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ANALYSIS OF DESIGNER EMOTIONS IN COLLABORATIVE AND TRADITIONAL COMPUTER-AIDED DESIGN

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ABSTRACT

Technology is transforming the way engineering designers work and interact with others; Synchronous collaborative computer-aided design (CAD) tools allow designers to manipulate the same model at the same time. We present a new method using automated facial emotion detection software and cursor tracking to map designer emotions and corresponding designer activities in synchronous collaborative CAD. We present findings from a dataset of 9 participants that were assigned to two distinct working styles in the same synchronous CAD environment: single participants working by themselves and paired participants working together. In general, our results show that designers working in the paired workflow exhibited more emotion compared to designers who worked alone. A frequency analysis was performed by linking occurrences of each emotional response to their antecedent activities, revealing that user emotions were predictable to some degree by specific antecedent activities of CAD work. We concluded that activities happening in the graphics area were the most frequent antecedent events of emotions for single-users, while for paired participants, activities in the chat section and feature menu were the most frequent antecedent events for joy and fear, respectively. Finally, logistic regression was applied for each combination of event and emotion for each participant in order to further investigate the relationships between the user activities and emotions, and meta-regression was used to aggregate the regression results for the two different working styles. In particular, for single-users, activities in the model tree were found to be positively correlated to joy and negatively correlated to disgust, and navigating the feature menu increased the likelihood of contempt. For participants in pairs, communicating with CAD partner and receiving communications from partner was associated with joy, navigating the feature menu was associated with sadness, anger and disgust were associated with partner's action in the model tree, and contempt corresponded to the designer's own activities in the model tree area. The approach and conclusions presented in this paper allow us to better understand designer emotions in fully synchronous CAD, which leads to insight related to designer satisfaction, creativity, performance and other outcomes valued by engineering designers in a virtual collaborative environment.

INTRODUCTION

In the field of engineering design research, progress has been made in understanding how to design for emotion, and we better understand how users experience emotions while interacting with the designed product [1–3]. Yet little work exists to investigate the *affect* of, or emotion experienced by, designers during engineering design tasks, whether individual or collaborative [4]. As will be reviewed in the following section, better understanding emotions in this context will lead to more understanding of designer satisfaction, creativity, performance and other outcomes valued by engineering designers.

Technology is transforming the way engineering designers work and interact with others; ubiquitous internet, digital tools, cloud computing and storage, and video conferencing have enabled new models of work in many industries, including the engineering and manufacturing sectors [5,6]. Engineering design tasks that have been traditionally solitary - such as model-building with computer-aided design (CAD) software - are now collaborative.

In recent years, the new trend of cloud computing has affected the computer-aided design (CAD) industry which has seen the advent of companies like Onshape and Autodesk developing applications that leverage these capabilities [7,8]. These new products offer various advantages over traditional CAD, like more secure data storage, use of mobile devices to view and edit CAD files, and access to the CAD environment through a standard internet browser. This new method of hosting CAD programs on the cloud allows multiple designers to simultaneously work on the same CAD file; this simultaneous collaborative functionality and its effect on user emotions are the points of interest in the present study.

We investigate "synchronous CAD" - a CAD environment wherein multiple designers can manipulate CAD models at the same time and see each other's changes in real time. Given the scale and complexity of products, collaboration has been required, and has existed, since the inception of CAD; In its traditional form, CAD collaboration was implemented using a top down or master modelling approach, heavy on decomposition [9]. Designers mostly worked by themselves and relied on predefined CAD interfaces to integrate everyone's work at a later stage. However, new synchronous collaboration models remove the need for later stage CAD integration and provides designers simultaneous access to each other's work. This also makes virtual collaboration easier for teams that need to work together remotely.

The change of a task from solitary to collaborative is hypothesized to result in differences not only in the outcome of the task, but also in the individuals' emotion while undertaking the task [10]. Some argue that working on a team fulfills a "social need" and results in increased sense of belongingness, as well as more fun and enjoyment [11].

This paper presents a novel approach for measuring the emotional experience of designers while designing using CAD software; we apply new tools which enable unobtrusive studies of emotion using video capture and facial emotion recognition. We observe and compare emotion trends of designers working in CAD individually and synchronously collaboratively.

BACKGROUND

Emotion and Task Performance

Affect is a general term referring to a subjective feeling state, encompassing both long-lasting moods as well as more specific moods, called emotions - as are the subject of this study [12]. Emotion is a subtype of affect, and is generally more strongly directed toward a specific stimulus, which could be a person, object or event [13].

The present paper uses the discrete emotion framework of Ekman [14], wherein there are distinct emotion categories [15], and emotions are driven by antecedent events. Initially, six universal emotions were conceptualized: joy, sadness, disgust, anger, fear and surprise. Later, evidence was found to include contempt - conceptualized as a negative interpersonal emotion, with a feeling of superiority - as a seventh universal basic emotion [16]. Emotion is a major area of research in the field of psychology and management, with a variety of studies seeking to characterize the link between affect (emotion) and job performance [17,18]. A distinction is made between trait affect (stable and enduring personality characteristic) and state or transient affect, which are shorter time-scale emotions, and the focus of the present study [19].

Pleasant affect has been found to positively relate to a number of performance metrics that matter in engineering design, including quality and quantity of work, creativity and innovativeness, as well as pro-social behaviors such as helping co-workers, and job satisfaction, in a number of settings [12,17,18,20,21].

Recent Progress in Designer Emotion Research

Recent works have made progress in our understanding of emotion at various phases in the engineering design process, as is the aim of our study. Behoora and Tucker present an automated method for identifying designer emotional state using unobtrusive non-wearable sensors for body language detection [22]. This method classifies emotions including engagement/interest, frustration and boredom.

Focusing on the design task of prototyping, Bezawada et al. developed a facial expression tracking system and method to automatically detect designers' comfort levels with prototyping equipment from video footage [23]. Hu et al. use electroencephalography to measure engagement and cognitive workload during ideation, which was then used as a predictor of ideation effectiveness [24]. While these works have built the beginning of our understanding of emotion during the engineering design process, there remains much to be explored. Little work has been done to link emotion of individuals working on teams and their behavior over-time, in product design or any context [18], and those studies that do exist are conducted with in-person, not virtual, teams [25].

With focus specifically on designers undertaking traditional (non-synchronous) CAD activities, Liu et al. propose a methodology for analyzing emotion using psycho-physiological signals (galvanic skin resistance, electroencephalography and electrocardiography), which could then be mapped to CAD activities [26]. This study did not include facial emotion recognition, as was used in the present study as input. Frustration, satisfaction, engagement and challenge were the emotions identified in the study, but the link between these emotions and CAD activities was not concluded. Similarly, Lim et al. present a novel multimodal method for capturing many channels of biophysical and CAD design activity data in traditional CAD systems [27]. Specific conclusions linking emotions to activity are not presented.

Facial Emotion Detection and Measurement

Facial expressions are crucial in human communication and they are one of the richest sources of affective and cognitive information [28]. There are a number of accepted ways to detect and collect facial emotion data. One of these is facial electromyography (EMG). Facial EMG involves detecting the electric potential generated by facial muscle cells through surface electrodes placed on the subject's face. Some problems identified in the literature with EMG are potential interference with the subjects' behaviour due to its obtrusive nature, and data inaccuracy due to signal crosstalk, which happens when surrounding muscular contraction interfere with the signal of an adjacent muscle group [29,30]. Another traditional method of measuring facial expressions used in the literature is manual coding using the Facial Action Coding System (FACS) [31]. FACS describes all visually distinguishable facial expressions using the combination of 44 unique action units (AUs), such as "nose wrinkler" and "cheek raiser" [32]. With proper training, FACS enables a person to measure and score facial activities in an objective and quantitative way. It is therefore a well-accepted method to systematically classify the facial expression of emotions [31]. However, FACS-coding is inherently laborious and expensive, and it requires up to 100 hours of thorough training [32]. As an alternative to manual coding, automated methods have become increasingly powerful for facial emotion recognition [33,34]. Software companies such as Kairos, Noldus, and Affectiva have created computer vision algorithms to detect human faces, and identify key feature points on the face, such as the tip of the nose and the corners of the mouth. These algorithms then utilize FACS to classify facial expressions through Action Units (AUs), and finally map these facial expressions to emotions [35].

Synchronous CAD

Studies of collaboration during various phases of the design process have shown that a successful outcome is contingent on a number of factors, including the nature of the problem, information richness, and team composition [36–38]. This means that studies of collaboration in the CAD context are particularly relevant to the present study, and will be reviewed below.

Prior work related to synchronous collaboration in CAD has been focused around the development and architecture of tools [39–41] . CAD software industry interest in developing synchronous CAD tools has burgeoned, leading to more robust and readily available tools for the design community to test. Previous studies of synchronous collaborative CAD have left designer emotion unaddressed.

Some researchers use the term Multi-User CAD (MUCAD) to describe synchronous CAD systems [42]. A study done by Eves et al. compared the use of MUCAD to traditional methods of collaboration [43]. It was found that overall, the use of MUCAD helped increase awareness of the design state. This study also highlights how teams that took more advantage of the synchronous nature of MUCAD may result in higher quality models. Finally, frustrations of user participants were recorded and mapped to study metrics; it was found that a mismatch in skill levels has a noticeable effect on other team member's frustration ratings. Hepworth et al. have articulated a method to avoid conflicts in MUCAD use [42]. This work focuses on solving feature level conflicts and relies on reservation and prioritization of features. Stone et al. propose a model to predict the optimal MUCAD team size for a given model [44]. In this study, part complexity was defined by a count of the number of features in a CAD file. Part complexity was then used to determine the optimum team size. This study also proposed a method to predict model completion times based on the team size; their prediction accuracy was positively correlated with team size. Phadnis et al. present a case study comparing different paired working styles using synchronous CAD to individual CAD users [45]. This work points to the importance of considering not only the synchronicity of CAD but also the effects of skill mismatch and communication presence or absence.

Synchronous CAD research is still in its nascent stage and full implications of synchronous CAD have not been uncovered. Most literature studying synchronous CAD has focused on time-based metrics, modelling task decomposition, and team composition. Research pertaining to human behaviour or emotions in synchronous CAD environments is missing.

METHOD

Experiment Overview

The goal of our study was to analyze and compare trends in designer emotion corresponding to different CAD working styles, and to link emotions to specific CAD activities. The study featured two distinct working styles in the same synchronous environment: single participants working in the CAD software by themselves and paired participants working on the CAD model together. The paired participants were able to communicate with each other via the software's inbuilt chat/commenting system. Each participant could work on their own part of the model independently, or edit their partner's work directly, or roll back the shared model tree to an earlier state. This level of access to each other's work meant that paired participants did not have full control of the current status of the model, which includes their previous work.

Data were collected from three single-users as well as three pairs working in a collaborative environment. Our participant pool comprised of graduate and undergraduate students from the mechanical engineering program at Massachusetts Institute of Technology (MIT). In total, four females and five males participated in our study, randomly assigned to either workflow. We required that all participants had at least a year of CAD experience and had taken a design class at MIT. The study was in compliance with the Committee on the Use of Humans as Experimental Subjects at MIT and was conducted in a controlled environment at the MIT Behavioral Research Laboratory. We use the following nomenclature for participant coding: S1, S2, S3 represent the three single-users; P1_1, P1_2, P2_1, P2_2, P3_1 and P3_2 represent Participant 1 and 2 from Pairs 1, 2 and 3, respectively.

The study's task was to execute 42 changes to a toy car design shown in Figure 1. These tasks were of varying difficulty. Two examples of changes include: "Add a chamfer to all wheel outside edges" and "Change the diameter of the wheels to 30mm". The participants were given a short overview of the provided software and then given 60 minutes to make as many changes as possible.

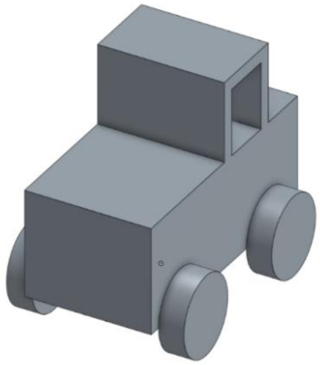


FIGURE 1. ISOMETRIC VIEW OF INITIAL CAD MODEL PROVIDED TO STUDY PARTICIPANTS

Web camera footage of the designer's face and their on-screen footage were recorded for post processing and data extraction. In the end, the activity data and emotion data collected in the experiment for each participant were synchronized and analyzed. The data extraction, collection and synchronization process in this experiment is summarized in Figure 2.

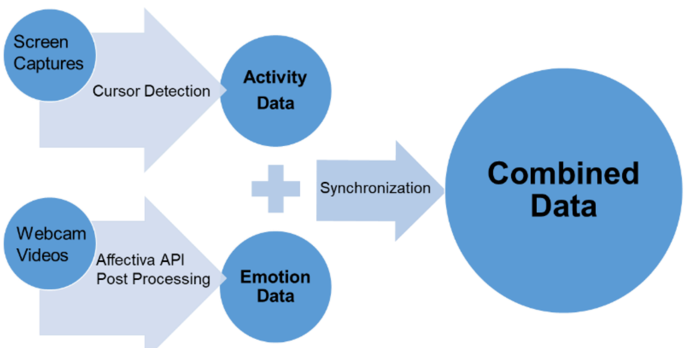


FIGURE 2. DATA EXTRACTION, COLLECTION AND SYNCHRONIZATION PROCESS IN THIS STUDY

Activity Coding

The user activities in screen videos captured during the study were coded with an automated coding schema using Python and OpenCV. Our code identified cursor location within the CAD environment using a template matching method and then binned the cursor location in one of the four regions of interest (see Figure 3). Similar automation techniques have been successfully implemented to segment design data [46]. Participants use the Feature Menu region to browse and select CAD features. The Model Tree region is where the user would check the model's history of sketches and features, roll-back the model, and suppress features. The Chat Window is where users type and send messages to their paired partner. Lastly the Graphics Area region is used to access and manipulate the CAD geometry. All videos were down sampled to a frame rate of 2 frames per second without sacrificing the resolution of data collected.

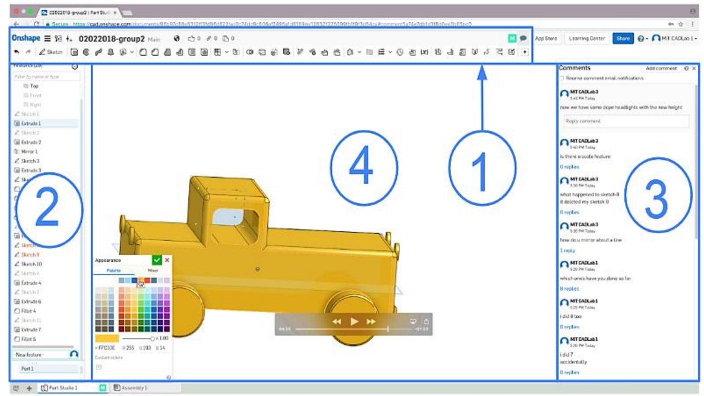


FIGURE 3. REGIONS OF INTEREST IN THE CAD ENVIRONMENT (1: FEATURE MENU; 2: MODEL TREE; 3: CHAT WINDOW; 4: GRAPHICS AREA)

Emotion Data

Affectiva's Software Development Kit (SDK) was used in the study to extract the emotion data from the facial recordings of the participants. Affectiva's emotion recognition technology uses computer vision algorithms and deep learning models to provide estimates of the seven basic emotions. Affectiva's algorithm was trained with a large global dataset of more than 7 million faces from 75 countries and has been proven to reliably identify emotions with results that are comparable to EMG findings [47,48]. We developed a program with the use of Affectiva's Application Programming Interface (API). Our program automatically processes videos at a frame rate of 2 frames per second, detects human faces in each frame, extracts 34 key feature points, and identifies action units defined in FACS [35]. Our program then maps these AUs to emotions, and outputs the estimated intensity for each basic emotion on a 0 - 100 scale. The webcam footage collected in the experiment were processed through this program and the emotion data of the 9 participants were extracted. Figure 4 depicts an example image from our study's facial video processing and feature points extraction. The nine face recording amounted to a total of 64,752 frames of video. In 52,490 (81.0%) of the frames a face could be detected. The frames in which a face could not be detected were discarded. As an example, Figure 5 illustrates the level of joy exhibited by participant P3_2 over the duration of the 1-hour experiment.

FIGURE 4. EXAMPLE OF IMAGE FROM STUDY WITH OVERLAID AUTOMATIC EMOTION DETECTION USING 34 FACIAL FEATURE POINTS

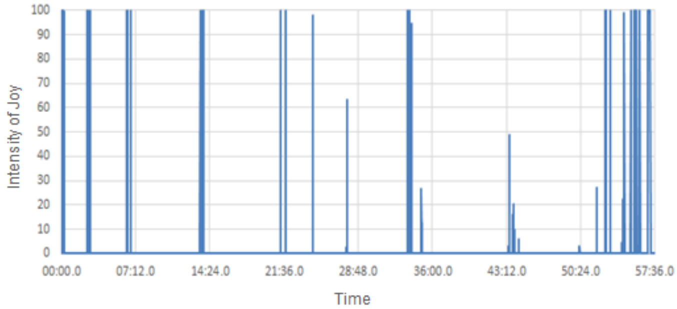


FIGURE 5. PARTICIPANT P3_2'S LEVEL OF JOY OVER THE 1-HOUR EXPERIMENT

Although the original emotion data extracted by the program using the Affectiva API were continuous on a 1 - 100 scale, all sets of data collected presented bimodal distribution with peaks at 0 and 100. As an example, Figure 6 shows the distribution of the data extracted for the level of contempt exhibited participant P3_1 in the 1-hour study. Therefore, all emotion data were converted to presence/non-presence binary data in our analyses, with an intensity of 50 being the threshold.

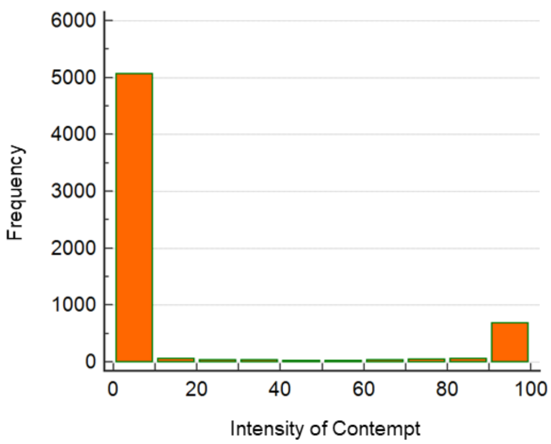


FIGURE 6. THE DISTRIBUTION OF THE CONTEMPT DATA EXTRACTED FOR THE LEVEL OF CONTEMPT EXHIBITED BY PARTICIPANT P3_1 IN THE 1-HOUR STUDY

Combined Data

The results from activity coding with the screen recordings were then synchronized with the emotion data from the webcam videos. The combined data contain each participant's activity and emotion in each 0.5s of the experiment. These combined data were then used to describe and explain the relationship between user CAD activities and their emotional responses through statistical analyses such as frequency analysis and logistic regression. For the participants working in pairs, each person's emotion data was also synchronized with their partner's activity data, in order to investigate the association of the interaction with emotions.

RESULTS AND DISCUSSION

Comparison of Overall Emotional Responses

An overall comparison of emotions between pairs and single-users was made by comparing the average amount of time each emotion is present over the duration of the experiment. The results are tabulated in Table 1. It can be seen that the top four emotions exhibited by single-users were, in decreasing order, disgust, contempt, surprise, and joy, whereas the order for pairs was contempt, surprise, disgust and joy. Both single-users and pairs experienced little to no sadness and fear. Comparing the two CAD working styles, on average, participants working in pairs exhibited notably more emotional responses than single-users for all emotions except disgust. In particular, on average, participants in pairs expressed 7.6 times more joy, 4.0 times more anger, and 1.8 times more contempt per person than participants working by themselves.

TABLE 1. AVERAGE NUMBER OF SECONDS OF EACH EMOTION EXHIBITED BY THE PARTICIPANTS (PER PERSON), WITH COMPARISON RATIO

	Single (s)	Pair (s)	Single : Pair
Joy	23.3	177.3	1 : 7.6
Sadness	7.3	12.0	1 : 1.6
Disgust	444.0	251.3	1.8 : 1
Contempt	328.7	587.7	1 : 1.8
Anger	9.3	37.7	1 : 4.0
Fear	0.0	8.0	0 : 8.0
Surprise	296.7	511.7	1 : 1.7

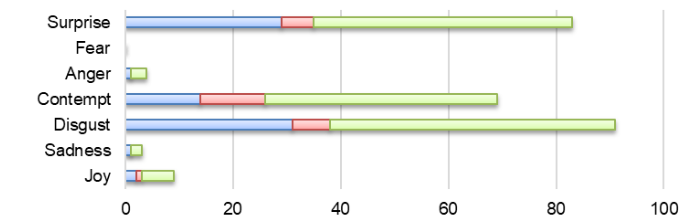
Comparing the activities involved in single-user CAD and collaborative CAD, we speculate that this difference in level of emotion might be due to the added capability of partners to be able to communicate with one another through the chat window. Therefore, it is speculated that communication was the main driver for the increase in emotional responses. Moreover, since the model tree is shared between the two users in a collaborative environment, not only were the participants able to check their partner's activity history, but they were also able to roll back to an earlier state or suppress existing features done by themselves or their partner. These activities might cause strong emotional responses in the participants working in pairs.

Our findings of increased levels of emotion found for those working in pairs aligns with previous emotion in organization research which suggests that working closely with other people brings new and changing stimuli, and that social interactions tend to be most salient emotional elicitors (summarized in [49]). We find this increase in emotion in spite of the virtual nature of the collaboration; the paired participants could only communicate through text, and so could not see each other's faces. Given the increase in virtual work, we can imagine application of our insight to generate systems for partner feedback, for example building on others' work related to immersive virtual reality for CAD [50].

In order to further investigate the increased level of emotion for pairs, and to reveal the relationship between each CAD activity and each basic emotion, a frequency analysis on the antecedent activities of the emotional responses was conducted.

Frequency Analysis for Antecedent Activities

A frequency analysis was performed for the antecedent activity for the occurrences of each emotional response. Here, an occurrence of emotional response is defined as the continuous presence of one emotion for at least 1 second. For instance, Participant P3_1 exhibited joy from 5.0 s to 12.5 s in the facial video, and the antecedent activity for this occurrence of emotional response was communication, which was the activity Participant P3_1 was doing at time 5.0 s in the screen recording. Figure 7 illustrates the total number of times each activity category acts as the antecedent event for each emotion of the three single-users. The data is presented with a segmented bar chart, in which each colour represents the number of occurrences for its corresponding activity type. The data is also presented in the table underneath the chart. Similarly, Figure 8 and 9 display the same information for all six paired participants, with their own activities and their partners' activities, respectively.



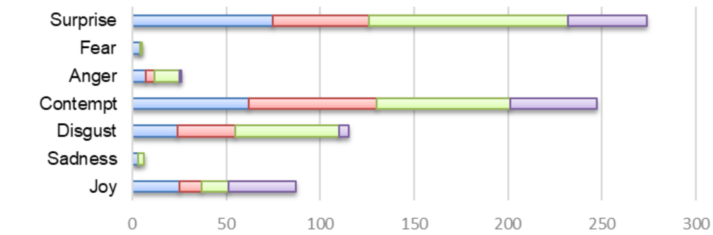
	Joy	Sadness	Disgust	Contempt	Anger	Fear	Surprise
Feature Menu	2	1	31	14	1	0	29
Model Tree	1	0	7	12	0	0	6
Graphics Area	6	2	53	43	3	0	48

NUMBER OF TIMES

Feature Menu Model Tree Graphics Area

FIGURE 7. TOTAL NUMBER OF TIMES EACH ACTIVITY CATEGORY ACTS AS THE ANTECEDENT EVENT FOR EACH EMOTION OF SINGLE-USERS

Among the single-users, activities happening in the graphics area were the most frequent antecedent events of emotions, corresponding to more than 55% of all occurrences for all emotions. This is expected because in the 1-hour experiment, single-users on average spent 80.1% of the total time in the graphics area manipulating the CAD model. Activities in the feature menu section accounted for 34.9% of all occurrences of surprise, 34.1% of disgust, and 22.2% of joy, even though activities in the feature menu only took up 12.6% of the total experiment time on average. This suggests that finding and selecting features might be closely related to the occurrence of emotions like surprise, disgust and joy for a single-user.

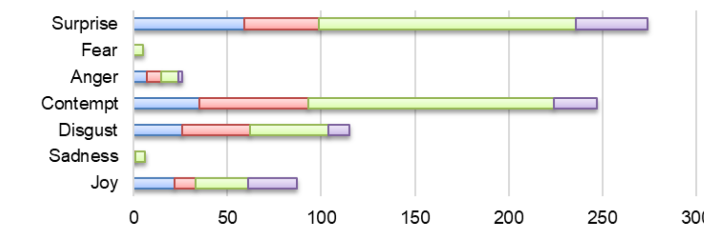


	Joy	Sadness	Disgust	Contempt	Anger	Fear	Surprise
Feature Menu	25	3	24	62	7	4	75
Model Tree	12	0	31	68	5	0	51
Graphics Area	14	3	55	71	13	1	106
Chat Window	36	0	5	46	1	0	42

NUMBER OF TIMES

Feature Menu Model Tree Graphics Area Chat Window

FIGURE 8. TOTAL NUMBER OF TIMES ACTIVITIES IN EACH CATEGORY ACT AS THE ANTECEDENT EVENT FOR EACH EMOTION OF PAIRED USERS



	Joy	Sadness	Disgust	Contempt	Anger	Fear	Surprise
Feature Menu	22	0	26	35	7	0	59
Model Tree	11	1	36	58	8	0	40
Graphics Area	28	5	42	131	9	5	137
Chat Window	26	0	11	23	2	0	38

NUMBER OF TIMES

Feature Menu Model Tree Graphics Area Chat Window

FIGURE 9. TOTAL NUMBER OF TIMES ACTIVITIES PERFORMED BY THEIR PARTNERS IN EACH CATEGORY ACT AS THE ANTECEDENT EVENT FOR EACH EMOTION OF PAIRED USERS

As for paired users, linking their own activities with their emotions, activities in the graphics area comprised less than 50% of the total number of antecedent events for each emotion, even though on average these paired participants also spent 71.3% of their total time in the graphics area. This suggests that the other three activity categories are potentially significant contributors for user emotions in a collaborative setting. Activities in the chat section and feature menu appears to be the most frequent antecedent events for joy and fear, respectively. Given that the participants only spent around 6.7% of their time in the chat window, it can be inferred that activities in the chat section can be highly emotion-evoking.

When their partners' activity data was used in the analysis, however, the graphics area again became the most dominant category for all seven emotions, constituting more than 50% of all antecedent events of sadness, contempt, fear and surprise.

This can be explained by the fact that participants can only see and react to the changes made by their partners once they click "confirm" for each action they take, but not while they are making them. Also, their partners' activities in the chat window also acted as antecedent events for 29.9% of the occurrences of their own joy. Finally, activities done by their partners in the model tree section comprised around 30% of the antecedent events of disgust and anger.

In order to further investigate these relationships established between the user activities and emotions, logistic regression was applied for each combination of event and emotion for each participant.

Logistic Regression and Meta-Analysis

Logistic regression is appropriate for describing and explaining the relationship between one dichotomous dependent variable and one or more independent variables [51]. In our case, for each regression, the dependent variable was the presence/non-presence of one basic emotion, and the independent variable was the participant's activity, which was categorial. The sample size was the number of detected frames in the participant's face recording. Since the independent variable had four categories (i.e. activities in feature menu, model tree, chat window and graphics window), three dummy variables were introduced for the first three categories, and graphics window was set as the baseline since it was the dominant activity area. From the logistic regression performed for each emotion, the coefficients obtained for each dummy variable describe the size and direction of the relationship between the corresponding category and the emotion. Positive coefficients indicate that the activities in the category positively associate with the likelihood of the emotion and negative coefficients suggests the opposite. Odds ratios were then calculated using the regression coefficients by taking the natural exponential of the coefficient.

To aggregate all the regression results for the three participants who worked alone and the six paired participants, and to determine the statistical significance of the predictor variable categories, quantitative meta-analysis is used [51]. The meta-regression aggregated the coefficients obtained in the logistic regressions and provided an estimate of the overall effect of interest, which was the weighted mean effect size of individual studies where the weights were the inverse of the variance of the study-level effect estimates. The random effects model was used to allow for between-study variations, such as individual differences in expression of emotions. A meta-regression was conducted for each activity-emotion combination. The aggregated odds ratios were then calculated by taking the natural exponential of the estimated overall regression coefficient. As an example, Figure 10 provides a visualization of the odds ratios obtained from the logistic regressions and the final meta-regression for the relationship between model tree and contempt using a forest plot. Odds ratios greater than 1 indicate a positive association while odds ratios less than 1 suggest a negative association. The odds ratios calculated from the meta-regressions and their 95% confidence intervals for single-users and paired participants are tabulated in Table 2 and 3, respectively. The asterisks denote significance at the 0.05 level.

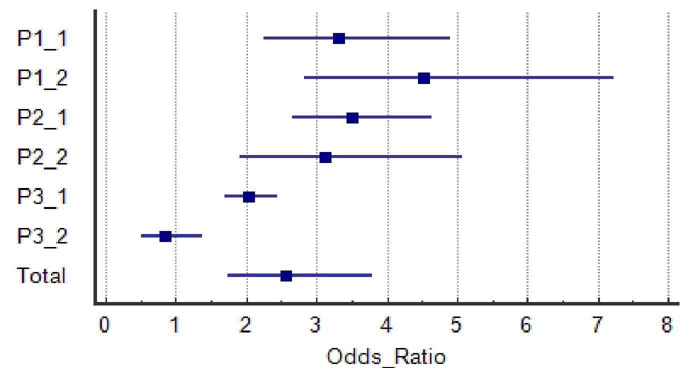


FIGURE 10. FOREST PLOT FOR ODDS RATIOS AND THEIR 95% CONFIDENCE INTERVALS FOR ACTIVITIES IN MODEL TREE ON CONTEMPT

TABLE 2. ODDS RATIOS FROM META-REGRESSIONS WITH 95% CONFIDENCE INTERVALS FOR SINGLE-USERS

	Odds Ratio	Lower CI	Upper CI
Joy			
Feature Menu	N/A	N/A	N/A
Model Tree	3.72*	1.40	9.93
Sadness			
Feature Menu	1.33	0.37	4.71
Model Tree	N/A	N/A	N/A
Disgust			
Feature Menu	1.10	0.89	1.37
Model Tree	0.45*	0.29	0.69
Contempt			
Feature Menu	1.78*	1.39	2.27
Model Tree	1.98	0.79	4.98
Anger			
Feature Menu	1.13	0.14	8.91
Model Tree	1.66	0.36	24.88
Fear			
Feature Menu	N/A	N/A	N/A
Model Tree	N/A	N/A	N/A
Surprise			
Feature Menu	1.24	0.59	2.61
Model Tree	0.79	0.49	1.27
* denote significance at 0.05 level			

For single-users, activities in the model tree were found to be positively correlated to joy and negatively correlated to disgust with statistical significance at the 0.05 level. Also, activities in feature menu resulted in higher odds of contempt being present.

As for paired participants, the correlations between activities in the feature menu and sadness, chat window and joy, model tree and contempt were statistically significant (at $p < 0.05$). It was found that activities in feature menu positively correlated to sadness, events in the model tree section resulted in higher odds of contempt, and activities in the chat window section significantly increased the likelihood of joy with a high odds ratio of 8.36.

When the effect of their partner's activities was studied, at the 0.05 level, activities in the chat window were again positively correlated with the participants' presence of joy, while actions in the model tree resulted in higher odds of the exhibition of disgust and anger.

Next, where emotions were present, we examined the participants' screen recordings, seeking additional evidence to explain the results from the meta-analysis.

TABLE 3. ODDS RATIOS FROM META-REGRESSIONS WITH 95% CONFIDENCE INTERVALS FOR PAIRED-USERS

	Self			Partner		
	OR	Lower CI	Upper CI	OR	Lower CI	Upper CI
Joy						
Feature Menu	1.80	0.91	3.58	1.37	0.95	1.98
Model Tree	1.18	0.59	2.39	0.59	0.23	1.49
Chat Window	8.36*	5.52	12.67	2.62*	1.66	4.15
Sadness						
Feature Menu	3.91*	1.13	1.83	1.69	0.64	4.45
Model Tree	0.54	0.07	4.31	0.73	0.17	3.10
Chat Window	1.33	0.29	6.00	2.63	0.89	7.75
Disgust						
Feature Menu	0.97	0.70	1.33	1.94	0.89	4.22
Model Tree	1.19	0.87	1.64	2.97*	1.41	6.25
Chat Window	0.58	0.30	1.11	1.16	0.58	2.31
Contempt						
Feature Menu	1.12	0.79	1.61	0.66	0.41	1.07
Model Tree	2.57*	1.74	3.80	1.43	0.86	2.38
Chat Window	2.65	0.98	7.18	1.21	0.58	2.51
Anger						
Feature Menu	1.28	0.87	1.87	1.15	0.61	2.19
Model Tree	1.68	0.66	4.25	1.67*	1.04	2.69
Chat Window	0.50	0.15	1.60	0.56	0.04	8.74
Fear						
Feature Menu	8.00	1.81	34.12	N/A	N/A	N/A
Model Tree	1.62	0.35	7.51	0.79	0.10	6.04
Chat Window	N/A	N/A	N/A	N/A	N/A	N/A
Surprise						
Feature Menu	1.30	0.94	1.78	1.10	0.64	1.92
Model Tree	0.80	0.53	1.19	1.05	0.72	1.53
Chat Window	1.27	0.75	2.14	1.26	0.71	2.23
* denote significance at 0.05 level						

Qualitative Findings from Screen Recordings

First of all, we found that in both independent and collaborative working styles, negative emotions such as sadness and contempt caused by activities in the feature menu happened when the participants had difficulties finding the features and commands they needed. Multiple participants had problems finding the measurement tool, or the unit conversion option, and they often furrowed their brows as an emotional response. Similar facial expressions were also observed as they selected a feature from the menu to apply changes to the model but received an error message or a preview that was different from their expectation.

Interestingly, the meta-analysis concluded that participant's activities in the model tree were positively correlated to joy and negatively correlated with disgust in the single-user studies, whereas these activities led to higher chances of the presence of contempt in a collaborative environment. This can be explained by the fact that single-users had full control of the model and all the changes made to it in the model tree, whereas paired participants saw changes that they were not fully aware of, as well as changes made by their partners that interfered with their own work. As an example, participant P2_2 expressed negative emotions when she discovered that Sketch 8 in the model tree created by her partner interfered with Sketch 9 that she worked on.

Moreover, it is evident that negative emotions such as disgust and anger were often triggered by the participants' partners' actions in the model tree, especially when they rolled back the model to an earlier state or suppressed interdependent existing features. For example, when participant P3_1 rolled back the model, her partner P3_2 exhibited anger and asked in the chat window "What happened to my beautiful fillets?". Similarly, when participant P3_2 suppressed some existing features on the model tree, her partner P3_1 expressed negative emotion and complained "Why did the car go back to a square though?"

Finally, in the collaborative CAD environment, numerous instances were found of participants expressing joy with a smile or grin while they communicate with their partners. Here are some examples where joy was exhibited as the participant was composing messages or as they received their partner's messages, especially when the team makes good progress, or the partners offer each other help:

"Perfect. I will let you know when the first ones are done."

"Adding a spoiler." "Sounds good. I will wait until you are done." "Done!" "Awesome!"

"What is the diameter of the wheels?" "you can select the wheel and it should show up in the bottom right corner." "Thanks!"

"I am trying to edit extrude 2 such that it does not merge with part 1." "That sounds good!"

General Discussion

Implications of this study further arise from the thought-action tendencies found to be driven by emotion [52]. Some emotions are "goal progress" such as: joy, which leads to urge to see connections, increase openness and spontaneous play; anger, which leads to urge to attack, mobilize and sustain high levels of energy; and, sadness, which leads to urge to withdraw, reflect and to communicate needs to others. On the other hand, certain emotions are classified as "personal threat," including: fear, which results in urge to escape, and mobilize to freeze resources to avoid threat; or disgust, which leads to urge to expel and mobilize body to close off senses.

Emotion researchers argue that there are advantages to both positive and negative emotions and the psychological mechanism linking them to performance [17]. Unpleasant affect, which signals threat and a change should occur, can elicit effortful, systematic and detail-oriented information processing strategies. Pleasant affect, signaling that the status quo can be maintained, elicits simple, novel, and creative information processing strategies. The behaviours induced by the emotions of designers is an interesting area of future research.

The task of CAD modeling requires attention from the designer while working in a rich environment of information flow. Designers in the paired workflow have an even increased level of information flow, including not only standard, predictable stimulus from their own design work but also novel or unexpected information from the partner's actions. Biological psychology research reveals that in general, these types of information - novel, unexpected or distinctively deviating in terms of its physical features relative to other competing stimuli - gain more processing attention and consciousness from our brains [53]. This research has also found that neural responses to stimuli with emotional information are greater than those of neutral stimuli.

In the field of communication, studies have shown that media are more persuasive when they are more interactive [54], including increased positivity toward the media interface and greater cognitive absorption of the message. Indeed, the literature suggests that computer-mediated communication, such as that enabled by synchronous collaborative CAD software, allows for the conversational ideal of interactivity, which presents a challenge for human-computer interaction, affective computing, and artificial intelligence systems [55]. Synchronous collaborative CAD environments can embrace the natural person-to-person communication afforded by this technology.

We are lacking agreement on the implications of fully synchronous CAD; in general, synchronous collaboration during the engineering design process occurs in the early phases. Yet research findings suggest that CAD is a modeling tool better suited for later phases of design to avoid fixation [56–58]. What is the improvement afforded by synchronous collaborative CAD - is it to parallelize modeling work? To involve the creative ideas of varied stakeholders in the design process? To reduce the separation of information between designers working on interfacing parts? To engage designers and create a more satisfying work flow? The present study suggests that there may be advantages (and frustrations) related to the final point, but there are many more questions to answer.

From another lens, CAD is a form of externalized model of the engineering design [59]. Using traditional CAD, the single-user has control over the externalization until he or she is ready to share with others. In fully synchronous CAD, the externalization is always open to collaborators. Are designers ready for this lack of full control? For relevant findings, we can look to the field of software engineering, where paired programming has become a popular approach to coding. A recent study of this work style did not find that the performance of a collaborating pair exceeded that of the pair's best member working alone; it did however find that pairs reported higher levels of satisfaction than individuals [60], indicating that designers might indeed be ready to sacrifice absolute control. The success of paired programming motivates continued studies to better understand the potential for synchronously collaborative CAD.

Limitations and Future Directions

Facial recognition classifiers have been found to be biased against certain gender and race intersections, in particular for dark-skinned women [61]. Our limited sample size did not include participants in this population (perhaps indicating a limitation in representation diversity of our sample pool, another flaw in its own right) however we remain conscious of the limitations of this tool for future studies with regards to unfair facial analysis algorithms.

Though studies have found a strong relationship between gaze position and cursor position during computer work [62], in future work there could be additional insights regarding collaborative synchronous CAD work revealed by data from eye tracking technology.

Text-based sentiment analysis techniques are becoming increasingly sophisticated, and present an interesting opportunity to systematically validate the facial analysis presented in this paper. However due to the low number of messages sent, and received, sentiment analysis of text was not possible in the present study.

Future work should include a larger sample size to further validate the results and findings from this study. Furthermore, one of the possible future work directions is to utilize tools and models such as Markov chain or Hidden Markov Model to address sequential features of the data, which could potentially reveal rich, complex responses.

CONCLUSION

This paper analyzed and compared the emotional experience of designers while designing in collaborative and traditional CAD working styles. We utilized unobtrusive tools to extract the participants' emotion and activity data and later performed statistical analyses on the synchronized data to establish the associations between CAD activities and user emotions. First of all, we found that designers working in the paired workflow exhibited more emotion compared to designers who worked by themselves. Next, through a frequency analysis performed for the antecedent activity for the occurrences of each emotional response, we found that user emotions were predictable to some degree by specific antecedent activities of CAD work. We concluded that activities happening in the graphics area were the most frequent antecedent events of emotions for single-users, while for paired participants, activities in the chat section and feature menu were the most frequent antecedent events for joy and fear, respectively. Finally, in order to further investigate these relationships established between the user activities and emotions, logistic regression was applied for each combination of event and emotion for each participant, and meta-regression was used to aggregate the regression results for the two different working styles. In particular, for single-users, activities in the model tree were found to be positively correlated to joy and negatively correlated to disgust, and navigating the feature menu increased the likelihood of contempt. For participants in pairs, communicating with CAD partner and receiving communications from partner was associated with joy, navigating the feature menu was associated with sadness, anger and disgust were associated with partner's action in the model tree, and contempt corresponded to the designer's own activities in the model tree area.

The approach and conclusions presented in this paper are important because as the world is getting more virtual, we expect that fully-synchronous tools on cloud-based platforms will be the future of collaboration. As emotion plays a major part in user experience, better understanding emotions in this context will lead to more understanding of designer satisfaction, creativity, performance and other outcomes valued by engineering designers. Furthermore, the analysis tools and methods introduced in this paper can be applied to studies of similar collaborative tools, and help researchers establish the links between user emotions and specific activities in the software.

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