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Smile! Studying Expressivity of Happiness as a Synergic Factor in Collaborative Information Seeking

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ABSTRACT
It is commonly expected that collaborative work will lead to better results than working individually. It has been demonstrated by some that teamwork is more than adding together the product of individual work, though this may depend on various factors such as time, space, the tasks or activities nature, as well as team members' personalities. To date, little is known about the specific elements that contribute to this synergic effect; however, some have argued that emotions, in particular positive ones, may have a fundamental role in teamwork. In this paper we take a closer look at users' smiles - as a way of expressing happiness- by studying how they participate in the information search process of both individuals and teams. We present a user study involving 30 participants (10 pairs and 10 individuals) and show how smiling contributes to the overall experience of team members as well as their performance in an exploratory search task with respect to individual seekers. Our results indicate that smiling is significantly more prominent in participants working together synchronously than those working individually and that smiling may contribute to particular dimensions of information coverage.

Keywords
Collaborative search, information seeking process, happiness

INTRODUCTION
In a recent study we showed that searching information collaboratively under certain experimental conditions, is more than simply adding the outcomes of individual information seekers, demonstrating thus the synergic effect in collaborative information seeking (CIS) (Shah & González- Ibáñez, 2011). Though we speculated about possible explanations of this phenomenon, we did not provide actual evidence for supporting them. In this paper we revisit our work by taking a closer look at a possible contributing factor to the synergic effect in CIS. We do this by framing our research under a positive psychology approach (Gable & Haidt, 2005; Seligman, Steen, Park, & Peterson, 2005). We study the exhibition of positive affects - more specifically, expressed happiness - in the information search process (ISP).

Although collaboration and emotions may seem to be two different areas of research, particular connections between these two fields of research have been described in the positive psychology literature. Psychologists have argued that positive emotions would have special effects on various dimensions of people's lives ranging from health to work (Fredrickson, 2004; Lyubomirsky, King, & Diener, 2005). In the context of work, especially when done in teams, Fredrickson and Losada (2005) have argued that specific proportions between positive and negative affects may enhance teams' performance.

To investigate the effects of emotions, in particular, the expressivity of happiness in collaborative settings, we designed a user study with two experimental conditions of information seeking, namely: single users and remotely located collaborators, where the former involved 10 participants and the latter 10 pairs (20 participants). It is important to note that our goal here is not to compare teams and single users but to focus on users as individual units, whether they are working alone or in a team.

In the following section we discuss some of the relevant literature on emotions in the field of information science as well as in collaboration. Following that, we present a detailed description of our study design. In the fourth section we describe the methodological approach developed for processing expressed happiness. In the fifth section we briefly explain the set of measures we devised in our previous work to evaluate the synergic effect of teams, and then we present our results and discussion. Finally, we conclude the paper with the implications of our study and pointers to further research in the field.

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BACKGROUND

Emotions Studies in Information Science

When searching for information, do we feel a certain way because we find (or do not find) information? Or do we find (or do not find) information because we feel a certain way? While the first question frames affective states as dependent on the information search process, the second one considers that emotions could change the process itself as well as its outcomes. Research in information science has focused primarily on the first question, looking at how users feel as they search information. In an early work, Kuhlthau (1991) introduced the participation of emotional states at different stages of her information search process (ISP) model. More recently, Arapakis and Gray (2008) studied the role of emotions in the information search process of single users through automatic facial expression recognition. Similarly, Lopatovska (2009a) explored emotional aspects experienced in online search using facial expression recognition and self-report. Other authors that have also studied emotions in information science are Diane Nahl and Dania Bilal, a good compilation of their own work as well as other studies can be found in Nahl and Bilal (2009).

With regard to the second question, Lopatovska (2009b) found experimentally that positive mood as the pre-task users' state, would be related to specific search behaviors. She also found, however, that both positive and negative mood did not have significant effects on the quality of the outcomes.

While a focus on the first question is particularly suitable for studying behaviors of individual information seekers, what happens when emotions vary as a result of external factors? How does this change the search behaviors of users as well as their outcomes? This is especially the case with CIS, where emotions are subject to change due to additional factors – besides information related aspects – such as social interactions. Emotions in collaborative settings may change either positively or negatively due to conflicts within the process, communication, personality, personal motivations, and so on. Works in collaborative information behavior (CIB) and CIS by Hyldegard (2006) and Shah and González-Ibáñez (2010) respectively, have incorporated the affective dimension of team members by using surveys and certain communication features to identify particular emotions. Nevertheless, none of these studies have addressed the particular implications of emotions, especially those that arise as a result of the collaborative process, in the ISP of teams. González-Ibáñez and Shah (2010), however, have recognized through the notion of Group's Affective Relevance (GAR) the active participation of emotions as well as their dynamic variations in the process of search and social evaluation of information relevance.

Positive Psychology and Collaboration

As pointed out in the previous section, our early study on synergy demonstrated that working in collaboration leads to better results than simply combining the outcomes of independent users. Supported by theories of positive psychology, we suspect that a possible factor that would explain the synergic effect could be found in positive emotions. For example, authors such as Frederickson (2004) have described that positive emotions would "broaden an individual's momentary thought". As Frederickson explains "joy sparks the urge to play, interest sparks the urge to explore, contentment sparks the urge to savor and integrate, and love sparks a recurring cycle of each of these urges within safe, close relationships" (Frederickson, 2004, p. 1367).

Frederickson also pointed out that "positive emotions promote discovery of novel and creative actions, ideas and social bonds, which in turn build that individual's personal resources; ranging from physical and intellectual resources, to social and psychological resources" (p. 1367). Later Waugh and Frederickson (2006) explained that positive emotions would have particular benefits in social settings; in the authors' words: "the social and interpersonal benefits of positive emotions seem intuitive. Joy and other positive emotions bring people closer and seem almost necessary for forming and maintaining relationships" (p. 93). The authors also suggest that based on their study "positive emotions broaden and expand people's sense of self to include close others" (p.103). This is especially relevant here due to the particular experimental conditions of our study, where subjects of collaborative teams knew each other and were asked to sign up in pairs.

At the organizational level, Losada and Heaphy (2004) provided mathematical support to describe relationship between teams' performance with the ratio of positivity and negativity (P/N) within teams. Later Frederickson and Losada (2005) showed that there is a specific range of P/N that characterize high performance teams, and those out of the boundaries of this range fall in the category of low performance teams.

Facial Expression and Emotions

We narrow down our study by focusing on the expression of one positive emotion (i.e. happiness), through the smile of participants during the search process. While one may argue that smiling does not necessarily imply happiness, studies have shown that in the same way emotions provoke changes at the expressive and physiological levels, this would also happen in the opposite direction. As stated by Kraut, "facial feedback has a small but reliable moderating effect on the emotional experience and on the evaluation of emotional stimuli" (Kraut, 1982; pp. 861).

In a research conducted by Strack, Martin, and Stepper (1988), the authors studied whether people's facial gestures had an effect on their emotional responses. The same idea was also studied by Bloch (1993) who developed Alba Emoting, a method to evoke emotions based on specific gestural, postural, and respiratory patterns.

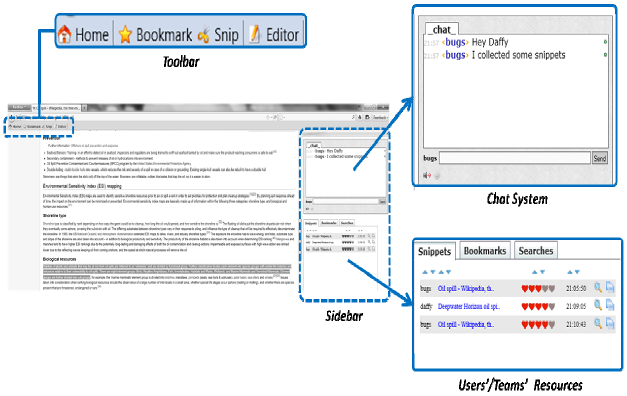

Figure 1: A snapshot of the experimental system with parts of it shown in details.

Research Questions and Hypothesis

From the literature review we found that (1) studies on emotions in information have focused mostly on individuals; (2) studies in this regard have mostly explored the idea of emotions as a result of experiences within the search process; (3) emotions, in particular positive ones, may contribute to individuals' and teams' performances; (4) positive emotions, such as happiness can be expressed through smiles, but more interestingly, smiling can also contribute to the emotional experience of happiness; and (5), none of these works have studied the direct implications of smiling nor the positive emotions in the information search process of individuals and teams.

In order to reach our goal of understanding the synergic effect in CIS, we focus in this paper on how positive affects participate in the information search process of both individuals and teams. As stated above, we analyzed the smiles of information seekers (below referred to also as users); operating under the assumption that smiling is either a way of expressing happiness or a contributor to it. With this assumption, we formulated the following research questions:

1. In a recall-oriented exploratory search task, to what extent, if any, do users searching information online smile?
2. To what extent, if any, do smiling episodes of single users differentiate from those who work in collaboration with others?
3. Can we explain the synergic effect in CIS, at least in part, in terms of the expressed happiness of users within the information search process?

The following section describes the study design that we used as we collected the data to address the above questions.

STUDY DESIGN

Considerations

As stated earlier in this paper, our original study involved five experimental conditions - single users, co-located at the same computer, co-located at different computers, remotely located, and artificially generated team (Shah & González-Ibáñez, 2011). From that study, the condition that reported better results was that of users collaborating synchronously, remotely located, and using instant messaging as a communication channel. We found this by comparing the results of teams in each collaborative condition with the results of artificial teams. Such artificial teams were created by generating all possible pair combinations of single users' outcomes.

The two real experimental conditions we use in this study (single users and remotely located collaborators) are particularly meaningful for the purpose of our research; however, it is important to note that those conditions in which participants worked co-located, present some technical difficulties for the kind of analyses we perform later in this paper (the details are discussed in the method section). This is one of the reasons we did not include these conditions in the current study. Regardless, we believe that comparing our two extreme cases (single users and remotely located collaborators) will be beneficial to better understand particular behaviors within the ISP of both single users and those who work in collaboration with others.

Participants

In the recruitment stage, we asked students from Rutgers University to participate in one of two laboratory studies. In one of them, participants could sign up individually. A second study required participants to sign up in pairs with someone with whom they had previous experience collaborating. It is important to note that participants were not allowed to participate in both. Along with the recruitment information, participants in both studies were informed of their compensation, which consisted of $10 in cash per person and the possibility of winning a prize based on their performance in the study. From this recruitment, 10 pairs were randomly assigned to the collaborative condition we investigate in this study; as well, 10 random participants were selected from the single users study.

System

Participants in both studies used a system designed to support the information search process of both single users and teams. This system, called Coagmento (Shah, 2010), was developed as an add-on for Firefox (Figure 1). The system provided two key components: the toolbar, which contains buttons that enable users to save useful pages (*Bookmark*) and also to collect highlighted text on a Webpage (*Snip*). Additionally, the toolbar contains a *Home* button that takes users to specific questionnaires during the experimental sessions and also the *Editor* button, which give access to users to a collaborative editor in which they could write the report assigned in the task. The second component is the sidebar, which is divided into two main regions: (1) the chat area, which enables users to communicate with each other (for the collaborative

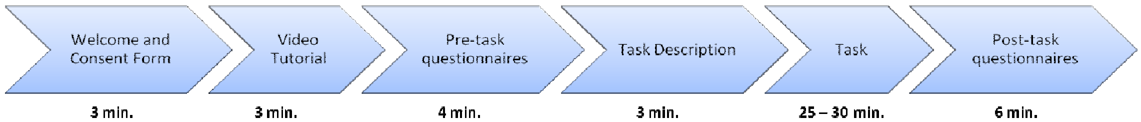

Figure 2: Study session workflow.

condition) and also to allow the researcher to provide specific instructions to participants during the session; and (2) the resources area, where users can access the information collected or generated during the task (i.e., bookmarks, snippets, and queries).

Session Workflow

Each experimental session lasted approximately 50 minutes and it was structured in six stages. A schema of the session workflow is presented in Figure 2 and the stages are described as follow from left to right:

1. Participants were introduced to the study and asked to sign a consent form.
2. Participants watched a brief tutorial in order to learn the basic functionalities required during the task.
3. Participants individually filled out a set of pre-task questionnaires. In the pre-task questionnaires users provided demographic information and reported how they felt right before starting the task, this through the PANAS instrument (Watson et al., 1988).
4. Participants read the task description (given later).
5. Each participant/team worked for approximately 30 minutes on the given task that included searching for relevant information and also using it to compile a report.
6. Participants filled out post-task questionnaires. These includes a PANAS to allow users to report how they felt right after complete the task; and a simplified version of NASA's Task Load index (TLX) (Fidel et al., 2004) to report cognitive load.

During the session, the researcher conducting the study communicated with the participants through the chat-box at different times instructing them to start/stop the task or fill in a questionnaire.

Protocol for Data Capturing

From the moment the subjects completed the consent forms, we captured data from all users' actions within Coagmento (visited pages, bookmarks, queries, chat messages, and so on). In addition, we used Camtasia Studio 7 to capture desktop activity, participants' faces, and voices. For facial data acquisition, we used 640x480 Web cameras, and captured video at 15 fps. Also, we kept the same light conditions for all participants in order to ensure the quality of images and facilitate the facial expression analyses. Finally, we asked participants to stay in front of the camera and not get too close to the screen in order to record their frontal faces; this is especially important because the tools we describe later perform better in this position.

Conditions

As explained previously, this study focuses on two specific conditions: (1) Single users and (2) collaborators remotely located. Both conditions will also be referred to in the rest of the document as C1 and C2 respectively. A schematization of both experimental conditions is depicted in Figure 3.

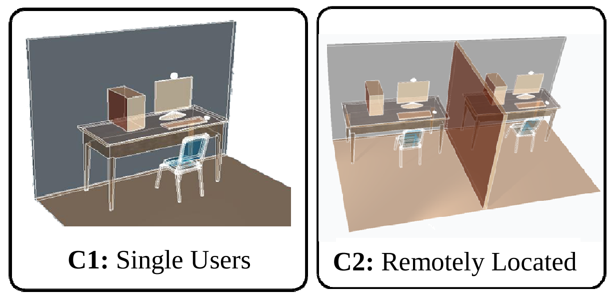

Figure 3: Experimental setups for two different conditions.

Task

Participants in both studies were asked to perform a brief research task about the "gulf oil spill". At the time we conducted this study, we found through some pilot runs that there was a substantial amount of material on this topic, and that the participants would find it both interesting and challenging as an exploratory search task. Below it is presented the actual task description that participants saw on screen (they were also given hard copies) after completing the pre-task questionnaires.

"A leading newspaper has hired your team to create a comprehensive report on the causes, effects, and consequences of the recent gulf oil spill. As a part of your contract, you are required to collect all the relevant information from any available online sources that you can find.

To prepare this report, search and visit any website that you want and look for specific aspects as given in the guideline below. As you find useful information, highlight and save relevant snippets. Make sure you also rate a snippet to help you in ranking them based on their quality and usefulness. Later, you can use these snippets to compile your report, no longer than 200 lines, as instructed.

Your report on this topic should address the following issues: description of how the oil spill took place, reactions by BP as well as various government and other agencies, impact on economy and life (people and animals) in the *gulf, attempts to fix the leaking well and to clean the waters, long-term implications and lessons learned."*

SAM: SMILING ANALYSIS METHOD

Similar to previous studies like those conducted by Arapakis and Gray (2008) and Lopatovska (2009a), we rely in our study on systems for automatic facial expression recognition. These computational tools are developed and trained using a variety of methods, such as machine learning techniques. We recognize, however, that such tools are subject to different sources of error, thus it is necessary to perform various processes in order to clean the data and ensure the validity of the results. Therefore, in order to accomplish the goals of this paper; it was necessary to devise a method robust enough to perform reliable detection of smiles during the search process of participants.

In the following subsections, we describe the data, tools, and the procedures that we used to analyze the data.

Data Description

Data in this study can be categorized in four major groups as presented in Table 1. As pointed out in the previous section, we discarded two out of three of our original collaborative conditions. We did this because in the two co-located conditions, participants were allowed to talk. Due to the high volume of communication in these two conditions, the video data of participants' faces is particularly noisy for the kind of analyses and tools that we use in the present study. As a result, participants' facial movements during conversations may be interpreted erroneously as smiles. In addition, if a participant smiled as he/she talks, the smile may be misinterpreted by the tools as other facial expressions or simply ignored.

Table 1: Data groups and descriptions.

Source	Description
Coagmento logs	Pages, bookmarks, snippets, actions, and chat messages.
Desktop activity	Approximately 23 hours of video (45 minutes per subject) recorded at 15fps.
Participants' faces	Approximately 23 hours of video (45 minutes per subject) recorded at 15fps.
Surveys	Participants responses to pre-task and post-task questionnaires (demographic, PANAS, and TLX)

Tools

We believe that using one single tool may be biased and subject to various sources of errors, and that having two or more tools would enable us to adjust and validate results. After researching several public and also commercial solutions for facial expression recognition, we selected three systems:

1. ***eMotion***: developed at the University of Amsterdam. This system was used previously by Arapakis and Gray (2008) and Lopatovska (2009a) in their studies. As reported in the literature, its recognition rate for happiness (over a group of seven emotions) reaches over 92% on testing sets. (Sebe et al., 2007)
2. ***FaceDetect***: developed at the Fraunhofer Institute of Integrated Circuits (Kueblbeck and Ernst, 2006; Face and Object Detection Webpage, 2011) According to the authors, this system reaches over 95% of happiness recognition rate on a specific face database. This system detects four facial expressions.
3. ***BMERS (Basic Moods and Emotions Recognition System)***: developed by one of the authors of this paper; it reports a happiness recognition rate of over 85%, on a group of seven emotions (González-Ibáñez, 2006)

Assessing and Weighting Tools

Even though the objective of this paper is not to compare the three systems, we do this in order to assess their performance and accuracy. In spite of the reported high recognition rates of the three tools we selected for this study, we are aware that such rates were computed over specific testing sets. Moreover, each system was implemented differently and the set of basic emotions does not overlap in all the cases. In order to estimate properly the happiness recognition rate – given that our interest is on smiles - we performed a simple test with the three tools. The test consisted of evaluating the performance of each system on a corpus of 187 images of subjects smiling and 187 images of subjects not smiling. This corpus was constructed by selecting random images from four face databases, namely Japanese Female Database (JAFFE) (Lyons et al, 1998), Indian Female Face Database, Indian Male Face Database (Jain and Mukherjee, 2002), and CVL Face DB (Peer, 2011; Solina et al., 2003). We then created a video at 15fps. replicating sequentially each image 15 times as a way to generate 1 second of expression for each subject in the images.

In order to ensure an accurate recognition of smiles we tested different thresholds. Arapakis and Gray (2008) as well as Lopatovska (2009a) used a threshold of 90% in order to control possible sources of noise. As we expected, by increasing the threshold, the recognition rate on the baseline video decreases significantly. We also notice that when using high thresholds values, the system is able to recognize most prominent forms of smiles (which are less likely to appear in information seeking settings); on the other hand, less prominent ones, but still perceptible smiles by the human eye, were not recognized. Our evaluations showed that the most suitable threshold for happiness for all three software was around 80%, so we used this to run our analyses.

As we explained before, the objective of this paper is not to evaluate these tools, so we do not report the specific recognition rates; however, we use this information to assign weights to the results provided by each system. Therefore, the system with the highest accuracy in the baseline was assigned with the highest weight. By having the weights assigned to each facial expression recognition system, we computed one single value for each unit of time (in our case established in 1 minute) using the formula presented in Equation 1.

$$WeightedAverageSmile = \frac{w_1 * eMotion + w_2 * BMERS + w_3 * FaceDetect}{w1 + w2 + w3} \quad ...(1)$$

Data Preprocessing
Prior to running any kind of automatic analyses, the data were properly treated in order to avoid potential sources of error. We did this in three stages:

Segmentation
Videos where segmented by analyzing desktop activity in order to identify when users started and terminated the task. We ran this process manually for all 30 participants.

Using the information obtained in this process, we eliminated pre-task and post-task segments from the videos of users' faces.

Synchronization
In addition to removing the initial and final segments from all videos, we also performed a synchronization of users' face videos with the logs on the Coagmento database. We did this at the level of seconds by removing all frames that were located right after the last pre-task questionnaire and right before the first post task questionnaire. Taking advantage of the synchronization of the system clock of the local computers used in the study and also our Coagmento server, we compared the local time (recorded in the videos) with the server time to verify if videos were properly synchronized. It is worth noting that this is not fine-grain segmentation, however, it is enough for the unit of time we use in this study (1 minute).

Normalization
Once videos were segmented and synchronized, we inspected the videos to locate a frontal neutral face for each user. Then, we replaced the very first second of each video with one second of the neutral face of the corresponding user. As a result, the three tools started analyzing a neutral face and we used this as a reference point for comparisons.

Facial markers
In order to obtain the best possible results with each tool, we followed the suggested calibrations. For the particular case of eMotion, the documentation establishes that the edition of facial markers (position of eyes, eyebrows, mouth, nose, and so on) will enhance a proper match, which is required for "accurate emotion recognition" (eMotion user's guide). Therefore, we manually edited the markers for all 30 subjects.

Facial Expression Analysis
After we preprocessed each video, we ended up with approximately 27,000 frames per video. This corresponds to roughly 30 minutes of video at 15 fps; overall, each tool analyzed approximately 810,000 images of faces.

Data Post processing
After processing all the videos with each system, we performed two additional procedures:

1. We established the unit of time for analyses purposes at 1 minute; so we segmented the data for each participant by computing the number of smiles per minute (900 frames). We then converted these values to seconds so that we knew how long a participant smiled within a minute during the experimental session.

2. Finally, we performed a visual inspection of the plots for each participant smiling episodes. We paid particular attention to prominent peaks and see what happened in the data; we found 2 cases in C1 and 8 cases in the C2 in which users were out of the range of detection and in some cases chewing gum. These sources of error/noise were not controlled when participants performed the task.

Based on this post processing stage we end up with validated analyses of 8 single users and 12 users that worked in collaboration with others.

Implications of SAM
Past studies on emotions in information science that have incorporated the use of tools for automatically recognizing certain facial expressions have relied on one single tool; this as we described above may be a potential source of error. In addition to considering more than one tool it is necessary to prepare the data adequately prior to any kind of analysis. In this sense the methodology described in this section is robust and could be helpful for further research using facial expression recognition systems in information science, as well as in other domains.

SYNERGIC EFFECT EVALUATION
We use in this study the same measures we proposed in our previous study (Shah & González-Ibáñez, 2011) to evaluate the synergic effect of teams. The measures are briefly described in Table 2.

Our original study involved five experimental conditions and all measures were computed using the data from all participants in all of them. For the purposes of this study, we recalculated all these measures for C1 and C2. We did this first with teams in order to verify that they performed at least better than single users. Then, because this study focuses on individuals, we recomputed all these measures for each participant (as individual units) in both conditions taking the data only from those participants that were selected in the facial expression analyses stage.

RESULTS AND DISCUSSION

Synergic Effect Evaluation

Teams vs Single Users
As expected, teams performed better than single users with respect to most of the measures we described in Table 2. This was verified through an independent *t*-test for

comparing the means (Table 4a). A summary of the means and standard deviations for each measure and condition is provided in Table 3. These results enabled us to continue with the analyses using subjects as units of analysis.

Table 2: Measure descriptions.

Measure	Description
Universe (U)	The union of all webpages visited by all of our participants (Total pages=234; Distinct pages =190)
Universe of relevant webpages (U_r)	The union of all webpages bookmarked or from where one or more snippets were collected (Total pages=85; Distinct pages =65)
Coverage (C)	The total number of distinct webpages visited by a given team/participant within U.
Unique Coverage (uC)	The total number of pages visited only by given team/participant within U.
Relevant Coverage (C_r)	The total number of distinct relevant webpages visited by a given team/participant within U_r.
Relevant Coverage (uC_r)	The total number of relevant pages visited only by given team/participant within U_r.
Precision (Prec), Recall (Rec), and F-Measure (F-m)	Three of the most common evaluation measures in information retrieval. We compute this measures using the results from U_r, C, and C_r.
Likelihood of discovery (LOD)	Effectiveness of team/participants to find relevant and diverse information. The closer the value to 0, the higher the effectiveness of the team/participant to find this kind of information.
Cognitive load (TLX)	Evaluation of the results obtained through the simplified version of TLX instrument (Fidel et al., 2004)
PANAS	Incorporated in this study to compare users in terms of their affects (Positive (P) and Negative (N)) before the task and after it.

Collaborators vs Single Users

By comparing users in C1 and C2 as individual units, it was found that the differences reported in the comparison between teams and single users do not remain (Table 4b), however, it is possible to observe based on the means for each measure, that results are slightly better in most cases for users in C2 (Table 3).

On the other hand, based on the instrument applied as pre-test (PANAS), no difference was found when comparing the ratio of positive affects over negative affects prior starting the task (Pre P/N) in both conditions. Indeed, as presented in Table 3, the means for both groups in this evaluation are about the same. This is particularly relevant because from these self-reports it is possible to infer that participants in C1 and C2 started from similar affective states, and that possible differences between groups at the end of the task would not be explained by their mood before performing the task.

In terms of the post-task tests, no significant difference was found on the post PANAS. Nevertheless, based on the means for Post P/N, it is possible to observe that those who worked in collaboration with others (C2) reported less variation in their affective state with respect to what they reported before starting the task, than those that worked individually (C1) (Table 3).

With regard to the cognitive load of participants, significant difference was found in the cognitive load reported through TLX, being lower for those in C1. We believe that the higher levels of cognitive load of users in C2 was due to additional factors involved in collaborative activities such as communication, coordination, and conflict resolution.

Table 3: Means and standard deviations for each condition.

	C1	C2 (teams)	C2 (collaborators)
C	9.00 (4.869)	21.714 (7.158)	11.333 (4.355)
uC	6.75 (3.955)	16.142 (4.74)	7.333 (3.725)
C_r	3.625 (2.326)	6.714 (2.927)	3.833 (1.749)
uC_r	2.25 (2.052)	4.857 (2.968)	1.833 (1.749)
Prec	0.408 (0.203)	0.32 (0.134)	0.442 (0.149)
Rec	0.055 (0.035)	0.103 (0.045)	0.073 (0.03)
F-m	0.095 (0.056)	0.153 (0.064)	0.123 (0.047)
LOD	-0.032 (0.019)	-0.239(-0.003)	-0.031 (0.01)
TLX	14.875 (2.031)		18.166 (3.352)
Pre P/N	2.228 (0.809)		2.34 (0.526)
Post P/N	1.807 (0.546)		2.315 (0.832)

Table 4: Means differences between conditions ($\overline{C1}-\overline{C2}$). (a) Comparison with respect to teams' outcomes and (b) comparison with respect to collaborators. Bold values correspond to statistical significant difference at p<.05 and italic bold values at p<.01.

		(a)	(b)
	Cond.	**C2 (teams)**	**C2 (collaborators)**
C	**C1**	***-12.714***	-2.333
uC	**C1**	***-9.392***	-0.583
C_r	**C1**	**-3.089**	-0.208
uC_r	**C1**	**-2.607**	0.416
Prec	**C1**	0.087	-0.034
Rec	**C1**	**-0.047**	-0.018
F-m	**C1**	-0.057	-0.028
LOD	**C1**	-0.008	-0.00089
TLX	**C1**		**-3.291**
PANAS-1	**C1**		-0.112
PANAS-2	**C1**		-0.507

Facial Expression Analysis

From the facial expression analyses we plotted the average smiling time (in seconds) per minute. As depicted in Figure 4, it is possible to observe that smiling episodes are higher in most segments for users in C2. Using these results, we computed the average smiling time for every user in C1 and

C2; and the overall smiling time for each session (the total amount of time that each user smiled during the session).

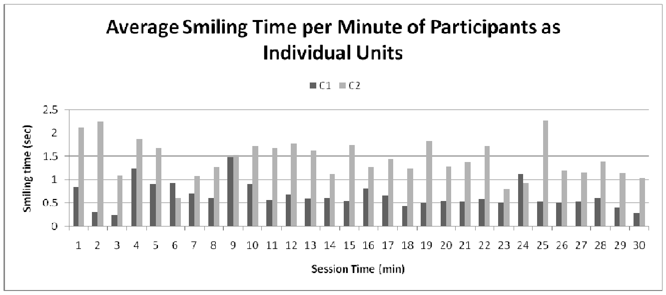

Figure 4: Average smiling time per minute of participants as individual units.

By comparing the means of both evaluations with *t*-test, statistical difference was found in the scores for average smiling time in C1 (M=0.663, SD=0.301) and C2 (M=1.1968, SD=0.588); $t(18)=-2.351$, $p<0.05$. Significant difference was also found in the scores for overall smiling time in C1 (M=18.562, SD=9.289) and C2 (M=35.903, SD=17.65); $t(18)=-2.539$, $p<0.05$.

These results are particularly useful in response to our first two research questions:

1. *In a recall-oriented exploratory search task, to what extent, if any, do users searching information online smile?*
2. *To what extent, if any, do smiling episodes of single users differentiate from those who work in collaboration with others?*

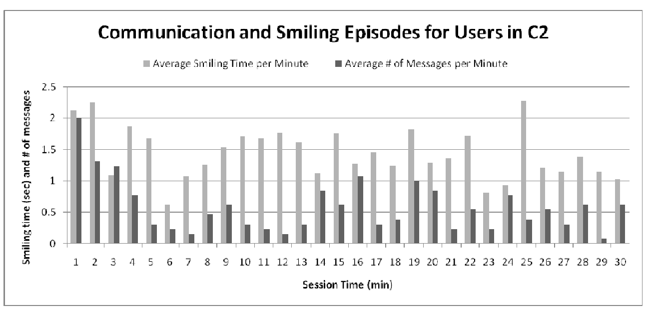

Figure 5: Communication and smiling episodes for collaborators remotely located.

As presented above, users in both conditions smile; however, those who worked with someone else (C2) almost doubled the smiling time of those working individually (C1). We explain such variability in terms of the inherent social interactions in C2. As shown in Figure 5, smiling episodes would be linked to the communication between users during the search process, especially at the beginning and somewhat in the middle of the session.

Combined Analyses

Results obtained were then combined in order to find possible correlations. We analyzed the effects of pre-task affective conditions as well as smile measures with both users' outcomes and post task self-reports.

We acknowledge that in our analyses we looked for correlation between pairs of continuous variables, pairs of rating scales variables, and also between continuous and rating scales variables. This is important to note because we are aware that the difference between values in rating scale variables are not exact and correlation techniques assumes the opposite; however, we do so assuming that such measures reflect the reality through the perception of users in the context of this study.

Pre-Task Affects and Synergic Effect Measures

We found modest significant correlations for some of our pre-task affective measures (Pre PANAS) with synergic effect measures (Table 5) and post task cognitive load responses (Table 7). No significant correlations were found between pre-task affective conditions and the smile measures computed from facial expression analyses.

Table 5: Pearson's correlation values between pre-task affective variables and synergic effect measures. Bold values correspond to statistical significant difference at *p<.05*.

		Synergic effect measures	
	N=20	C_r	u C_r
Pre PANAS	Upset	0.467	
	Hostile	**0.604**	**0.539**

By looking at results in Table 5, it is possible to observe that two negative affects would be better predictors than positive ones. More interestingly is that these two negative affects reported positive effects in two synergic effect measures.

Smiling Time and Post-Task Self-Reports

When looking at correlations between smile measures and post-task self-reports (Table 6), modest positive correlation was found between the overall smiling time and the feeling of proud among users. As a result, those who smiled more during the session reported higher levels of proud and also (though significantly marginal) an increase of proud with respect to their pre-task reported levels of the same feeling (Pos-Pre).

On the other hand, it was also found that smiling measures (both average and overall) were positively correlated with the feeling of rush (measured through TLX). Based on observation of communication messages in C2, we attribute such effect to the cooperative awareness between collaborators and the positive attitude to inform about the remaining time during the task. Therefore, messages like: "*User1: 7 mins left User2*", "*User2: haha ok I got it already!*" would be one possible factor of why users felt rushed but at the same time they took it positively.

Table 6: Pearson's correlation values between smile measures and post-task variables. Bold values correspond to statistical significant difference at p<.05, italic bold values at p<.01, and underlined values (marginal significance) at *p<.06*.

	N=20	PANAS		TLX
		Pos Proud	Proud Difference (Pos-Pre)	Rushed
Smile Measures	Avg. smiling time			***0.546***
	Overall smiling time	**0.424**	**<u>0.465</u>**	***0.523***

With regard to our third research question (*Can we explain the synergic effect in CIS, at least in part, in terms of the expressed happiness of users within the information search process?*), no significant correlation was found between smile measures and any of the synergic measures, so smiling time would not influence, at least directly, the outcomes of participants.

Table 7: Pearson's correlation values between pre-task affective variables and synergic effect measures. Bold values correspond to statistical significant difference at p<.05 and italic bold values at *p<.01*.

N=20	TLX		
	Mental demand	Failure	Perceived task difficulty
Determined			**0.524**
Active		**-0.520**	
Scared		**-0.508**	
Afraid	**0.498**		

Pre-Task Affects and Reported Cognitive Load

Finally, we looked at possible correlations between pre-task reported affects (Pre PANAS) and the reported cognitive load of users. Since one of the aspects measured by TLX overlaps with some negative affects in PANAS, the correlation between some negative affects and the last column in Table 7 was expected. Besides that, an interesting observation is that the feeling of determination, which happens to be positive, was found to be positively correlated with the perceived task difficulty (negative). This may be attributed to prior expectations, a positive attitude to accomplish the task, and then the frustration of not having enough time to complete it, as they would have done if they had more time.

Other interesting correlations is that those who felt active and also those who felt scared prior start the task, found themselves more successful at the end of it; On the other hand, those who reported to be somehow afraid at the beginning of the task found at the end that the task was mentally demanding.

CONCLUSIONS

In this exploratory study, we have taken a closer look to the role of expressed happiness (smiles) in the search process of single users and collaborators working remotely and synchronously, this as a way to look for possible contributors to the synergic effect of teams in CIS. Our analyses showed that smiles do not have direct impact on users' performance, however, we noticed possible implications of smiles are indicators of the overall experience of users in the information search process (ISP).

As we have showed, users who search information in collaboration with others tend to smile significantly more than those searching information individually. We attributed this phenomenon to the social interactions that took place in the collaborative condition (Argyle & Lu, 1990; Csikszentmihalyi, 2003).

We also found that those who smile more during the ISP also reported feeling more proud than those who did not smile that often. Moreover, those who smiled more reported feeling more rushed as they worked in the task. We attributed the latter correlation to communication episodes in which participants talked about the remaining time at various instant during the search sessions; what was more interesting is the positive attitude that participants showed when exchanging this kind of messages, which may explain why users smiled more in this circumstances. We believe that such correlations for tasks like the one users had to perform in this study would be a positive contributor.

Something interesting that we found is that certain negative emotions may contribute to the synergic effect of teams. Indeed, we found moderate positive correlation between two negative affects (upset and hostile) and measures for coverage and relevant coverage. From observations of audio and video, we also found that negative emotions such as disgust may have contextual positive effects; for example, some users expressed disgust toward certain Web pages (e.g. a Web page displaying various animals agonizing and dead as a result of the oil spill), however, such emotional reactions were crucial in that context for selecting such Web pages as relevant information.

Though unexpected from the positive psychology standpoint that we adopted in this paper, some explanations for the role of negative affects can be also found in the positive psychology literature (Losada & Heaphy, 2004; Fredrickson & Losada, 2005). Furthermore, studies in other collaborative domains such as marriage have showed that negative affects may also have positive implications (Rauer & Volling, 2005).

We believe from this study that a smile may be a positive indicator of collaboration in teams. Though it does not necessarily influence directly the outcomes of team members, its effects could have indirect implications in terms of the experience of participants. This could explain why teams in CIS performed better than simply combining the outcomes of independent parts, which is the main result of our previous study (Shah & González- Ibáñez, 2011).

Finally, in order to properly understand the role of emotions in the ISP (beyond the expressed happiness) we plan to work with particular stimuli in order to influence specific emotional state prior start the task.

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