Media Naturalness, Emotion Contagion, and Creativity: A Laboratory Experiment Among Dyads

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Abstract Workplaces have evolved to rely on digital media for collaboration. Previous research has demonstrated how different characteristics of these tools, such as richness and naturalness, can enable and constrain communication among online teams. However, the role of affect in these collaborations, and the degree to which teams are able to communicate affective information, remains less clear. This research-in-progress presents a laboratory experiment that compared creative task performance under two conditions (i) dyads were online or in-person (ii) dyads began with similar or different affective states.

Keywords Digital teams · Media naturalness · Mood synchronicity · Emotion contagion

1 Introduction

Communication media allow different types of information to be communicated, including both cognitive and affective information. The *media naturalness hypothesis* suggests humans prefer face-to-face-like communication because our biological apparatus has evolved to prime us with the necessary symbolic tools and heightened physiological alertness for these face-to-face processes [1, 2]. Thus, media naturalness helps to explain some of our difficulties with digital media by showing how

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humans rely on capabilities that evolved over thousands of years to perform modern tasks [1]. Yet, despite the limitations of digital media, there is evidence that people sometimes perform as well or better using less natural media (e.g., instant messaging) rather than natural media (e.g., video conferencing).

One explanation is that collaboration is not a purely cognitive endeavor; rather, it includes a strong affective component [3]. At the offset of collaboration, team members likely exhibit different moods and affective states [4, 5]. These dissimilar moods can promote generative behavior and new possibilities as individuals confront their differences [6]. This is important, as it allows teams to harness their different perspectives and find possibilities they may not have found on their own [7, 8]. It can also lead to discomfort and emotional uncertainty among team members, who may even suffer relationship breakdowns if the affective conflict becomes engrained in their relationship [9].

Provided teams can battle through these divergent affective states, they will typically converge towards a common mood through processes of affective contagion [10, 11], which acts to reinforce specific emotions and reduce ambivalence [12–14]. The resulting shared affective "vantage point" helps team members align their expectations [15], limiting the potential distraction of exploring new possibilities.

For this reason, the ability to communicate affective information appears to be both a blessing and a curse. It is both an engine for a team's creativity and ability to push each other and a source of distraction that can create interpersonal obstacles to collaboration. We argue that, if we are to make sense of conflicting findings about teams' media preferences and performance outcomes, we must make sense of how digital media impact collaboration and allow individuals to find a suitable balance of affective conflict. Hence, this study proposes a laboratory experiment to study the effect of communication media (in-person vs. via video conference) on creativity and explore emotion contagion as a mediating factor. The remainder of this work-in-progress paper presents the research design and early results from preliminary analyses of partial data.

2 Methods

Study Design

Participants. Participants were recruited from the compensated subject pool of a West Coast American university and the study was conducted on campus. Participants were all 18 years or older, affiliated with the university, and were compensated with a $20 gift card.

Task. Participants were paired into dyads and asked to complete three consecutive trials of the so-called "alternative use task" (AUT) (e.g., [16–18]). For each trial, participants were given the name of an object and asked to generate as many alternative uses for this object as possible in 5 min. They were informed that their ideas will be evaluated based on originality, number, uniqueness, and level of detail. After instructions were displayed through a set of slides, the page automatically advanced to a blank Google Sheet with instructions and the name of the object for the ongoing trial. The order of the trials was consistent for all dyads: frisbee, newspaper, and plastic bottle. Once the 5 min were up, the page automatically advanced to the next trial.

Treatments. The experiment used a two by two, between-subjects design with four treatments: (i) in-person communication, (ii) video-conference-based communication, (iii) convergent mood, and (iv) divergent mood. Assignment to treatment was randomized. The experiment was created using Qualtrics software (www.qualtrics.com) for questionnaires, Google Sheets for task completion, and iMotions software (www.imotions.com) to program the experiment. Only one participant in each dyad was permitted to type into the Google Sheet, while the other participant could only view the shared spreadsheet. The writer's role was assigned randomly before the session and remained assigned to the same participant for all three trials.

In-person dyads completed the task face-to-face, only separated by their respective laptops, while online dyads were connected via Zoom after the mood induction. In-person dyads were brought into a shared room and seated at a round table with two workstations (14″ laptops) across from one another, separated by a divider. The divider was removed after the mood induction, right before starting the collaborative task. Online dyads were placed in separate rooms and seated at individual workstations in front of a 14″ laptop and 22″ monitor (display only) placed one behind the another. The Zoom conference was displayed on the larger monitor.

Convergent and divergent moods were manipulated via pre-task induction. Divergent moods were induced by getting the two participants of a dyad to play two different versions of a Pac-man game, one version to induce positive affect (PA-Pacman) and one to induce negative affect (NA-Pacman). Convergent moods were induced by getting both participants of a dyad to play the same version of the Pac-man game (either both positive or both negative). The game lasted five minutes, after which it stopped automatically, similar to [19]. The respective effects of the two versions of the Pac-man game were validated in a pilot of this study [20].

Instruments. Convergent and divergent moods were measured using a version of the Positive Affect and Negative Affect Scale (PANAS) administrated via a Qualtrics questionnaire before and after the mood induction. Creative performance was measured through "fluency" [21], that is, the number of ideas produced per dyad. Moreover, we used self-report measures of affective states [22], cognitive consensus [23, 24], team processes [24–28], and perceived affective friction [20]. The task outcome was measured as the mean fluency of each dyad [21].

Physiological data. During the experiment, eye gaze was measured by Tobii Pro x3-120 eye trackers, skin conductance and cardiac rhythms were recorded using Shimmer3 GSR+ and ECG, and Affectiva performs facial expression analysis (FEA).

Within each dyad, we considered a range of different analytical techniques to measure physiological synchrony as a proxy for emotional contagion, including cross-correlation [29–33], coherence, cross-recurrence, and delayed coincidence count [33, 34]. We also plan to analyze gaze overlap signals [35, 36], which have been associated with affective engagement [37, 38].

Data preparation. Prior to running statistical tests, we pre-processed the FEA data. Because each dyad performed the experimental task on two different machines, the data needed to be synchronized pairwise. iMotions provides a Unix timestamp that marks the start of data collection for each participant as well as an integrated timestamp for all sensors in milliseconds since recording started. This allowed us to derive the real-time data point for all signals and participants. However, because the data was recorded on different machines, the data was imperfectly synchronized within dyads. To allow for accurate comparison within dyads, we performed an interpolation technique on the smile coefficients and the real time of the session. We used a one-dimensional piecewise cubic Hermite interpolating polynomial [39], also known as PchipInterpolator. This technique constructs a smooth curve that passes through the given data points while maintaining monotonicity (i.e., it does not produce any local maxima or minima between data points). First, the data was filtered and cleaned, converting the 'real_time' column to numeric values. Then, the Python Scipy PchipInterpolator function [40] was used to interpolate the data for each participant. The time range was determined by finding the maximum and minimum time values for the two participants being analyzed and using this range to create a new time array with a uniform time step of 20 ms (2e7 ns). Finally, the interpolated smile values for each participant were appended to a new list that was used for the rest of the analyses.

3 Preliminary Analysis

Manipulation Check

A 2×2 analysis of variance (ANOVA) with time (pre-manipulation vs. post-manipulation) as a within-subjects factor and game (NA-pacman vs. PA-pacman) as a between-subject factor was conducted on the PANAS positive affect data. Post hoc dependent samples t-tests revealed a significant difference between post-manipulation NA-pacman dyads and pre-manipulation PA-pacman dyads, $t(47) = 3.80$, $p < 0.001$, $r = 0.12$. Overall, the results suggest that positive affect was higher after playing PA-pacman ($M = 36.0$, $SD = 8.5$) compared to pre-manipulation ($M = 34.1$, $SD = 7.4$). We also found a significant difference between post-manipulation and pre-manipulation for NA-pacman dyads, $t(51) = 3.41$, $p = 0.001$, $r = 0.17$. The results also suggest that negative affect was higher after playing NA-pacman ($M = 21.1$, $SD = 7.6$) compared to pre-manipulation ($M = 18.6$, $SD = 6.8$).

Table 1 Descriptive statistics of fluency per condition

	N	Mean	SD	SE	95% conf.	Interval
CM O	30	14.2000	3.8899	0.7102	12.7475	15.6525
CM P	24	15.7083	3.5322	0.7210	14.2168	17.1999
DM O	27	15.7778	4.1169	0.7923	14.1492	17.4064
DM P	24	16.1667	4.6966	0.9587	14.1835	18.1499

CM convergent mood, *DM* divergent mood, *O* online, *P* in person

Descriptive Statistics

We recruited 86 participants, grouped into 43 dyads (in-person: n = 23, online: n = 20, convergent mood: n = 21, divergent mood: n = 21). A total of 1998 ideas were produced across all trials, of which 145 were removed from the dataset because they either (i) did not constitute a use of the object (e.g., selling the object) or (ii) constituted a non-alternative use of the object (e.g., playing frisbee) (frisbee: n = 600, bottle: n = 668, newspaper: n = 730). Our preliminary analyses of emotional contagion used the smiling percentage of dyads based on Affectiva AFFDEX: M = 34.06 (t1, SD = 41.48), 24.36 (t2, SD = 37.53), 24.21 (t3, SD = 37.49). Table 1 provides an overview of the fluency data based on the experimental conditions.

To continue our preliminary exploration of the data, we assumed that the participant who was not writing (NW) led the smiling behavior, based on the idea that this role takes up some of the participant's attention. We performed a Wilcoxon rank-sum test to test this assumption. The results suggest that there is a significant difference in smiling scores between the writers' smiling scores and the non-writers' smiling scores (F = −104.595, $p < 0.001$), with non-writers showing slightly lower scores. However, the effect size of the difference was small, with a Cohen'd of −0.02. Furthermore, we visually inspected the difference in smiling scores within dyads through each trial, looking for variability patterns throughout the trials. Figure 1 suggests that participants within a dyad show greater fluctuation in the range of difference with respect to each other on a second-per-second basis. In other words, when measuring the difference between the writers' and non-writers' smiling scores each second, it seemed that this difference was more dynamic throughout Trial 1, then progressively more homogeneous as we progressed through the trials.

Preliminary Findings

We first ran a fixed effect OLS to confirm the presence of smile contagion within dyads and across trials. The results show support for emotional contagion across each of the three trials, both from the dyad member who was writing down ideas (Smile_W) on the dyad member who was not (Smile_NW), and in the opposite direction (see Table 2).

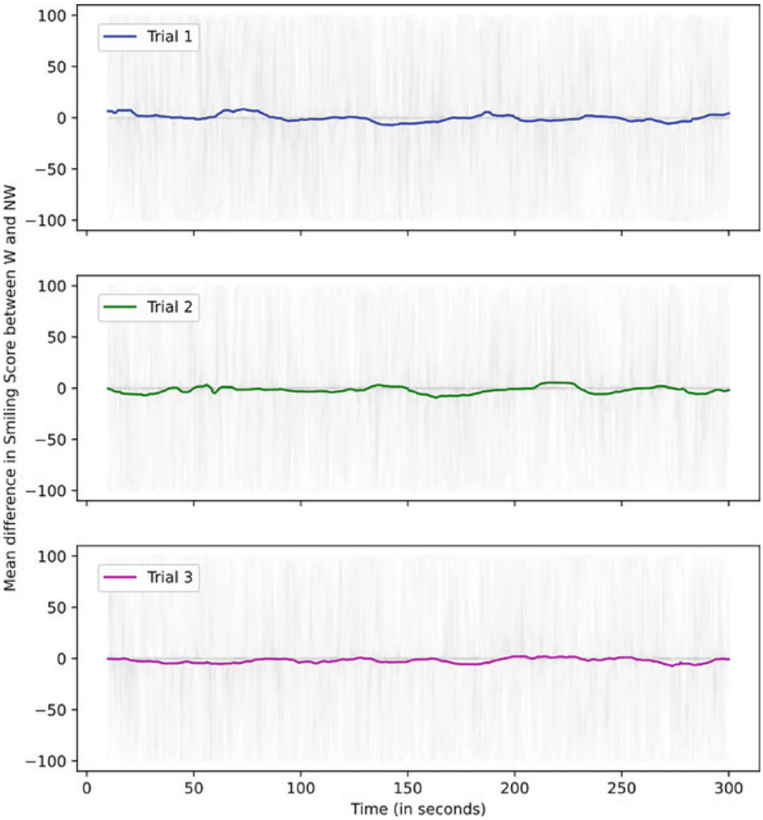

Fig. 1 Visual representation of smile variability within dyads across trials

For our preliminary analysis, we calculated a separate basic correlation score for the smiling measures for each member within a dyad. We did this by running a simple fixed effects ordinary least squares (OLS) for each dyad as follows,

$$Smile\_W_{it} = \alpha_i + \beta_1 Smile\_NW_{it} + u_{it}$$

where *Smile_W* denotes the smiling score for the team member writing down ideas, *Smiling_NW* denotes the other team member, i denotes a specific dyad, t denotes each time unit during a brainstorming session, α_i is the unobserved time-invariant individual effect, and u_{it} is the error term. We treated the smiling score for the individual who was asked to write down ideas treated as the dependent variable, and the smiling score for the other individual as the independent variable. We called this variable *Smile_contagion.*

We next performed a mixed ANCOVA using our Smile_contagion coefficient, and dummy variables derived from our experimental conditions to study their effects on fluency. The results show support for an effect of the mood condition (i.e., divergent

Table 2 Results from fixed effects OLS for contagious smiling across trials

	Dependent variable					
	Smile_NW			Smile_W		
	Frisbee	Newspaper	Plastic bottle	Frisbee	Newspaper	Plastic bottle
	(1)	(2)	(3)	(1)	(2)	(3)
Smile_W	0.357^{***} (0.009)	0.388^{***} (0.009)	0.402^{***} (0.009)			
Smily_NW				0.345^{***} (0.009)	0.356^{***} (0.008)	0.362^{***} (0.008)
Obs.	11,060	11,064	11,114	11,060	11,064	11,114
R^2	0.123	0.138	0.146	0.123	0.138	0.146
Adj. R^2	0.121	0.135	0.143	0.121	0.135	0.143
F stat.	$1{,}550.929^{***}$ (df = 1; 11,024)	$1{,}763.124^{***}$ (df = 1; 11,028)	$1{,}889.804^{***}$ (df = 1; 11,078)	$1{,}550.929^{***}$ (df = 1; 11,024)	$1{,}763.124^{***}$ (df = 1; 11,028)	$1{,}889.804^{***}$ (df = 1; 11,078)

Note $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

vs. convergent) on fluency, as well as an interaction of smile contagion and mood condition (see Table 3). This analysis suggests that dyads in the divergent mood condition are more likely to score higher on fluency, but their fluency score drops significantly when they have strong smile contagion (see Fig. 2 for visuals).

Table 3 Mixed ANCOVA results on fluency

Mixed linear model regression results						
	Coef.	Std. err.	z	P > |z|	[0.025	0.975]
Intercept	12.904	2.033	6.349	0.000	8.920	16.887
is_DM	7.776	3.321	2.342	**0.019**	−1.267	14.284
is_P	−2.450	3.253	−0.753	0.451	−8.827	3.926
Smile_contagion	4.644	6.148	0.755	0.450	−7.405	16.693
Smile_ contagion:is_DM	−19.088	9.013	−2.118	**0.034**	−36.752	−1.423
Smile_ contagion:is_P	11.744	9.040	1.299	0.194	−5.974	29.463
is_DM:is_P	−1.265	2.369	−0.534	0.593	−5.909	3.379
Group var	9.447	1.392				

Variables: *is_DM* dummy variable for divergent mood (default, the alternative is convergent mood), *is_P* dummy variable for in-person (default, the alternative is online), *Smile_contagion* coefficient

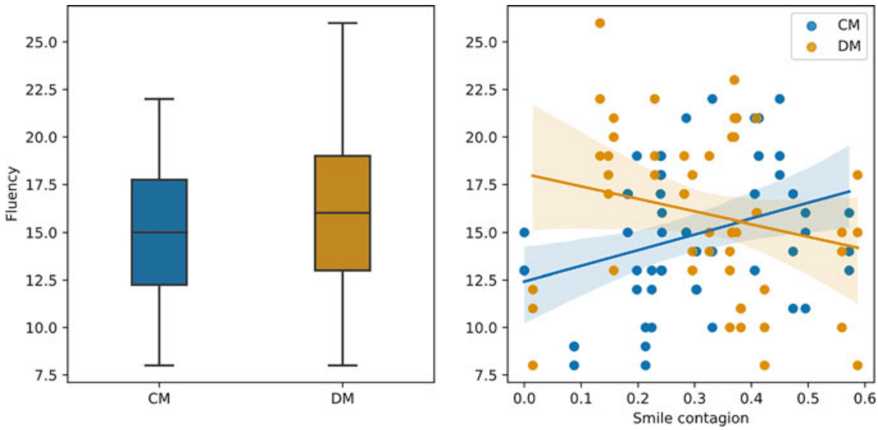

Fig. 2 Boxplot of fluency depending on the mood condition (left) and linear regression model fit for fluency versus smile contagion for the mood condition (CM = convergent mood, DM = divergent mood) (right)

Preliminary Conclusions

The early-stage results show encouraging evidence that emotional contagion could play an important role in creative fluency. This study showed that placing participants in divergent moods seemed more likely to yield greater fluency, whereas convergent dyads would produce fewer ideas. When controlling for smile contagion, however, it seemed that greater smile contagion reduced overall fluency for divergent dyads. This could be a sign that the participants have to expend more effort to overcome their emotional divergence, which may take away their attention from the task at hand—as they focus on re-establishing emotional stability within their team. These results are promising, considering that our full dataset includes other measures of creativity, including aspects such as originality, elaboration, etc. Moreover, including other variables from the questionnaires will help understand the level of awareness involved in these affective processes, as well as tangible experiences like perceived performance, quality of teamwork, etc.

4 Analysis Plan and Expected Contributions

This work-in-progress focused on reporting descriptive statistics and simple tests, allowing us to better understand the dataset and draw basic conclusions. However, this study produced a rich and complex dataset that offers great potential for further exploratory analysis. So far, the data highlighted important challenges that are unique to the interactive nature of the experiment. Among others, signal synchronization within dyads has made it difficult to calculate the co-occurrence of physiological events due to the inconsistency in physiological "leadership'—that is, there is no consistent trend as to which participant experiences physiological changes first. However, smiling data proves to be a suitable testbed for the preparation and analysis of dyadic psychophysiological data, because the signal shows low levels of noise and can easily be validated through visual inspection of the video recordings.

Plan for the Complete Analysis

We plan to continue searching for the optimal way to derive a proxy for emotional contagion in facial expression data, as well as including the rest of the sensor data that was recorded during the experiment. Specifically, we will investigate a variety of measures of emotional contagion, creativity, and quality of teamwork, taking full advantage of the richness of the data we collected thanks to our multi-modal, dyadic experimental design. Common measures of signal and physiological synchrony include cross-correlation and Mutual Information. However, these techniques both have a limited capacity to handle dynamic leadership, meaning that while they would be reliable when it is always the same participant smiling first (one leader and one follower), their derived variable become heavily biased when leadership changes dynamically throughout the experimental session (participants lead the smiling behavior interchangeably, with no consistent leader/follower).

We therefore plan to derive a variable based on smile overlap with a custom function. iMotions estimates a 50% likelihood to represent a moderately strong display of facial response. Based on this, we propose to code smiling peaks in each signal as a binary variable based on a threshold of 50 (>= 50 = 1; <50 = 0). Based on the interpolated sample for our time series, we can then filter through both signals of each dyad at an interval of 20 ms and multiply them element-wise to create a third signal that represents smile overlaps (time units where the product of the signals is equal to 1, meaning that both participants have a smiling score of at least 50 for the current time unit). Figure 3 exemplifies this process for a sample dyad randomly select in our sample. The top graph shows the signals of both participants (orange and blue). In green, we emphasize smiling peaks, which are defined as a smiling score above the threshold of 50 for both participants. The bottom graph shows the binarization of the signals and the creation of the third, overlapping signal. We can then calculate the duration of each overlapping peak by multiplying consecutive values of 1 in the third signal by our time unit of 20 ms. For each dyad, we thus obtain a count of overlapping smiling peaks (>=50) and their duration, from which we can derive the total duration of overlapping smiling behavior in seconds.

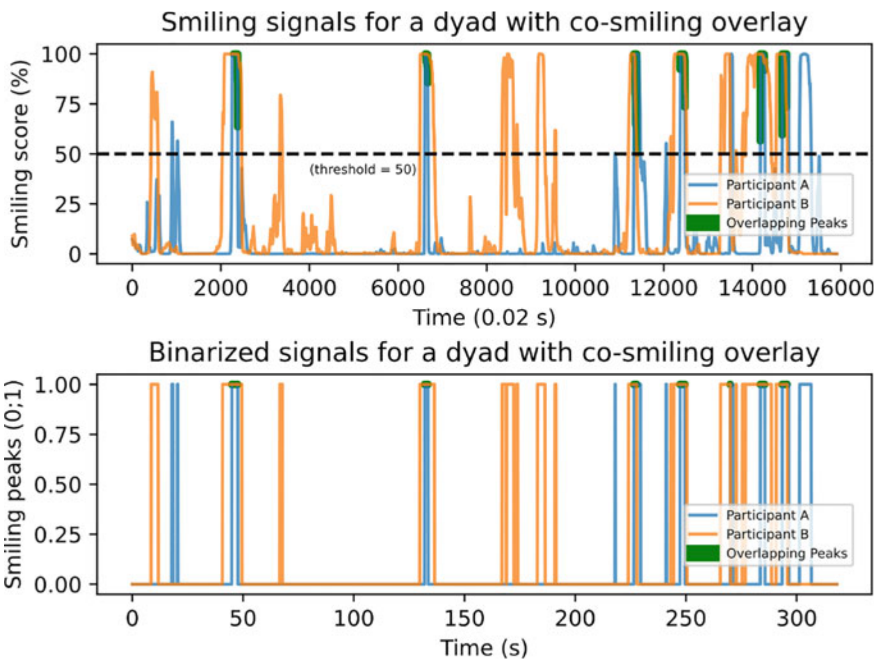

Fig. 3 Binarization of the signals and overlap detection

Although promising, this proposed variable is complex and can be sensitive to several factors. First, deriving a binary variable out of a continuous variable based on arbitrarily-defined threshold results in considerable data loss. We will thus need to carefully consider the analytical purpose of such a variable and whether 50% is a suitable threshold. Second, this technique is quite insensitive to time delays as it only accounts for synchronous peaks. This means that it could potentially overlook important information about smile contagion lag. We plan to further refine this variable to increase its accuracy, precision, and usability.

Expected Contributions

Despite the early stage of our analysis of the data, this study already shows encouraging signs of significant contributions. First, we show that placing dyads in divergent moods before the task may improve their creative fluency, as long as smile contagion is low. This finding is significant because as teams work remotely, they are more likely to be in a range of affective states, whereas when they are co-located in a shared office space, they are more likely to experience a narrower range of affective states. In other words, teams could benefit from being geographically dispersed when working on ideation tasks. If they wanted to capitalize on this advantage, they might achieve even better results when prioritizing communication media that make it harder for emotions to spread. Such media could be those types that were traditionally considered lean in the media richness and synchronicity literature—although more research is needed to specifically investigate the affective nature of communication media.

Second, we propose an experimental design to study dyadic interaction in a laboratory while using a naturalistic protocol. Using applications like Zoom and Google Sheets is uncommon in laboratory experiments. While these tools presented some limitations in terms of experimental control, we chose to prioritize ecological validity by selecting tools that are already commonly used by teams in organizations. Our research design and protocol contribute to expanding the applicability of laboratory experiments in the fields of business and management.

Third, we suggest new directions for preparing and analyzing dyadic psychophysiological data. After we complete our analysis, we plan to make our data processing pipeline publicly available. In doing so, we want to encourage other scholars to pursue dyadic psychophysiological experiments involving physiological synchrony.

References

1. Kock, N. (2004). The psychobiological model: Towards a new theory of computer-mediated communication based on Darwinian evolution. *Organization Science, 15*, 327–348. https://doi.org/10.1287/orsc.1040.0071

2. Kock, N. (2011). Media naturalness theory: Human evolution and behaviour towards electronic communication technologies. In *Applied evolutionary psychology*. OUP Oxford.
3. Amabile, T., Barsade, S., Mueller, J. S., & Staw, B. M. (2005). Affect and creativity at work. *Administrative Science Quarterly, 50*, 367–403. https://doi.org/10.2189/asqu.2005.50.3.367
4. Frijda, N. H. (1993). Moods, emotion episodes, and emotions. In *Handbook of emotions* (pp. 381–403). The Guilford Press.
5. Weiss, H. M., & Cropanzano, R. (1996). Affective events theory: A theoretical discussion of the structure, cause and consequences of affective experiences at work. *Research in organizational behavior, 18*, 75.
6. Jarvenpaa, S. L., Standaert, W., & Vlerick Business School. (2018). Digital probes as opening possibilities of generativity. *JAIS,* 982–1000. https://doi.org/10.17705/1jais.00516
7. Barsade, S., & Knight, A. P. (2015). Group affect. *Annual Review of Organizational Psychology and Organizational Behavior, 2*, 21–46. https://doi.org/10.1146/annurev-orgpsych-032414-111316
8. Fong, C. T. (2006). The effects of emotional ambivalence on creativity. *Academy of Management Journal, 49*, 1016–1030. https://doi.org/10.5465/AMJ.2006.22798182
9. Barsade, S., Ward, A. J., Turner, J. D. F., & Sonnenfeld, J. A. (2000). To your heart's content: A model of affective diversity in top management teams. *Administrative Science Quarterly, 45*, 802–836. https://doi.org/10.2307/2667020
10. Barsade, S., Coutifaris, C. G. V., & Pillemer, J. (2018). Emotional contagion in organizational life. *Research in Organizational Behavior, 38*, 137–151. https://doi.org/10.1016/j.riob.2018.11.005
11. Hatfield, E., Cacioppo, J., & Rapson, R. (1992). Primitive emotional contagion. In *Current directions in psychological science* (pp. 151–177).
12. Bettenhausen, K. L. (1991). Five years of groups research: What we have learned and what needs to be addressed. *Journal of Management, 17*, 345–381. https://doi.org/10.1177/014920639101700205
13. Jehn, K. A., Northcraft, G. B., & Neale, M. A. (1999). Why differences make a difference: A field study of diversity, conflict and performance in workgroups. *Administrative Science Quarterly, 44*, 741–763. https://doi.org/10.2307/2667054
14. Zhu, D. H. (2013). Group polarization on corporate boards: Theory and evidence on board decisions about acquisition premiums. *Strategic Management Journal, 34*, 800–822. https://doi.org/10.1002/smj.2039
15. Vuori, T. O., & Huy, Q. N. (2016). Distributed attention and shared emotions in the innovation process: How Nokia lost the smartphone battle. *Administrative Science Quarterly, 61*, 9–51. https://doi.org/10.1177/0001839215606951
16. Brucks, M. S., & Levav, J. (2022). Virtual communication curbs creative idea generation. *Nature*. https://doi.org/10.1038/s41586-022-04643-y
17. Harada, T. (2020). The effects of risk-taking, exploitation, and exploration on creativity. *PLoS ONE, 15*, e0235698. https://doi.org/10.1371/journal.pone.0235698
18. Klein, A., & Badia, T. (2022). Where divergent ideas converge: Answers to AUT found on short list of word co-occurrences terms. *Creativity Research Journal,* 1–17. https://doi.org/10.1080/10400419.2022.2103314
19. Reuderink, B., Nijholt, A., & Poel, M. (2009). *Affective Pacman: A frustrating game for brain-computer interface experiments* (pp. 221–227).
20. Saigot, M. (2022). Leveraging affective friction to improve online creative collaboration: An experimental design. In F. D. Davis, R. Riedl, J. vom Brocke, P.-M. Léger, A. B. Randolph, & G. R. Müller-Putz (Eds.), *Information systems and neuroscience* (pp. 237–250). Springer International Publishing.
21. Guilford, J. P. (1975). Varieties of creative giftedness, their measurement and development. *Gifted Child Quarterly, 19*, 107–121. https://doi.org/10.1177/001698627501900216
22. Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology, 54*, 1063–1070. https://doi.org/10.1037/0022-3514.54.6.1063

23. Mohammed, S., & Ringseis, E. (2001). Cognitive diversity and consensus in group decision making: The role of inputs, processes, and outcomes. *Organizational Behavior and Human Decision Processes, 85*, 310–335. https://doi.org/10.1006/obhd.2000.2943
24. O'Leary, K., Gleasure, R., O'Reilly, P., & Feller, J. (2022). Introducing the concept of creative ancestry as a means of increasing perceived fairness and satisfaction in online collaboration: An experimental study. *Technovation, 110*, 102369. https://doi.org/10.1016/j.technovation.2021.102369
25. Hoegl, M., & Gemuenden, H. G. (2001). Teamwork quality and the success of innovative projects: A theoretical concept and empirical evidence. *Organization Science, 12*, 435–449. https://doi.org/10.1287/orsc.12.4.435.10635
26. Nunamaker, J. F., Applegate, L. M., & Konsynski, B. R. (1987). Facilitating group creativity: Experience with a group decision support system. *Journal of Management Information Systems, 3*, 5–19. https://doi.org/10.1080/07421222.1987.11517775
27. Valacich, J. S., Dennis, A. R., & Nunamaker, J. F. (1992). Group size and anonymity effects on computer-mediated idea generation. *Small Group Research, 23*, 49–73. https://doi.org/10.1177/1046496492231004
28. Wu, I.-L., & Chiu, M.-L. (2018). Examining supply chain collaboration with determinants and performance impact: Social capital, justice, and technology use perspectives. *International Journal of Information Management, 39*, 5–19. https://doi.org/10.1016/j.ijinfomgt.2017.11.004
29. Chanel, G., Kivikangas, J. M., & Ravaja, N. (2012). Physiological compliance for social gaming analysis: Cooperative versus competitive play☆. *Interacting with Computers, 24*, 306–316. https://doi.org/10.1016/j.intcom.2012.04.012
30. Dehais, F., Vergotte, G., Drougard, N., Ferraro, G., Somon, B., Ponzoni Carvalho Chanel, C., & Roy, R. (2021). *AI can fool us humans, but not at the psycho-physiological level: A hyperscanning and physiological synchrony study.*
31. Elkins, A. N., Muth, E. R., Hoover, A. W., Walker, A. D., Carpenter, T. L., & Switzer, F. S. (2009). Physiological compliance and team performance. *Applied Ergonomics, 40*, 997–1003. https://doi.org/10.1016/j.apergo.2009.02.002
32. Järvelä, S., Kivikangas, J. M., Kätsyri, J., & Ravaja, N. (2014). Physiological linkage of dyadic gaming experience. *Simulation & Gaming, 45*, 24–40. https://doi.org/10.1177/1046878113513080
33. Verdiere, K. J., Albert, M., Dehais, F., & Roy, R. N. (2020). Physiological synchrony revealed by delayed coincidence count: Application to a cooperative complex environment. *IEEE Transactions on Human-Machine Systems, 50*, 395–404. https://doi.org/10.1109/THMS.2020.2986417
34. Mønster, D., Håkonsson, D. D., Eskildsen, J. K., & Wallot, S. (2016). Physiological evidence of interpersonal dynamics in a cooperative production task. *Physiology & Behavior, 156*, 24–34. https://doi.org/10.1016/j.physbeh.2016.01.004
35. Schneider, B., & Pea, R. (2017). Real-time mutual gaze perception enhances collaborative learning and collaboration quality. In M. Orey & R. M. Branch (Eds.), *Educational media and technology yearbook* (pp. 99–125). Springer International Publishing.
36. D'Angelo, S., & Begel, A. (2017). Improving communication between pair programmers using shared gaze awareness. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (pp. 6245–6290). ACM.
37. Kret, M. E. (2015). Emotional expressions beyond facial muscle actions. A call for studying autonomic signals and their impact on social perception. *Frontiers in Psychology, 6*. https://doi.org/10.3389/fpsyg.2015.00711
38. Janssen, J. H., Bailenson, J. N., IJsselsteijn, W. A., & Westerink, J. H. D. M. (2010). Intimate heartbeats: Opportunities for affective communication technology. *IEEE Transactions on Affective Computing, 1,* 72–80. https://doi.org/10.1109/T-AFFC.2010.13
39. Fritsch, F. N., & Butland, J. (1984). A method for constructing local monotone piecewise cubic interpolants. *SIAM Journal on Scientific Computing, 5,* 300–304. https://doi.org/10.1137/0905021

40. Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., … Vázquez-Baeza, Y. (2020). SciPy 1.0: Fundamental algorithms for scientific computing in Python. *Nature Methods, 17,* 261–272. https://doi.org/10.1038/s41592-019-0686-2