Moody Man: Improving creative teamwork through dynamic affective recognition

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ABSTRACT

While a significant part of communication in the workplace is now happening online, current platforms don't fully support socio-cognitive nonverbal communication, which hampers the shared understanding and creativity of virtual teams. Given text-based communication being the main channel for virtual collaboration, we propose a novel solution leveraging an AI-based, dynamic affective recognition system. The app provides live feedback about the affective content of the communication in Slack, in the form of a visual representation and percentage breakdown of the 'sentiment' (tone, emoji) and main 'emotion states' (e.g. joy, anger). We tested the usability of the app in a quasi-experiment with 30 participants from diverse backgrounds, linguistic analysis and user interviews. The findings show that the app significantly increases shared understanding and creativity within virtual teams. Emerged themes included impression formation assisted by affective recognition, supporting long-term relationships development; identified challenges related to transparency and emotional complexity detected by AI.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in collaborative and social computing**.

KEYWORDS

affective recognition, emotions, creativity, virtual teams, chat app

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1 INTRODUCTION

We two - if we could ever think as one, the Trojans' evil day would be postponed no longer - [22, 2.356-428]

As innovation became a critical notion for competitive advantage for firms to survive in uncertain environments, and creativity being its pre-requisite [3, 47], the growing interest in creative collaboration has been vivid during the past three decades. With the turbulent changes brought by the COVID-19 pandemic, technology-enabled remote work has emerged as a new norm for many professional workers [20, 44], and is predicted to at least partly be remained [33]. However, computing professionals have been focusing mainly on developing tools that support productivity for users to work faster, more efficient, and to reduce errors [40]. It has been raised in prior works [18, 40] that there are still challenges and "untapped potential" for creativity-oriented tools among HCI researchers. A study by [32] highlights further obstacles for creativity in virtual work including the lack of shared understanding, domain knowledge, and social influences. Commonly, previous attempts for augmenting HCI environments in prototype-driven research included visualisations of group dis/agreements or contribution level [24, 28]. However, [37] conducted a medium-scale survey showing that virtual meetings suffer also from the negative tone and lack of social cues among other obstacles. A small body of literature addresses this through experimenting and testing emotion management systems in education [17, 46], video meetings [17, 37, 38], or through chatbots [6, 35]. Given pre-COVID-19, chat apps were the number one collaboration tool for teams [42], recent post-COVID-19 industry surveys reveals that semi-synchronous instant messaging are becoming even more important for teams, reported with 35% dramatically increase of use, and 54% beginning to use [43]. To date, no interactive systems exists that explicitly provides dynamic affective recognition feedback (including both sentiment and emotions), and specifically there has not been conducted empirical studies targeting this concept in terms of virtual teams' creativity.

This paper seeks to address our interest in how affective recognition (including sentiment and emotion) affect shared understanding and creativity in text-based communication. To do so, we developed a solution for dynamic affective recognition feedback system seamlessly integrated into a market-leading team communication tool (Slack) with the leading AI system (IBM Watson), and examined how it can affect user's shared understanding and creativity through a quasi-experiment with online surveys, in-depth post-workshop interviews, and linguistic analysis of chat transcripts.

2 AFFECTIVE RECOGNITION FEEDBACK SYSTEM: RATIONALE AND DESIGN

Findings from prior work informed the design of the emotion recognition dashboard. The app included behavioural features related to the notion of team shared mental model: sentiment and emotions of text messages supported by emojis through a modal view (see Fig. 1), as emojis can facilitate conversational functions [13]. We designed the dashboard with an infrastructure (see Fig. 2 in Appendix) that is seamlessly integrated with existent Slack chat messenger (as chatbot-based emotion management systems are found to be intrusive to participants [6]) due to technical feasibility, the ability to add own software to the existing developer environment through API, and to reduce the Hawthorne effect. The basic design of Moody Man followed design specifications from Slack documentation[1], and consists of a Slack Bot presenting a Modal View[2]. The Python server, run in the background, manages processing the text and inputting the text into IBM Watson Natural Language Understanding (Watson NLU) to provide the relevant information. The results were then saved on a MongoDB database, better suited for query data into a data structure native to Python, which allowed the participant to re-view the information without any delay.

3 METHODOLOGICAL APPROACH

The objective is to assess how affective feedback (i.e. sentiment and emotions) in text-based communication affects online meeting creativity and team shared mental models. In this study, affective feedback is provided by the affective recognition feedback system that we developed - Moody Man - and tested through a series of quasi-experiments at design workshops with online pre-test (T1) post-test (T2) surveys. We followed the investigation with in-depth post-workshop interviews for qualitative analysis and performed linguistic analysis of post-workshop chat transcripts to study real affect development. The affective recognition feedback system was leveraging the *natural language processing* (NLP) for advanced text analysis through Watson NLU technology. It is identified as the leader in the Garner's Magic Quadrant for data science and machine learning [19] and also the highest-rated NLP platform in Software Engineering considering the aspects (intents classification, confidence scores, and entity extraction) investigated by Abdellatif et al. [1] with the highest accuracy (79.2%) according to Ermakova et al. [16].

3.1 Participants

A total of 30 participants took part in the study, in line with similar studies listed in Table 1 in the Appendix. Participants were recruited among students from five universities in the United Kingdom. They were required to have a prior experience in (1) virtual communication channels and (2) multidisciplinary and creative teamwork. The participants' ages ranged from 20 to 36, and 63% were women. To control the factor of potential existing shared mental models, the matching of the dyads was based on the fact that the team members had not previously worked with each other. The study was approved by the Science Engineering Technology Research Ethics Committee under the SETREC reference 21IC6717. The participants were compensated 50 GBP for their participation.

3.2 Protocol

To explore how the affective recognition system affects virtual teams shared understanding the creativity, we adopted a quasi-experimental research design with within-subject users under a given intervention, using *one-group pre-test post-test* method informed by literature [2, 30]. For each group, the team was given an hour to ideate, envision and discuss a solution for future mobility[3]. First, participants were invited to work on a given design brief through a text-based communicator (Slack) and to complete an interim online survey (T1). In the second stage of the study (i.e. after 30 min of the workshop), the participants were introduced to the Moody Man app and explained how they could utilise the tool to learn about affective (sentiment and emotion) feedback on the messages within Slack. Post-intervention phase, and at the end of the workshop, all participants were asked to fill out an exit online survey (T2). Following the design workshops, all participants were asked for 60-min in-depth post-workshop interviews to share their reflections and feedback on the collaboration process and the solution app.

3.3 Survey Measures

Our measures were each adapted from prior research for the context and consisted of multi-item statements with Likert-scale response formats. The Appendix provides the texts of the statements items for our primary measures. Table 2 in the Appendix present used measurement scales and source works. Results of the quasi-experiment assessing creativity and shared understanding were obtained pre-intervention (T1) with the interim online survey after 30 min of the design workshop, and post-intervention (T2) with exit online survey using the same multi-item statements. The exit questionnaire included additionally a scale evaluating the feedback system dashboard. For all measures, we confirmed the statistical appropriateness of aggregation by computing the Cronbach α coefficients for the various measures. Items were averaged into an overall scale score.

3.4 Post-workshop interviews

Following the experimental workshops, we conducted in-depth semi-structured self-reflective interviews, with one participant leaving the study (N=29). Previous empirical works in HCI includes

[1]https://api.slack.com/surfaces/modals/using

[2]When the participant clicks on the shortcut, it will send a request to the app server to notify the shortcut has been clicked. The app will then retrieve the message the participant wants to view and understand the message's sentiment and emotion. Afterwards, the app will query within the MongoDB database and find the sentiment and emotion values for the text. The app will then put the values into a JSON so that the Slack modal view in which participants can check the sentiment and emotion of a message. The front-end consists of a JSON object payload that Slack would understand and present feedback to the participant.

[3]During the design workshops the participants were asked to discuss and brainstorm in their dedicated Slack channel a given design brief on the future of mobility. This concept is one of the challenges identified in ARUP Drivers of Changes [4]. We selected this brief due to the following reasons: it requires creative thinking, multidisciplinary collaboration, is challenging enough, and can be completed in an experimental duration of the workshop.

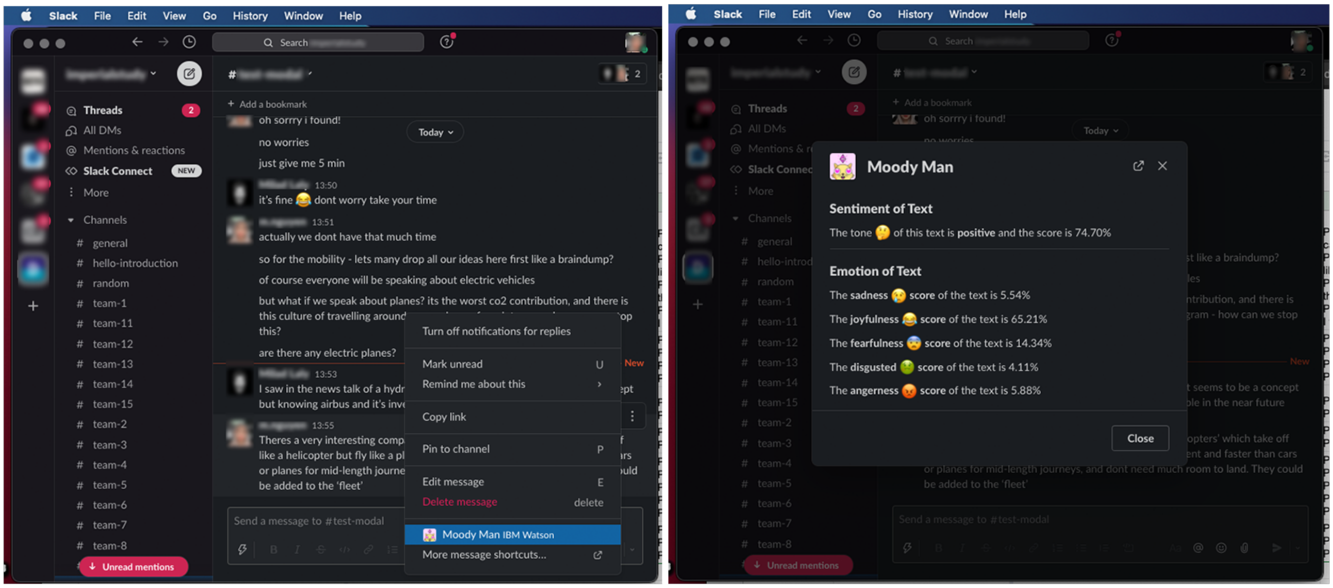

Figure 1: The Moody Man dashboard and it's components.

studies on Slack chat usage [15] with 8 interviews, meetings sentiment analyser [37] with 9 interviews, or AI explainability [29] with 20 informants. The interviews ranged from 30-60 minutes. A total of 1122 minutes of interviews were recorded and transcribed verbatim. We performed axial coding [10], and followed grounded theory for our thematic analysis [12, 21], widely used to study societal interactions in social science research disciplines. Our coding process has been conducted by the two first authors, where detailed annotation instructions were collaboratively pre-developed and intercoder reliability was performed (% of agreement: 85.7, Cohen's k: 0.695) based on extracted 1300 transcription lines. Both kappa and percent agreement has been performed and reported. The researchers frequently discussed between each other on an everyday basis and the iterative coding process resulted in 22 axial codes.

4 RESULTS: QUANTITATIVE ANALYSIS OF CREATIVE WORKSHOP SURVEYS AND LINGUISTIC ANALYSIS

Overall, the results from the exit survey (T2) showed that all measures have increased compared to the interim survey (T1). Since the quasi-experiment included within-subjects participants, we used Paired Wilcoxon test for the nonparametric independence test (Related-Samples Wilcoxon Signed Rank Test) to validate the statistical significance of the changes between the exit and interim surveys. All scales are statistically significant in terms of the increases after the intervention. We discuss these improvements in this section.

Shared Understanding To measure shared understanding within teams, we asked the participants to rate four statements at both the pre-intervention (T1) and post-intervention (T2) periods, to see if there was a difference after using Moody Man. Shared Understanding has increased with statistical significance (p-$value < 0.001$) between T1 (Mean = 5.38, S.D = 0.94, $\alpha = 0.71$) and T2 (Mean = 6.10, S.D = 1.00, and $\alpha = 0.89$).

Attitude To assess if attitude has increased within participants, we asked participants to answer ten questions that would present if there is a difference between participant's attitude after Moody Man being available or not. Attitude has increased with statistical significance (p-$value < 0.05$) between T1 (Mean = 3.59, S.D = 0.51, and $\alpha = 0.80$) and T2 (Mean = 3.66, S.D = 0.48, and $\alpha = 0.85$).

Creativity To evaluate whether creativity within participants has increased, we looked at two dimensions: a five-item Self-Perceived Creativity [14] and a six-item Creative Self-Efficacy [14]. We reported a statistically significant increase in the exit surveys with a p-$value$=0.012, between T1 (Mean = 4.19 and S.D = 0.39) and T2 (Mean = 4.28 and S.D = 0.43).

Team Satisfaction After the experiment, we asked participants to answer seven questions to evaluate whether team satisfaction [41] has increased during the experiment within participants. Exit surveys T2 resulted in with the minimum and maximum on the 5-point scale ranging between 4.31 to 4.69 (Mean = 4.54, S.D. = 0.59, $\alpha = 0.906$), higher as compared to reports at T1 (Mean = 4.29, S.D. = 0.64, $\alpha = 0.859$). Team satisfaction has reported a statistically significant increase from T1 to T2 with a p-$value < 0.001$.

App evaluation The 11-item scale adopted from [37] was only measured after the intervention with the app at T2. The responses on the evaluation of the prototype app showed the ambiguous and uncertain perception of the participants of the system. On the 5-level Likert scale, participants at the exit survey revealed uncertainty about the app (M = 2.831, S.D =0.818, $\alpha = 0.897$). We use this as guidance to garner further substantially valuable feedback and opinions from interview accounts following an in-depth inquiry post-workshop.

5 RESULTS: COMPUTATIONAL LINGUISTIC ANALYSIS

In order to triangulate our findings, we conducted a linguistic analysis of all chat entries from the quasi-experiments exported from the MongoDB database. We collected in total 1574 plain-text inputs, posted by workshops participants as text messages (overall 21 008 words). We classified them according to the timestamps to messages before and after the intervention, i.e. at T1 and T2. Watson NLU affective recognition analysis has been applied to both batches in order to measure the change in sentiment and emotion in these two study periods.

The results have further strengthened our confidence that the affect during T2 (sentiment: 0.68, sadness: 0.14, joy: 0.64 fear: 0.10, disgust: 0.05, anger: 0.08) has improved as compared to T1 (sentiment: 0.57, sadness: 0.18, joy: 0.56 fear: 0.14, disgust: 0.08, anger: 0.12). Statistical significance of the improvement has been analysed by using the Related-Samples Wilcoxon Signed Rank Test with results for each variable at p-value<0.001.

6 FINDINGS: QUALITATIVE ANALYSIS OF INTERVIEWS

Going back and forth to the literature, and following grounded theory we grouped the axial codes into categories from literature and identified two overarching themes that emerged from this iterative process.

6.1 Motivations for affective recognition

Unclear results from the surveys about the app evaluation triggered our interest to understand better and more in-depth how and when the app would be found useful for the study participants. Our interviews revealed specific environments that would motivate informants to use affective recognition dashboards.

6.1.1 Usage points. We identified several usage points that echoed the argument of Clore and Palmer [11] on specificity of the collaboration constraints concerning **team size**, as the feedback tool *would have been more useful if the team was bigger* (P-17), because *when we there's a bigger group and you can't, you know, like, think about how everyone's feeling.* (P-10). It is specifically crucial in creative collaboration phase of **ideation** *when you are doing design, but being critical in like a constructive way that you're not coming across as like, negative* (P-1). From the individual level, it helps team members for defining an online portrayal and **self-verification** is a *quick indication whether it's comes across as good or not* (P-5) which in turn may be *a solution to have a better relationship with colleagues* (P-20)

6.1.2 User type. Referring to the affective recognition, motivations for usage depend heavily on the user type, that is described by the characteristics of users including domain knowledge, **cultural background** and language barriers [29]. Participants hint at use cases for the affective recognition tools being useful when *English is not (his) first language* (P-22) or when one is *trying to learn English* (P-26). Differences in **domain knowledge** can also be mitigated by affective recognition, for example as reported by P-26, when the collaborator is *not a designer, it would definitely be a tool to try and say what is it you're trying to convey.*

6.1.3 Emojis. Previous research on emoticons has revealed several key applications for this feature: depicting emotion toward a subject (or recipient), helping to control emotion levels, representing emotions that are absent in the text, better expressing the writer's meaning, and either reinforcing or softening the writer's commentary. Cramer et al. [13] suggest that emojis can fulfil similar emotion-oriented roles as emoticons. Our interview accounts' reveal how this took place in a work context in creative collaboration. In order to **enhance affective communication**, all participants reached out to emojis to improve the collaboration process, as they felt *it's necessary to, like create more of like, friendly vibe* (P-19) or *make the conversation a little less bureaucratic* (P-16). Emojis helped to **clarify the context**, for example by using *smiley face or a question mark or whatever, like, it just clarifies your thought, as if you're face to face a little bit better* (P-28). For Cramer et al. [13], emojis are now often used to elaborate on contextual information or show how a situation has changed, for example providing or re-emphasising situational context. Emojis can be used for convenient conversation management for cases such as quickly **acknowledging** the last turn, ending a conversation when not knowing what to say or not wanting to say anything, or when saying nothing would be inappropriate. Participants found emojis as a way to show agreement (P-13, P-15), or complete the trail of thoughts, when they *don't need to add anything more to these ones, or, okay, this thread is done, like this job is done* (P-22).

6.1.4 Impression formation. In all aspects of communication, impression management is a one of the key considerations. Some authors has previously examined the notion of impression management in computer-mediated communication (CMC) from the perspective of casual social relationships [5] or romantic relationship [48]. In an online setting, the variety of nonverbal clues that typically help in the development of impressions is significantly reduced [45]. In line with this our participants highlighted the need to use Moody Man in **less familiar relationships**, for examples when they *don't know the person [their] talking to* (P-29). The affective and emotion recognition feedback system would be hence used *quite a lot, especially at start getting to know people* (P-3). More specifically, such feedback system would be utilised by the study participants when speaking to a **figure of authority**, for example when *talking to my boss, or my boss's boss, for example, or a professor even at uni* (P-28), especially when one's *need to be more careful about the word I use* (P-3). Self-presentational concerns can be mitigated, by utilising emotion and affective recognition that can in turn support **positive self-portrayal**. Prior work reports that textual cues were more dominant in the process of impression formation [34]. For example, one of the participants recalled if *the feedback that is neutral, then like, that's okay to send, and you don't really have to worry about if you're coming across to* (P-1). The motivations to use affective feedback tools include moments when the user needs to be *be careful with the way you express yourself* (P-19) and when one wants to *make sure that [he is] coming across well* (P-5).

6.2 Design Goals for AI affective recognition adoption

6.2.1 Delivery timing. While previous work on the delivery timing of feedback systems with sentiment analyser suggests usefulness of reports on behaviour features **post-meeting** [37], our study revealed that workshop participants, albeit would *find it interesting* (P-5), they would not *even review it* (P-20), as *damage has already been done* (P-30). This is due to the fact that in terms of building a shared understanding within online teamwork, it is *quite difficult sometimes to compensate afterwards* and hence participants would not have *any reason to reflect on that* (P-26). The in-depth interviews revealed further concerns about this and stronger preference towards a **pre-sentence delivery timing**. P-12 recalled that she does not *feel [that] there's any point in finding out [her] message is angry and might cause a bit of friction after [she] sent it.*

6.2.2 Usability. Specifically, we found a detailed suggestion on how this pre-sentence feedback could be designed: *as you're typing, there's like a little emoji that sort of changes color as your sentences are completing. And maybe like a really easy way, because I can also see that being kind of annoying after a long time, if you're just having a normal conversation, you don't need to see it, so maybe like a very quick toggle - then you can just toggle them on and off in the corner, and then it changes color, or it just becomes sort of transparent* (P-28). Moreover, from our interviews, we have learnt about obstacles for the greater adoption of such feedback systems. User experiences and usability have been seen salient in multiple interview accounts, and the critique was often related to the **number of clicks** required to access the feedback information. Since the Moody Man app required *extra click* (P-24), as it *was hard to access [and] a bit of a pain to having to click on other stuff* (P-14). Another challenge for adoption was the **numeric data representation**. It seemed that sentiment and emotion measurement displayed as percentages were unclear to the workshop participants, where some reported that they were not aware if that was *noise or whatever that it is reading of that emotion* (P-21). This would also affect the speed of participants' comprehension, as they would prefer something *more visual, something more easy to understand; because percentages, you might understand that but if you just look at a chart or something, it's like quick one second* (P-14).

6.2.3 Trust. Trust in accuracy, algorithm, and the data source is one of the frequent themes that emerge in discussions regarding adoption hurdles for AI-based products, from the very end users of the systems created through utilising machine learning (ML) models. Our study participants reported concerns about **accuracy** that *there's a possibility it wouldn't be accurate* (P-30). This was affected by the perceived accuracy of one of the respondents recalled *didn't think it really reflected the message very accurately (...) I don't think I think I got it completely the wrong way. So I thought okay, I don't think this is really that helpful for me* (P-28). Prior work on AI explainability raises concerns about such models and the lack of trust in the **algorithm**, being considered as "black boxes" since they don't provide any information about how they arrive at their estimates. Determining how to visualise, explain and understand deep learning models is becoming more important in research [29]. Our participants challenged the accuracy as they were *trying to understand how the what the algorithm was, or the code was behind* (P-22). According to a study from Kennedy et al. [26], users pay more attention to the size of the training data set, the algorithm's source, and the stated accuracy, and less attention to the model's transparency or the relevance of the training data. However, the source of the **trained data** seems to be of interest for our participants, as they *would assume that the AI has been taught with Native users, so I wouldn't trust it to assume from non native uses* (P-10) as similar, questions arose, whether the model was *based on British slang, or normal English* (P-22).

6.2.4 AI design (complexity of emotions detected). "Labelled" emotions, for example, anger or happiness, have a special place in the affective computing world. However, some researchers are still debating the concept, value, and existence of such "labelled" states [36]. Even while most AC applications seem to rely on such categorisations, some research in HCI suggests that alternative methods may better serve computer system development. There's a debate over what the right degree of representation should be for the applied use of affective computing [8]. Some of the participants mentioned that they did not continue to use Moody Man as the AI did not contain **emotional nuances** they deemed useful to their mannerism such as *irony and sarcasm* (P-11). This implies that participants wanted to have a wider range of emotions including various situational and contextual nuances. Additionally, P-1 mentioned that *you can't really judge some message based on if it's positive or negative.* This implies that further research is needed to display and present an extensive range of emotions of AI to be adopted by a wider audience.

7 DISCUSSION AND FUTURE WORK

This study was performed as a quasi-experiment, as opposed to a traditional experiment, because the random assignment of participants to conditions for between-subjects treatment was not feasible for the given total sample size. However, although every possible attempt was made to control many aspects, several factors remained that could not be controlled in the setting. We are aware that our research may have the following limitations, that are advised to be addressed in future work: (1) time passed, (2) cultural context, and (3) reflective bias. As our findings present how affective recognition facilitates online impression formation, and following studies on impression management being a predictor for long-term relationships, we present evidence for how AI-based affective recognition can support virtual teams in building long-term relationships. The study also presents threefold directions for further research: (1) ethical, (2) social, and (3) technological implications.

The theme of concern over the transparency of Artificial Intelligence (AI) is a common one in applications that utilise AI, as highlighted in the work of the United Nations publication 'Resource Guide on Artificial Intelligence (A.I) Strategies' [31]. This legitimate concern can stem from questions of trust, fairness, and particularly accuracy, as highlighted in this study. Concerns over transparency may seem to be particular to the implementation of AI, however, in reality, these same concerns have also historically been levied at technologies governing areas such as privacy and security. Artificial Intelligence, particularly in the form of neural networks is a younger technology, requiring time for best practices such as transparency to become embedded as a critical element of AI itself. Also, an area for consideration regarding this study is the topic of sentiment itself. There are few functions of intelligence that appear to be in the purview of the human experience quite so much as sentiment. The application of sentiment to language for communication can be considered core to what it is to be human, being a solely human behaviour. It is therefore difficult to disregard this perspective when analysing the reports of the participants in their perceptions of accuracy.

Whilst prior works on sentiment recognition in virtual teamwork focuses on team performance *in situ*, especially in respect to short-term real-time team behaviour, our study sheds light on how AI-based models for affective recognition can affect long-term relationships. Through post-workshop interviews, research participants shared multiple reflective accounts on how dynamic sentiment and emotion recognition feedback systems would motivate them to use for impression formation with strangers or figures of authority. Such technology may provide opportunities to self-evaluate their language, to change their behaviours, and to revise their text in real-time/during a meeting, reported as valuable for their online impression formation. As Human et al. [23] suggested, initial impression formation is a significant predictor of longer-term relationship development, and establishing accurate impressions among new acquaintances has a positive impact on the development of their relationship. Our study, therefore, presents the potential of the affective recognition technology for building long-term relationships through facilitating impression formation.

The present findings suggest several courses of action to improve future designs of AI-based tools. With regard to the feedback systems and their delivery timings, in contrary to previous works with tone analyser, our participants found pre-message feedback more useful than post-meeting. A further important implication for design guidelines refers to the usability of the developed systems, especially in terms of the UX and UI. Participants advocated the minimum required a number of clicks to access the feature, suggesting a potential toggle to active the affective recognition feedback on demand. They also raised an aversion to the numerical representations of the AI-generated feedback in terms of user readability and quick comprehension. Lastly, our findings suggest that designers of future AI-based communication support systems tailor the solution to specific usage points, concerning affect being crucial in more personal feedback and social collaboration including ideation, brainstorming, newcomer onboarding, or promotion opportunities.

Our results are encouraging and present promising insight into how dynamic affective recognition feedback systems can improve shared understanding and creativity in virtual teams. We hope that this study will serve as a base for future investigations in this limited, yet fascinating intersection of the two disciplines of creative research and HCI, and help inform future AI-based solution designers with guidelines for stronger adoption.

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REFERENCES

[1] Ahmad Abdellatif, Khaled Badran, Diego Elias Costa, and Emad Shihab. 2021. A Comparison of Natural Language Understanding Platforms for Chatbots in Software Engineering. *arXiv:2012.02640 [cs]* (July 2021). http://arxiv.org/abs/2012.02640 arXiv: 2012.02640.

[2] Mike Allen. 2017. *The SAGE Encyclopedia of Communication Research Methods*. SAGE Publications, Inc, 2455 Teller Road, Thousand Oaks California 91320. https://doi.org/10.4135/9781483381411

[3] Teresa M Amabile. 1988. A model of creativity and innovation in organizations. *Research in organizational behavior* 10, 1 (1988), 123–167.

[4] ARUP. [n.d.]. Drivers of Change. https://foresight.arup.com/our-tools/drivers-of-change/

[5] Natalya N. Bazarova, Jessie G. Taft, Yoon Hyung Choi, and Dan Cosley. 2013. Managing Impressions and Relationships on Facebook: Self-Presentational and Relational Concerns Revealed Through the Analysis of Language Style. *Journal of Language and Social Psychology* 32, 2 (June 2013), 121–141. https://doi.org/10.1177/0261927X12456384 Publisher: SAGE Publications Inc.

[6] Ivo Benke, Michael Knierim, and Alexander Maedche. 2020. Chatbot-based Emotion Management for Distributed Teams: A Participatory Design Study. *Proceedings of the ACM on Human-Computer Interaction* 4 (Oct. 2020). https://doi.org/10.1145/3415189

[7] Michael Brooks, Cecilia R. Aragon, Katie Kuksenok, Megan K. Torkildson, Daniel Perry, John J. Robinson, Taylor J. Scott, Ona Anicello, Ariana Zukowski, and Paul Harris. 2013. Statistical affect detection in collaborative chat. In *Proceedings of the 2013 conference on Computer supported cooperative work - CSCW '13*. ACM Press, San Antonio, Texas, USA, 317. https://doi.org/10.1145/2441776.2441813

[8] Rafael A Calvo and Sidney D'Mello. 2010. Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications. *IEEE Transactions on Affective Computing* 1, 1 (Jan. 2010), 18–37. https://doi.org/10.1109/T-AFFC.2010.1

[9] Janis A. Cannon-Bowers, Eduardo Salas, and Sharolyn Converse. 1993. Shared mental models in expert team decision making. In *Individual and group decision making: Current issues*. Lawrence Erlbaum Associates, Inc, Hillsdale, NJ, US, 221–246.

[10] Kathy Charmaz. 2006. *Constructing grounded theory: A practical guide through qualitative analysis*. sage.

[11] Gerald L. Clore and Janet Palmer. 2009. Affective guidance of intelligent agents: How emotion controls cognition. *Cognitive Systems Research* 10, 1 (March 2009), 21–30. https://doi.org/10.1016/j.cogsys.2008.03.002

[12] Juliet Corbin and Anselm Strauss. 2014. *Basics of qualitative research: Techniques and procedures for developing grounded theory*. Sage publications.

[13] Henriette Cramer, Paloma de Juan, and Joel Tetreault. 2016. Sender-intended functions of emojis in US messaging. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '16)*. Association for Computing Machinery, New York, NY, USA, 504–509. https://doi.org/10.1145/2935334.2935370

[14] Trudy C. DiLiello, Jeffery D. Houghton, and David Dawley. 2011. Narrowing the creativity gap: the moderating effects of perceived support for creativity. *The Journal of Psychology* 145, 3 (June 2011), 151–172. https://doi.org/10.1080/00223980.2010.548412

[15] William Easley, Darius McCoy, Shawn Grimes, Steph Grimes, Foad Hamidi, Wayne G Lutters, and Amy Hurst. 2018. Understanding How Youth Employees Use Slack. (2018), 4.

[16] Tatiana Ermakova, Max Henke, and Benjamin Fabian. 2021. Commercial Sentiment Analysis Solutions: A Comparative Study:. In *Proceedings of the 17th International Conference on Web Information Systems and Technologies*. SCITEPRESS - Science and Technology Publications, Online Streaming, — Select a Country —, 103–114. https://doi.org/10.5220/0010709400003058

[17] Mohamed Ez-Zaouia, Aurélien Tabard, and Elise Lavoué. 2020. EMODASH: A dashboard supporting retrospective awareness of emotions in online learning. *International Journal of Human-Computer Studies* 139 (2020), 102411. Publisher: Elsevier.

[18] Jonas Frich, Michael Mose Biskjaer, and Peter Dalsgaard. 2018. Why HCI and Creativity Research Must Collaborate to Develop New Creativity Support Tools. In *Proceedings of the Technology, Mind, and Society*. ACM, Washington DC USA, 1–6. https://doi.org/10.1145/3183654.3183678

[19] Gartner. 2021. Magic Quadrant for Data Science and Machine Learning Platforms. https://www.gartner.com/doc/reprints?id=1-25DOZD29&ct=210304&st=sb

[20] Cristina B. Gibson, Patrick D. Dunlop, Ann Majchrzak, and Terence Chia. 2021. Sustaining Effectiveness in Global Teams: The Coevolution of Knowledge Management Activities and Technology Affordances. *Organization Science* (Aug. 2021). https://doi.org/10.1287/orsc.2021.1478 Publisher: INFORMS.
[21] Barney G Glaser and Anselm L Strauss. 1967. *The discovery of grounded theory: strategies for qualitative research.* OCLC: 253912.
[22] Homer. 1998. *The Iliad.* Oxford University Press. Google-Books-ID: OT9pj8chUbQC.
[23] Lauren J. Human, Gillian M. Sandstrom, Jeremy C. Biesanz, and Elizabeth W. Dunn. 2013. Accurate First Impressions Leave a Lasting Impression: The Long-Term Effects of Distinctive Self-Other Agreement on Relationship Development. *Social Psychological and Personality Science* 4, 4 (July 2013), 395–402. https://doi.org/10.1177/1948550612463735 Publisher: SAGE Publications Inc.
[24] Jeroen Janssen, Gijsbert Erkens, Gellof Kanselaar, and Jos Jaspers. 2007. Visualization of participation: Does it contribute to successful computer-supported collaborative learning? *Computers & Education* 49, 4 (2007), 1037–1065. Publisher: Elsevier.
[25] Karen A Jehn. 1995. A multimethod examination of the benefits and detriments of intragroup conflict. *Administrative science quarterly* (1995), 256–282. Publisher: JSTOR.
[26] Ryan P Kennedy, Philip D Waggoner, and Matthew Ward. 2021. Trust in Public Policy Algorithms. *The Journal of Politics* (July 2021). https://doi.org/10.1086/716283 Publisher: The University of Chicago Press.
[27] Miikka Kuutila, Mika V. Mäntylä, and Maëlick Claes. 2020. Chat activity is a better predictor than chat sentiment on software developers productivity. In *Proceedings of the IEEE/ACM 42nd International Conference on Software Engineering Workshops.* ACM, Seoul Republic of Korea, 553–556. https://doi.org/10.1145/3387940.3392224
[28] Gilly Leshed, Diego Perez, Jeffrey T. Hancock, Dan Cosley, Jeremy Birnholtz, Soyoung Lee, Poppy L. McLeod, and Geri Gay. 2009. Visualizing real-time language-based feedback on teamwork behavior in computer-mediated groups. In *Proceedings of the 27th international conference on Human factors in computing systems - CHI 09.* ACM Press, Boston, MA, USA, 537. https://doi.org/10.1145/1518701.1518784
[29] Q. Vera Liao, Daniel Gruen, and Sarah Miller. 2020. Questioning the AI: Informing Design Practices for Explainable AI User Experiences. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems.* ACM, Honolulu HI USA, 1–15. https://doi.org/10.1145/3313831.3376590
[30] Yu Liu, Yue Liu, and Kane Yue. 2021. Integration of Concept Maps into the Mixed Reality Learning Space: Quasi-Experimental Design and Preliminary Results. In *2021 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW).* 627–628. https://doi.org/10.1109/VRW52623.2021.00196
[31] United Nations. 2021. Resource Guide on Artificial Intelligence (AI) Strategies | Department of Economic and Social Affairs. https://sdgs.un.org/documents/resource-guide-artificial-intelligence-ai-strategies-25128
[32] R.J. Ocker. 2005. Influences on creativity in asynchronous virtual teams: a qualitative analysis of experimental teams. *IEEE Transactions on Professional Communication* 48, 1 (March 2005), 22–39. https://doi.org/10.1109/TPC.2004.843294 Conference Name: IEEE Transactions on Professional Communication.
[33] Adam Ozimek. 2020. The Future of Remote Work. *SSRN Electronic Journal* (2020). https://doi.org/10.2139/ssrn.3638597
[34] Ayellet Pelled, Tanya Zilberstein, Eran Pick, Yael Patkin, Alona Tsironlikov, and Nurit Tal-Or. 2016. Which Post Will Impress the Most? Impression Formation Based on Visual and Textual Cues in Facebook Profiles. In *Proceedings of the 7th 2016 International Conference on Social Media & Society (SMSociety '16).* Association for Computing Machinery, New York, NY, USA, 1–10. https://doi.org/10.1145/2930971.2930997
[35] Zhenhui Peng, Taewook Kim, and Xiaojuan Ma. 2019. GremoBot: Exploring Emotion Regulation in Group Chat. In *Conference Companion Publication of the 2019 on Computer Supported Cooperative Work and Social Computing.* ACM, Austin TX USA, 335–340. https://doi.org/10.1145/3311957.3359472
[36] Sandra Walker Russ. 1993. *Affect and Creativity: the Role of Affect and Play in the Creative Process.* Routledge, New York. https://doi.org/10.4324/9780203772621
[37] Samiha Samrose, Daniel McDuff, Robert Sim, Jina Suh, Kael Rowan, Javier Hernandez, Sean Rintel, Kevin Moynihan, and Mary Czerwinski. 2021. MeetingCoach: An Intelligent Dashboard for Supporting Effective & Inclusive Meetings. (2021), 13.
[38] Samiha Samrose, Ru Zhao, Jeffery White, Vivian Li, Luis Nova, Yichen Lu, Mohammad Rafayet Ali, and Mohammed Ehsan Hoque. 2018. Coco: Collaboration coach for understanding team dynamics during video conferencing. *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies* 1, 4 (2018), 1–24. Publisher: ACM New York, NY, USA.
[39] Taylor Jackson Scott, Katie Kuksenok, Daniel Perry, Michael Brooks, Ona Anicello, and Cecilia Aragon. 2012. Adapting grounded theory to construct a taxonomy of affect in collaborative online chat. In *Proceedings of the 30th ACM international conference on Design of communication - SIGDOC '12.* ACM Press, Seattle, Washington, USA, 197. https://doi.org/10.1145/2379057.2379096
[40] Ben Shneiderman. 2009. Creativity Support Tools: A Grand Challenge for HCI Researchers. In *Engineering the User Interface*, Miguel Redondo, Crescencio Bravo, and Manuel Ortega (Eds.). Springer London, London, 1–9. https://doi.org/10.1007/978-1-84800-136-7_1
[41] Paul Spector. 1997. *Job Satisfaction: Application, Assessment, Causes, and Consequences.* Thousand Oaks, California. https://doi.org/10.4135/9781452231549
[42] Spiceworks. 2017. Distribution of collaboration tools used in organizations worldwide, as of 2016, by company size.
[43] Statista. 2020. COVID-19 digital engagement report. http://www.statista.com/study/86023/covid-19-digital-engagement-report/
[44] Statista. 2020. Remote work frequency before/after COVID-19 2020. https://www.statista.com/statistics/1122987/change-in-remote-work-trends-after-covid-in-usa/
[45] Jamie S. Switzer. 2008. Impression Formation in Computer-Mediated Communication and Making a Good (Virtual) Impression. https://doi.org/10.4018/978-1-59904-893-2.ch008 ISBN: 9781599048932 Pages: 98-109 Publisher: IGI Global.
[46] Thiemo Wambsganss, Christina Niklaus, Matthias Söllner, Siegfried Handschuh, and J. M. Leimeister. 2021. *Supporting Cognitive and Emotional Empathic Writing of Students.* SSRN Scholarly Paper ID 3910431. Social Science Research Network, Rochester, NY. https://papers.ssrn.com/abstract=3910431
[47] L. Alan Witt and Mark N. Beorkrem. 1989. Climate for creative productivity as a predictor of research usefulness and organizational effectiveness in an R&D organization. *Creativity Research Journal* 2, 1-2 (1989), 30–40. https://doi.org/10.1080/10400418909534298 Place: US Publisher: Lawrence Erlbaum.
[48] Douglas Zytko, Sukeshini A. Grandhi, and Quentin (Gad) Jones. 2014. Impression management through communication in online dating. In *Proceedings of the companion publication of the 17th ACM conference on Computer supported cooperative work & social computing (CSCW Companion '14).* Association for Computing Machinery, New York, NY, USA, 277–280. https://doi.org/10.1145/2556420.2556487

A APPENDIX

A.1 Flowchart of the app design

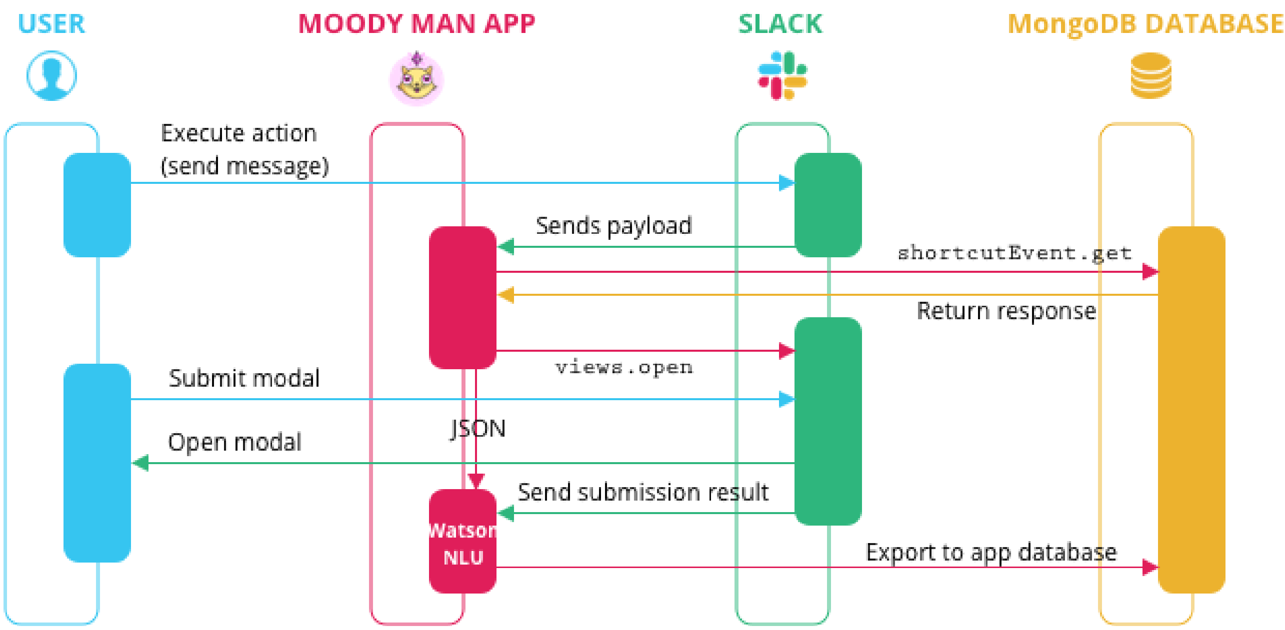

Figure 2: Flowchart of the app design

A.2 Prior studies samples

	Publication body	Article	Survey participants	Interview participants	Linguistic analysis of chat transcripts	Sample
Real-time language-based feedback	CHI '09: CHI Conference on Human Factors in Computing Systems	[28]	25	-		undergraduate students
Explainable AI	CHI '20: CHI Conference on Human Factors in Computing Systems	[29]	-	20		UX and design practitioners
Affect Detection in Collaborative Chat	CSCW '13: Proceedings of the 2013 conference on Computer supported cooperative work	[7]			32	astrophysics scientists
Taxonomy of Affect in Collaborative Online Chat	SIGDOC '12: Proceedings of the 30th ACM international conference on Design of communication	[39]			30	astrophysics scientists
Chat activity and chat sentiment	ICSEW'20: Proceedings of the IEEE/ACM 42nd International Conference on Software Engineering Workshops	[27]			8	software developers
Real-time meeting feedback dashboard	CHI '21: CHI Conference on Human Factors in Computing Systems	[37]	23	9		employees of a large tech company

Table 1: Prior relevant studies' sample sizes

A.3 Sources of questionnaire questions

ID	Measurement	Scale	Source
Q1_1 - Q1_4	Shared understanding	Likert Scale 1-7 (1 = strongly disagree, 7 = strongly agree)	[9]
Q3_1 - Q3_4	Attitude (Team Relationship)	Likert Scale 1-5 (1 = far too much, 5 = far too little)	[25]
Q5_1 - Q5_4	Attitude (Task Conflict)	Likert Scale 1-5 (1 = far too much, 5 = far too little)	[25]
Q9_1 - Q9_2	Attitude (Climate for Creative Productivity)	Likert Scale 1-5 (1 = strongly disagree, 5 = strongly agree)	[47]
Q6_1_Q6_5	Self-perceived creativity	Likert Scale 1-5 (1 = strongly disagree, 5 = strongly agree)	[14]
Q7_1 - Q7_6	Creative self-efficacy	Likert Scale 1-5 (1 = strongly disagree, 5 = strongly agree)	[14]
Q4_1 - Q4_7	Team Satisfaction	Likert Scale 1-5 (1 = extremely dissatisfied, 5 = extremely satisfied)	[41]
Q8_1 - Q8_10	App evaluation	Likert Scale 1-5 (1 = strongly disagree, 5 = strongly agree)	[37]

Table 2: Survey measurement scales and source works

A.4 Scale and statements

ID	Statements	Measurement	Scale	Source
Q1_1	In my team, the team members have a similar understanding about the procedures, strategies and contingency plans involved in decision making.	Shared understanding	Likert Scale 1-7 (1 = strongly disagree, 7 = strongly agree)	[9]
Q1_2	In my team, the team members have a similar understanding of each other's responsibilities, interdependent roles and communication patterns.			
Q1_3	In my team, the team members have a similar understanding about the technology, resources and tools needed to make decisions.			
Q1_4	In my team, the team members are familiar with the preferences and abilities of each other.			
Q3_1	How much friction is there among members in your team?	Attitude (Team Relationship)	Likert Scale 1-5 (1 = far too much, 5 = far too little)	
Q3_2	How much are personality conflicts evident in your team?			
Q3_3	How much tension is there among members in your team?			[25]
Q3_4	How much emotional conflict is there among members in your team?			
Q5_1	How often do people in your team disagree about opinions regarding the work being done?	Attitude (Task Conflict)	Likert Scale 1-5 (1 = far too much, 5 = far too little)	
Q5_2	How often are there conflicts about ideas in your team?			
Q5_3	How often are there differences of opinion in your team?			
Q5_4	How often are there disagreements within you team about the task you are working on?			
Q9_1	In my team, we are encouraged to develop new ways of doing things.	Attitude (Climate for Creative Productivity)	Likert Scale 1-5 (1 = strongly disagree, 5 = strongly agree)	[47]
Q9_2	In my team, when team members come up with new ideas they receive appropriate praise.			
Q6_1	I feel that I am good at generating novel ideas.	Self-perceived creativity	Likert Scale 1-5 (1 = strongly disagree, 5 = strongly agree)	
Q6_2	I have confidence in my ability to solve problems creatively.			
Q6_3	I have a knack for developing the ideas of others further.			
Q6_4	I am good at finding creative ways to solve problems.			
Q6_5	I have the talent and skills to do well in my work.			[14]
Q7_1	I feel comfortable trying out new ideas.			
		Creative self-efficacy	Likert Scale 1-5 (1 = strongly disagree, 5 = strongly agree)	

Q7_2	I have opportunities to use my creative skills and abilities at work.			
Q7_3	I am invited to submit ideas for improvements in the workplace.			
Q7_4	I have the opportunity to participate on team(s)			
Q7_5	I have the freedom to decide how my job tasks get done.			
Q7_6	My creative abilities are used to my full potential at work.			
Q4_1	How satisfied are you with your team?			
Q4_2	How satisfied are you with the functioning of your team?			
Q4_3	How satisfied are you with your participation in the workshop?	Team Satisfaction	Likert Scale 1-5 (1 = extremely dissatisfied, 5 = extremely satisfied)	[41]
Q4_4	How satisfied are you with the decisions made by your team?			
Q4_5	How satisfied are you with communication among your team members?			
Q4_6	How satisfied are you with the strategy of your team?			
Q4_7	How satisfied are you with the interpersonal relationships among the team members?			
Q8_1	The real-time feedback app improved my awareness of meeting behaviours.			
Q8_2	The real-time feedback app improved meeting effectiveness.			
Q8_3	The real-time feedback app improved meeting inclusivity.	App evaluation	Likert Scale 1-5 (1 = strongly disagree, 5 = strongly agree)	[37]
Q8_4	I think the app is important.			
Q8_5	I think the app is useful.			
Q8_6	I'm satisfied with the app.			
Q8_7	The app drew insights from my meeting.			
Q8_8	The app determined if sentiment in the meeting changed.			
Q8_9	The app determined the attitude of each attendee in the meeting.			
Q8_10	The app determined the emotions of each attendee in the meeting.			

Table 3: Statements used in measurement scales and source works

A.5 Data Structure

Themes	Second order codes	First order codes	Quotes
Design goals	AI design	Complexity of emotions	P-11: like I use a lot of irony and sarcasm. And I cannot imagine that our computer would even remotely be able to. To identify that. P-23: if there was like, I don't know, an option to extend the range of emotions that you can detect, like, you know, you have your defaults. P-1: the dimension of the different motions, emotions was an important because I think you can't really judge some message based on if it's positive or negative P-16: ut pick it up on on nuances. Like when you ask a question and like a bit of a passive aggressive way, because you're trying to get a point across, I think it struggled with that maybe
	Delivery timing	Post-sentence	P-15: I think it would be nice if it was live and automatic. Like it's just like, as you're typing a message P-30: if it's after then, I mean, the damage has already been done if it's offensive P-20: If it's at the end, maybe I wouldn't even review it, you know
		Pre-sentence	P-12: I would say before you hit send because as I don't know, I personally don't feel like there's any point in finding out my message is angry and might cause a bit of friction after I've sent it because the damage is already done P-28: it would be very, very handy to like, as you're typing, there's like a little emoji minute sort of changes color as as your as your sentences are completing, and maybe like a really easy way, because I can also see that being kind of annoying after a long time, if you're just having a normal conversation, you don't need to see the so maybe like a very quick toggle, like shift slash or something, then you can just toggle them on and off the little emoji in the corner, and then it changes color, or it just becomes sort of transparent, I would definitely use something like that
		Post-meeting	P-7: I'd rather try and compensate. But I think it's quite difficult sometimes to compensate afterwards P-29: I guess it's better to have it in a sentence. Because if it's overall you don't want to change. P-26: In general, like, I wouldn't have any reason to kind of, like, reflect on that.
	Trust	Accuracy	P-29: I don't know if I would be confident enough in this in this feature. P-30: it could maybe sometimes lead to certain misinformation. I'd say maybe. Maybe in the expression that's detected by the Moody Man, is that there's a possibility it wouldn't be accurate P-28: I didn't think it really reflected the message very accurately (...) I don't think I think I got it completely the wrong way. So I thought okay, I don't think this is really that helpful for me. P-22: but then I feel it all depends on the algorithm and you know, how accurate it is and how I think people need to be made aware of how it works a little bit more.
	Trust	Algorithm	P-22: I was trying to understand how the what the algorithm was, or the code was behind how it's saying that something is like 22.23% aggressive rate. So something is like that. What is it? If I if you're telling me that it's based on British slang, or something like that, then I would say that maybe probably I would have, but I didn't know at that point. You know, if it was based on British slang, I just thought it was based on like, normal English, you know

	Trust	Trained data source	P-8: So I feel I doubt whether so I actually i don't i don't i feel this is not something related to this workshop, but I feel like humans, like how they perceive the emotion is very, sometimes it's very intuitive. Or we really need to, like use a very quantitative approach to try to get this done. So this is where I doubt Yeah. P-10: I think it'd be the opposite. I would assume in my mind, I would assume that the AI has been taught with Native users, so I wouldn't trust it to assume from non native uses. P-10: I just wouldn't trust the ball, as I would have seen in my head, that I would be better at interpreting someone with a foreign way of talking, as opposed to a bot who was poorly trained with just English pieces. Yeah.
	Usability	Data presentation	P-8: I don't know whether the percentage thing just makes sense to me. P-21: So, for me when I see numbers like this, yeah, when it gets to a single digit percentage that feels, I'm not aware of it that is noise or whatever it is slightly. It's like that reading of that emotion. P-29: I think that those two decimal points on unnecessary Yeah, it's too detailed. P-14: you'd want it more visual, something more easy to understand because percentages, you might understand that but if you just look at a chart or something, it's like quick like one second P-16: sometimes it would be like, minus percent of happiness. And I'd be like, is this supposed to be like, super sad, super unhappy, or
	Usability	UX	P-24: because if the moody man requires extra click P-5: if it was like, easily, more easily accessible, that maybe I'd be more inclined to use it P-14: it was hard to access, it was a bit of a pain to having to click on other stuff.
	Emojis	Bridging role	P-15: that's why sometimes I will use the sort of symbols smiley face in my emails, because I still do want to come across as friendly. But usually emails seem as a more formal type of communication. Whereas emojis seem like quite a, like a colloquial, almost casual thing that like you use it when you are messaging your friends, as opposed to in a professional setting. P-19: I felt it's necessary to, like create more of like, friendly vibe, I guess P-26: there's Seems to be like this overlap or a bridge that allows both both or all all cultures to, like understand what people are saying and get the joke.
Motivations			
	Emojis	Revealing emotions	P-28: So using a smiley face or a question mark or whatever, like, it just clarifies your thought, as if you're face to face a little bit better. P-1: emoji is replacing that sort of feedback that you would get emotionally from your group members. P-16: I think are just easier to like, make the conversation a little less bureaucratic, it's just, it tries to attempt to put some motion in a conversation.

Emojis	To quickly react and acknowledge	P-24: as in as a method of kind of communicating things like a thumbs up, I guess it's a way to kind of convey emotion. So they're not used extensively before, or distracting things. But if there's a certain kind of sentiment to them, or just as a quick response to like P-15: So I think I might not use emojis, but reactions could be quite a good substitute. So you can see that Archie and I use reactions quite a lot. And partly also because I felt like that was another way to organize our reactions to each other's messages. So because we didn't really use the reply in thread, a good way to express that we agreed with each other was to react to each other's messages P-13: it's kind of like show some agreement almost instead of having to say, Oh, yeah, no, I agree with you. Like give him a thumbs up P-22: he tick mark one was pretty good. Just to show that, okay, this thread is complete, I don't need to add anything more to these ones, or, okay, this thread is done, like this job is done.
Impression Formation	Figure of authority	P-8: Because for him for manager, I need to be more Be more careful about the word I use P-28: If I was talking to my boss, or my boss's boss, for example, or a professor even at uni, than I probably, when I really needed to be careful about what I was saying.
	Positive self-portrayal	P-1: the feedback that is neutral, then like, that's okay to send, and you don't really have to worry about if you're coming across to, like a negative way. P-19: So it's probably useful. As far as you know, you have to be careful with the way you express yourself to not come across one way or another. P-5: Because you'd want to make sure that you're coming across Well, on the communication is as good as like other people's.
	Speaking to strangers	P-29: I think if I don't know the person I'm talking to, I would probably use it. P-3: I think I'd use it quite a lot, especially at start getting to know people
Usage Points	Useful for idea evalutaion	P-1: I think it wouldn't be particularly useful when you're ideating because content, but when you are making decisions and when you are discussing the ideas, so that evaluation, and from that evaluation, what you decide on, I think that is a really important aspect to know. If you mean, you can be critical and that's important when you are doing design, but being critical in like a constructive way that you're not coming across as like, negative.
	Self-verification	P-5: it's like a quick indication whether it's comes across as good or not. P-20: If someone realizes that, oh, people think I'm rude. Why is that? Or, you know, maybe it's all a matter of how they are communicating. And and this could be a solution to have a better relationship with colleagues.

User type	Useful for bigger teams than dyads	P-17: moody man as a whole would have been more useful if the team was bigger because like, they were just that would have been just so many other people you'd have to talk to and like, you know, you can't always like read everybody just from like the messages so like, then you could, you know, click on that and just and use it, but when the second When there's only two people, it's just like, you know, you sort of yourself get the vibe from them like you don't. You don't have to, like necessary use moody man. P-10: I believe when we there's a bigger group and you can't, you know, like, think about how everyone's feeling or like, everyone's interactions, because I could see it being released. P-1: sometimes the mood can be really tense, like in a group messenger chat. But then when you actually meet in person, it's like, everyone's like, cool. And like, I think it's easy for that tension to start in a group chat. P-13: I think that's probably a more useful tool, if you have like, a conversation between more people.
	Cultural difference	P-26: just looking at like those sort of cultural barriers between people. I could see it being mega useful for people trying to learn like there's the English language. Yeah. And then there's like, the, the underbelly of it, which every language has, which is like, the jokes the sarcasm.
	Not native speaker	P-22: I was trusting, moody man more so than questioning it, I would say, some degrees, like I was looking at what I was saying more than not taking bad as what the truth is. because English is not my first language. P-26: to certain native English speakers, I don't think it's particularly particularly useful. Yeah. But if it's an an English speaker to a non native, then I think it could, it could definitely help
	Domain knowledge	P-8: So if you're a designer, someone else's designer, [..] I wouldn't use that as if I was speaking with an engineer P-26: in terms of understanding the other person who I don't know, and he's not a designer, it would definitely be a tool to try and say, like, what, what is it you're trying to convey to me in this project

Table 4: Data structure with exemplary quotes