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Aligning the smiles of dating dyads causally increases attraction

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Social interaction research is lacking an experimental paradigm enabling researchers to make causal inferences in free social interactions. For instance, the expressive signals that causally modulate the emergence of romantic attraction during interactions remain unknown. To disentangle causality in the wealth of covarying factors that govern social interactions, we developed an open-source video-conference platform enabling researchers to covertly manipulate the social signals produced by participants during interactions. Using this platform, we performed a speed-dating experiment where we aligned or misaligned the facial smiles of participants in real time with face transformation algorithms. Even though participants remained totally unaware that their faces were being manipulated, aligning their smiles causally enhanced the romantic attraction they felt toward each other, compared to unaligned scenarios. Manipulations also influenced how participants synchronized and vocally reacted to each other. This paradigm causally manipulates the emergence of romantic attraction in free social interactions. Moreover, our methodology opens the possibility to perform causal inferences during free social interactions.

social interactions | face transformations | speed dating | smiles

It is remarkably difficult to study how specific social signals (e.g., smiles) or behaviors (e.g., expressive alignment) causally influence social interactions. On the one hand, research analyzing interaction recordings can identify signals that covary with behavior, but can only provide correlational findings (1). On the other hand, experiments that control for individual factors using, e.g., research confederates, scripted interactions, or virtual avatars, can perform causal inference, but are limited by being unrealistic (1). To overcome these limitations, we built an experimental platform that gives researchers the ability to covertly manipulate the social signals produced by participants in real time. This platform enables researchers to catch the social signals "in the air"—after being produced but before being perceived—, manipulate them along specific social dimensions (e.g., increase or decrease the smiles in participants' faces) and reinsert them back in the social communication chain without the participants noticing. Here, we use this paradigm to study how smile alignment causally influences the emergence of the romantic attraction, expressive synchrony, and vocal reactions of dating participants.

The factors that influence liking between romantic partners have been the matter of a wealth of studies (2). Physical and personality traits can predict whether a person is more likely to attract others (3, 4) and computational models can estimate and predict rejection and matching rates based on participants' ratings of attraction (5). However, while the features of the partners (e.g., their subjective attractiveness) and their link to romantic attraction have been broadly investigated, much less is known about how specific features in the interactions, such as participants' production of emotional expressions, can causally trigger the emergence of romantic attraction. Indeed, while previous research has found associations between subjective measures of attraction and vocal (6) or physiological alignment (7), these findings remain correlational. To our knowledge, no research so far has uncovered causal links between specific social signals and the subsequent emergence of romantic attraction.

A key candidate to causally influence the emergence of romantic attraction is smiling behavior. Smiles are among the most emblematic and ubiquitous human emotional expressions (8). Their perception in e.g. static pictures can increase the perceived attractiveness (9), sincerity, sociability, competence (10), and trust of a person or virtual avatar (11, 12). One important feature of smiles during interactions is social alignment, i.e., the fact that interacting agents often produce smiles synchronously. In interactions, smile alignment has been associated with well-being (13), cooperation (14), and collective intelligence (15). This tendency to share emotional displays with an interactive partner is thought to happen during interactions through imitation and facial mimicry (16, 17). In interactive contexts, studies report that when a research confederate

Significance

Our experimental platform enables researchers to manipulate the social signals produced by participants in real time during social interactions. This platform opens the possibility to uncover how social behaviors (e.g., facial/vocal expressions) and social characteristics (e.g., vocal gender) causally influence social contexts (e.g., dating, job interviews, etc). Using this platform, we manipulated expressive alignment—the fact of sharing an expressive display with an interacting partner. This behavior has been at the forefront of psychological theories for the past decades, but previous studies could not control it in free conversations. Here, we were able to control alignment during free dating conversations. Our findings reveal that expressive alignment can causally increase romantic attraction, as well as affect participants' expressive synchronization.

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imitates a participant during an interaction, the confederate is perceived as more likable (18, 19) trustworthy (20), persuasive (21, 22), and attractive (23). This is why models of emotional contagion pose mimicry (and interindividual coordination) in social contexts as a crucial mechanism underlying emotion contagion (24) and attraction (25).

Our aim with the current study is to artificially align the smiles of dating participants with face transformation algorithms, to investigate its effect on romantic attraction. To do this, we leveraged recent advances in video manipulation algorithms (26) to create an experimental videoconference setup in which we were able to manipulate participants' smiles in a covert and realistic way. We used a digital signal processing algorithm (26) able to parametrically increase or decrease the smiles seen on a person's face (Fig. 1*A*). We then recruited N = 31 single heterosexual participants with the desire to participate in four 4-minute video-conference speed-dating interactions. During the interactions, we digitally manipulated participants' smiles in two congruent and two incongruent directions. During congruent interactions, we increased (or decreased) the smiles of both participants at the same time. During incongruent interactions, we decreased the smile of one participant while increasing the smile of the other one (Fig. 1*B*). Each participant participated in four dates, one in each condition (2 congruent, 2 incongruent). After each date, participants rated 1) their impression of liking the other person, 2) their desire to see the other person again 3) the quality of the conversation, and 4) the other participant's smile. At the end of the experiment, we asked participants a series of increasingly specific debriefing questions to determine whether they had consciously detected the video manipulations. We then extracted the time series of smiling activity from both manipulated and nonmanipulated video recordings (i.e., "what participants saw" vs "what participants produced") with computer vision algorithms to investigate how manipulations influenced the expressive synchronization between participants during the dates (Fig. 1*C*). We also extracted vocal features to investigate how manipulations influenced vocal behavior.

Our predictions were the following: First, we predicted that participants seeing artificially increased smiles would be more attracted to the other participants compared to when seeing artificially decreased smiles. Second, we predicted that congruent and positive manipulations (when we increased both participants' smiles at the same time) would trigger higher levels of attraction and conversation quality compared to the other conditions. Third, we predicted that artificial smiles would propagate, i.e., influence participants' own behavior, triggering e.g., facial mimicry, vocal emotions, or expressive synchronization between participants.

Results

Manipulation Check. To validate that the video manipulations worked as expected, we investigated how smiling varied between manipulated and nonmanipulated video recordings. We confirmed that both face manipulations and subsequent face-tracking algorithms worked as expected for both male and female participants and for both increased and decreased smile conditions (Fig. 2; *SI Appendix* for analyses details, control analyses for different types of motor production, and general methods).

Similarly, to check that participants remained unaware of the face manipulations, we manually transcribed the semantic content of all interactions and analyzed the comments during the debriefing questions (*SI Appendix*, Supplemental Information). Our results confirmed that participants were not consciously aware that the faces in the video streams were being manipulated.

Psychological Ratings: Did the Video Manipulations Affect Participants' Ratings of Attraction and Rapport? For each date, participants rated their impression of attracting the other person, their romantic attraction, the conversation quality as well as their partner's smiling levels with seven-point Likert scales before and after the interactions. We investigated whether such psychological ratings were influenced by video manipulations. To do this, we converted post–pre participant ratings using the Social Relation Models (SRM)—a modeling technique that controls for inter/intra-rater variability specialized in the analysis of round-robin dyadic experiments (*Materials and Methods*).

First, we investigated how *participant condition* (2 levels: increase, decrease) and *other condition* (2 levels: increase, decrease) affected how much participants thought their partner liked them (*other seeing me again* measure, Fig. 3*A)*. We found no main effect of *participant condition* ($\chi^2(1) = 1.3$, $P = 0.24$) but a significant main effect of *other condition* ($\chi^2(1) = 5.9$, $P = 0.01$, Fig. 3*A*). Specifically, participants judged that the other person liked them more when the other participant was manipulated with increased smile (0.33 ± 0.13 SE, $P = 0.01$). The interaction between *participant condition* and *other condition* was not significant ($\chi^2(3) = 0.77$, $P = 0.37$).

Second, we analyzed participants' ratings of *romantic attraction* toward the other person (their desire to see the other person again; Fig. 3*B*). We found no main effect of *participant condition* ($\chi^2(1) = 2.5$, $P = 0.11$), a marginally significant effect of *other condition* ($\chi^2(1) = 3.7$, $P = 0.05$) and, crucially, a significant interaction between *participant condition* and *other condition* ($\chi^2(3) = 9.7$, $P = 0.001$). Bonferroni corrected paired t-tests (Bonferroni-$\alpha = 0.008$) revealed that the trials where we increased smiles in both participants at the same time were the ones where participants felt most attracted to each other. Specifically, there was a significant difference when we increased the smiles of both participants, compared to when we increased the smile of only one participant while decreasing the smile of the other participant (all $P < 0.004$; $t > 3$, $d > 0.55$).

Third, we analyzed participants' ratings of *conversation quality* (Fig. 3*C*). Again, we found no main effect of *participant condition* ($\chi^2(1) = 1.1$, $P = 0.28$), no main effect of *other condition* ($\chi^2(1) = 1.9$, $P = 0.16$), but a significant interaction between *participant condition* and *other condition* ($\chi^2(1) = 17.4$, $P = 0.0001$). Trials where manipulations were congruent were rated as being of highest quality. Bonferroni corrected post hoc comparisons revealed that conversations where we decreased the smiles of both participants were perceived as being of significantly higher quality than incongruent trials where we increased the smile of one participant while reducing the smile of the other ($P < 0.006$, $d > 0.5$).

Finally, we analyzed participants' rating of the smiliness of the other participant (Fig. 3*D*). We found no significant main effect of *participant condition* ($\chi^2(1) = 0.5$, $P = 0.47$), no significant main effect of the *other condition* ($\chi^2(1) = 2.07$, $P = 0.14$), and no significant interaction between *participant condition* and *other condition* ($\chi^2(1) = 3.06$, $P = 0.08$).

We controlled for the robustness of our effects by running GLMM analyses on raw post–pre ratings as well as with post-ratings (*SI Appendix*, Supplementary Information for details).

Expressive Synchrony Analysis: Did the Video Manipulations Affect Participants' Facial Expressive Synchrony? Facial expressive synchrony—the fact that interacting partners spontaneously produce the same emotional expressions synchronously— has

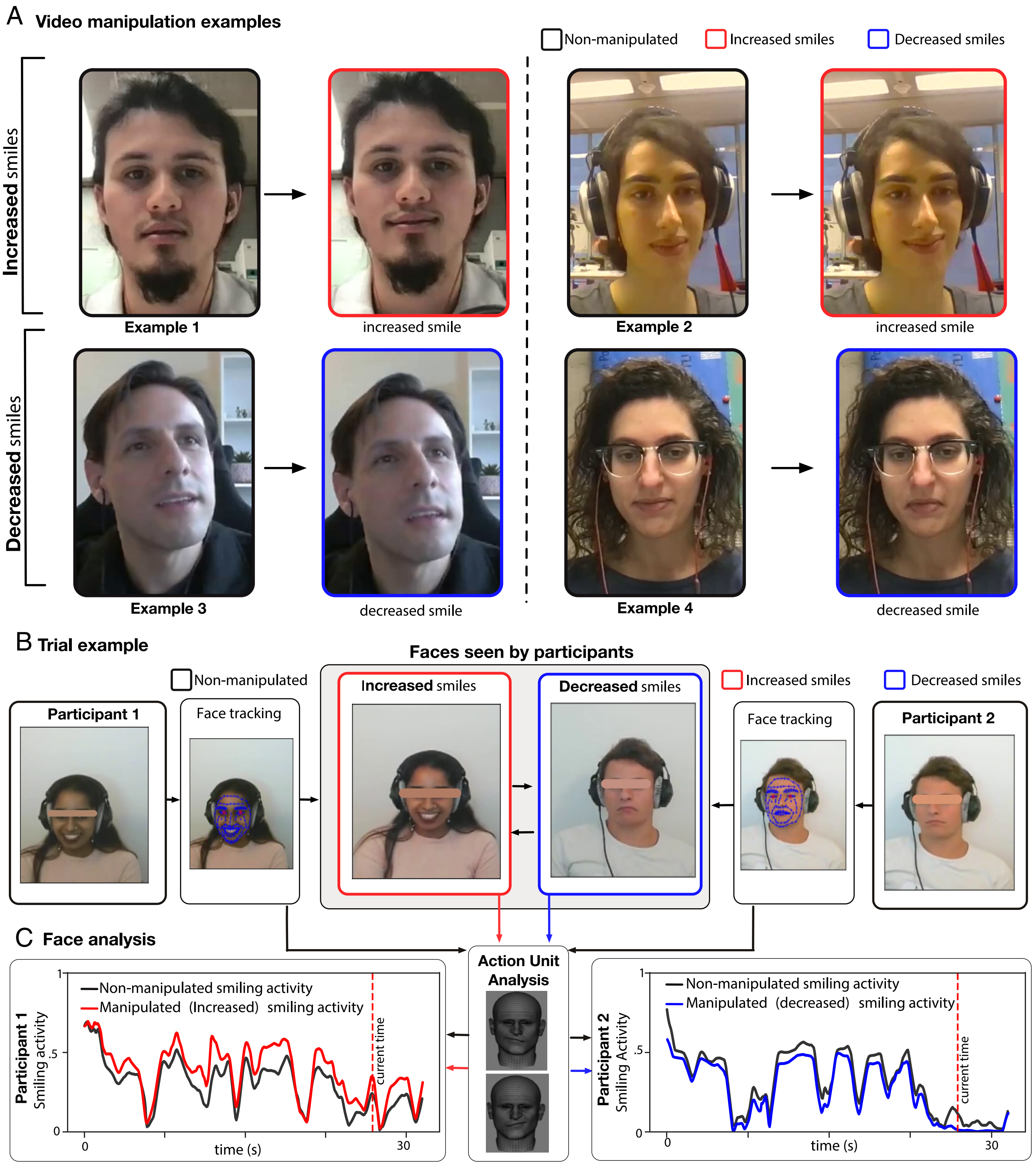

Fig. 1. (*A*) Face manipulation examples. Nonmanipulated faces (black) and the corresponding increased (red frame) and decreased (blue frame) smile manipulation examples. (*B*) Schematics of the experimental paradigm and facial expression analysis. Participant 1 nonmanipulated (black frame) face is tracked and manipulated to increase her smile (red frame). In parallel, participants' 2 original facial expression (black frame) is tracked and manipulated to decrease his smile (blue frame). Participants only see the manipulated videos of their interacting partners and not their own (shaded gray box); the bar over the face is to preserve anonymity. (*C*) After the experiments, we use video recordings to extract participants' manipulated (red and blue) and nonmanipulated (black) smiling activity over time. Note that the manipulation only changes the time series on the y-axis and by a small amount, i.e., the manipulation is a static shift in smiling activity levels. The horizontal red bar indicates the moment in the interaction when pictures were taken.

been associated to positive interacting outcomes (13–15). Here, we investigated whether participants' expressive synchrony was affected by video manipulations. To do this, we extracted happiness time series for each participant and each trial with an emotion extraction model (*Materials and Methods*). We then computed a maximum cross-correlation measure between the happiness time series of participants for each interaction (Fig. 4*A* for an example of highly synchronized time series). The distribution of maximum cross-correlation coefficients significantly differed from 0 (P = 1.6e^{-27}, d = 2.7, Fig. 4*B*). This shows that the baseline state of interaction in our task is that of highly synchronized expressive behavior (27).

We then investigated how video manipulations affected expressive synchrony. To do so, we ran a GLMM analysis testing for main effects of *female condition* (2 levels: increase, decrease),

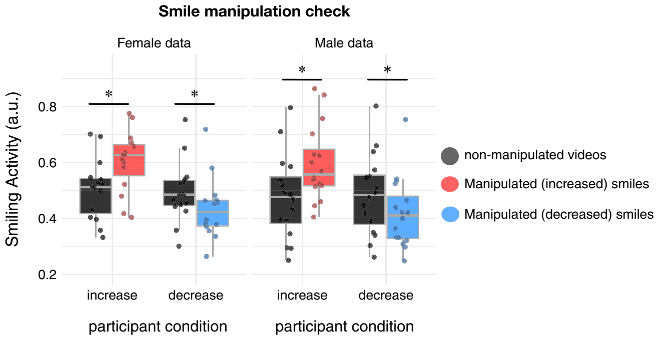

Fig. 2. Smile manipulation check. Analysis of smiling activity for both manipulated and nonmanipulated video recordings and for both the increased smiles and decreased smile conditions; Analysis for both male and female participants. * indicates statistical significance between the distributions assessed with the Bonferroni corrected paired *t* test (Bonferroni-α = 0.0125).

male condition (2 levels: increase, decrease), and *recording* (transformed or not). We used female id and male id as random factors. For the cross-correlation measure, we found a main effect of *female condition* ($\chi^2(1)$=41.0, P = 1.46e^{-10}), but no main effect of *male condition* ($\chi^2(1)$ = 1.05, P = 0.30) and no main effect of *recording* ($\chi^2(1)$ = 0.13, P = 0.71, Fig. 4*C*). For the best fit model, which included only *female condition,* increasing female smiles reduced synchrony by –0.10 ± 0.01 (p = 1.76e^{-10}), compared to when we decreased female smiles. We found no significant interactions between the factors (all χ^2< 1.3, all P > 0.05)—see also Fig. 4*D* to see cross-correlation coefficients as a function of the temporal lag. Moreover, GLMM analyses revealed that trials where we increased both participants' smiles had less synchrony by –0.12 ± 0.01 (P = 6.39e^{-07}) than trials where we decreased both participants' smiles. We found similar results when measuring synchrony with Mutual Information (*SI Appendix*, Supplemental Information). Taken together, our results suggest that video manipulations influenced participants' synchrony. Surprisingly, the most synchronized trials were the ones where we reduced the smiles of both participants. We ran a series of control analyses to control for possible confounding factors. First, we controlled that our effects were also present when considering only nonmanipulated recordings (what participants actually produced). Second, we investigated whether our effects were mediated by a higher variability of time series in one condition compared to another one, which was not the case (*SI Appendix*). Therefore, our control analyses suggest that the effects of the video manipulation on expressive synchrony were not mediated by changes in time series due to the video manipulations, or by higher time series variability, but rather by actual affective synchronization behavior.

Voice analysis: Did the Video Manipulations Influence Voice Production Patterns? Vocal features such as pitch (vocal intonations) and formants (facial expressions and articulation) are important to communicate emotions (28). Therefore, we investigated how these vocal features were affected by video manipulations with a hierarchical GLMM analysis. We studied the effects of *sex* (Male, female), *participant condition* (increase, decrease), and *other condition* (increase, decrease), as well as their interactions.

We found very similar effects for the first, second, and third formants (Fig. 5 *A*–*C*). First, we found the well-known main effect of *sex* for F1 ($\chi^2(1)$ = 24.4, P = 7.7e^{-7}), F2 ($\chi^2(1)$ = 52, P = 4.5e^{-13}), and F3 ($\chi^2(1)$ = 15.8, P = 6.9e^{-15}). Second, we found no main effect of *participant condition* for any formant (F1: $\chi^2(1)$ = 0.04, P = 0.83; F2: $\chi^2(1)$ = 0.18, P = 0.66; F3: ($\chi^2(1)$ = 0.24, P = 0.61). Third, we found a main effect of *other condition* for F2 ($\chi^2(1)$ = 4.2, P = 0.04) and F3 ($\chi^2(1)$ = 5.3, P = 0.02). Finally, we found a significant interaction between *other condition* and *sex* for F1 ($\chi^2(1)$ = 4.7, P = 0.03) and F3 ($\chi^2(1)$ = 5.1, P = 0.02), and this interaction was marginally significant for F2 ($\chi^2(1)$ = 3.3, P = 0.07). Specifically, males tended to increase their first (45.7 Hz ± 20 SE, P = 0.03), second (28.7 Hz ± 15 SE, P = 0.07), and third (43 Hz ± 19 SE, P = 0.02) formant when speaking to a female that was manipulated with an increased smile, compared to when talking with a female that was manipulated with a decreased smile.

For vocal pitch (Fig. 5*D*), we found the well-known main effect of *sex* ($\chi^2(1)$ = 68.7, P = 2.2e^{-16}), but no main effects of *participant condition* ($\chi^2(1.1)$ = 1, P = 0.27), *other condition* ($\chi^2(1)$ = 0.08, P = 0.77), or interaction between factors (all χ^2< 2, all P > 0.05).

In short, while female participants did not seem to change their voice production patterns depending on video manipulations, males increased their formant frequencies when interacting with females whose faces were manipulated with an increased smile.

Discussion

In the current study, we used real-time face transformations to investigate the social signals that causally influence the emergence of romantic attraction between dating participants. This paradigm enabled us to go beyond the correlational findings of interaction recording analyses (7), as well as improve the ecological validity of studies using confederates or virtual avatars (1). Therefore, digital transformations may enable researchers to overcome current limitations in the field of social interaction research (1). A handful of experimental studies have tested these possibilities, particularly in the field of affective computing (30, 31). Moreover, several digital signal processing technologies could be used to manipulate vocal and facial signals realistically, in real time (32), and in a wide variety of social contexts (e.g. job interviews, multiperson games, cooperation tasks). These techniques seem ripe for adoption in social interaction research. To facilitate its adoption, we are sharing for free and in open-source format the experimental platform DuckSoup, which we built to enable researchers to perform these experiments online.[*]

Using this paradigm, we found that participants were influenced by the artificial smiles they saw on the face of their interacting partner. Specifically, participants thought the other person was more attracted to them when we increased the smiles seen in the other person. This is in line with findings that highlight the prosocial function of smiles (33), and how smiling can positively influence social affiliation (14), trust (34), or interactive cooperation (11). However, while previous findings show how smiling pictures, prerecorded smiling videos, and smiling virtual avatars can positively influence social scenarios (12, 35, 36), our study provides empirical evidence showing that digitally altering smiles during conversations can causally and covertly influence the inferences individuals make about each other's social intentions. Nevertheless, the specific mechanisms triggered by our artificial smiles to create prosocial reactions remain unknown. This is in part because our manipulation altered the smiles of participants' statically across the trial. Therefore, our

[*]https://github.com/ducksouplab/ducksoup.

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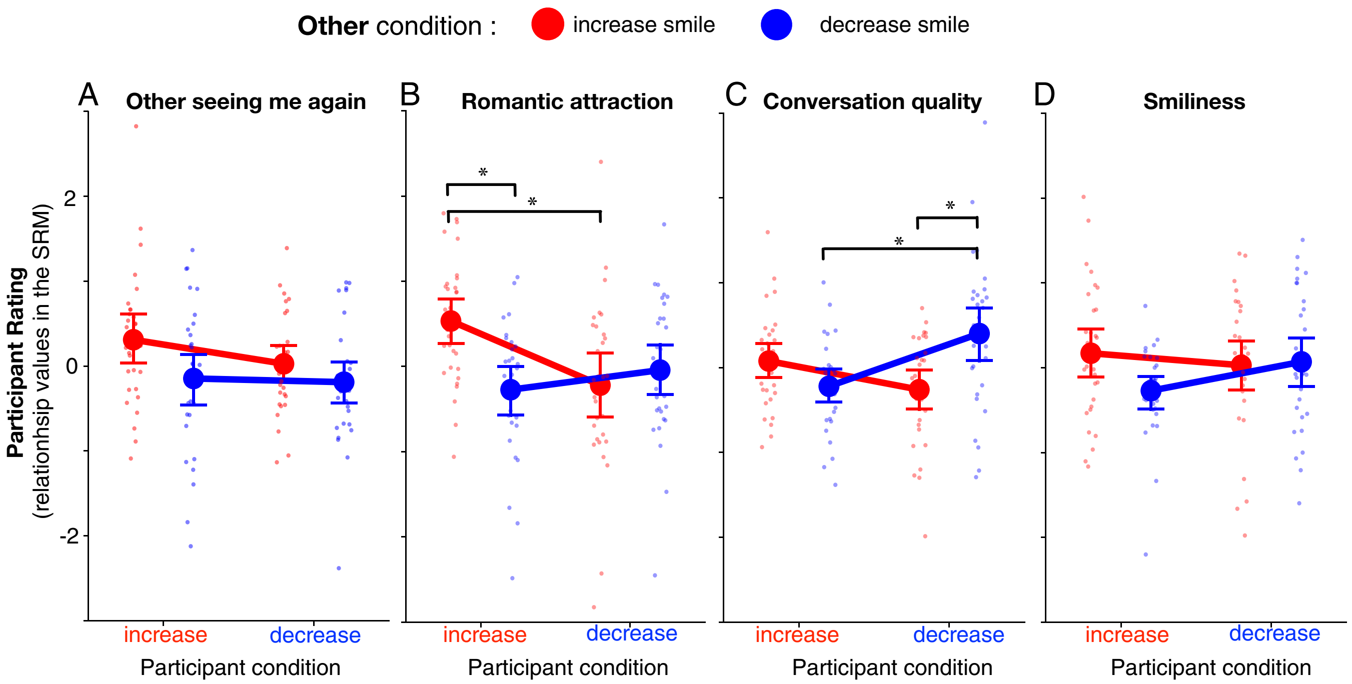

Fig. 3. Mean SRM ratings for the psychological questions in the experiment for both participant condition (increase/decrease) and other condition (increase/decrease) (*A*) Other seeing me again: To what extent do you think the other person wants to see you again? (*B*) Romantic attraction: To what extent do you want to see the other person again? (*C*) Conversation quality: To what extent was the conversation pleasant and interesting? (*D*) Other smiliness: To what extent was the other person smiling? Error bars are 95% CI on the mean; * indicates statistical significance between the distributions assessed with the Bonferroni corrected paired *t* test (Bonferroni-α = 0.008).

manipulation influenced all types of smiles produced by participants (e.g. genuine, coy, affiliative (37), feigned or not feigned Duchesne smiles (38, 39)—*SI Appendix* analyses). As a result, manipulated smiles may have been interpreted as different kinds of smiles across the interaction context. However, while the interaction of our manipulation with specific kinds of smiles remains unknown, our results demonstrate that shifting average smiling levels across the interaction is enough to trigger prosocial responses.

More importantly, we found that participants were most attracted to each other when we increased the smiles of both participants at *the same time*. Similarly, participants rated interactions where we used congruent manipulations as being of higher *conversation quality* compared to interactions where we used incongruent manipulations. Therefore, the manipulations in participants' own face influenced their ratings even if they were not seeing these manipulations. Previous research investigated the link between expressive alignment and prosocial behaviors. However, experimental paradigms were not able to investigate these behaviors in free human–human interactions—because researchers had to rely either on research confederates (18, 19) or virtual avatars (1). Our paradigm manipulates the alignment of facial expressions in real time and demonstrates a causal role of such artificial alignment on free dating interactions.

Interestingly, we did not find evidence of video manipulations propagating to participants' own facial expressions in the form of facial mimicry (*SI Appendix*). This suggests that the effect of our video manipulations on behavior is independent of participants' facial imitation of the manipulations. This uncovers the phenomenological difference between "experiencing an interaction where

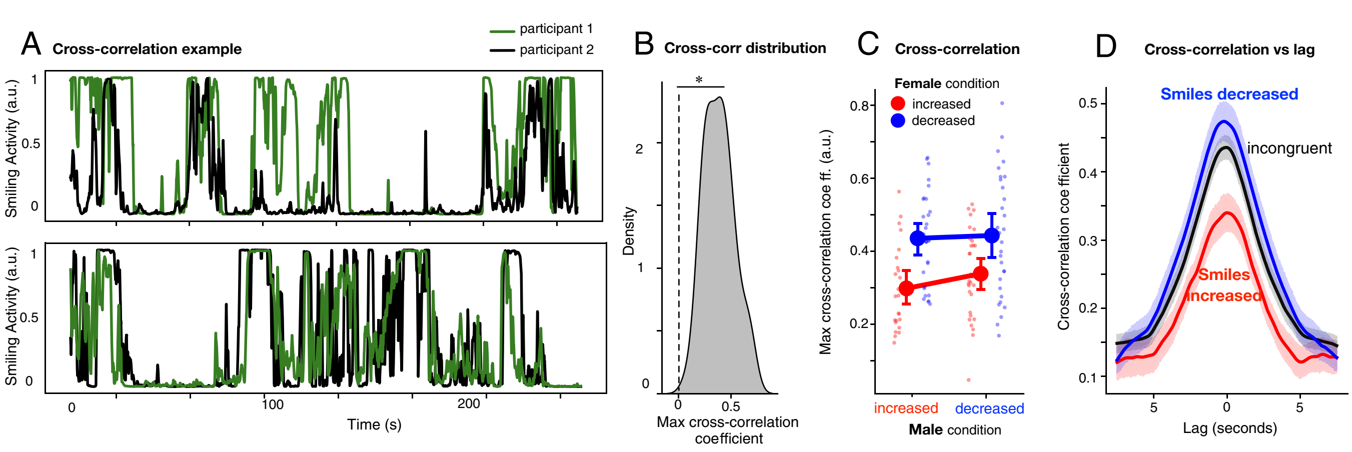

Fig. 4. (*A*) Time series example of an interaction with a high max cross-correlation coefficient. (*B*) Distribution of maximum cross-correlation coefficients; *statistically significant difference from 0 ($P < 0.05$). (*C*) Maximum cross-correlation coefficient for both female and male conditions. Error bars are 95% confident intervals. (*D*) Cross-correlation coefficient for trials where we increased both participants' smiles (red), trials where we decreased both participants' smiles (blue), and trials where we increased the smile of one participant and decreased the other one (black) as a function of cross-correlation lag; Error bars are SEM.

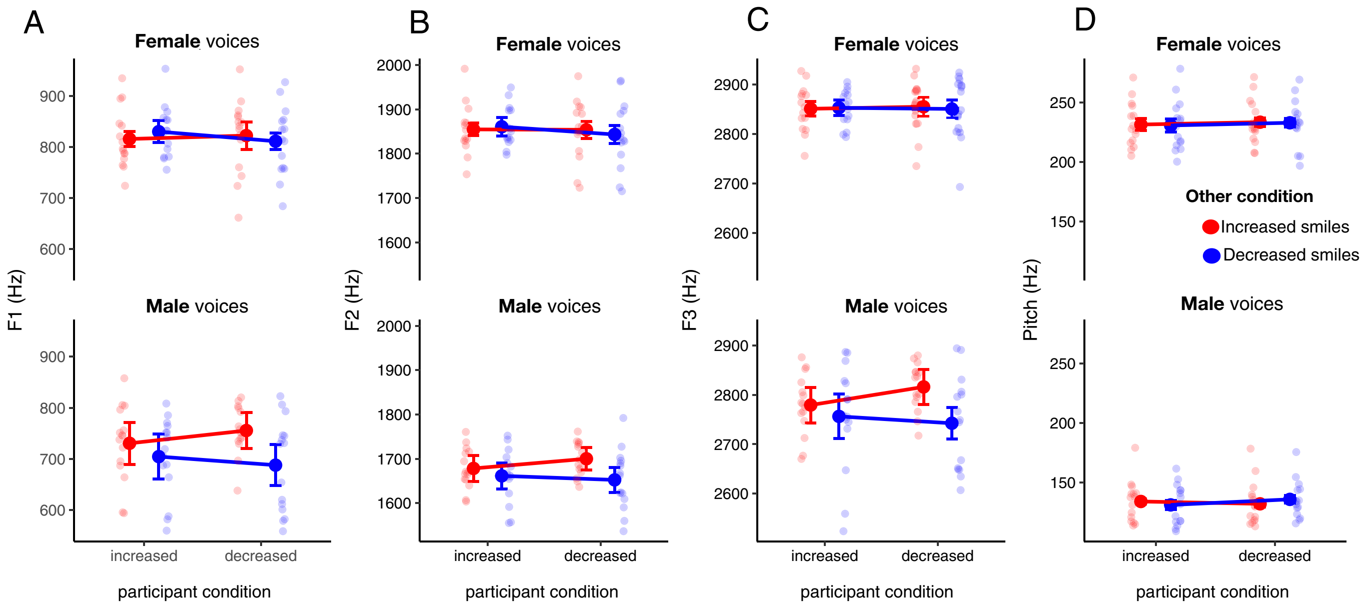

Fig. 5. First (*A*), second (*B*), and third (*C*) formant frequencies and (*D*) vocal pitch (Hz) for each condition and each participant sex. Error Bars are 95% CI (CI) computed for within-subjects designs (29).

faces are aligned," and "being physically aligned." More specifically, our data suggest that experiencing an interaction where faces are aligned is enough to trigger prosocial behavior, even if participants are not physically aligned. This is an interesting distinction that has, to our knowledge, not been mentioned in previous research. This distinction suggests that multimodal feedback loops can be causally triggered by concomitant smile perception, while also being, to some extent, independent of participants' own motor production and interoceptive reflections thereof.

In this line, video manipulations affected how participants facially synchronized to each other. Specifically, participants' production of happy facial expressions was significantly *more synchronized* when we *decreased* the smiles of both participants—compared to when we *increased* the smiles of both participants. Previous research associated expressive synchrony with well-being (13), cooperation (14), and collective intelligence (15). Our results complement these findings by showing that artificial social signals can causally trigger the emergence of expressive synchrony. One possibility is that seeing decreased smile manipulations in the other person's face, triggered e.g., an urge to synchronize with them compared to when seeing increased smiles. This behavior may be driven by an increased desire of participants to build rapport with their interacting partner, when seeing that their partner is not portraying a positive facial display, and possibly less attracted (c.f. *other seeing me again* ratings).

Previous correlational studies on romantic attraction (40) reported that smile synchronization was not associated with attraction in dating contexts. Our findings further demonstrate that artificially aligning participants' smiles by increasing their smiling activity promotes attraction, but not smile synchronization. To put these findings into perspective, it is important to highlight that our smile manipulation is conceptually different from synchrony measures using e.g. cross-correlation. Indeed, our manipulation shifts the average level of smiling activity by a static amount across the trial. Therefore, it does not change the synchronization per se of time series. In our experiment, actual synchronization behavior (i.e. the one that relies on the dynamics of time series) is only changed by participants' overt production strategies. Therefore, both our data and previous literature (7) suggest that smile synchronization might not be as directly linked to attraction in speed-dating settings as it is to prosocial responses in other social contexts (13–15).

We also found that male and female participants reacted differently with their voice to the video manipulations. Specifically, male participants increased their formant frequencies when we manipulated female faces with an increased smile—an effect that was absent in female voices. Both human and animal males seem to use formants as mating signals (41, 42). In line with the previous literature, our results also suggest a sexual asymmetry in the use of formant vocal signals in reaction to facial expressions. On the one hand, artificially increased (vs decreased) female smiles may have made males react with higher formants to communicate positivity and prosocial intentions (28). On the other hand, lower formants may be a reaction to the decreased smile manipulation in female's faces, to try to appear more attractive (43). These vocal reactions may be unconscious and mediated by e.g., attraction, or arousal mechanisms which are triggered in males in response to seeing their interacting partner smiling and thinking they are romantically attracted (c.f. *other seeing me again* ratings). Although the specific function of such vocal signals remains unknown, our data highlight that males adopt specific vocal patterns in reaction to the emotional expressions they see in the face of their interacting partners.

Finally, we finish highlighting the ethical considerations of the present study. The ability of AI technologies to manipulate human social signals is unprecedented (44). Some of these tools were recently deployed to the smartphones of billions of social media and video-conference users worldwide in the form of transformation filters (45). Psychological research is progressively uncovering the impact of these new technologies in users' mental health (46, 47) and behavior (48, 49). However, the ability of transformation filters to causally influence human interactions is still mostly unknown. In the current study, we give a glimpse of how such transformation filters may impact social interactions. Interactions where individuals can realistically transform other's social signals open the potential to create social contexts in which e.g. race, gender, identity, social traits, or emotional expressions can be digitally controlled for both ethical and unethical applications (50). A discussion about the regulation of transformation filters should take place at a societal level. This discussion should consider that transformation filters can be used by individuals to control how they are perceived by others (46), how they perceive others (51), or, in the most dystopic scenario—which is the one studied in this article—to covertly control how third party individuals perceive each other.

Materials and Methods

Participants. We estimated the required sample size for a within-participants paired *t* test to achieve 80% power at a significance level of alpha = 0.05, with an assumed medium effect size of 0.5, using the R package pwr. This yielded a group size of N = 33. We also ran Monte Carlo simulation to investigate how sample size influenced power in our specific data structure (for results and an in-depth rationale on power estimation please see *SI Appendix*).

Therefore, we aimed to recruit N = 32 participants (16 males, 16 females)–because data collection was organized in batches of 4 male and 4 female participants (see below). One participant was absent for data collection. In total, N = 31 participants (male = 15, female = 16, mean age = 22, min = 20, max=27) took part in this experiment. No participant reported psychological/neurological disorders. All participants were heterosexual, single, and were willing to participate in a real speed-dating experiment where they would have the option to potentially connect with their partners at the end of the experiment. All participants gave their written consent and were paid at standard rate for their participation.

Procedure and Apparatus. We asked participants to participate in four subsequent four-minute video-conference speed-dating interactions (2) while seated in a windowless cubicle. The conversations were entirely unscripted: We instructed participants to talk about any conversation topic they wanted with their interacting partner for the whole length of the interaction. We equipped participants with Beyerdynamic DT770 pro headphones. We recorded all interactions with Logitech C920 webcams at 30 frames per second.

We organized data collection in batches of eight participants. For each batch, four males and four females interacted with each other, following a round-robin design (52). We collected 4 batches of 8 participants in total. One female participant was absent in one of the sessions. Thus, we collected a total of 60 interactions from 31 different participants.

Real-time Face Manipulation. To realistically transform participants' smiles in real time, we used a digital signal processing algorithm able to parametrically increase or decrease the smiles seen on a person's face (26). The algorithm tracks morphological features of the face, such as the mouth, and deforms their shape using a predefined parametric model. Then, the algorithm recreates textures and colors with a Moving Least Square algorithm. In the current work, the smile transformation algorithm is static, which means that it linearly increases/decreases smiles independently of participants' original facial posture. That is, the manipulation can increase/decrease smiling activity when participants are talking or already smiling (see SI). *SI Appendix*, Fig. S1*A* shows an example of increase/decrease smile manipulations. We validated this algorithmic model in previous research both on emotional and smile rating scales (26).

In the current work, we used this smile manipulation algorithm to transform participants' facial expressions in two congruent and two incongruent conditions. During congruent interactions, we either increased or decreased the smiles of both participants at the same time. During incongruent interactions, we used opposing face manipulation algorithms on the two participants: We either decreased the smile of one participant while increasing the smile of the other participant, or vice versa (*SI Appendix*, Fig. S1*B*). At the beginning of the interaction, the experimenter calibrated the intensity of the algorithm, so its effect was subtle but visible on participants' faces.

Psychological Ratings. Before each interaction, we presented participants with a photograph of the participant they were going to interact with and asked them to answer four questions, aiming to assess the romantic interest of participants toward their date (subsequently referred to as "pre ratings"). Participants gave their response using seven-point Likert scales. The questions were the following:

- To what extent do you think this person will want to see you again after the date? (*Other seeing me again*).
- To what extent do you think you will want to see this person again after the date? (*Romantic attraction*).
- To what extent do you think the conversation will be pleasant and interesting? (*Conversation quality*).
- To what extent is this person smiling? (*Other smiliness*).

After each interaction, participants answered these four questions again, but now basing their ratings on the interactions rather than on the photographs of participants (post-ratings). The four questions were the following.

- To what extent do you think the other person wants to see you again? (*Other seeing me again*).
- To what extent do you want to see the other person again? (*Romantic attraction*).
- To what extent was the conversation pleasant or interesting (*conversation quality*).
- To what extent was the other person smiling? (*other smiliness*)

Debriefing Procedure. After the experiment, we debriefed all participants to investigate whether they had detected the face manipulations. We used a 3-stage debriefing procedure, where we asked participants three increasingly specific questions. First, we asked participants to rate sound and image quality in a seven-point Likert scale ranging from "much worse than Skype or Zoom" to "much better than typical videoconferencing software like Skype or Zoom" (later referred to as question 1: image quality). Second, we asked participants to rate conversation fidelity, which we explained was a measure of participants' impression of whether they thought the other person was able to make a fair impression of themselves (later referred to as question 2: fair impression). Finally, we asked participants whether they thought we had manipulated the face of their partners with real-time smile transformation algorithms (later referred to as question 3: smile manipulation). To introduce this question, we first explicitly told participants that we manipulated the facial expressions of a fraction of randomly selected interaction with signal processing algorithms and asked whether they thought their interaction was one of them. Participants gave their answer on a seven-point Likert scale ranging from "I'm sure there was a manipulation" to "I'm sure there was no manipulation" (middle point: "I don't know"). For all the questions, participants could write comments to complement their ratings.

At the end of the experiment, all participants were carefully informed that the faces that they had seen and interacted with were subtly manipulated with face algorithms. We explained to participants that if anything uncomfortable happened during the interactions it could be attributed to the face manipulations. We also explained that these manipulations were subtle and did not change the general dynamics of the facial expressions or any content of what was being said.

Debriefing Measurements. Please find below the translated text we used to debrief participants at the end of the experiment.

1. **Sound and image quality:** "Evaluate the sound and image quality of the conversation you had, by comparing them to those that you are used to have in other platforms such as Skype, FaceTime, Messenger, or Hangouts. An image of bad quality may be cut, deformed, out of focus, or difficult to see. Bad quality sound may be noisy, cut, saturated, or difficult to understand." *SI Appendix*, Fig. S2*A* presents the results to this question.
2. **Conversation fidelity:** "Some video-conference conversations give us the impression that the other person was not able to make a fair impression of ourselves, because e.g., the image quality didn't do us justice, or because the other person could not really hear what we were saying. To what extent do you think that the videoconference setup influenced the impression that your interlocutors had from you, and the impression that you had from them?" *SI Appendix*, Fig. S2*B* presents the results to this question.
3. **Possibility of a smile transformation:** "For some participants in the experiment (chosen randomly), the face that they saw from their interlocutor was manipulated with computer vision algorithms to make the person either more smiling or less smiling than what they really were. These participants interacted with a real person, who was not aware that we could had increased or decreased their smile in his/her face. This algorithmic manipulation, for the participants who saw it, is quite realistic and not easy to detect. However, a certain number of other participants had perfectly natural interactions, without

their smiles being manipulated algorithmically. Based on the memories of the interactions that you had, to what extent do you think that you were part of the participants who saw an interlocutor whose smile was manipulated?" See *SI Appendix*, Fig. S3C for the results to this question.

Ethics. All experiments were approved by the Institut Européen d'Administration des Affaires (INSEAD) IRB. In accordance with the American Psychological Association Ethical Guidelines, all participants gave their informed consent and were debriefed and informed about the purpose of the research after the experiment.

Data Preprocessing—Audiovisual Recordings. For each interaction, we recorded both manipulated and nonmanipulated videos. Manipulated videos are the videos that participants saw during the interactions and included manipulated smiles. Nonmanipulated videos are what participants physically produced (without any manipulation). We synchronized video recordings for each interaction using the time-tag of creation of each recording with millisecond precision and used it to compute the lag between recordings of the same dyad. We trimmed videos using a python wrapper around the ffmpeg library (53).

Data Preprocessing—Analysis of Facial Activity. To analyze the recorded interactions, we leveraged recent advances in computer vision to extract participants' facial activity in the form of Action Units (A.Us) (54) and emotional expressions (e.g. happiness). To do this, we used the AI-based face analysis python module py-feat (55). Essentially, after a face detection stage, these models extract facial landmarks to extract its Action Units–or individual muscle movements. To extract Action Units, py-feat extracts Histogram of Oriented Gradient (HOG) features within the landmark coordinates using a convex hull algorithm, compresses the HOG representation using Principal Components Analysis, and uses these features to predict Action Units. To measure facial expressions of happiness, which are often composed of both AU12 (zygomatic major) and AU06 (orbicularis oculi) activity, emotion detectors were trained on emotional facial expressions to classify new images based on how much they resemble a canonical emotional facial expression (55). See also (55–57) for algorithmic explanations of these procedures, validations, and reviews.

To optimize the performance of the face-tracking algorithm, we preprocessed videos with a contrast and luminance filter. To do this, we extracted the frames in each video at 30 frames per second and used the luminance (gamma: 2, saturation: 1.2) and sharpness filters of the ffmpeg library to improve facial exposure and the performance of face detection algorithms. We used the action unit, emotion, and landmark models built into py-feat for automatic extraction of face features (parameters: Face model *retinaface*, landmark model: *mobilefacenet*, action unit model: *xgb*, emotion model: *resmasknet*, face pose model: img2pose).

This way, we extracted synchronized AU12 and happiness time series sampled at 30 Hz for all participants and for all interactions. To control for noise stemming from locally inaccurate facial tracking, we performed a moving-average normalization of time series using a window size of 30 samples–as is usually done with more classic Electromyography (EMG) data (28).

Analysis of Psychological Ratings. To analyze participants' ratings, we first computed the difference between ratings after the interaction minus ratings before the interactions (post - pre). We then used Social Relation Models to control for inter- and intrarater variability (52, 58). The Social Relation Model is a data analysis technique developed to analyze Round-Robin social interaction experiments–where participants interact in dyads with more than one partner. The SRM allows researchers to quantify how ratings are affected by participants' intrinsic characteristics (e.g., their physical attractiveness, personality, etc.), as well as their specific rating strategies. This is done by modeling each rating as a function of the average of all the notes given and received by a specific person, and adding a trial-specific term that quantifies how much each rating deviates from that average baseline.

For instance, suppose that Esther reports a strong feeling of attraction toward Julian after their speed-dating interaction. By analyzing all the ratings given and received from and by Esther during the experiment, the Social Relation Model computes three independent measures affecting the ratings. First, Esther may report high attraction toward all the men at the event (e.g., she is naturally attracted to people, and rates them accordingly). This is called an "actor effect." Second, all the women at the event may find Julian attractive. This is called a "partner effect." Third, there might also be something unique about the interaction between Esther and Julian, which made her feel attracted during the interaction (e.g., a shared music interest, hobby, etc.). This is called a "relationship effect." More generally, the rating that participant A gives to participant B is modeled using the following equation:

$$X_{A\to B} = \mu + \alpha_A + \beta_B + \gamma_{AB} + \epsilon,$$

where $X_{A\to B}$ is the rating of A to B; μ is the mean of all scores; α_A is participant's A actor effect; β_B is participant's B partner effect; γ_{AB} is the unique response of AB after controlling for each other's actor and partner effects respectively; and ϵ is a random error term.

In our data, we computed actor and partner effects for each participant, as well as relationship estimates for each participant and each interaction (estimates are presented in *SI Appendix*, Table S1). For the GLMM analysis in the main text, we used per trial and per participant relationship estimates (but see *SI Appendix*, Supplemental Information analyses for replication of the effects using raw ratings).

Analysis of Facial Expressive Synchrony. Inspired by recent literature investigating behavioral and physiological synchrony between interacting partners during interactions (7, 13, 15, 59–61), we investigated whether our manipulations affected facial expressive synchrony between participants. In this work, we consider that facial expressive synchrony refers to participants producing a happy facial expression, with a temporal lag of ~5 s [e.g., one participant smiles, and the other participant smiles in return within five seconds (60]

We assessed synchrony using two different methods. First, we used cross-correlation. To do so, we z-normalized happiness time series from interactions and computed the maximal cross-correlation coefficient between both participants' time series within ±5 s temporal lag (13). We then Fisher z-transformed the coefficients for statistical analyses (13, 62, 63). Second, we computed Mutual Information (MI), an information theoretic measure of the mutual dependence between two random variables. Compared to cross-correlation, Mutual Information does not quantify a temporal lag between the variables, but the strength of information coupling (64). We computed mutual information using the scikit-learn (65) mutual_info_regression function, which relies on nonparametric methods based on entropy estimation from k-nearest neighbors distances (66, 67).

Note the conceptual distinction between our video manipulation and the "expressive synchrony" measure. On the one hand, our video manipulation statically increases/decreases average smiling levels across the interaction. On the other hand, our measure of expressive synchrony quantifies the temporal coupling between participants' happy facial expressions. That is, we measure high synchrony when participants do (or stop doing) the same facial expression at the same time (± 5 seconds), which is independent of the average levels of time series.

Voice Analysis. Finally, we extracted vocal formants and vocal pitch to investigate the voice production patterns and strategies of participants during the task (68). Specifically, we measured the first, second, and third formant frequencies (F1, F2, F3), which represent the articulatory resonances of the vocal tract (69). Formants are not only essential to convey phonetic information, but also key to convey emotional information such as emotional facial expressions and articulation (28, 69–71). We also extracted vocal pitch, a measure of the speed of vibration of the vocal folds, resulting from the expiration from the lungs and the contraction of muscles in the pharynx. Vocal mean pitch and SD have been linked with emotional prosody (72, 73), speaker reliability (74), and social attitude communication (68, 75).

We extracted both formants and pitch using custom python wrappers on the Praat software (76). First, we extracted pitch with a time step of 0.01, with a maximum and minimum frequency tuned manually for each speaker by considering the spectrograms. Second, we extracted formant time series using a window size of 0.03 s, a time step of 0.2 s, a pre-emphasis of 50, 5 number of formants, and a max formant frequency which varied depending on the speaker's sex (male: 5,500 Hz, Female: 4,900 Hz–values chosen with manual inspection of speaker's spectrograms). To clean time series, we extracted harmonicity time series for all recordings using IRCAM's Analysis/Synthesis super-vp command-line Tool. Because formants and pitch can only be estimated for harmonic speech content, we discarded all disharmonic samples from the data (typically silence and unvoiced speech excerpts). We used a harmonicity threshold of 0.02 (maximum = 1). After cleaning time series, we averaged time series for each recording and for each acoustic feature.

Statistical Methods. We used GLMMs (Generalized Linear Mixed Models) to test for main effects and interactions. We report p-values, estimated from hierarchical model comparisons using likelihood ratio tests (77), and only present models whose residuals satisfy the assumption of normality (validated by visually inspecting the plots of residuals against fitted values), and whose results were significantly different from the nested null model—a model that included all significant main effects except the main effect of interest being tested. To test for main effects, we compared models with and without the fixed effect of interest. To test for interactions, we compared models including fixed effects versus models including fixed effects and their interaction. We included participants as a random factor. We used the paired *t*-test for post hoc tests.

Data, Materials, and Software Availability. Anonymized .CSV data and analysis code for this article can be found here: https://github.com/Pablo-Arias/speed_dating (https://archive.org/details/data_20231023_20231023) (78). All study data are included in the article and/or *SI Appendix*.

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