Emotional Contagion throughout Relationship Formation: A Longitudinal Dyadic Conversation Study

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Abstract

Emotional contagion is seen to be an affiliation tool and a byproduct of all different stages of relationships, from strangers to romantic relationships. Although the processes and implications for emotion contagion has been studied at different levels of relationships independently, limited research has documented how emotion contagion occurs over the course of relationship development. In our exploratory study, participants were paired with people they previously did not know and had conversations with each other once a week for six weeks. At each session, we measured participants' valence and arousal of emotion and how close they felt to their partner. We found that how much people changed their emotions over the course of the interaction and how similar the two members of a dyad were in emotion valence after the interaction were both more associated with how close they felt to their partner in the first sessions but were not associated with the change in closeness over time. In other words, emotion contagion seems to matter more for the onset of relationships than for the development. We discuss how this work expands upon the existing research of emotion contagion in relationships.

Emotional Contagion through Relationship Formation: A Longitudinal Dyadic Conversation Study

Emotion contagion, the process of synchronizing emotional states (Hatfield et al., 1993), is a ubiquitous phenomenon that can be readily observed across many situations (Chartrand et al., 2006), groups of different sizes (Barsade et. al., 2018), and different levels of relationship intimacy. Feelings of happiness and of depression have been shown to spread within communities (Cacioppo et al., 2009), and positive and negative affect can spread rapidly through social media (Kramer et al., 2014). Contagion can happen in groups, including in the workplace (Totterdell et al., 1998), and families (Larson & Almeida, 1999). Lastly, it can happen in dyads, including between parent and child (Harrist & Waugh, 2002), between two college students in a laboratory setting (Hsee et al., 1992), or between romantic partners and college roommates (Anderson et al., 2003). These studies also demonstrate how emotion contagion happens in short time periods, such as through single interactions in the lab, or over long time periods, such as weeks or months.

The process of emotional contagion can happen automatically and easily or deliberately and intentionally. Sometimes, it happens without one's awareness. A study by Neumann & Strack (2000) had participants listen to an affectively neutral speech that was spoken in a slightly happy or slightly sad voice and found that the tape affected people's moods even though the participants in the study were not aware of the effect. People also automatically and spontaneously mimic others' facial expressions, which can result in matching the underlying emotion (Hatfield et al., 2014; Lakin et al., 2003). Emotion contagion can also occur intentionally through empathy or affective social learning (Clément & Dukes, 2017).

However, one limitation in the research on emotion contagion is that it has not been frequently studied across longer time scales and changes in relationships. Relationships among dyads are constantly developing, including their levels of interdependence (Clark & Reis, 1988). With the knowledge that emotions are also not stable, but are instead dynamical processes (Frijda, 1986), emotional contagion processes in dyads should be studied at various points in relationships. Therefore, our study aims to explore how emotion changes and contagion associate with feelings of closeness over time by documenting how strangers became closer friends through repeated conversations.

Emotion contagion in interpersonal relationships

Emotion contagion plays a large role in increasing liking and rapport. Contagion can serve as a signal of empathy or agreement, letting the other know that one appraises a situation in a similar way (Fischer & Manstead, 2008). People like strangers that feel similar emotions more (Gibbons, 1986), since it can be indicative of alignment. The synchrony and coordination from convergence is rewarding because it reduces cognitive effort, making people evaluate the other person and the situation more favorably (Wood, 2020). Therefore, when one has more emotional contagion with another, one likes them more.

However, people do not indiscriminately pick up on the emotions of anyone they come into contact with; instead, one’s desire to affiliate and one’s preexisting relationship limit how much contagion occurs. For example, people laugh more when watching a funny movie with friends than alone (Hess et al., 1995). People also report feeling more similar to those they had a greater affiliation with when face with stressful situations (Gump & Kulik, 1997). To test how different interpersonal relationships impact emotional contagion, Kimura, Daibo & Yogo (2008), had participants listen to a friend, acquaintance, senior, or junior talk about intensely positive or negative events and found that emotional responses were significantly stronger in the friend, senior, and junior conditions than in the acquaintance condition for both positive and negative episodes. Since emotional contagion can be used to signal desires to affiliate, it's unsurprising that people who do not have a desire to affiliate do not mimic emotions as much. For example, people in a sad mood are less likely to mimic others, perhaps because sadness implies a lack of a desire to socially engage with the environment. This then blocks affiliation goals and decreases the tendency to mimic (Likowski et al., 2011). People also mimic their ingroup members more than their outgroup members (Bourgeois & Hess, 2008). For instance, McHugo et al (1991) found that people were more likely to emotionally match politicians that belonged to their own political party, as opposed to those in the opposing party.

Even among couples, those who already have close-relationships and long-term bonds, emotional contagion still seems to play a crucial role. As the lives of two relationship partners' become more intertwined, so do their emotions (Butler, 2011). Anderson et al. (2004) posited that relationship partners develop increasingly similar emotion responses over time because it enhances coordination, understanding, and closeness. In support of this hypothesis, Anderson, Keltener, & John (2003) found that people in close relationships, specifically dating partners and college roommates, were more similar in their emotional reactions to the same stimuli at the end of one year together than at the beginning, and that this effect for college students was moderated by how close they felt at the end. Additionally, couples that showed greater amounts of similarity in emotion responses were more cohesive and less likely to dissolve. Other daily-diary and experience-sampling studies have found that emotions in one family member's experiences are frequently transmitted to other family members (Larson & Almeida, 1999), and negative experiences are especially prone to spillovers (Butler, 2011).

However, emerging research has also shown that healthy couples do not always exactly match emotions; rather, emotion independence and coregulation is important as well. Emotion contagion involves two people influencing each other in a positive feedback loop. If one person is happy, the other becomes happier, and if one is sad, the other person also becomes sad. This is not always beneficial. For example, if couples are likely to catch each other's feelings of anger or frustration, it can lead to more conflict. When partners discuss and rediscuss their worries, co-rumination can result in both partners' increased anxiety (Parkinson & Simons, 2012). On the contrary, coregulation involves a negative feedback loop, such that the direction of one leads to the opposite direction of another. Many times, complementing a partners' emotions, rather than matching it, can be beneficial. If one person in a relationship is experiencing psychological distress, their partner's expression of positive affect may help stabilize or dampen their affect, leading to a reduction in distress. Randall & Schoebi (2015) studied couples over a period of 10 days and found results that supported this idea. They found that men felt more positive affect after their partners' expressed feelings of hurt or fear, and women felt less hurt and fear after their partner felt more. When one person feels negative affect, the other helps them regulate their affect to become more positive, bringing them back towards a more stable, neutral state (Butler & Randall, 2013).

Individual differences in susceptibility to emotional contagion

While emotional contagion can be seen generally across people and situations, individuals differ on their ability, or susceptibility, to catch the emotions of others. Certain personality traits have been linked to greater susceptibility of emotional contagion. Hatfield et. al. (1994) proposed that emotionally susceptible people are those who pay attention to others and are able to read facial expressions, see themselves as more interrelated with others, are able to read facial expressions well, are more predisposed to mimicking facial expressions, vocalizations, and postures of others, and are more aware of their own emotions. To measure these individual differences, Doherty (1997) developed the Emotional Contagion Scale (ECS), a 15-item unidimensional measure of susceptibility of emotions. In support of Hatfield's hypothesis, studies have found that self-esteem, self-monitoring, and emotional intelligence, or the ability to accurately read emotional expressions, all positively correlate with emotional contagion. Ilies, Wagner, and Morgeson (2007) found that among team members, those who had more collectivistic tendencies were more susceptible to emotional contagion. Zeleknski & Larson (2001) found that higher reward sensitivity is predictive of greater positive emotional influence while higher punishment sensitivity is predictive of greater negative emotional influence.

Research has also examined whether demographic variables influence emotional contagion, although some findings have been mixed. Totterdell (2000) found that among professional sports players, older ones were more prone to contagion. An early study by Doherty et al., (1995) found that women scored higher than men in the ECS, although later studies have found no differences (Hatfield et. al., 1994). Taken together, susceptibility to emotion contagion can be predicted by traits related to how socially attuned individuals are.

Limitations in existing emotional contagion research

So far, the literature is diverse in studying the individual differences, settings, and relationships surrounding emotional contagion, yet there are several limitations. First, many of the studies on emotional contagion involve short time scales, such as a single lab session. These studies demonstrate how quickly and easily the process of emotional contagion happens but don't allow for any conclusions about the lasting effects. Researchers show that giving people affiliative goals leads to more emotional contagion, yet single-session studies in themselves don't show how well these goals are actually met, and how long these relationships can sustain. Even if people report liking each other more during an initial setting, is that enough to lead to a substantial relationship?

Additionally, many studies that involve close relationship pairs, or attempt to study how relationship moderates emotional contagion, use a between-subjects design. One of the issues with a between-subjects design is that individual differences create a lot of background noise, which can obscure genuine patterns. Another issue is that trying to answer a within-person question, (how people change over time), with between-person data (e.g., measuring different people at various time points) can sometimes lead to incorrect conclusions. For example, people might all act similarity towards strangers, but how they change their behaviors can be moderated by time and individual differences. Statistically, this can result in nonstationary, or that the variance at one time point differs significantly from the variance at another time point. For these reasons, within-subjects designs are often much more statistically powerful and can be more fitting for certain research questions.

Therefore, longitudinal studies are needed when single-session studies cannot illuminate how emotional contagion and relationship formation interact over time. To understand the process, studies are needed that measure over many time periods. Fischer & van Kleef (2010) write:

> "Despite the fact that various scholars have emphasized that emotions are not momentary, static states, but rather processes that wax and wane, only few researchers

actually examined this process-like nature of emotions and the development of emotions during the course of interactions." (pg. 211)

Previous studies have used longitudinal studies and have measured dyads over periods of days or weeks, but all of them used couples that were already in close relationships. In other words, very few existing studies showed a change in relationship dynamic. One study, aforementioned, conducted by Anderson et. al. (2013) examined how relationship status changed emotional reactions to positive or negative events. However, their study assessed emotional response specifically to the events, and not to each other. In this case, participants might have reacted more similarly over time because having more similar views can help mutual understanding and cohesion. This does not necessarily imply that interpersonal emotional contagion is happening to a greater degree, only that their views are aligning more. Another study by Sels et al. (2020) looked at the correlates of emotional interdependence in romantic relationships. They tracked how couples showed interpersonal emotional connections (compared to pseudocouples) and analyzed its consistency across timescales and how it can be moderated by relationship closeness. The authors found that the overall mean level of convergence of couples was higher than of pseudocouples, but only to a small extent. Also, there were no consistent effects across timescales, nor any associations with relationship closeness. However, since their study used romantic couples, relationship closeness might already be at a high level.

The present study

In the literature so far, we have seen how emotional contagion can be automatic or deliberate, can be associated with personality measures, and can increase with goals to affiliate. We have also seen how the pre-existing relationship moderates the amount of emotional contagion, and that it exists in ingroups and close relationships. Yet no research to our knowledge has documented the process of how emotion matching affects relationship closeness over time as a dyad goes from strangers to friends.

Our study aims to fill a gap in the literature by using longitudinal data to examine how relationships form over time and how emotional contagion associates with the change. We paired unacquainted college students to talk to each other once a week for six weeks. We measured how each felt emotionally before and after each interaction, and also how close they viewed their relationship to be. We calculated three emotion-related measures: (1) how positively or negatively each person felt after their conversation, (2) how much they changed their emotion over the course of the conversation, and (3) how much closer in valence the dyads became during the conversation. We also collected information on personality variables that we plan to analyze in the future. The longitudinal aspect of our study design, as well as the random pairing, allow us to explore how emotion contagion and relationship closeness covary over time.

Method

Participants

We recruited a total of 118 undergraduate students (M_{age} = 18.88, SD_{age} = 1.26, Female = 83%) to participate in our longitudinal study in exchange for course credit or pay. Students who signed up for payment received $5 for each session and a bonus of $10 if they completed all six sessions. Students who signed up for credit received 0.5 credits per session and had the option of stopping after 4 sessions. Out of the total 59 dyads, 52 completed all six sessions and 7 stopped after four sessions. In our final sample, 55% identified as white, 32% Asian, 4% Black/African American, and 9% as mixed race or “other”.

Procedure

Students were randomly paired up to interact with each other for the entirety of the study. Prior to starting the study, the experimenters confirmed with the participants that they did not previously know their conversation partner. Participants that had indicated that they were familiar with their assigned partner were reassigned.

Each dyad had a 10-minute conversation once a week for 6 weeks, resulting in six meet-up sessions per dyad. For each session, the two members of the dyad and the research assistant running the study met over the video calling platform Zoom at a pre-established time in the week. Participants were told they could join the meeting from any location as long as they were alone and somewhere where they would not be interrupted. During the first meeting only, participants completed a survey asking for their demographic information and a battery of individual difference measures related to social flexibility, social motivation, and emotion contagion. At the beginning of each session, the researcher sent out a link to the online survey where each participant privately indicated their current emotion. After both participants confirmed they had finished answering the question, the experimenter left the participants alone in the Zoom meeting to talk. The conversations were recorded with the participants' consent. Participants were told, "You can converse freely about anything you want for 10 minutes". After 10 minutes, the experimenter returned to the Zoom call and the participants ended their conversation. After each conversation, the participants privately completed a post-conversation survey asking their current emotion state again, how much they liked their partner, how similar they felt to their partner, and how close they felt to their partner.

Measures

Background measures. In the first session only, participants reported their gender, age, year in school, and race. They also completed the Ten-Item Personality Inventory (Gosling et al., 2003), the Battery of Interpersonal Capabilities (Paulhus & Martin, 1988), the Revised Self-Monitoring Scale (Lennox & Wolfe, 1984), and the Emotion Contagion Scale (Doherty, 1997). We chose these scales because we were interested in how one's ability to be socially flexible, as well as one's motivation to connect with others, related to their friendship formation over the course of the study.

Emotion state. Immediately before and after each conversation, participants indicated how they were currently feeling on a Cartesian coordinate plane plot with valence on the x-axis (negative to positive) and arousal on the y-axis (mild to intense). To make sure participants understood this measure, we gave them the instructions, "Below is a graph with examples of emotions plotted to give you an idea of where you might fall in terms of how PLEASANT and how INTENSE your emotional state could be. Using the plot below, please describe your emotional state as you felt 5 minutes ago/before the beginning of the session." They saw an example plot with some emotions labeled at different parts of the plot, and then were asked to indicate their emotion on a blank plot (Figure 1). They were instructed to click on a point within the circle. The scale ranged up to 100 in each direction, so that the total positive points for valence and arousal ranged from - 200 to +200.

Partner evaluation. To assess partner liking, we asked participants, "How much do you like your partner?" (1 = *not at all,* 7 = *a great deal*). To assess perceived similarity, we asked, “How much do you have in common with the other person?” (1 = *nothing or almost nothing*, 7 = *a great deal*) and “How similar do you think you and the other participant are?” (1 = *not at all,* 7 = *a great deal*). To assess relationship closeness, we asked, “If you were to ‘rate’ your relationship with your conversation partner in terms of how close you feel to him/her, how would you do it?” (0 = *basically strangers*, 100 = *close friends*). Lastly, we asked participants if they had any interactions with their conversation partner during the week outside of the experiment, and if so, how much (1 = *less than an hour*, 2 = *1-2 hours*, 3 = *2-4 hours,* 4 = *4-6 hours,* 5 = *6+ hours*).

Analysis

We used a latent growth curve (LGC) approach to identify the interrelationships between relationship building and three emotion variables in our dyads over time. The three emotion variables, all calculated from participants’ pre- and post-conversation reported emotion states, are the following: (1) *post conversation valence*, taken directly from the x-axis of the post-conversation emotion measure, (2) *emotion distance,* calculated by taking the distance between a person’s pre conversation emotion point and their post conversation emotion point, and (3) *emotion convergence*, calculated by finding the absolute distance between the two partners’ valence scores after the conversation; the smaller the distance, the greater the convergence.

LGC analysis for longitudinal data describes how variables change over time by incorporating time with a latent intercept and slope for each variable. For each variable of interest, the intercept describes the initial starting point for an individual’s trajectory of change over time and the slope describes the pattern of change (Olsen & Kenny, 2006). Additionally, LGC can determine if there are relationships between two variables in either their values at baseline and/or how they change over time.

LGC modelling offers several benefits over other methods, such as multilevel regression, due to its flexibility (Hox et al., 2003). As mentioned, LGC allows us to not only examine the change patterns for our variables across time, but also how these variables relate to one another initially and over time. Second, LGC, and in general, structural equation modelling (SEM), is better at handling alternative structures for residuals that do not strictly meet assumptions. One assumption that must be met for proper analysis in multilevel modelling is that the residuals are homoscedastic and independently distributed over time. However, this assumption is impractical to meet with longitudinal dyadic data because there are correlations between variables measured over time within each person and within each dyad (Gistelinck & Loeys, 2018). With SEM, since each occasion is treated as a separate variable, we can better estimate the covariance structure without violations. Next, SEM is more flexible in cases with multiple outcome variables, as it is possible to estimate all means and covariances associated with latent growth parameters or model them explicitly. Lastly, LGC is better suited to estimate mediation effects of covariances, which we anticipate using in the future when we incorporate individual difference variables. Taken together, LGC is the best method to analyze the effects over time in our variables.

We used conditional LGC models to evaluate the change over time between the relationship closeness variable and the emotion variable. From each model, we examined which covariances were significant, indicating meaningful relationships between the variables. A significant covariance from a latent intercept to another latent intercept indicates that these two variables are correlated at the baseline. A significant covariance between two slopes indicates that the growth trends of the two variables are related. We used covariances, as opposed to one-directional path diagrams, because we do not have any theoretical reasons to expect a one-directional effect. Instead, we wanted to capture the bi-directional relationship between relationship and emotion, which can be best represented with covariance instead of path coefficients.

In our models, we are also interested in the actor and partner effects of emotion on relationship closeness. Actor effects are the effect of one person's behavior on his/her own score. In our model, the actor effect is the association between one person's relationship closeness and their emotion score. Partner effects are the effect of one partner's behavior on the other partner's score. In our model, the partner effect is the association between one person's relationship closeness and the other partner's emotion score.

We constrained parameters for theoretical reasons based on the design of our study. First, our dyads are indistinguishable, or interchangeable, meaning that the two members cannot be differentiated in a meaningful way (Kenny, 1996). Participants were arbitrarily assigned to be "partner 1" or "partner 2" in our model. To incorporate this indistinguishable dyad aspect, we constrained all actor effects to be equal to each other (e.g., partner 1's covariance between the relationship variable intercept and emotion variable interception is equal to partner 2's covariance between their relationship variable intercept and emotion variable intercept) and all partner effects to be equal (e.g., the covariance of partner 1's relationship variable intercept and partner 2's emotion variable intercept is equal to the covariance of partner 2's relationship variable intercept and partner 1's emotion variable), because there is no theoretical reason that they should differ.

The overall fit indices that we used to examine model fit were the comparative fit index (CFI), the Tucker Lewis Index (TLI), the root mean square error of approximation (RMSEA), and the root mean square residual (SRMR, the most common fit indices used in structural equation modeling (McDonald & Ho, 2002). Because each fit index is subject to some limitations, it has become standard practice to examine and report more than one fit measure(Taasoobshirazi & Wang, 2016). A model is considered to be acceptable if the CFI and TLI are greater than 0.9, and "acceptable" if the RMSEA is less than 0.08 and "good" if it is less than 0.05. All analyses were conducted in R using the "lavaan" package (Rosseel, 2012)

Results

Effect of time on perceived relationship

Table 1 presents the average scores of our variables of interest at each time point across all individuals. The ratings of relationship closeness increased linearly over time, beginning with an average of 33.6 out of 100 at the end of the first session and ending at an average of 55.1 at the end of the last session (Figure 1). The standard deviation remained the same throughout all six sessions. We used a conditional LGC linear model with six repeated conversation sessions stages to evaluate the overall fit of the linear trajectory (see supplemental materials). Following SEM convention, the path loadings from the latent intercept to each of the outcome measures were fixed at 1.0, and the fixed loadings from the latent slope factor to each of the sessions were 0, 1, 2, 3, 4, 5, respectively, to reflect the time interval of interest. The overall fit indexes for the linear LGC model (CFI = 0.978, TLI = 0.977, RMSEA = 0.092, SRMR = 0.042) indicated a good fit of the model. Although the RMSEA score of 0.092 is slightly higher than the conventionally accepted <0.08 as "acceptable", studies have suggested that RMSEA values tend to falsely indicate a poor model fit more when the sample size is small, as ours is (Kenny et al., 2015). With the overall fit indices, we can conclude that the linear model appropriately fits the data, and therefore, we use the linear model for relationship closeness in subsequent analyses. The model suggests that people significantly increased how they felt to their partner over time, and that the rate of growth was consistent from session to session.

In this conditional LGC model examining the intercepts and slopes of each person, as well as the relationship between the two, we also find that there is a significant correlation between the intercepts of the dyad members ($r = 0.354$, $z = 2.27$, $p = 0.025$), suggesting that when one member likes their partner after the initial conversation, the other person does as well.

Model 1: Association between relationship closeness and post conversation positive valence

Our first model focuses on the emotional valence participants reported after each conversation-in other words, how negatively or positively they felt after talking to their partner, and how that covaried with how close they felt to their partner. Figure 4 shows the full LGC model. The second column in Table 2 presents the average post conversation emotional valence scores at each session, scored from -200 to + 200. We examined if there were any significant covariances between the relationship closeness and post conversation valence. We found no significant covariances in actor or partner effects of emotion on relationship closeness, suggesting that post-conversation emotion valence does not affect relationship closeness.

Model 2: Association between relationship closeness and emotion change

Emotion change was calculated by taking the distance between a person's pre conversation emotion point and their post conversation emotion point. The third column in Table 2 presents the average emotion change at each session. In the model (Figure 5), we see that over time, there is a slight decrease in pre/post conversation emotion change across sessions, with an average “emotion distance” of 121.35 at the first session to 92.25 at the last session. This suggests that as people converse more and get to know each other, they stay more consistent with their emotions from before the interaction until after. We found a significant correlation between each person’s intercept for relationship closeness and their intercept for emotion distance ($r = 0.34$, $z = 2.04$, $p = 0.041$), suggesting that at the onset of a relationship, when people feel close to their partner, they also change their emotions more over the course of the conversation. All other covariances in the model were not significant.

Model 3: Association between relationship closeness and emotion valence convergence

In this model, relationship closeness was again modeled with a latent intercept and latent slope. Emotion valence convergence was calculated by finding the absolute distance between the two partners’ valence scores after the conversation; the smaller the distance, the greater the convergence. We calculated convergence in this way because we believed the value of the valence of emotion was more theoretically significant than their arousal. Unlike our first two models, emotion convergence was modeled here as time varying regression parameters. In doing so, we allow the convergence variable to vary across sessions and affect relationship closeness at different levels for each session, instead of binding it to a linear growth trajectory (Stoel, 2003). We were curious about if emotional convergence varied at different levels across sessions. Modeling it as a latent intercept and slope would constrain the association to be similar across all sessions, which could be too limiting. Here, emotion convergence at each time point was represented as its own exogenous variable (See Figure 6), to be regressed onto the respective time point score of relationship closeness.

As labeled in Figure 6, there was a significant negative regression coefficient in the first session when emotion convergence was regressed onto relationship closeness (beta = -0.06, z = -3.189, $p < 0.01$). The negative coefficient indicates that the closer people rated their relationship, the more similar their post-conversation emotional valence. In the second session, the same pattern was observed; by the third session, the effect disappeared. This indicates that emotion closeness is strongly related to relationship closeness at the onset of meeting someone, but as time progresses, emotion matching does not play as much of a role in relationship closeness.

Discussion

In our exploratory dyadic data study, we looked at how 3 types of emotion variables that emerge during an interaction affect relationship formation over time. We randomly paired participants to get to know each other over 6 weeks for a longitudinal dyadic study and used latent growth curves in structural equation modeling to analyze our data. First, we looked at whether a participant's self-reported post conversation valence had an effect on self-reported relationship closeness and found that there was no significant effect. Next, we looked at whether a participant's magnitude of change in emotion from before the conversation to after was related to closeness, and found that there was a significant correlation between the latent intercept of the relationship closeness variable and the emotion distance variable, suggesting that how much one changed emotionally during the interaction predicted how much they initially liked their partner, but this effect did not vary over time. Lastly, we looked at whether a dyad's emotional convergence in valence, as measured by their difference in post-conversation valence, affected relationship closeness. We found that emotion convergence predicted initial relationship closeness, but the effect attenuated over time.

Our work extends previous research on emotional contagion by examining how it associates over time with relationship development. The strengths of our study lie in the design and implementation: a longitudinal design allowed us to assess changes over time and how variables covary in ways that between-subjects designs had not. Our participants had the opportunity to start as stranger and finish as friends, whereas many previous longitudinal studies use pre-existing couples and therefore do not really change in relationship closeness. While previous studies in emotion contagion have looked cross-sectionally at different levels of relationships, we looked at trends over time, and found that emotion contagion did not occur as much once participants became more familiar with each other as it did when they were first getting to know each other.

Due to the exploratory nature of our study, as well as the multitude of possible associations, we refrained from making binding hypotheses a priori. Speculatively, our finding that post conversation valence did not have an association over time may be possibly due to a plateau or ceiling effect in post emotion valence. Additionally, people do not need to always feel extreme positive valence when interacting with someone. Instead, an ideal affect can be moderately happy but calm (Tsai, 2017). This finding supports previous literature on how partners in close relationships coregulate each other's emotions. Instead of pushing each other in one emotion valence direction, couples bidirectionally influence each other to fluctuate around a stable, neutral baseline, allowing for greater emotional and physiological stability (Butler & Randall, 2013). Therefore, people do not always need to feel happier than before when making friends; simply, they can be "happy enough".

Next, our finding from our second model that more emotion change in the first interaction is associated with more initial liking of a partner may support previous research that emotion contagion can be used to affiliate. If people like their partner and they desire to match emotionally, that desire can be reflected in the emotion distance score. However, we also found that this effect does not change the trajectory of relationship growth. This could suggest that when people have an established friendship, in other words, they have already affiliated with another, they don't have as much of a motivation to change their emotion. Another possible explanation is that once people are more affiliated, they engage in more emotion coregulation, such that they try to influence another's emotion in a specific direction, than they do in merely trying to copy another's emotion (Butler & Randall, 2013).

Lastly, our finding that a dyad's emotion convergence in valence mattered more in the initial sessions than in the latter sessions reveals how important emotion convergence is over the course of a relationship. It seems that at first, being more in sync emotionally makes people like each other more. However, as the relationship progresses, emotional contagion is not as important. This finding supports some of the recent literature suggesting that emotional independence is also important in relationships (Sels et. al., 2020). Another interpretation is that emotional convergence at first is used as a method to communicate affiliation. However, after the goal to affiliate is met, people do not feel as much of a need to converge with the other.

Our study includes some limitations that can be addressed in follow-up studies. First, our study might have not been long enough for people to develop a substantial friendship. Hatfield (1993) posits that a relationship exists if there is some interdependence between the two. Even though our dyads might have gotten to know each other well, they might not have any interaction with each other outside of the lab setting and therefore may still not be truly integrated in each other's lives. Or, ten-minute conversations may not be enough time to get to know each other enough. Additionally, our study is not realistic in the sense that the participants might not interact with each other after the study's conclusion, and therefore participants' knowledge of the study's conclusion might affect their emotion contagion. Our study also comprised of college students, who might already be motivated to make friends, and have been well-practiced in talking with strangers. These limitations can all be addressed in future studies that use more naturalistic sampling data, such as conversations between roommates at various points in the semester, or people who have all recently started working together.

Next, our measure of relationship closeness may have been interpreted very differently by participants. We intentionally made our scale larger so that we could capture more variation in ratings (to limit the chances of ceiling effects), but this could also lead to more noise in the data. Future studies would benefit by measuring relationship closeness in different ways, such as asking for specific behaviors (how much time people spend together) or if the other is included more in one's sense of self (Aron et al., 1992). Also, people might interpret the relationship closeness question differently in systematic ways. For example, people high in openness to experience may befriend others more easily, or communicate their desire to befriend (Laakasuo et al., 2017). Therefore, we plan to next incorporate our individual difference measures of personality traits into our models. By adding personality traits as covariates, we can also see if the individual differences in susceptibility to emotion contagion as aforementioned affect our results.

Another limitation in our study is that the measures of emotion contagion may be lacking construct validity. First, we constrained people to feeling emotions in the circle that we used, which may limit the possible scope of emotions that people could feel. Second, we cannot tell from the emotion measure alone what people were basing their emotions off of. For example, one person may have said that they were feeling sad because they didn't like their partner, while another may have answered the same way because they were talking about something sad. In the first case, negative valence would correlate with lower relationship closeness. In the second case, negative valence might actually correlate with higher relationship closeness, as self-disclosure and vulnerability can lead to greater bonds (Burger, 1981). In another case, some people might indicate high positive affect in the last session because they really liked their partner and the study, while others may indicate negative affect if they are sad the study is over.

In order to more accurately understand the emotion processes happening, we plan to transcribe the texts of the conversations, and then use text analytic software to gauge the emotional tone of conversations. By doing so, we can see more moment-to-moment emotion changes during the conversation, and also see if people are aligning in their emotion tone.

Despite these limitations, our study uncovers how emotion changes occur through repeated interactions as people get closer. Levels of closeness in relationships are not discrete, and therefore interpersonal processes, such as emotion contagion, should also be studied dynamically. We hope that this work can serve as the first of many that examine social functions of emotions within every-changing interpersonal relationships.

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Tables and Figures

Figure 1 Emotion plot. The valence-arousal plot that we presented participants with to indicate their emotion. The plot on the left shows the example plot of emotions, shown to participants to help them understand the plot. The plot on the left shows the blank plot on which participants indicated their emotion.

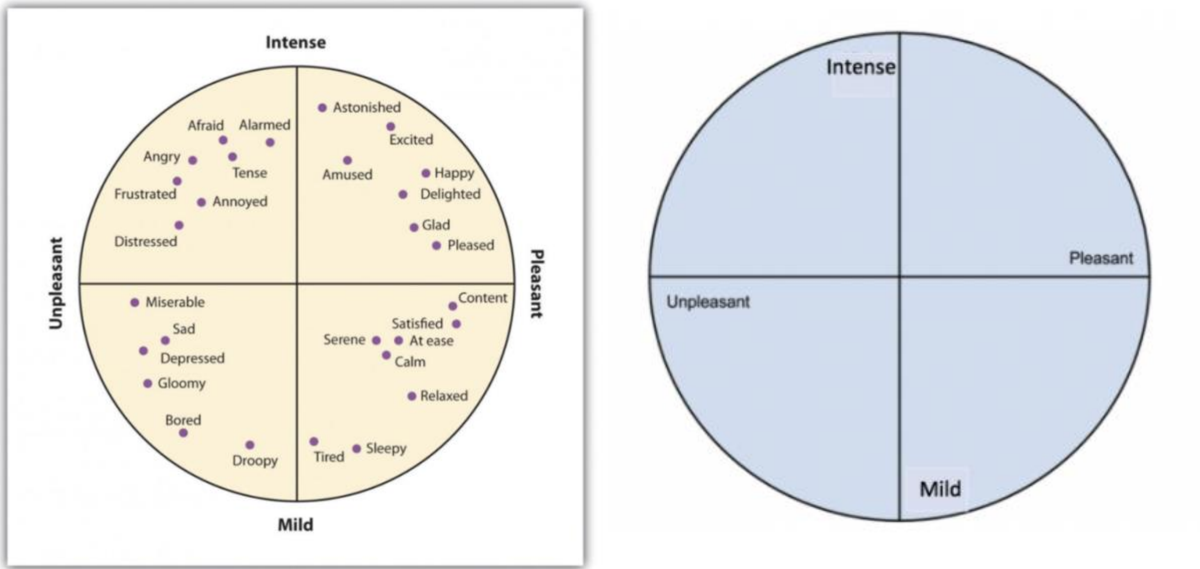

Figure 2. Emotion variables

The figure below shows the results of the emotion question from a dyad in the first session. Crosses represent pre-conversation ratings, and circles represent post-conversation ratings. Each person is represented with a different color. Post-conversation emotion valence was measured with the x-coordinate of the post conversation for each participant. Emotion distance was calculated by taking the distance of each participant's pre-conversation and post-conversation score, represented by solid black lines. Emotion valence convergence was calculated by taking the difference in post-conversation valence in each dyad, represented by a solid red line.

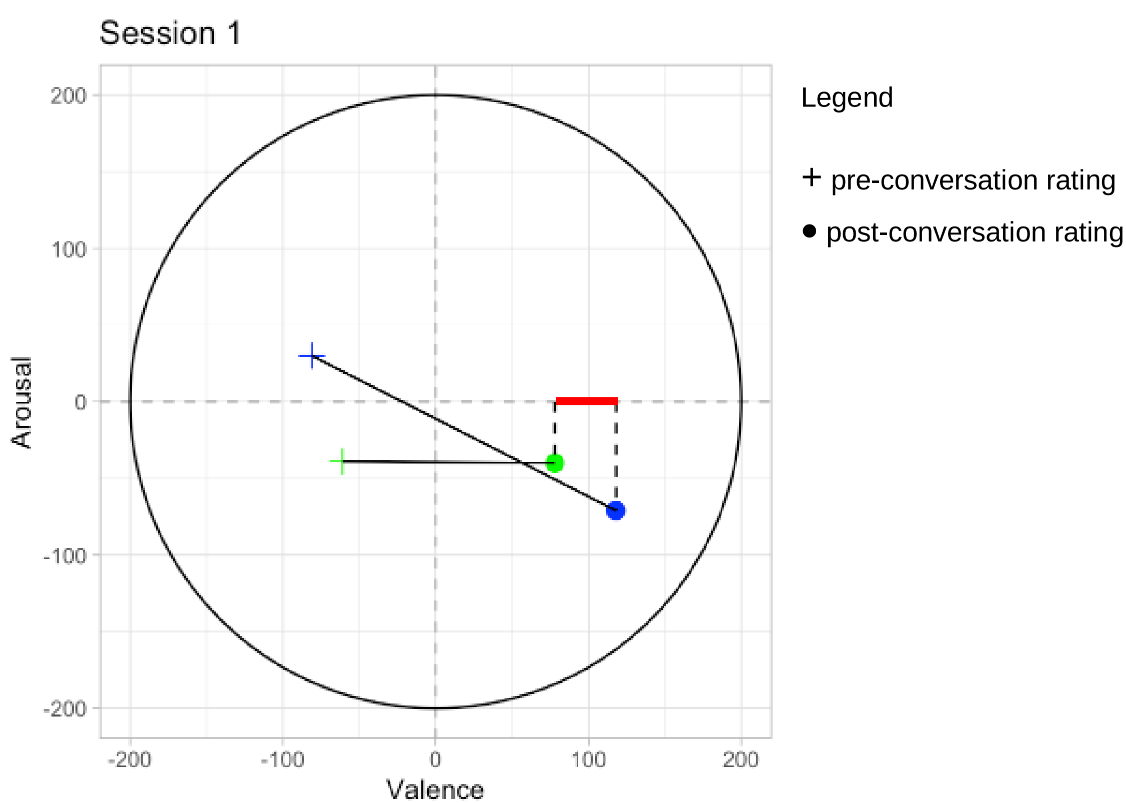

Table 1. Average scores of variables of interest at each time point

Relationship closeness and emotion by session (N = 118)

Session #	Relationship closeness		Post conversation emotion valence		Emotion distance		Emotion Convergence	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Session 1	33.56	24.17	107.03	40.98	121.35	64.18	39.78	37.91
Session 2	39.12	22.52	103.04	46.20	106.41	68.14	39.31	37.34
Session 3	44.10	22.04	96.81	49.30	98.36	66.81	47.38	35.84
Session 4	47.01	22.55	94.32	46.56	102.90	70.26	44.88	34.17
Session 5	50.75	22.44	88.91	55.92	101.41	70.83	57.94	53.82
Session 6	55.13	22.83	80.15	65.60	92.25	66.29	59.42	53.56

Table 2. Measures of overall fit for each latent growth curve model

Model	CFI	TLI	RMSEA	SRMR
Relationship model	0.978	0.977	0.092	0.042
Model 1	0.940	0.935	0.081	0.112
Model 2	0.927	0.921	0.091	0.115
Model 3	0.960	0.957	0.091	0.107

Figure 3. Average relationship closeness from session 1 to session 6

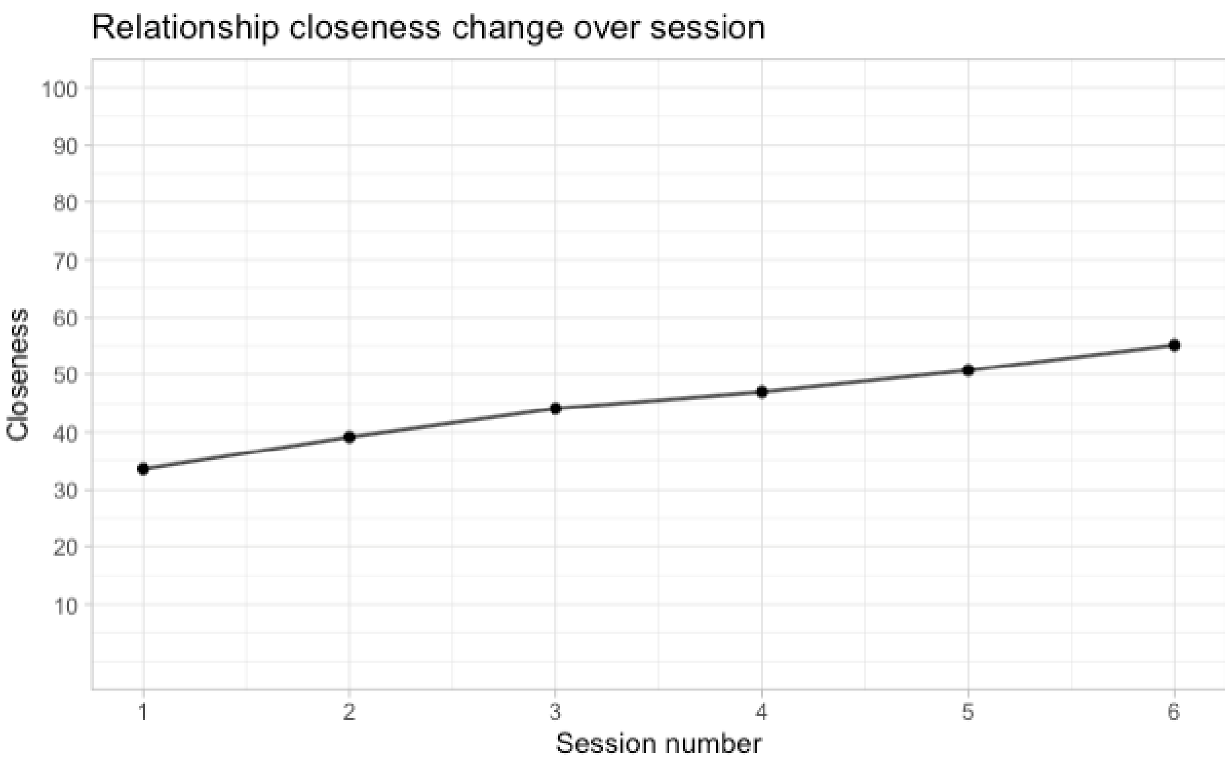

Figure 4. Latent growth curve model of relationship closeness and post-conversation emotion valence showing correlations of intercept variables and slope variables from session 1 to session 6. Only significant correlations are labeled in the diagram. rship1(2) = relationship closeness of partner 1(2); emo(1) = post conversation emotion valence 1(2); T = session number. Fit indices are presented in Table 2. **p* < 0.05. ** *p* < 0.01*

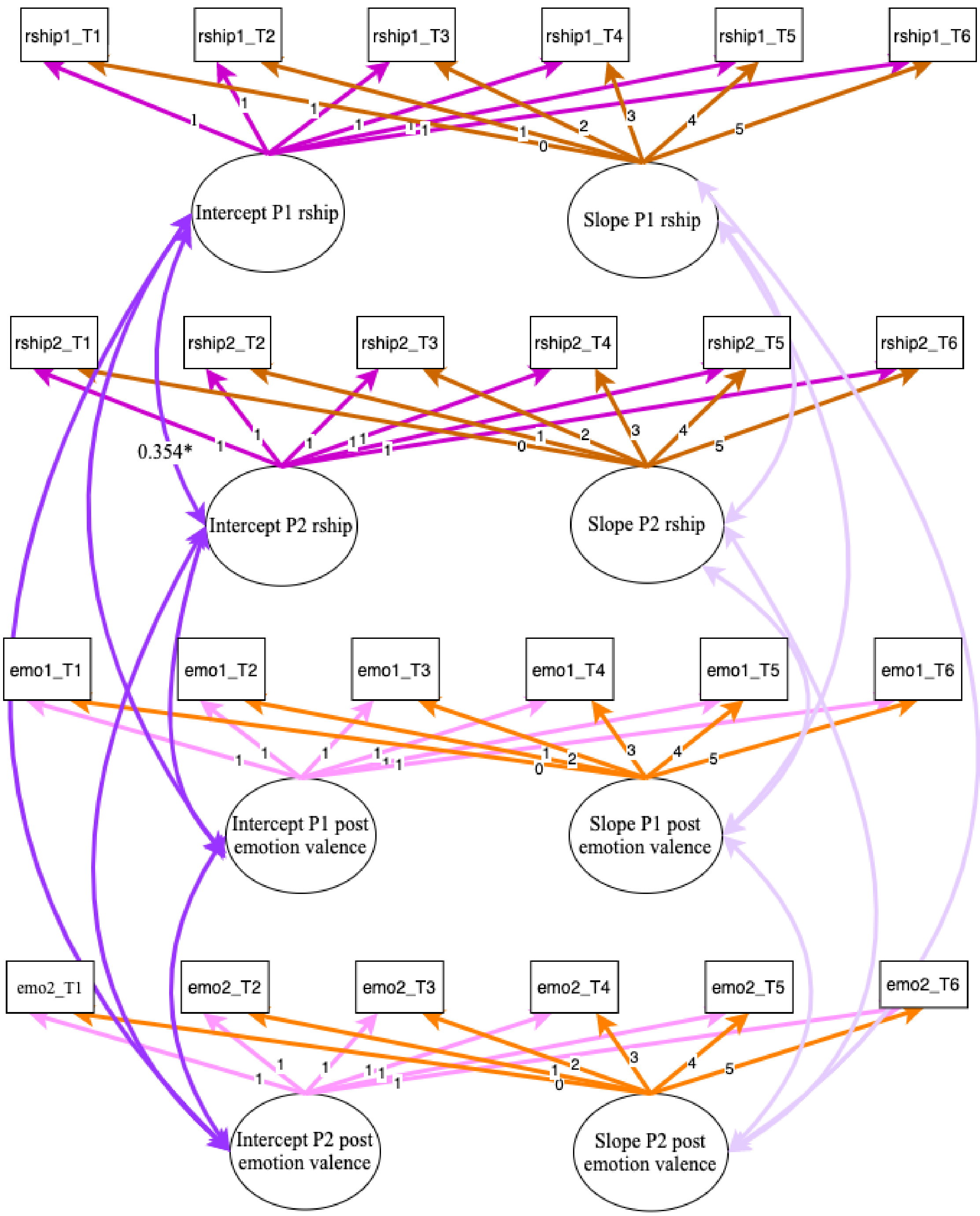

Figure 5. Latent growth curve model of relationship closeness and emotion change showing correlations of intercept variables and slope variables from session 1 to session 6. Only significant correlations are labeled in the diagram. rship1(2) = relationship closeness of partner 1(2); emo(1) = emotion distance before and after conversation of partner 1(2); T = session number. Fit indices are presented in Table 2. **p* < 0.05. ** *p* < 0.01*

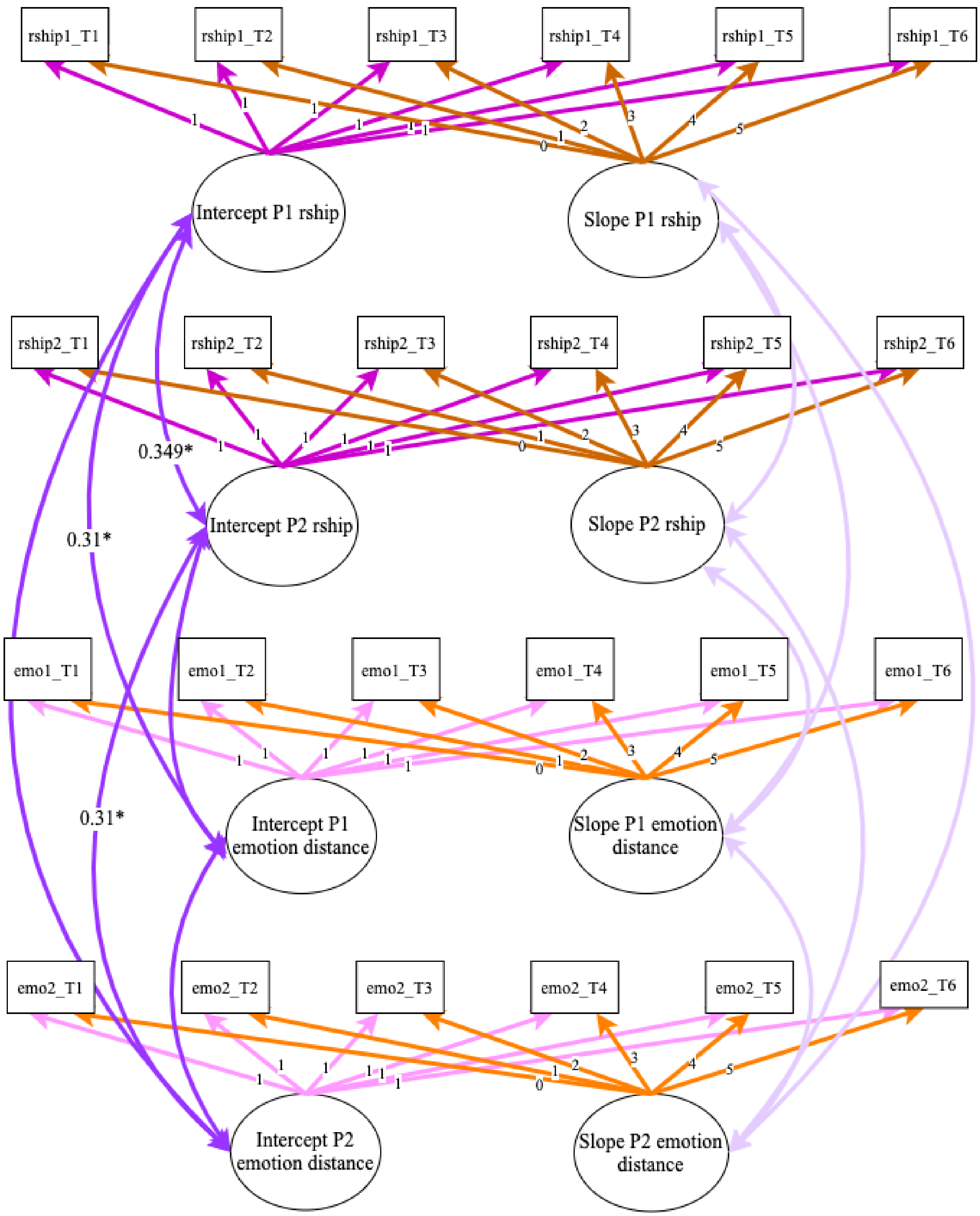

Figure 6. Latent growth curve model of relationship closeness and post conversation emotion valence convergence from session 1 to session 6. Only significant correlations are labeled in the diagram. rship1(2) = relationship closeness of partner 1(2); T = session number. Fit indices are presented in Table 2. *$p < 0.05$. ** $p < 0.01$*