Synchronized affect in shared experiences strengthens social connection

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Abstract

People structure their days to experience events with others. We gather to eat meals, watch TV, and attend concerts together. What constitutes a shared experience and how does it manifest in dyadic behavior? The present study investigates how shared experiences - measured through emotional, motoric, and cognitive alignment - promote social bonding. We recorded facial expressions of participants as they watched four episodes of a TV show for a total of four hours with another participant. After each episode, participants rated their impressions of each character and reported how connected they felt to their viewing partner. We found that participants displayed temporally and spatially synchronized emotional facial expressions and the amount of synchrony predicted perceived social connection between viewing partners. Dyads who shared similar impressions of characters also reported feeling more connected. We found that all three of these processes independently contributed to a latent factor of a shared experience that predicted social connection with temporal synchrony explaining the most variance. Our findings suggest that the development of interpersonal affiliations in shared experiences emerges from shared affective experiences comprised of multiple synchronous processes and demonstrate that these complex interpersonal processes can be studied in a holistic and unified framework leveraging naturalistic experimental designs.

Introduction

People value shared experiences¹. Experiences in large groups such as religious ceremonies, music concerts, and sporting events often involve synchronization in movements, vocalizations, feelings, and thoughts with others, which has been thought to strengthen group cohesion²⁻⁶. This amplified feeling of connection following a shared experience can also occur in everyday settings. For example, simply watching an emotional film rather than a neutral documentary in a crowd can foster feelings of connection with the audience⁷. However, we know very little about *how* the different synchronous processes that occur in social contexts contribute to the feeling that an experience is shared between individuals and facilitate social connection.

Frequently observed group behaviors such as synchronous singing in concerts or simultaneous reactions during a movie has led to a common assumption that co-experiencing the same external stimuli elicits equivalent responses across people. However, just as people do not all enjoy the same scenes or like the same characters in a movie, individuals' thoughts and feelings may occasionally deviate from each other reflecting idiosyncrasies in attention, goals, and preferences⁸⁻¹⁰. These variations in endogenous signals can impact cognitive appraisals of unfolding events and the generation of affective meaning^{8,11,12}. Consequently, individuals' physiological arousal^{4,13}, neural responses^{9,14,15}, and facial expressions^{16,17} may converge and diverge throughout the course of an experience reflecting dynamically shifting alignments of thoughts and feelings^{4,18,19}.

Synchronous alignment of experiences may be reflected in moment-to-moment temporal dynamics of facial expressions²⁰. Most facial expression research, however, has traditionally focused on comparing summary statistics across experimental conditions (e.g., amplitude difference or frequencies)²¹⁻²⁴. For example, based on counting the frequency of positive and negative facial expressions when watching a video revealed that roommates and dating partners appear to become more similar over time in how they respond to the videos²⁵. However, this measure of convergence does not directly test if individuals display the same positive and negative expressions at the same moments in time. Alternatively, convergence could also arise as a result of emotional contagion in which one person's emotional state directly influences another's subsequent state²⁶⁻³². Therefore, examining moment-to-moment fluctuations in emotional facial expressions may provide a more nuanced understanding of how and when individuals "click" during shared experiences.

Individuals may also synchronize in *how* they express certain emotions through different configurations of facial muscle movements during a shared experience. Though emotion research has typically focused on a limited number of canonical expressions³³, recent efforts to uncover natural variations of emotional facial expressions in the wild and across cultures have highlighted considerable diversity in the specific spatial configuration of muscles that comprise a facial expression³⁴⁻³⁷. Subtle variations in these expressions, such as types of smiles, can convey vastly different meanings to an observer^{38,39}. Within an interaction, convergence on a

shared ontology of communication signals (e.g., facial expressions) may improve the ease of communication and degree of social connection⁴⁰. This can be observed in “chameleon” effects, in which individuals mutually adapt to each other’s behavior during an interaction^{41–51}. Greater degrees of behavioral similarity (e.g., smiling, face touching, and leg shaking) between individuals tends to yield smoother and more enjoyable interactions^{41,44} although these findings may not be consistent across contexts^{52,53}.

In this study, we examine how the alignment of emotions, expressions, and thoughts during shared activities arise from a shared experience and contribute to the development of social connection (Figure 1). We used a naturalistic paradigm, in which participants ($N = 86$) watched four episodes of a character-driven television drama, *Friday Night Lights*, for approximately four hours over two viewing sessions. Participants either watched the show alone or with another previously unacquainted participant sitting next to each other (Figure 2A). During the show, we continuously recorded participants’ faces using head-mounted cameras⁵⁴ to probe moment-to-moment displays of emotion and facial muscle movements and used a pre-trained convolutional neural network⁵⁵ to convert each video frame into predicted emotions and action units, which reflect the firing intensity of different groups of facial muscles. After each episode, participants independently rated their impressions of the characters (e.g., How much do you like this character? How much do they remind you of someone you know?) and the dyads rated how connected they felt to their viewing partner. We predicted that participants watching videos in dyads would exhibit greater synchronization in emotional facial expressions during viewing and that the degree of temporal and spatial synchronization of facial expressions along with the similarity of character impressions would predict feelings of connection. Finally, we attempted to disentangle how these synchronous processes that concurrently arise during a shared activity contribute to the feeling that an experience is not merely experienced together but is actually shared between individuals that ultimately help form social bonds.

Figure 1. Components of shared experiences. Simultaneously experiencing a stimulus between individuals can lead to affective experiences synchronized in time (temporal affective synchrony), synchronized patterns of facial muscle activations in how emotion is displayed (spatial motor synchrony), and similar appraisals of the experience (appraisal synchrony) that can facilitate the development of interpersonal affiliation.

Results

Temporal alignment of affective facial expressions

First, we evaluated if participants watching the show in a social context exhibited greater synchronization of facial expressions compared to those who watched alone. We specifically looked at the probability of predicted emotions aggregated into positive and negative valence at each frame of the video. Next, we computed the temporal alignment between participants by calculating the Pearson correlation between pairs of participants' facial expression trajectories for positive and negative emotions separately for each group per episode, and assessed the significance using subject-wise bootstrapping against a null correlation⁵⁶. In episode 1, we found significant synchronization in positive facial expressions for both the dyad (Pearson $r_{\text{Episode1}} = .23, p < .001$) and alone groups ($r_{\text{Episode1}} = .06, p < .001$), with comparable significant results in all subsequent episodes (Figure 2B; Table S1). Across all episodes, positive facial expression synchrony in dyads was significantly higher than synchrony among participants who watched alone with an average correlation difference of $\beta = .20, t(31) = 5.21, p < .001$ and this difference increased over subsequent episodes ($\beta = .03, t(34) = 3.20, p = .003$). To test if the increased synchrony was specific to the dyads who watched together or was a general phenomenon of social context, we also compared the alignment of paired dyads to random combinations of unpaired dyad participants (random pairs of participants from the dyad group who did *not* physically watch the episodes together). Across episodes, we found that paired dyads exhibited greater synchronization compared to unpaired dyads with an average

correlation difference of $\beta = .13$, $t(28) = 6.81$ $p < .001$, and unpaired dyads synchronized more than participants that watched alone with a difference of $\beta = .07$, $t(74) = p < .001$ (Figure S1). Overall, we did not observe a significant main effect of synchronization in negative facial expressions. However, dyads did synchronize more than the alone group in specific episodes (episode 1: $r = .07$, $p = .01$; episode 2: $r = 0.05$, $p = .047$; episode 3: $r = .02$, $p = .44$; and episode 4: $r = .07$, $p = .0013$) (Figure 2B). As the synchrony was minimal for negative facial expressions, we focus the rest of our analyses on positive facial expressions unless otherwise stated.

Next, we examined whether positive facial expression synchrony was driven by specific events during the show. To test this we used a 30-second sliding window correlation to compute local positive facial expression synchrony at every second of the show (Figure 2C). These trajectories were then compared with self-reported emotion ratings from participants recruited on Amazon Mechanical Turk watching episode 1 ($N = 182$) collected from a previous study⁸. Overall, we found that moment-to-moment positive facial expression synchrony in dyads positively correlated with average subjective feelings of joy ($r = .24$, $p < .001$) and negatively with feelings of sadness ($r = -.12$, $p < .001$). We then located specific moments in the show when dyads displayed greater synchrony than the alone group using a cluster-based permutation test⁵⁷. This analysis identified five short temporally contiguous scenes in which dyads synchronized more than the alone group in Episode 1 (see Figure S2 for other episodes) including scenes of (a) two male characters awkwardly approach a female character (8th minute), (b) many characters socialize at a party (18th minute), and (c) an underdog character scores a winning touchdown (42nd minute). These scenes appeared to evoke largely “feel-good” or humorous feelings, as average joy ratings were significantly higher than other emotion ratings, $\beta = 12.14$, $t(24) = 4.08$, $p < .001$ (Figure S3).

(A) Facial expression behaviors

Synchrony comparison in dyad group

Synchrony comparison in alone group

(B) Global facial expression synchrony

(C) Local expression synchrony and scene emotion ratings

Figure 2. Temporal facial expression synchrony. (A) Examples of participant facial expressions. Synchrony in the alone group was computed between all pairwise participants who watched individually whereas synchrony in the dyad group was computed only between the pairs of participants who watched physically together sitting next to each other. (B) Synchrony of positive facial expressions while watching episodes between conditions in each episode. Significance of group differences was tested with a two-sample permutation test (error bars indicate 95% confidence intervals * $p < .05$, ** $p < .01$, *** $p < .001$). (C) Local facial expression synchrony for the dyad and alone group in episode 1. Dotted boxes indicate clusters at which dyad participants synchronized more than alone participants. Select screenshots for the significant clusters are shown above. These moments correspond to scenes with high joy ratings rated by $N=188$ independent observers and are indicated by orange color bars along the x-axis (shaded area indicate standard error of the mean). Colored ticks along the horizontal axis indicate the most representative emotion at that time from online crowdsourced self-reported emotion ratings (see Supplementary Methods).

In summary, co-viewing appears to lead to a significant temporal alignment of facial expressions during shared experiences beyond levels of pure stimulus-driven synchrony. All viewers tended to synchronize positive facial expressions during amusing scenes, but this effect was stronger in the dyad condition. These synchronization effects were observed in both long (45 minute episodes) and short timescales (30-second sliding windows) and corresponded to positive sentiments of the show based on crowdsourced emotion ratings.

Temporal affective synchrony and self-reported social connection

Next, we examined the relationship between temporal affective synchrony and the development of affiliation, measured as the average of how connected each participant reported feeling to their partner after each episode. Participants were asked, “How much do you feel connected to the other participant?” Using a linear mixed-effects regression, we found a significant

relationship between the degree of temporal alignment of positive facial expressions in dyads and self-reported connectedness across all four episodes, $\beta = 1.04$, $t(88) = 3.36$, $p = .001$) (Figure 3A). We also observed a significant effect of episode number, $\beta = .25$, $t(81) = 5.96$, $p < .001$, indicating that average connection ratings generally increased over time. An interaction between episode number and positive facial expression synchrony, $\beta = .38$, $t(81) = 2.15$, $p = .034$, revealed that the relationship between positive emotional synchrony and social connection strengthened over time. Negative expression synchrony, on the other hand, was not significantly related to connectedness except in the last episode (Figure 3B).

In order to assess how the alignment of other canonical emotional facial expressions contribute to developing interpersonal connections, we trained a penalized regression model to predict self-reported connection with the temporal alignment of different emotional facial expressions (i.e., joy, anger, fear, disgust, surprise, and sadness). In a leave-one-dyad-out cross validation, we were able to accurately predict connectedness out of sample at $r = .51$. We used a linear mixed-effects regression to evaluate the independent contribution of each type of expression while controlling for time effects and found that only the synchrony of joy facial expression significantly predicted feelings of social connection, $\beta = .78$, $t(80) = 2.16$, $p = .034$. This indicates that synchrony of positive expressions contributes most to affiliation feelings, although this may be in part due to the nature of the stimuli that is mostly driven by positive events based on the crowdsourced emotion ratings for episode 1 (Figure S4).

Figure 3. Correlation between connectedness and facial expression synchrony in each episode. (A) Synchrony of positive facial expressions and average connectedness ratings after each episode. (B) Synchrony of negative facial expressions and average connectedness ratings after each episode.

Spatial alignment of facial expressions and self-reported social connection

The previous analyses examined the synchronization of canonical expressions of specific emotions, but it is possible that individuals might have subtle nuances in *how* they smile or frown and that shared experiences might facilitate convergence to a dyad-specific facial expression ontology⁴⁰. To investigate this question, we employed a data-driven approach that allows the estimation of subject-specific facial expressions representing common emotional trajectories across subjects. We compared the spatial similarities in these idiosyncratic facial expressions between dyads to assess if a greater alignment was associated with greater reports of social connection.

To estimate idiographic facial expression models representing similar affective response trajectories across participants, we fit a reduced-rank two-dimensional shared response model⁵⁸ to the 20 facial action unit muscle movements time series⁵⁹. This model estimates common latent temporal components across participants, but allows each person to have a unique spatial configuration for a facial expression that is represented by the subject-specific weight matrix that projects participant data into a shared latent space.

This data-driven approach was able to successfully capture subjective facial expression variations representing shared affective trajectories. The first shared response correlated with the crowdsourced joy ratings ($r = .42, p < .001$) and peaked at positive scenes such as when the characters were winning the football match or when they were joking around (Figure 4A). Interestingly, even though we placed no constraints on how to combine the action units to represent a shared response, we were able to extract participant-specific variations in spatial configurations of facial expressions (Figure 4B, left panel) that resemble positive emotion expressions with activations in action units 6 (cheek raiser), 10 (upper lip raiser), 12 (lip corner puller), and 14 (dimpler).

The second shared response correlated with crowdsourced fear ratings ($r = .29, p < .001$) and sadness ratings ($r = .23, p < .001$) and peaked at negative or serious scenes, such as when the football coach is warned about the potential consequences for losing a match and when one of the main characters sustains a serious injury (Figure 4A). We observed diverse, subject-specific spatial configurations of facial expressions for this shared response (Figure 4B, right panel) that resemble facial expressions associated with negative feelings including activations of action units 4 (brow lowerer), 5 (upper lid raiser), and 15 (lip corner depressor).

Next, we tested if viewing partners with more similar spatial patterns of facial expressions developed stronger social connections. Participants sat physically next to each other without partitions as they viewed the episodes allowing them to see each other's expressions, when similar, may promote social bonding. To evaluate the relationship between the spatial alignment of facial expressions and social connection, we computed the spatial similarity of subject-specific facial expression patterns for each dyad and correlated these synchrony measures with the dyad's average self-reported feelings of social connection. Connection

ratings were positively correlated with spatial facial expression synchrony of the first shared response (Figure 4C) in episodes 1 ($r = .4, p = .036$), episode 2 ($r = .36, p = .062$), and episode 3 ($r = .47, p = .011$) but not in episode 4 ($r = .21, p = .292$), indicating that similarities in how positive emotions are expressed may contribute to stronger social affiliation and feelings of a shared experience. In contrast, connection ratings were not significantly correlated with spatial synchrony of the second shared response in any of the episodes.

(A) Average shared response trajectories and scene emotion ratings

(B) Participant-specific Variations of Facial Expressions

(C) Spatial configuration similarity and affiliation development

Figure 4. Spatial configuration synchrony results. (A) Estimated average shared response trajectories. The trajectory of the first shared response (Shared Response 1; solid line) included peaks at scenes when crowdsourced joy ratings (orange) were high, such as when the characters were joking around or when a football team won the match. The trajectory of the second shared response (Shared Response 2; dotted line) included peaks at scenes when crowdsourced fear ratings (purple) were high, such as when the coach was warned about the social consequences of losing a football match or when the main character gets injured during a football match. Shared response trajectories were linearly detrended and standardized for visualization. (B) Examples of participant-specific spatial patterns of action units activated for each shared response. Note the variability in expressions despite their occurrences are aligned to the shared response trajectories shown in Figure 4A. These values have been

exponentiated for display purposes. (C) Shared Response 1 spatial configuration pattern similarity is associated with connectedness ratings in dyads.

Similarity of character impressions and self-reported social connection

Next, we examined if dyads with similar impressions about the characters reported stronger feelings of affiliation. To account for potential overlap and redundancies in the collected impression ratings (e.g. ratings of liking and wanting to be friends with a character are correlated at $r = .72$), we reduced the dimensionality of the ratings using Principal Components Analysis while preserving approximately 90% of the variance with 5 components (Figure 5A). As expected, the first component represented a generally positive sentiment towards characters loading on questions related to liking and how much participants wanted to be friends with characters (Figure 5B). The second component also loaded on liking ratings but with loadings in the opposite direction for attractiveness suggesting a dimension of a positive impression without physical attraction. In contrast, the third component reflected both liking and attractiveness towards a character. The fourth component represented an impression of how the characters either reminded participants of someone they knew or elicited the desire to be that character. The fifth component reflected a dimension of caring and wanting to be friends with that character.

Using these impression dimensions, we computed the inter-subject similarity of impressions^{9,10,14} for each character, then averaged the similarity of characters for each dyad. Across episodes, dyads with higher average impression similarity across characters also showed greater connection ratings ($\beta = 1.01$, $t(85) = 2.40$, $p = .018$) and this association was most pronounced in the last episode ($r = .49$, $p = .009$; Figure 5C). In addition, impression similarity among dyads generally increased after each episode ($\beta = .03$, $t(83) = 3.05$, $p = .003$).

Figure 5. Synchronization of character impressions. (A) Cumulative explained variance of principal components across impression ratings. The dotted line indicates 90% cumulative explained variance. (B) Component loadings on each impression dimension. (C) Correlation between impression similarity and dyad average connection ratings for each episode.

Shared experience as a latent process

The previous results demonstrate that synchronization of facial expressions in time and space and appraisals of characters are all related to feelings of connection when viewing a show with another person. An important question is whether these different measurements reflect independent constructs or are manifestations of a common latent shared experience. To test this question, we used structural equation modeling to estimate a latent factor model using synchronization across all of our data^{60,61}. Our model predicts connection ratings using episode number to indicate time, and a shared experience latent factor measured by manifestations of temporal affective synchrony, spatial affective synchrony, and impression synchrony (Figure 6). As hypothesized, temporal synchrony, spatial synchrony, and impression synchrony were all significant components of the shared experience (Figure 6; Table S2) and higher levels of shared experience significantly predicted connection ratings (standardized variance = .68, $p < .01$) independent of the amount of time spent together.

Figure 6. Structural equation model of relationships between synchrony measures, shared experience, and connection ratings. Temporal affective synchrony, spatial motor synchrony of facial expressions, and similarities in character impression ratings are modeled as measures that may indicate a shared experience, which promotes increases in social connection ratings between individuals. Episode number reflects the time spent by participants together during the experiment and controls for the general increase in connection ratings due to spending time together over four viewing sessions. Numerical values along the paths indicate standardized contributions showing that temporal affective synchrony most strongly represents shared experiences followed by spatial motor synchrony and character impression similarity. Circular arrows represent residual variances and curved arrows indicate covariance between measures. $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Discussion

In this study, we examined three different interindividual manifestations of a shared experience - temporal synchrony in affective facial expressions, spatial motor synchrony in how different patterns of facial muscles are used to display facial expressions, and similarities in impressions of characters from the audio-visual stimuli experienced together - to investigate how they indicate and contribute to feelings of social connection. We created a shared experience using a naturalistic viewing paradigm, in which participants spent approximately four hours watching a character-driven television drama together. We used displays of emotions and facial muscle movements extracted from videos of participants' facial expressions using computer vision algorithms to objectively and unobtrusively measure affective experiences as they unfolded over time. We explored how synchronization of facial expressions in time and space, as well as cognitive evaluations of the characters, contributed to the development of social connection with a viewing partner. This unique approach allowed us to disentangle the degree to which each process is associated with a shared experience that helped form social bonds.

As hypothesized, we observed significant temporal affective synchrony in participants who watched in dyads compared to those who watched alone. The level of synchrony between viewing partners was also greater than that of randomly paired dyads suggesting that co-viewing in physical proximity offers a unique experience beyond watching alone or watching with someone else. These synchronized affective responses seemed to serve an adaptive social function in which greater synchrony, especially in positive facial expressions, predicted greater feelings of interpersonal connection. We also found that individuals not only synchronized *when* they emoted but also *how* they emoted by comparing idiosyncratic spatial configurations of facial muscle movements that mapped onto shared affective trajectories. Similarities in these spatial configurations of expressions also predicted increases in social connection. In addition to synchronization in displays of emotion, we observed that dyads with more similar impressions about the characters developed stronger social bonds. These processes were collectively modeled as measurements of a shared experience that predicted social rapport development, with the strongest loadings from temporal affective synchrony.

Why do individuals feel more connected after a shared experience? It has long been speculated that individuals form tighter social bonds after sharing a meal, watching a movie, or attending a concert or sporting event together and that they value and prefer shared experiences over solo experiences¹. People may seek shared experiences because they provide opportunities for comparing their views of reality with others'⁶² through which individuals can satisfy epistemic motives such as wanting to establish socially approved beliefs and worldviews⁶³ or relational motives such as the need for a sense of belonging⁶⁴. Our findings point to potential avenues that support this process. Synchronous facial expressions may act as social signals that communicate the presence and the development of shared feelings and thoughts about the unfolding events. However, facial expressions can also be feigned, suppressed, and exaggerated, requiring further investigations into the extent to which they can be credible readouts of internal feelings and thoughts^{21,59,65}.

Our work extends previous findings on how the presence of others or existing relationships increase the intensity or frequency of emotions that are expressed^{21,23,24} and response patterns across different stimuli^{25,66}. We demonstrate that individuals naturally display temporally and spatially synchronized facial behavior during shared experiences, which contribute to newly formed feelings of social connection. Our findings are also consistent with the notion of homophily that similar individuals attract each other^{19,67}. We extend previous findings that compare similarity in existing friendship by taking a longitudinal approach in which we tracked the development of affiliation and similarities in character impressions in dyads spending multiple hours together. Critically, we demonstrate that it is possible to experimentally elicit an affective shared experience and have individuals form social connections while measuring the different interpersonal emotions and cognitive dynamics that arise during the interaction. We believe that observing individuals in these naturalistic paradigms can provide a more comprehensive view of the multidimensional and dynamic processes underlying social interactions.

Our experimental design, however, is not free of limitations. We chose episodes from a character drama so that participants can freely form impressions about the characters as well as experience a variety of emotions such as joy, surprise, sadness, and fear. However, different facial expressions of emotions may be more prominent in different genres. For example, it remains an open question whether synchrony of fearful facial expressions may contribute more to developing social rapport when watching a horror film. In addition, our participants were recruited from a small private undergraduate college and likely comprised of a more homogenous group than randomly sampled groups from the general population which may have allowed individuals to be more conducive to developing social connections. We also focused on facial expression synchrony that occurs at the same moment in time because we were interested in reactions triggered by the show which we assumed would happen within a short latency. However, many real-life interactions such as conversations involve time-lagged exchanges of emotions which may also be a factor that determines the degree to which one feels that an experience is truly shared. Although it is difficult to distinguish if our observed facial expression synchrony is a result of simultaneous elicitation of feelings, emotional contagion, or mimicry⁴³, we note that most dyads displayed maximal synchrony within one second of each other, suggesting that our observations most likely reflect simultaneous experiences rather than contagion of experiences (Figure S5).

In summary, we find evidence for multiple synchronous processes in a social interaction setting that gives rise to the realization that an experience is not merely experienced together but shared together. Each of these processes appears to provide unique contributions that give rise to a shared experience and that they jointly promote the development of social connections between individuals. Our work demonstrates that these processes can be observed, measured, and analyzed together in a more naturalistic setting, which provides an important advance for developing a more unified framework for studying social interactions and relationships.

Methods

Participants

We recruited 86 participants who either watched the four episodes of Friday Night Lights alone ($N=22$, 68% female; $M_{age} = 18.90$, $SD = .92$) or as a dyad with another participant ($N=64$, 32 dyads; 68% female; $M_{age} = 19.26$, $SD = 1.13$). Five dyads recognized each other and two dyads identified themselves as friends. Omitting the dyads that recognized each other did not affect the main results. Twelve of the dyads were mixed-gender pairs. Two dyads did not return for the second session and were excluded from analyses. All participants provided informed consent to participate in this study and received \$10 per hour or course credit in compensation for their participation. This study was approved by the Institutional Review Board at Dartmouth College.

We also recruited participants from the Amazon Mechanical Turk workplace ($N = 192$, 55% female, $M_{age} = 37.11$, $SD = 10.71$) to periodically self-report emotion ratings while watching the first episode of Friday Night Lights online. Four subjects were excluded who did not

respond to more than 75% of the time when they were asked to report how they were feeling. All participants provided informed consent to participate in this study and received monetary compensation (\$9). This study was approved by the Institutional Review Board at Dartmouth College and was previously described in more detail in ⁸.

Procedure and materials

Participants watched four episodes of a TV character drama (*Friday Night Lights*) in two separate sessions scheduled an average of 2.65 (SD=2.78) days apart. No participants had seen the show prior to the experiment. In the shared viewing condition, both participants were briefly introduced to one another as they filled out consent and demographics forms to check if they were acquainted with one another, which they indicated on a separate form. The two participants sat side-by-side at a slight angle towards the monitor and were instructed to watch the shows naturally as they would with a friend. Participants in the solo viewing paradigm watched alone in the same room. All participants wore a head-mounted GoPro camera ⁵⁴.

The episodes were presented on a 15-inch Apple Macbook Pro laptop and the average length of each episode was 43.6 minutes (*range* = 42 - 46 minutes). Facial behaviors were recorded at a resolution of 1280 x 720 resolution at 120hz using a GoPro Hero4 Black camera attached to the custom head-mount setup ⁵⁴. Electrodermal activity was also recorded during the sessions but this data is not discussed in this paper.

After each episode, participants rated 13 characters on eight social impression dimensions and three character relationship dimensions (i.e. How much does character A like, trust, or listen to character B?; not discussed in this paper) in separate rooms (see Table 1 for exact wording). In addition to the character ratings, dyad participants reported on a Likert scale on how much they enjoyed the show (1: Not enjoyed, to 9: Very enjoyed) and how much they felt connected to the other person (1: Not connected, to 9: Very connected) ^{3,49}.

Table 1. Questions asked to participants.

Character impression questions

How *annoying* do you find this character?
 How much do you *like* this character?
 How *attractive* do you find this character?
 How much do you want to be *friends* with this character?
 How much do you want to *be* this character?
 How much does this character *remind* you of someone you know?
 How much do you *relate* to this character?
 How much do you *care* what happens to this character?

Social connection question

How much do you feel connected to the other participant?

For online participants, we delivered the first episode of Friday Night Lights through a web application built using Flask (<http://flask.pocoo.org/>), jsPsych (<https://www.jspsych.org/>), psiTurk (<https://psiturk.org/>), and MySQL (<https://www.mysql.com/>), served on an NGINX (<https://www.nginx.com/>) webserver hosted in our laboratory (https://github.com/cosanlab/moth_app, https://github.com/cosanlab/moth_turkframe). The video was paused at pseudo-random intervals at approximately 200 to 280 seconds at which participants rated the intensity of 16 emotions they were experiencing including joy, surprise, sadness, fear, anger, disgust, contempt, relief, envy, shame, interest, elation, satisfaction, guilt, hope, and pride. Each subject provided on average 11.46 ratings (SD = 1.94), totaling 66,714 ratings across the six emotion categories of primary interest (joy, surprise, sadness, fear, anger, and disgust). These emotion ratings were averaged across subjects, interpolated, and smoothed with a 30-second sliding window. See ⁸ for additional details.

Video preprocessing and feature extraction

Each face recording video was aligned and trimmed to the stimulus video by finding the audio offset that maximizes the correlation of the audio envelope using the FaceSync toolbox ⁵⁴ which yields comparable results (within 3ms error) to the current gold standard of manual alignment. Facial features including 20 action units and 6 emotion predictions were extracted using the FACET algorithm accessed via iMotions 6.0 ⁶⁸ software. FACET is a deep convolutional neural network that improves upon the computer expression recognition toolbox (CERT) ⁶⁹ and predicts evidence of different emotions and action units based on the FACS annotations ^{59,70} coded by experts using pixel information from each frame of the video. Predictions values are represented as evidence scores which are logarithmic odds of the presence of emotional facial expressions. The extracted facial feature predictions were downsampled to 1hz. We applied a minimum face detection failure cutoff so that videos in which the algorithm failed to detect a face for more than 10% of the video were excluded from the analysis resulting in the exclusion of two dyads. In the solo viewing condition, one subject was excluded due to file corruption while transferring video data.

Measuring facial expression synchrony in long and short timescales

For both positive and negative emotion evidence time series, we computed the pairwise intersubject similarity using a Pearson correlation over the duration of each episode. This synchrony measure was computed for every pairwise combination of subjects in the alone group and for the pairs of participants who physically participated together in the dyad group. This technique captures the degree to which facial expressions covary at similar moments in time over the course of the episode. The significance of the average level of synchrony was determined by a non-parametric subject-wise bootstrapping procedure in which subjects were resampled with replacement over 5,000 iterations to account for subject-level exchangeability and independence ⁵⁶. Similarly, the between group comparison was computed using a subject-wise permutation technique that generates a null distribution of the correlation matrix by shuffling the participants between the groups repeatedly for 5,000 iterations ^{56,71}. To check for potential time-lagged coupling of expressions between dyads, we also computed the cross correlation between 3 seconds for each dyad at 100ms intervals (Figure S4) and found that the

majority (>50%) of the maximum synchrony occurred within 1 second (median offset = 850ms) of each other suggesting rapid synchronous response to external stimuli.

To measure moment-to-moment synchrony, a 30-second moving window correlation was computed for all pairwise combinations of subjects for the alone group and for each pair of dyads who watched together for the positive facial expression synchrony. These correlation values were z-transformed and compared between groups to generate t statistic at every second. The moments when the group differed significantly were computed using a cluster-based nonparametric test⁵⁷ to detect consecutive moments showing group differences. After identifying the moments in the episode at which dyads showed greater synchrony of positive facial expressions, we compared which emotions were dominant at those times. We used average emotion ratings collected from 192 participants from Amazon Mechanical Turk who viewed the first episode of the show which was periodically paused to allow them to rate their emotions (see Supplementary Methods). The emotion ratings were averaged across subjects, interpolated, and smoothed using a sliding window of 30 seconds. These ratings were then correlated with the moment-to-moment synchrony of joy facial expressions. In addition, we computed the average rating for each cluster and contrasted the difference between the joy and the average of other emotion ratings (Figures S3).

Synchrony of facial expressions in predicting social connectedness

The degree of social connection that each dyad participant reported towards their partner after every episode was averaged to represent the combined affiliation level following the shared viewing of each episode. These values were then compared to the positive and negative facial expression synchrony levels for each episode using a Spearman rank correlation to assess the monotonic relationship as unit increases in synchrony may not necessarily reflect a proportional change in connectedness. We also tested for a linear relationship in conjunction with time effects using a linear mixed effects regression (M1) with random effects at the dyad level estimating the average connection ratings (Conn) from the positive facial expression synchrony (PosExpSync), episode number as an indicator of time (Epn), and their interactions.

$$M1: Conn = b0 + b1 * PosExpSync + b2 * PosExpSync * Epn + (1|Dyad)$$

Prediction of connectedness ratings was computed using the pairwise synchrony for each of the six emotion predictions of joy, anger, surprise, fear, sadness, and disgust. We evaluated our model using a leave-one-dyad-out cross validation scheme where every fold estimated a new model using a penalized L2 regression with a nested 5-fold cross validation search for the optimal regularization strength for values of [.1, 1.0, 10.0]. The accuracy of the overall model was evaluated as the Pearson correlation between actual average connectedness ratings and the predicted connectedness ratings across all folds.

To evaluate the significance of the contributions from each emotion synchrony, we fit a linear mixed effects regression (M2) with random dyad effects to predict connection (Conn) based on synchronization of the six canonical emotional expressions.

$$M2 : Conn = b0 + b1 * Joy + b2 * Anger + b3 * Surprise + b4 * Fear + b5 * Sad + b6 * Disgust + Epn + (1|Dyad)$$

Latent shared response model estimation

The latent shared response model was fit using the SRM module ⁵⁸ in the BrainIAK package (Brain Imaging Analysis Kit, <http://brainiak.org>). The latent shared response performs a factorization of the multivariate facial expression data into k shared response features with an orthogonal transformation matrix for each subject. This allows each participant's time by action unit data to be decomposed into a subject-specific action unit by shared response transformation matrix and a common time by shared response matrix. This procedure is akin to estimating a joint PCA, where each participant has a unique transformation into the common latent space shared across participants. The number of shared responses k was determined by iterating through the full range of k 's that maximizes the shared response similarity (i.e., time) for all participants from both groups (i.e., dyad and alone) across the four episodes resulting in $k=2$ components (Figure S6). To interpret the shared response trajectories estimated for the first episode, we correlated each trajectory with the joy, anger, surprise, fear, sadness, and disgust crowdsourced emotion ratings both with and without detrending which yielded identical results (Table S3).

The spatial configuration of facial expression synchrony was computed for each shared response by taking the idiosyncratic transformation matrix of each subject for each feature and computing the intersubject similarity for each group. The intersubject similarities in the spatial configuration of facial expression were then compared with connection ratings using a Spearman's rank correlation. The average weights and subject-specific facial expression maps for each feature were plotted using the Facial Expression Analysis Toolbox (FEAT; Cheong et al, In prep) and were depicted by scaling using cubic exponentiation for clarity.

Impression similarity analysis

After each episode, participants answered eight questions for each of the 13 characters (Table 1). We conducted a principal components analysis to find orthogonal dimensions of the impression rating space. Character ratings were demeaned within each subject to adjust for individual variability and we treated each character rating from each subject as samples of the impression space captured with the eight questions. We found that at least 5 components were necessary to retain approximately 90% of the variance. We projected the impression ratings for each character for each subject into this space and computed the inter-subject similarity ^{9,10} separately for each character and then averaged across characters. We then fit a linear mixed effects model (M3) in which impression similarity (ImpSim), episode number (Epn), and their interaction were used to estimate average connection ratings.

$$M3 : Conn = b0 + b1 * ImpSim + b2 * ImpSim * Epn + (1|Dyad)$$

Structural equation modeling

We fit our structural equation model predicting connection ratings with shared experience as a latent factor using the lavaan package in R ⁷². Shared experience latent factor was estimated using measurements of positive temporal facial expression synchrony, positive spatial facial expression synchrony, and character impression similarity. We modeled residual correlations between the temporal and spatial facial expression synchrony measures to account for the fact that they are both derived from facial expression data. We also included residual correlations between episode number and the other synchrony measurements to control for the residual covariance due to time.

Softwares and packages used in analyses

We used the following tools for statistical analyses and visualizations: Pandas ⁷³, brainiak ⁵⁸, seaborn ⁷⁴, matplotlib ⁷⁵, scipy ⁷⁶, numpy ⁷⁷, sklearn ⁷⁸, feat, FaceSync ⁵⁴, nltools ⁷⁹ in Python, and lme4 ⁸⁰, lmerTest ⁸¹, and lavaan ⁷² in R.

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Supplementary materials

Supplementary Figures

Figure S1. Temporal synchrony of facial expressions across conditions

Figure S1. Comparison of temporal facial expression synchrony between all pairwise combinations of participants who watched alone (Alone), pairs of participants who watched in dyads (Dyad), and all pairwise combinations of participants in the dyad group less those who actually watched together (DyadNP).

Figure S2. Moment-to-moment synchrony comparison between groups

Figure S2. Moment to moment synchrony comparison between groups across all episodes.

Figure S3. Average crowdsourced emotion ratings at scenes with greater dyadic synchronization in episode 1.

Figure S3. Average crowdsourced emotion ratings at scenes with greater dyadic synchronization in episode 1. Joy emotion ratings were compared with the average across all other ratings. Average joy rating across clusters in which dyads showed significantly higher synchrony than the alone group was greater than the ratings of other emotions $\beta = 12.14$, $t(24) = 4.08$, $p < .001$.

Figure S4. Distribution of crowdsourced emotion ratings for episode 1.

Figure S4. Distribution of crowdsourced emotion ratings for episode 1. The pie chart illustrates the percentage of the show at which each emotion was rated the strongest elicited emotion from the average self-reported ratings collected from online participants.

Figure S5. Offset maximizing synchrony in dyads.

Figure S5. Distribution of offsets that maximizes cross correlation for each dyad on positive facial expressions. Each dot represents a dyad in each episode and the dotted line marks the offset of 1 second. The distribution of offsets indicate that the majority of subjects synchronized within a second of each other.

Figure S6. Average Intersubject Correlation of Shared Responses

Figure S6. Average Intersubject Correlation of Shared Responses. The average intersubject correlation across the shared response estimated for $k=[2, 3, \dots, 20]$ are shown. Error bars indicate 95% bootstrapped confidence intervals.

Supplementary Tables

Table S1. Average group correlations for positive and negative facial expressions

<i>Episode</i>	<i>Group</i>	<i>Positive Expression Synchrony</i>	<i>Negative Expression Synchrony</i>
		<i>Average r (bootstrapped significance)</i>	
1	dyad alone	.23 (<.001)	.06 (<i>n.s.</i>)
		.06 (<.001)	-.01 (<i>n.s.</i>)
2	dyad alone	.22 (<.001)	.05 (<i>n.s.</i>)
		.04 (<.01)	.00 (<i>n.s.</i>)
3	dyad alone	.22 (<.001)	.02 (<i>n.s.</i>)
		.02 (<i>n.s.</i>)	.00 (<i>n.s.</i>)
4	dyad alone	.38 (<.001)	.07 (<i>n.s.</i>)
		.12 (<.001)	.00 (<i>n.s.</i>)

n.s.: not significant

Table S2. Structural equation modeling fit results.

<i>Parameter Estimate</i>	<i>Unstandardized</i>	<i>Standardized</i>	<i>p</i>
Latent variables			
Shared Exp → Temporal Sync	1.00	.81	NA
Shared Exp → Spatial Sync	.83 (.22)	.43	.000
Shared Exp → Impression Sim	.29 (.11)	.32	.012
Error in Temporal Sync	.02 (.01)	.34	.142
Error in Spatial Sync	.11 (.02)	.81	.000
Error in Impression Sim	.03 (.00)	.89	.000
Covariance of Temporal Sync - Spatial Sync	.01 (.01)	.18	.517
Covariance of Episode Num - Temporal Sync	.06 (.03)	.38	.022
Covariance of Episode Num - Spatial Sync	.12 (.04)	.32	.003
Covariance of Episode Num - Impression Sim	.05 (.02)	.27	.007
Structural Model			
Shared Exp → Connection Ratings	5.84 (2.14)	.68	.006
Episode Num → Connection Ratings	.32 (.13)	.22	.016
Residual for Connection Ratings	1.29 (.47)	.48	.006

Note: $\chi^2(1) = 3.30$, $p = .068$; GFI = .99; NFI = .97; CFI = .97; RMSEA [95%CI] = .14 [.00, .33], SRMR = .038.

Table S1. Unstandardized, standardized, and significance levels for model in Figure 6 (Standard error in parentheses; N = 112).

Table S3. Average shared response trajectories correlated with crowdsourced self-reported emotion ratings.

Shared Response	Joy	Disgust	Anger	Surprise	Sadness	Fear
1	.42 *** (0.12***)	0.01 (-0.02)	-.18 *** (-0.12***)	-.26 *** (-0.27***)	-.31 *** (-0.41 ***)	-.40 *** (-0.24***)
2	-.38 *** (0.10***)	.11 *** (0.03)	-.16 *** (0.30***)	.09 *** (0.63***)	0.23 *** (0.49***)	.29 *** (0.65***)

Note: Correlations are shown for with detrending and without detrending in parentheses.

Emotions with the highest correlations for each shared response are in bold. *p<.05, **p<.01,

***p<.001