjective data containing users' feelings and thoughts, and can be used to support the results of the experiment. To the best of our knowledge, there is not any *de facto* standard survey model used in studies that perform facial expression analysis for emotion detection. For example, in the research driven by Mcduff et al., two questionnaires were administered, one of which was conducted prior to the experiment (McDuff et al., 2015). The prior experiment questions were mostly about whether the user liked the ad or bought the product featured in the ad. The questionnaire used by Staiano et al. consisted of 3 different sections: (i) UX evaluation; (ii) user's media-player usage information and (iii) demographic information. In the user experience evaluation section, they examined 6 different dimensions of web site design (Staiano et al., 2012). Faisal et al. developed a 26-question questionnaire, in which they assessed web design features (typography, colour, content quality, interactivity, and navigation) to determine trust, satisfaction, and loyalty (Faisal et al., 2017). In this study we used a questionnaire based on this last paper. The final set of items, which were measured using a 7-point Likert scale, was the following:

1. It is easy to read the text on this website with the used font type and size.
2. The font color is appealing on this website.
3. The text alignment and spacing on this website make the text easy to read.
4. The color scheme of this website is appealing.
5. The use of color or graphics enhances navigation.
6. The information content helps in buying decisions by comparing the information about products or services.
7. The information content provided by this website meets my needs.
8. Contents and information support for reading and learning about buying process.
9. This website provides adequate feedback to assess my progression when I perform a task.
10. This website offers customization.
11. This website offers versatility of ordering process.
12. This website provides content tailored to the individual.
13. In this website everything is consistent.
14. Navigation aids serve as a logical road map for buying.
15. Obviousness of buying button and links in this website.
16. It is easy to personalize or to narrow buying process.
17. It is easy to learn to use the website.
18. This website supports reversibility of action.
19. Overall I am satisfied with the interface of this website.
20. My current experience with this website is satisfactory.
21. Overall. I am satisfied with the amount of time it took to complete the tasks for buying products.
22. Overall. I am satisfied with accuracy for this website related to the buying process.
23. I trust the information presented on this website.
24. This website is credible for me.
25.I would visit this website again.
26. I would recommend this website to my friend.

3 OUR APPROACH

Our purpose was to check whether it is possible to measure the satisfaction of the user with a website through the analysis of the expressions of their face, processed by means of affective computing algorithms. We developed a shopping site simulation to collect data. To know their subjective perception of the website, participants were asked to complete two tasks, browsing the website and completing the questionnaire about their experience using the website. Figure 1 shows the method pipeline.

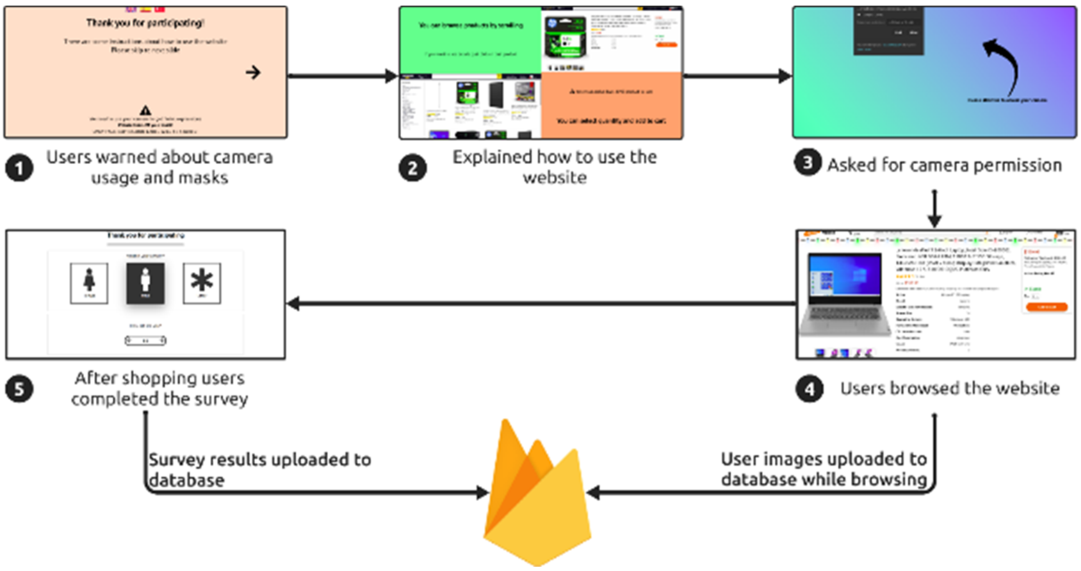

Figure 1: Method pipeline.

3.1 Data Collection

To develop the website user interface, we used the popular JavaScript library ReactJS[4]. We adapted the design from a popular shopping website and created a different look and feel by changing some features in the design, such as the logo, colours and layout, so as not to bias participants. Before starting the simulation, we included a start page that explains how the participant must use the website, asks them to remove their masks (when this is relevant) while using the website, and for the necessary permissions from the participant so that we can use the camera and take snapshots.

After obtaining the necessary permissions, the participant is redirected to the web site and the purchase simulation starts. To distinguish the participants, an artificial unique id is assigned to each of them. The participant is asked to do some simple tasks: browse the products and add at least 1 product to the shopping cart to complete the simulation. A photo of the subject is taken every 2 seconds while they are browsing the website.

Additionally, photos are taken when the subject adds a product to the shopping cart and finish the shopping. The captured photos are saved in the database in Base64 format in real-time. Moreover, the information of the page viewed by the user at the time the photo is taken, and the time information are also recorded in the database. Due to possible errors, simulation sessions are limited to 10 minutes in order to avoid taking too many photos of the participants and therefore to fill the database unnecessarily.

At the end of the simulation, the questionnaire is shown to the subjects. The questionnaire is presented in 3 different languages, English, Spanish and Turkish. This questionnaire is designed based on the one used by Faisal et al. in a similar study (Faisal et al., 2017), which was designed based on well tested previous relevant TAM studies.

In addition to these, Google Analytics web analytics service, was used to analyse website traffic and audience. The unique ids we assigned to the participants enabled us to track each subject separately.

The Google Cloud Firestore service is used to store collected data. The website is hosted on Vercel, a free platform for hosting static websites.

We kept the website open for 3 months. At the end of the experiment, we wrote a simple JavaScript script to retrieve data from the database. Survey data was stored in CSV format. Subjects' photos were converted from Base64 format to PNG image format using a Python script and stored temporarily for use in the analysis.

3.2 Participants

At the end of the data gathering process, a total of 119 participants visited the site. Although we offer the survey in 3 different languages (English, Spanish and Turkish), we made the site accessible to all countries. Most of the participants were from Pakistan and

[4] https://es.reactjs.org/

Spain. We did not try to balance factors such as the gender of the participant or the platform they used so that the shopping process would proceed naturally. Figure 2 shows the distribution of participants by gender, age, and the platform they use.

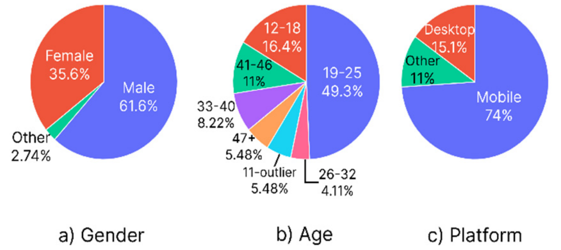

Figure 2: Distribution of participants by gender, age, and the platform they use.

Not all respondents who visited the website completed the survey or were willing to allow their photos and responses to be recorded. In these cases, participants' data were not used in the analysis. 61% of the participants who visited the web site allowed their photos to be saved and completed the survey.
In addition, not all the participants had a properly working webcam or they did not read the warnings carefully and take off their masks before starting the simulation. After examining the collected photographs and cleaning the data, 49.3% of the participants who completed the survey (30.25% of all participants) provided valid data to be used in the analysis.
In summary, data from 36 participants, with an average of 57 photos, were used for the analysis.

3.3 Detecting Facial Expressions

To predict facial expressions, we first detected the faces of the participants from the captured photos and then saved these facial photos in the subjects' folders. For the sentiment prediction, we used 3 pre-trained deep learning models that were previously trained on the facial expression dataset. We mentioned this process in the Emotion Detection section. Figure 3 shows the facial expression recognition pipeline.

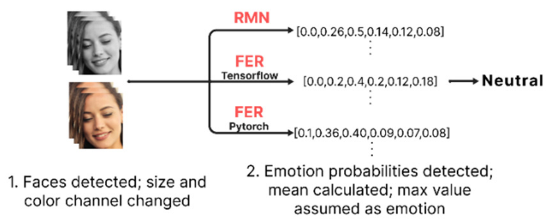

Figure 3: The facial expression recognition pipeline.

3.3.1 Face Detection

MediaPipe is a framework that provides cross-platform machine learning solutions. We used the MediaPipe framework's face detection tool to detect faces. We set the MODEL_SELECTION parameter to 0. 0 value, which works better at finding faces up to 2 meters, and parameter 1, better at finding faces up to 5 meters. For the MIN_DETECTION_CONFIDENCE parameter we set 0.5, which means that face detection is considered successful if the value is greater than 0.5.

In some photos, more than one face was detected, in which case we saved the detected faces in a separate folder and then manually filtered the faces that did not belong to the participant. We manually reviewed the obtained data again and removed any invisible, blurred or duplicate faces.

3.3.2 Facial Expression Detection

We used 3 pre-trained models, trained with ready-made datasets, to detect facial expressions.

RMN: It was developed using Pytorch, trained using the FER2013 and VEMO datasets, and achieved 76.82% and 65.94% accuracy on these datasets, respectively (Pham et al., 2020).

FER-Tensorflow: It was developed using TensorFlow, trained using the FER2013 dataset and achieved 65% accuracy (*GitHub - Xionghc/Facial-Expression-Recognition: Facial-Expression-Recognition in TensorFlow. Detecting Faces in Video and Recognize the Expression(Emotion).*, n.d.).

FER-Pytorch: It was developed using Pytorch, trained using the FER2013 and CK+ datasets and achieved 73.12% and 94.64% accuracy on these datasets, respectively (*GitHub - WuJie1010/Facial-Expression-Recognition.Pytorch: A CNN Based Pytorch Implementation on Facial Expression Recognition (FER2013 and CK+), Achieving 73.112% (State-of-the-Art) in FER2013 and 94.64% in CK+ Dataset*, n.d.).

Each model predicts 7 emotions, namely happy, sad, neutral, angry, fearful, disgusted, surprised. To get the final result from 3 different predictions, we averaged each emotion and assumed the emotion with the highest probability to be the overall emotion of the participants while shopping. We combined the results with the survey results and saved them in CSV format.

3.4 Data Analysis

Once the data had been gathered, we assessed whether certain facial expressions were statistically associated with certain responses to the questions in the questionnaire. To do this we discarded all the facial expressions except neutral and sad, as they did not have enough observations to conduct statistical tests. For the case of neutral there are 16 cases in the sample and for the sad expression 15.

As we have only two valid expressions and the total sample is of small size, we used the non-parametric Mann-Whitney test (Wilcoxon rank sum test) instead of the usual t-tests to assess whether the responses of the participants with sad expression were significantly different from those of individuals with neutral expression. Also, as the prior theoretical developments do not suggest a direction in the relationship, we used two-tailed tests.

4 RESULTS

Table 1 shows the results of the Mann-Whitney tests. The results of each test (one for each question) are displayed in a row in the table. We include the mean rank for neutral and sad expressions, and the p-value associated to the z statistic associated to the Mann-Whitney's U in the test. Tests evidencing significant differences ($p<5\%$) are displayed in bold typeface while tests suggesting slight differences ($5\%<p<10\%$) are displayed in italics.

Table 1: Results of the Mann-Whitney tests.

Question	Mean rank for neutral (n=16)	Mean rank for sad (n=15)	p-value
1	**10.44**	**21.93**	**<0.001**
2	*13.00*	*19.20*	*0.054*
3	**12.19**	**20.07**	**0.014**
4	13.56	18.60	0.115
5	**11.06**	**21.27**	**0.002**
6	13.56	18.60	0.117
7	14.34	17.77	0.284
8	14.50	17.60	0.337
9	17.22	14.70	0.438
10	17.47	14.43	0.348
11	15.56	16.47	0.779
12	16.69	15.27	0.660
13	16.28	15.70	0.856
14	14.50	17.60	0.330
15	*13.25*	*18.93*	*0.078*
16	16.94	15.00	0.549
17	14.66	17.43	0.386
18	15.97	16.03	0.984
19	16.31	15.67	0.842
20	14.69	17.40	0.400
21	14.47	17.63	0.324
22	14.53	17.57	0.347
23	15.34	16.70	0.673
24	14.88	17.20	0.467
25	13.75	18.40	0.148
26	15.91	16.10	0.952

It is evidenced that for questions 1, 3 and 5 the mean rank for the individuals with sad expression are significantly higher than the rank for those with neutral expression. This means that the values obtained in the questionnaire were significantly higher for individuals with a sad expression. Then, this kind of users finds easier to read the text with a) the used font type and size and b) the text alignment and spacing. Users with sad expression have also a stronger conviction that colour / graphics in the website enhance navigation. For questions 2 and 15 the test evidences that differences, if not so strong, are still present. So, the font colour is slightly more appealing for sad users and they find a bit more obvious the buying button and links in the website. For the rest of the questions, tests do not show significant differences.

5 CONCLUSION

These results of the study are initially confusing. The three questions that evidence a strong relation with subjects showing a sad expression are emphasizing positive aspects of the design (regarding font, text layout and readability and colours selection). That is, results suggest that users who appreciate these aspects of the design as positive are sad. After analysing the results, we reviewed the pictures classified as sad by the algorithms, and what we found out is that most of them seem to be concentrated instead of sad. Thus, it seems more reasonable to think that users that found out the application more useable where more focused on the task and so, were classified as sad.

Obviously, this is just a conjecture, and should be checked with a new experiment, so we cannot assume that as a valid result of the experiment. Nevertheless, results suggest that there is a relation between the subjective perception of some of the aspects of the design and the information we gather using AC algorithms. This encourages us to repeat the experiment with a bigger and controlled sample of users.

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