Learning how to feel again: Towards affective workplace presence and communication technologies

ABSTRACT
Affect influences workplace collaboration and thereby impacts a workplace's productivity. Participants in face-to-face interactions have many cues to each other's affect, but work is increasingly carried out via computer-mediated channels that lack many of these cues. Current presence systems enable users to estimate the availability of other users, but not their affective states or communication preferences. This work investigates relationships between affective state and communication preferences and demonstrates the feasibility of estimating affective state and communication preferences from a presence state stream.

Author Keywords
Affect, affect awareness, affect computing, workplace communication, presence, myUnity.

INTRODUCTION
Affect plays a fundamental role in achieving effective communication and collaboration in the workplace [7, 21, 22]. In traditional work environments, where face-to-face interactions predominate, workers can leverage their perception skills to pick up on behaviors and non-verbal feedback to recognize others' affective states [13, 23, 25]. They use these cues to facilitate communication and decide when to initiate interactions [11, 18, 19]. Many of these cues are absent from computer-mediated communication channels, such as e-mail and instant messaging. As work becomes increasingly distributed, and reliance on computer-mediated communication increases, many of these cues will be absent. Misinterpreting others' affective state may lead to ineffective communication among workers, possibly forming barriers to the development and maintenance of cooperative relationships.

Developing technology that supports communication and coworker awareness has been a focus of much research, including several projects exploring presence systems [4, 12, 17, 40, 43, 44]. These systems fuse software and environmental sensing with communication tools to provide users with insights into physical presence and availability of workers, providing states such as *in office*, *in a meeting*, or *working remotely*. Presence systems have proven valuable in improving workplace communication [4,40,44].

Current state-of-the-art presence technologies provide users with little support for assessing others' affective states. Typically presence systems are designed to be passive, running in the background with little user intervention. In contrast, current techniques to measure affect are quite invasive or burdensome to users. Many techniques require users to wear sensors, to accept linguistic analysis of their writing as they type, or to actively input their affective state [5, 14, 26, 32, 36, 38].

In this work, our main goal was to explore the feasibility of leveraging information already being shared in a particular presence system, myUnity [44], to model users' affect and communication preferences. A secondary goal was to assess the existing level of affect awareness in a workplace whose employees are technologically sophisticated and fluent in the use of computer-mediated communication media. Many participants had several years working together. Most had more than one year of experience using a presence system. We also examined and quantified the relationship between affect and communication preferences in a modern office.

The results of our modeling approach using only presence states compared favorably to results from prior approaches. We also modeled affect using a rich array of keyboard, mouse, and desktop window activity data. The accuracy of our lower bandwidth and less invasive presence-stream approach is comparable to the more comprehensive approach. Combining both approaches provides yet higher overall accuracy.

The major contributions of this paper are:

- Results showing that a method that uses less invasive sensing to model affect and communication preferences that can achieve accuracy rates as high as 87%.
- Confirmation that users fluent in the use of computer-mediated technology and experienced with presence systems have poor estimates of each other's moods.
- Quantification of the relationships between affect and communication preferences, providing grounding for what future affect technologies should measure and, in turn, represent to users.

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RELATED WORK

Presence systems

Early projects, such as the Active Badge system [43] and the Portholes project [12], provided awareness of people's physical environments via a closed-circuit video feed. Instant message systems often show whether contacts are online or not and generally provide means for users to set their status. More advanced systems, such as MyVine [17], ConNexus [40], and Connecto [4], collect information from a variety of sources, including shared calendars, IM status, and various sensors, to report a user's activity and location.

One such system is myUnity [44]. Our work leverages myUnity's data stream to provide estimates of affect and communication preferences. We chose it because it is one of the only presence systems that has been adopted for daily use in a workplace: myUnity has been in continuous use by more than 30 users for over two years. Like other presence systems, myUnity collects data from cameras, bluetooth device sensors, mouse and keyboard activity, network connectivity, IM availability, and employee calendars. At regular intervals, each user's data is aggregated and summarized into a presence state. These states include, but are not limited to: *in office, has visitor, in building, active online remotely,* and *connected via mobile client*.

A field study [44] showed that myUnity has been well received by its users, who incorporated it into their daily routine to help coordinate with colleagues. It has been effective in improving users' awareness of others' availability. While users have found myUnity to be useful in choosing communication media, it does not provide information on communication preferences or emotional state. In our work, we examine the feasibility of estimating communication preferences and emotional states from presence data.

Affect in Communication and Collaboration

We are interested in estimating affect, because it plays such a key role in communication, from capturing attention through the entire communication process [11]. According to the Affect Infusion Model (AIM) [19], the extent to which affect influences people's behavior depends on the complexity of a situation. Tasks that require elaborate, substantive processing are more likely to be influenced by affect than simple tasks. Empirical findings show its effects on decision making and many cognitive processes involved in communication [18]. Its effects are significantly greater when people are responding to unexpected rather than expected requests. Also, people in negative moods form a more negative impression of the requests.

Affect influences a variety of performance-relevant outcomes, such as judgments, attitudinal responses, creativity, risk taking and absenteeism [6]. Positive affect enhances creative problem solving and cognitive flexibility [31, 33], and facilitates the generation, selection, and amplification of ideas during collaboration [1]. Positive mood enhances altruistic behavior, including in the workplace [31]. A study involving self-report of positive moods over a week predicted workers ratings of altruism on the job [21]. Helping others was found to be useful in maintaining a momentary positive mood [15].

Ekman demonstrated that facial expressions for anger, disgust, fear, joy, sadness and surprise are universally recognized across cultures [13]. While Guillory et al. showed that affect information can be transferred via linguistic cues in computer-mediated channels [23], there are cultural and individual differences in the ability to perceive this information [35]. Affect awareness is an essential component of *emotional intelligence* [35]. Workers with higher emotional intelligence demonstrate higher social competence [7], better strategic decision-making [22], stronger workgroup cohesion, employee performance, and organizational commitment [10]. Our work examines the degree of affect awareness in the modern workplace and proposes techniques to enhance affect awareness among workers.

Systems that estimate affect

Systems can estimate affect from a variety of features, such as facial expressions, gestures, vocal intonation, language, and physiological factors [38]. Signals from wearable sensors, such as pupil dilation, arm movement, skin temperature, and heat flux, can be used to infer users' affective states [32]. Affect can be linguistically inferred in the textual domain via word choice, word count, punctuation, and timing (text-based chat [26], weblog [36], microblog [5]). Epp et al. [14] utilize keystroke dynamics to determine users' affective states. Their method is less invasive and more likely to be accepted than linguistic analysis or wearable sensors. However, the model performs well only when users type predefined text. In this work, we explore the less invasive approach of using a passive awareness system's data stream to estimate emotional state.

Communication medium selection

Our work also examines communication medium selection. Media richness theory suggests that different communication channels have different capacities for resolving equivocality and uncertainty. Rich media such as face-to-face communication and phone conversation are suitable for handling equivocality, while lean media such as email are more appropriate for reducing uncertainty [9]. Context also influences communication medium selection [27, 41]. Contextual information such as availability, interruptibility [16], breakpoints [30], and activity content [34] can help workers decide when to contact their colleagues.

Systems that estimate communication preferences

Horvitz et al. have a successful line of work inferring the cost of interruption based on activity sensing [28]. Their system recognizes office activities [37] and can make automated decisions to defer communication requests such

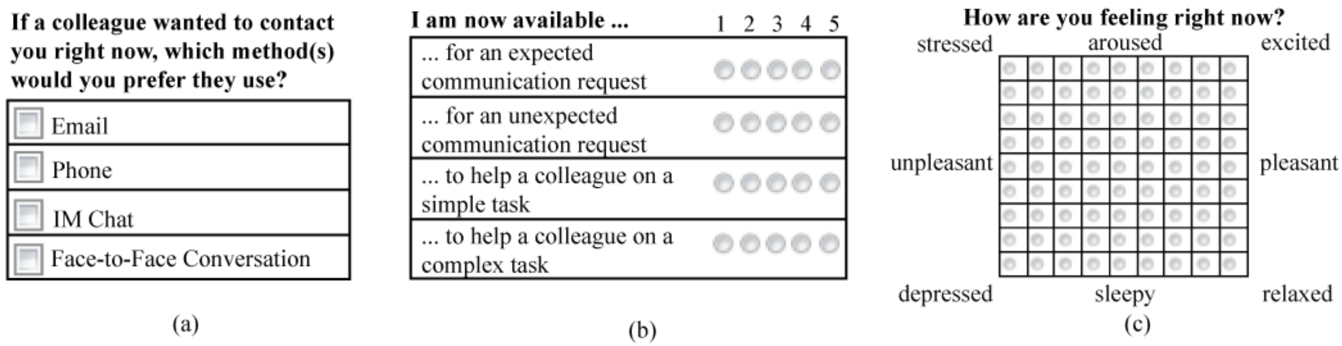


Figure 1. An example of questions in the survey. (a) Communication channel preference; (b) Responses to communication and task requests, using a 5 point scale (1=strongly disagree, 2 = disagree, 3=neutral, 4=agree, 5=strongly agree; and (c) the affect grid.

as phone calls according to its users' cost of interruption [29]. ActivitySpotter can estimate the content or topic of a user's activity from accessed documents. This information can influence other users' decisions as to whether and when to contact the user [34]. Our work is complementary to this research. It advances the state of the art by proposing an estimation technique that is less invasive than prior techniques. In addition, our method produces valid predictions even when users are not using their desktop computers, a limitation of many prior approaches.

AFFECT AND GROUND TRUTH

As discussed in the introduction, two of our goals are to obtain a better understanding of the ability of workers to assess their colleagues' affective states and to gain the ground truth data needed to build and evaluate a predictive model of affect. While affect is covered well in prior work, this investigation seeks to provide further evidence of the need for and potential value of affect awareness technologies. More importantly, it would show the existence of such need and value *within* the same population that yielded the data from which our predictive models are to be created.

Twenty-three employees from a multi-national corporation were recruited to participate in our study. They were all knowledge workers who were familiar with modern communication technologies. The primary work location was the same for all participants, on a single floor of an office building located on the US West Coast. All have been using the myUnity presence system, many for well over a year. Participants consisted of 17 men and 6 women ranging in age from the late twenties to the early sixties. Most participants generally worked in teams on several projects at a time, where the project team members varied by project. Six participants were summer interns who shared a room. Two were administrative assistants who could see each other from their cubicle desks. Other included staff members, executives, IT, and administrators, all of whom had their own offices or cubicles.

Experience Sampling Study

To gather as accurate an assessment as possible from participants, we chose an in-situ experience sampling methodology [8] for data collection. In this method, participants are asked to stop at certain times to make notes of their experience, such as current feelings and preferences. We sent participants a link to a survey form via both text message (SMS) and email five to eight times a day during their working hours over a two-week period. We collected data only during normal work hours of 8 AM to 7 PM. Thus, the number of times the survey was sent varied, because we had some participants that work part time or irregular hours.

At each time period, participants were asked to report their location, their current preferred communication media preferences (Figure 1a), their preferences with respect to requests from their colleagues (Figure 1b), current affective state (Figure 1c), and, optionally, their estimate of another colleague's affective state. Participants had a 20-minute window to fill out the survey after receiving the alert.

They reported their feelings via an *affect grid*, a frequently used, in situ measure [39]. This visual 9×9 grid places pleasantness along the horizontal dimension and arousal along the vertical one. The endpoints are marked with emotion words to facilitate reporting. The fifth row and column of the grid are neutral. Participants were instructed to mark the position in the affect grid that best corresponded to how they felt at the sampling moment.

In our instructions, we provide several examples of each type of communication request and task. For instance, expected communications included scheduled meetings or discussions with colleagues the user works with closely and talks with daily. An example of a complex task was helping a colleague generate ideas for a project. A number of examples were also provided for the use of the affect grid.

Awareness Data

During the two weeks of the experience sampling study, we also collected two types of empirical awareness data from the participants:

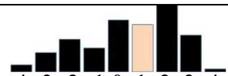
	Distribution	Mean	sd
Pleasure Score		0.44	1.93
Arousal Score		0.55	1.84

Figure 2. Statistical description of participants' affective states. The column "Distribution" shows the distributions of pleasure score and arousal scores with the light red bar showing the medians. Also shown are means and standard deviations.

- MyUnity usage data. 18 total presence states are provided by myUnity (e.g., *in office*, *in building*, *connected via mobile client*). For each transition in presence state, the state was captured with its corresponding timestamps.

- Computer usage data. Three types of computer activities were recorded: desktop, keyboard, and mouse with corresponding timestamps. We logged the state of each user's desktop (e.g., number of maximized, minimized, normal windows, window size, window coordinates) every second. Also, whenever a participant moved the mouse or pressed a key, the action was logged. These data were captured to allow us to compare our new method against those already proposed in the literature.

Post-study Questionnaire

At the end of the experiment, participants answered a post-study, semi-structured questionnaire designed to elicit quantitative responses regarding their subjective experience with perceiving and sharing affect information.

RESULTS

We received 1,445 responses from the participants with an overall response rate of about 76%. The number of responses per participant ranges from 26 to 97, with a median of 58 (mean = 60.2, sd = 24.3).

Figure 2 shows the distributions of participants' affect for both pleasure and arousal. Both distributions are slightly skewed in the direction of positive pleasure and arousal. The median score for pleasure is 1 (mean = 0.44, sd =1.93); the median for arousal is also 1 (mean = 0.55, sd = 1.84). We observed no significant correlation between the level of pleasure and the level of arousal (Pearson correlation, r = 0.03, p = 0.23), consistent with past psychology research [39]. To ensure high bin counts for statistical analysis, we grouped both the affect dimension and the pleasure dimension into two categories: positive (score > 0) and negative (score < 0). Following Forgas et al. [19, 20], we ignored the neutral category and use only the positive and negative categories in our analyses.

	Pleasure (n=1184)	Arousal (n=1217)	Location (n=1445)
Email	χ^2 (1) = 4.33 $p < 0.05$	χ^2 (1) = 2.09 *ns*	χ^2 (1) = 34.16 $p < 0.001$
Phone	χ^2 (1) = 65.55 $p < 0.001$	χ^2 (1) = 1.33 *ns*	χ^2 (1) = 0.95 *ns*
IM	χ^2 (1) = 4.29 $p < 0.05$	χ^2 (1) = 11.09 $p < 0.001$	χ2 (1) = 15.08 $p < 0.001$
Face-to-Face	χ^2 (1) = 44.71 $p < 0.001$	χ^2 (1) = 2.47 *ns*	χ^2 (1) = 96.82 $p < 0.001$

Figure 3. Each cell shows the chi-square test with Yates correction for preference differences for a communication channel by pleasure, arousal, or location.

Media Preference

Figure 3 shows the results of chi-square tests comparing participants' preference for each medium by their pleasure ratings, arousal ratings, and location (in or out of office). In general, participants are willing to receive emails most of the time, consistent with the findings of Turner et al [41]. Participants are more likely to select face-to-face communication when they are in a positive affective state than when they are in a negative one (34.5% vs. 14.8%). Similarly, the preference rates for phone and IM increase from 17.7% to 40.9% and from 30.3% to 36.5%, respectively, as affect changes from negative to positive. In contrast, preference for email decreases from 91.0% to 86.7% as affect changes from negative to positive. AIM

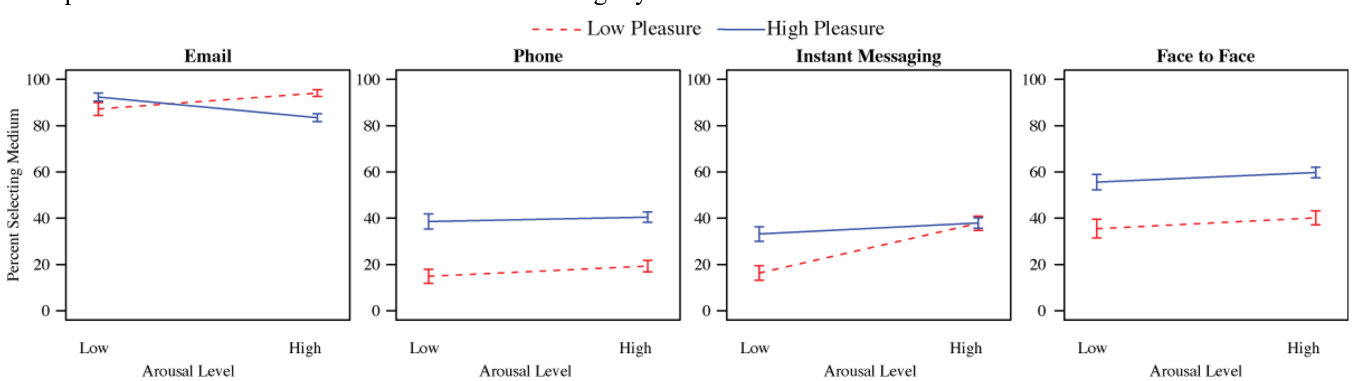


Figure 4. Comparison of selection for four types of media by arousal and pleasure. A three-way chi-square test among pleasure, arousal, and preference was conducted. The results of assessing interactions been arousal and each communication channels are (a) χ^2 = 16.56, p<.001; (b) χ^2 = 1.48, p = 0.48; (c) χ^2 =22.68, p <.001; (d) χ^2 = 1.94, p = 0.38. Each test has two degree of freedom.

theory suggests that when people are in a negative mood, they are more likely to wish to delay their responses [35] thus preferring communication channels that do not require immediate feedback.

Figure 4 shows the relationship between pleasure and arousal on media selection. Participants were more likely to select IM when both pleasure and arousal were positive. The effect of arousal was stronger when participants were in a negative affective state.

Participants were in their own offices 66.1% of the time. Their locations (in or out of office) did not influence the distributions of pleasure ($\chi^2(1) = 1.66$) and arousal ($\chi^2(1) = 1.22$); however, the location influenced participants' preferences for face-to-face, IM, and email communication (Figure 5). Specifically, when out of the office, participants selected face-to-face and IM less frequently (61.5% to 35.5%, 38.3% to 26.5%, respectively), and e-mail more frequently (85.5% to 93.4%). Location had no effect on preference for phone communication.

The effects of pleasure and arousal on the face-to-face and IM communication preferences become more salient when participants were in their offices (Figure 5). One possible explanation is that since participants were not in their offices, the increased uncertainty about location may reduce the effects of pleasure and arousal on selecting the face-to-face and IM communication channels.

Request Preference

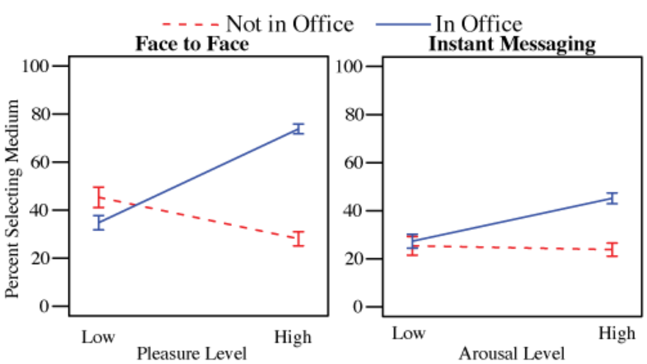
Figure 6 provides an overview of the participants' responses to four types of requests from colleagues. They are usually willing to accept expected communication requests from colleagues, but less willing to help colleagues on complex tasks. We performed an analysis to assess the relative independence and possible interactions among pleasure, arousal, and location on willingness to accept each type of request (Figure 8). Positive pleasure increases willingness to have an unexpected communication and help a colleague on a task, particularly a complex one. Thus, pleasure plays a larger role in request preference as communication uncertainty or the task complexity is increased. This result reflects AIM theory, which postulates that negative affect negatively impacts peoples' feelings about unexpected or uncertain events and tasks requiring higher levels of cognitive processing more than it does for certain or simple tasks [18].

Figure 8 shows that arousal level impacts all types of request except for complex task. Furthermore, pleasure and arousal interact (Figure 7). When participants had positive affect, their level of arousal made no difference in their willingness to accept any types of request. However, when their affect is negative, their willingness to accept all types of requests was significantly higher when they were aroused than when they were not. Thus, arousal plays a more significant role when participants have a negative than a positive affective state.

Additionally, location interacted with pleasure and with arousal for type of request. Similar to the interaction between pleasure and location for selecting communication media, when participants are in their offices, the positive effects of pleasure and arousal on accepting the communication and task requests become more significant.

Awareness of others' affect

Participants were only confident in inferring the affective state of a colleague participating in the study 26.9% of the time. Nevertheless, most participants (82.6%) felt confident enough to infer a co-workers' affect at least once during the study. Since all participants received the survey links at the same time, we can compute the accuracy of the participants' inference of another's affective state by comparing with the other person's self-report. Of the samples in which a participant inferred another colleague's affective state, that colleague reported his/her current affect 85.1% of the time. In these samples, participants inferred



(a) (b)

Figure 5. (a) Comparison of selection of face-to-face by pleasure and location. (b) Comparison of selection of IM by arousal and location. In a chi-square test of pleasure, arousal, and method, significant effects were obtained for pleasure and face-to-face ($\chi^2(2) = 113.56$, $p < 0.001$) and for arousal and IM ($\chi^2(2) = 19.62$, $p < 0.001$).

	Distribution	Mean	sd
Expected Comm.		2.76	0.94
Unexpected Comm.		2.12	1.11
Simple Task		2.23	1.07
Complex Task		1.60	1.08

Figure 6. Statistical description of the participant responses to four types of request. The column "Distribution" shows the distributions of willingness to accept each type of request (using a five-point scale from strongly disagree to strongly agree), with light red bar indicating the median.

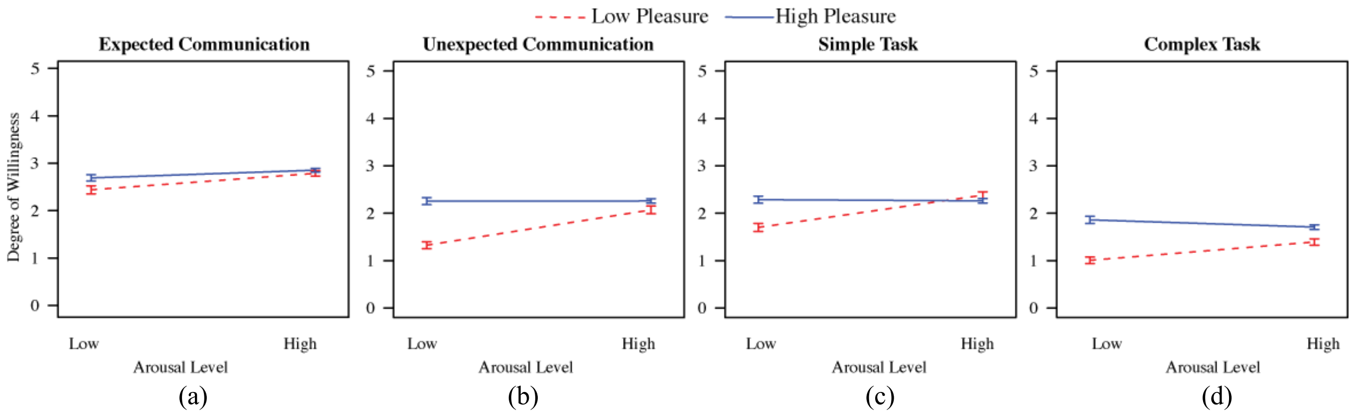


Figure 7. Comparison of willingness to accept four types of request by arousal and pleasure. The three way ANOVA results for the interactions between pleasure and arousal are (a) $F = 3.11$, $p = 0.078$; (b) $F = 26.51$, $p < 0.001$; (c) $F = 5.63$, $p = 0.018$; (d) $F = 14.23$, $p < 0.001$. F-ratios have 1 and 1088 degrees of freedom.

the valence (positive or negative) of a co-workers' pleasure and arousal correctly only 57.4% and 55.9% of the time, respectively.

Participants can be clustered into three groups based on their inferring behavior (Figure 10). In the first group (two solid nodes and two empty nodes on the left), the four participants work on joint projects, and two of them share a cubicle (solid nodes) while the others have private offices (empty nodes). The six participants of the second group (six solid nodes in the top right) work in a shared room but on separate projects. The third group's participants have private offices and are frequently working on joint projects. Workers in shared offices more frequently inferred each other's affective states than workers in private offices.

Echoing these results, participants' comments in the post-study questionnaire suggest that having face-to-face communication greatly increases their confidence in inferring another's affect, and that sharing an office and working collaboratively increases the chance of face-to-face communication. For example, one participant explained that he/she was confident to infer a colleague's affective state "*when I can see my co-worker*", while another was unable to make an inference "*when co- worker is not in sight*". Another commented, "*I am confident to infer a co-worker's mood, when I've just had a face-to-face meeting with them.*" One participant explained that he/she could not infer another's affective state *"If I have not had face-to-face contact, but I have had other (e.g., email) contact, I was unsure how to interpret."* These comments underscore how more frequent use of computer-mediated communication channels and less frequent chance face-to-face communication may hinder affect awareness among workers.

	Pleasure	Arousal	Location
Expected Communication	$F = 0.86$, $p = 0.35$	$F = 19.76$, $p < 0.001$	$F = 10.25$, $p = 0.0014$
Unexpected Communication	$F = 32.98$, $p < 0.001$	$F = 26.63$, $p < 0.001$	$F = 0.02$, $p = 0.90$
Simple Task	$F = 4.41$, $p = 0.036$	$F = 25.63$, $p < 0.001$	$F = 5.36$, $p = 0.0179$
Complex Task	$F = 42.82$, $p < 0.001$	$F = 4.94$, $p = 0.0265$	$F = 1.3$, $p = 0.2389$

Figure 8. Analysis of variance for pleasure, arousal, and location on willingness to accept a certain type of request. F-ratios have 1 and 1088 degrees of freedom.

MODELING AFFECT TO IMPROVE AWARENESS

The results above reinforce the importance affective state has on workers' communication preferences and willingness to interact with colleagues. In addition, and important for this work, they provide a corpus of presence and desktop behavior data that is coupled with ground truth data about the participants affective state. Thus, they provide a rich data set on which algorithmic techniques could be explored to model a worker's affective state and communication media preferences using both more traditional data (e.g., desktop behavior) and presence data (e.g., passive sensing data from myUnity).

In this exploration, we started by removing neutral samples, then clustered both the pleasure and arousal dimensions into two classes (positive and negative) based on affect score in

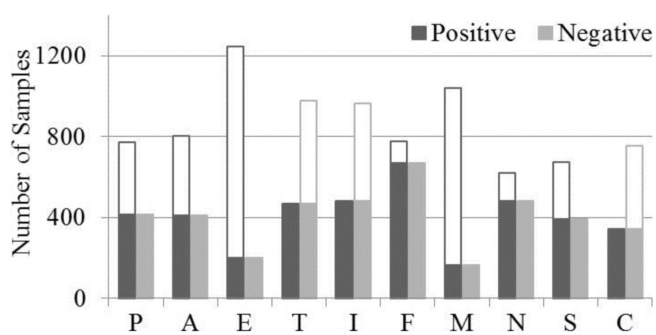


Figure 9. Distribution of responses before (empty bars) and after under-sampling (solid bars). P = Pleasure, A = Arousal, E = Email, T = Telephone, I = Instant Message, F = Face-to-Face, M = Expected Communication, N = Unexpected Communication, S = Simple Task, C = Complex Task.

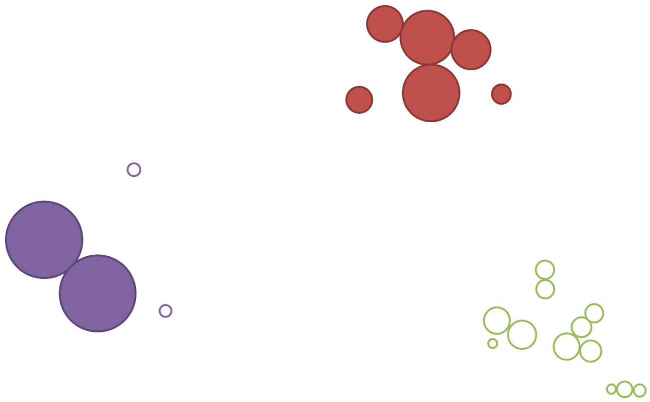


Figure 10. Visualization of inferring activities among participants. Each node denotes one participant. Solid nodes represent participants in shared offices, while empty nodes denotes participants in private offices. Node size represents the total number of inferences made by the participant. The distance between two nodes is proportional to the frequency of inference between two participants.

order to obtain high cell counts.

Following methods used in prior work on affect modeling [14, 42], we performed an under-sampling technique to address class skew. This method is straightforward; it randomly removes samples from the majority class so that it has an equal number of instances as the minority class (Figure 9). It also avoids having to perform algorithm-dependent methods of correction (e.g., increasing the penalty for misclassification of a minority class point).

For each sample in the data, our classification model considers myUnity usage data and computer usage data for the 10 and 20 minutes, respectively, prior to when the corresponding survey link was sent. Only 43.6% and 72.4% of the samples have data from keyboard activity and mouse activity respectively, indicative of the fact that workers do not use their keyboard and mouse all the time. Finally, all features are normalized for each participant using z-scores to account for individual differences [14, 42].

The correlation-based feature subset attribute selection method [24] was applied to select salient features for each estimation model separately. To handle missing values in the features of the dataset, we used Weka's J48 Decision Tree classifier. The decision tree is constructed by selecting the node with the highest information gain as the root node, then continuing the calculation recursively. Decision trees were implemented with a 15% confidence threshold for pruning.

To evaluate performance, 10-fold cross validation was employed. Figure 12 shows that the overall accuracy for estimating pleasure is 76.5% (true-positive (TP) rate 76.1%, true-negative (TN) rate 76.9%) and for arousal is 76.4% (TP rate 74.5%, TN rate 78.1%), and that the estimation accuracy exceeds human performance.

Feature	P	A	E	T	I	F	M	N	S	X
Num. of myUnity States			○	●	○	○	●	○	○	●
Duration of a myUnity state	●	●	●	●	○	●	●	●	●	●
STD Interval of myUnity states				○			○			○
Median Interval of myUnity states								○		○
Min Interval of myUnity states			○							
Max motion pixels changed										○
Median motion pixels changed	○									
STD motion pixels changed					○					
Avg. motion pixels changed						○				
Num. of Focused Wins (Windows)		●		○		○		○	○	
Avg. Interval of Win Switch	●	●		●	○		○	●	○	○
Median Interval of Win Switch		○		○						
Max. Interval of Win Switch								○	○	
Min. Interval of Win Switch	○		○			○		○		
states of Focused Win	○	○		○	○	●	○	●	○	○
Min. Height of Focused Win			●		○	○		○		
Max. Width of Focused Win			○							
Min. Width of Focused Win										○
Median. Size of Focused Win				●						
Avg. Size of Focused Win										○
Avg. of X-Coord of Focused Win				○						
Min of Y-Coord of Focused Win			○							
Min. of the Max. Sizes of Wins									●	●
Median. Of the Max. Sizes of Wins										●
Avg. of the Max. Sizes of Wins					●					
S.D. of the Max. sizes of Wins							●			○
Max. of the Min. Sizes of Wins			○						●	
Min. of the Min Sizes of Wins	○			○		●	○			
Median. of the Min Sizes of Wins	○		●							
Avg. of the Min Sizes of Wins		○		○	●			○	○	○
S.D. of the Min Sizes of Wins	●	○		○	○	○				
Max. of the Median Sizes of Wins				○		○			○	
Median of the Median sizes of Wins	○		○							
S.D. of the Median sizes of Wins						○				
Avg. of the Avg. sizes of Wins		○								
S.D. of the Avg. sizes of Wins								○		
Max. Num. of Maximized Wins					●				○	
Min. Num. of Maximized Wins				○		○		○	○	
Avg. Num. of Maximized Wins				○						
S.D. Num. of Maximized Wins	●									
Max. Num. of Minimized Wins							○			
Median. Num. of Minimized Wins	○			○						
S.D. Num. of Minimized Wins									○	
Min. Num. of Normal Wins								○		
S.D. Num. of Normal Wins	○									
Num. of Backspace				○			○			
Num. of Keystroke						○				
Min. Velocity of Mouse					○	○				
Median Velocity of Mouse	○									
Median. Acceleration of Mouse									○	○
Jerk Index of Mouse	○					●	○		○	

Figure 11. Circles represent features selected for each estimation model. Solid circles indicate a feature located in the upper level (top 3 levels) of nodes in the decision tree. P = Pleasure, A = Arousal, E = Email, T = Telephone, I = Instant Message, F = Face-to-Face, M = Expected Communication request, N = Unexpected Communication request, S = Simple Task, X = Complex Task.

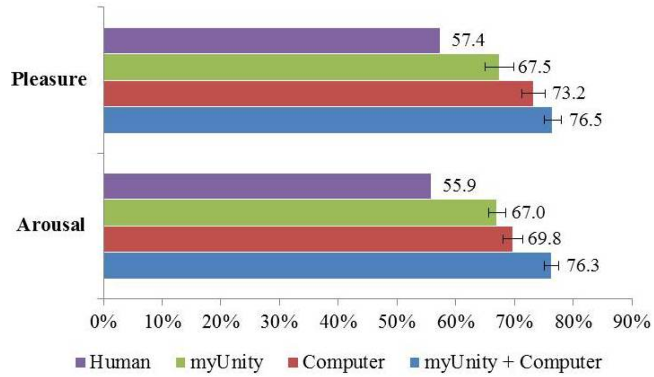


Figure 12. Performance of classifier on affect states of pleasure and arousal. Error bars represent the standard deviation in classification rates after 10 random under-samplings.

Figure 11 shows that features related to myUnity presence states and users' desktop information were frequently selected to construct prediction models and that these features were often located in the top 3 levels of nodes in decision trees for most prediction models. This indicates that the two types of features have higher information gain than other features, such as keyboard and mouse information. For example, the feature "duration of a myUnity state" was used to construct all prediction models and it was located in the top 3 levels of nodes in decision trees. In contrast, the feature "number of keystrokes" was only selected in the models of preference for IM and face-to-face communication. The poor predictive power of keystroke data is likely due to the fact that keyboard use throughout a workday is not persistent in the data set we collected. While previous studies [14, 42] claimed that keystroke information can be a general technique to infer affective state, this result shows that considering keyboard information alone is not sufficient to estimate affective state in real working environments.

Following prior studies on routing phone calls [37] and estimating preference for IM communication [2], the collected awareness data can be used to directly estimate participants' preferences for communication channels (Figure 13). Using myUnity data alone can achieve an accuracy higher than 70% for the preference of phone, IM, and face-to-face communication. The accuracy is increased above 80% for IM and phone by considering both myUnity and computer usage data. Prior studies [2,3] can successfully predict user response time to incoming instant messages, while our method can reliably predict whether a user wants to be engaged in an IM chat at the first place.

More importantly, the awareness data can successfully estimate preference for communication and task requests in workplace communication, going beyond predicting just channel preference. It can help workers decide when to initiate a communication as well as assist in forming communication strategies [20]. Specifically, presence data alone can reach an accuracy of over 70% for preferences for

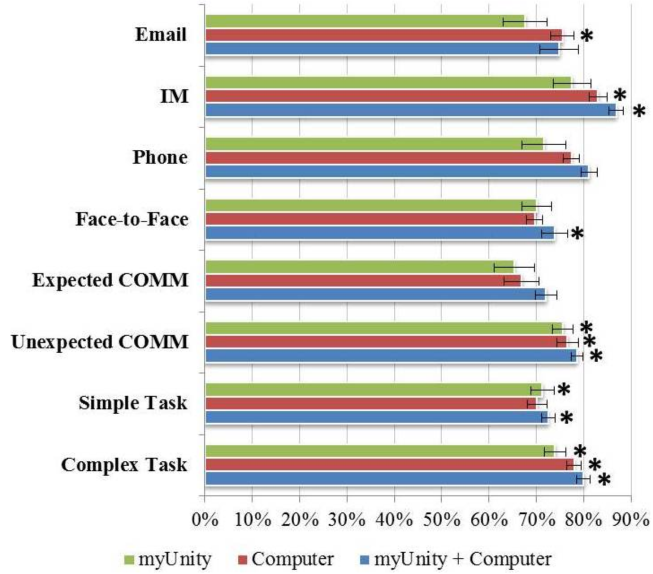


Figure 13. Performance of classifier on media and request preferences. Error bars represent the standard deviation in classification rates after 10 random under-samplings. Asterisk "*" means that TP rate > 70%, TN rate > 70% for each class.

unexpected communication, and requests for simple and complex tasks. The accuracy is improved to over 80% for preference of complex task request when considering both presence and computer usage data (Figure 13).

The prediction model does not perform well on willingness to accept an expected communication request. One possible reason is that our dataset for expected communication request contains few examples of the negative class (see "M" in Figure 9). However, users accept these requests most of the time, reducing the overall utility of such a model. In contrast, the accurate prediction of unexpected communication requests by our approach is much more meaningful to users (see "N" in Figure 10).

DISCUSSION

This work represents a significant step forward in the design and evaluation of technologies that can detect and measure affect and estimate communication preferences. Here we discuss some broader implications of the work, its current limitations, and directions for future work.

Our findings underline the importance of affect on media preferences. As such, we were surprised by how infrequently participants felt confident enough to assess a colleague's affective state (only 25.9% of the time), and how poor their assessments were (42.6% and 44.1% incorrect for pleasure and arousal estimates, respectively). A clear trend in the results was that participants had difficulty estimating the affective state of colleagues unless they had frequent face-to-face interactions. This trend may be a preview of the larger communication difficulties office workers will face as they spend less time co-located with colleagues.

Our results highlight the need for practical technologies to aid workers in assessing the affective state of peers, especially in work settings where most communication is computer mediated. We explored using presence state data streams to estimate affective state as a step toward such a solution. Our work demonstrates the feasibility of modeling affect and communication preferences from a stream of presence information that is already shared in myUnity, an existing presence system that uses passive sensing. We believe this work is the first to explore and show the effectiveness of using a low-bandwidth signal such as presence states to model affective states. MyUnity is just one of many presence systems that could be leveraged to provide such models. The successful use of myUnity data is particularly meaningful, given that it has achieved strong acceptance by its users and is extensively used by them.

This work suggests that such a system could provide salient information about people's affect and communication preferences. However, these models of affect and communication preferences must be presented in a form that is usable and acceptable to users. How to do so is not straightforward. Just because an affective state can be inferred from the data does not mean that users will be comfortable having it shared explicitly. For instance, users may not accept a system that communicates their negative affective states (e.g., stressed or overwhelmed).

Users must be comfortable with the information shared otherwise they may not accept the system or may learn to game the system. In any system attempting to estimate potentially sensitive information about its users' affective states, some amount of discretion and user control is desirable. However, affect modeling can still be of high value even if the model's results are not present to end users. For example, predictions of communication media preference can be made without exposing the underlying reasoning. Doing so would also allow user to maintain some level of plausible deniability. A future thrust of our research will be to investigate this tension.

Display of this information is further complicated by the inevitable errors of estimation due to imperfect models. In addition, there will always be information that cannot be sensed or is not accessible to a reasoning algorithm. A person's affect is impacted by outside experiences, such as a fight with a spouse or concerns about a child's health. These influences are difficult to quantify and detect, making them difficult to model.

We are interested in how well these techniques can be applied to estimating the affect of groups, such as teams or divisions within a company. For example, the overall affective state of call centers or sales offices could be used to route calls and customers to less 'stressed' centers.

While we feel our participants are representative of information workers, replication of our approach in other populations is critical. As future work, we plan to deploy the system and collect ground truth data from several different populations, across a variety of work practices and geographic locations. Some of our deployments will be to overseas offices, enabling us to explore cultural differences. Of particular interest is the variation in predictive power of features in Figure 11 across populations.

This work is an initial step that demonstrated the feasibility of our approach and the predictive power of the features selected. Although we observed significant individual differences, our classifiers were for the entire population. Classifiers customized to each user are likely to yield improved results. Also, we will explore online learning techniques to minimize initial data collection and labeling.

We are particularly interested in understanding how sharing estimates of affective state impacts overall communication and collaboration behaviors. As we develop ways to visualize affective state, we will have the opportunity to study how this information impacts work. We are particularly interested in examining how it impacts the communication structure and feeling of "connectedness" in teams that spend little or no time working face-to-face.

CONCLUSION

We show that affect awareness is important in achieving effective communication in the workplace. Adequate affect awareness is difficult with the increase of computer-mediated communications tools. In this work we quantify the relationship between affect and communication preferences, providing grounding for what affect awareness technologies should measure and represent to users. We also present a new method to model affective state using non-invasive sensing to predict affect and communication preferences with accuracy rates as high as 87%.

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