1. INTRODUCTION

When engaging in conversation, people often need to regulate their emotions so that they are consistent with those of their conversational partners; it is a form of empathy [1]. People further need to recognize whether their emotions are in agreement when deciding the flow of the subsequent dialogue. For example, when many people share the same feelings, the remaining people also tend to share the same emotions, which they suppress to promote a smooth conversation. This constitutes a kind of social pressure [2]. Another everyday case is a circumstance where people are forced to agree with one of two conflicting groups. In either case, the key to decision making is to judge the degree of emotion matching between the self and the other person, or that between others. If dialogue agents and conversation support systems that understand and predict human interactions are developed, they can be expected to enhance the quality and efficiency of communication. However, the mechanism by which people create and perceive their emotional similarity is not well understood.

Similarity judgment plays a fundamental role in theories of knowledge and behavior. It serves as an organizing principle by which individuals classify objects, form concepts, make generalizations, trace memory, and make decisions [3-5]. Two of the most influential approaches to similarity are spatial approaches and feature-set approaches [4,5]. Space-based approaches assume that similarity is judged based on the perceived distance (rather than the perceived similarity) between the stimuli in a dimensionally organized metric space [6]. A monotonic relationship is assumed between the distance of the stimulus and the perceived similarity [7]. Space-based approaches are further divided into psychophysical approaches and scaling approaches depending on whether the component dimensions or the appropriate spatial model, respectively, is known or assumed [6]. Feature-set approaches assume that similarity increases as a function of the common features and decreases as a function of the distinctive features of compared items [3].

Emotion is one of the central topics in psychology and researchers have agreed upon the two major theories of emotion: dimensional theory and categorical theory. The dimensional theory describes emotion as a point in a psychological space, while the categorical theory assumes basic emotions, such as joy, angry, and sadness [8]. Although which theory most accurately describes the way emotions are actually handled in the brain is still under debate, the key point here is that basic emotional categories can be mapped onto emotional dimension space using similarity scaling methods, e.g. multidimensional scaling [8,9]. On the other hand, social scientists have long been investigating the way in which people understand others’ emotions, and now most of them agree that there are two ways: the theory of mind and simulation theory [1]. Recently, some researchers have been working on the real time measurement of brain activity during social interaction [10]. However, as yet
there has been no attempt to combine these findings to explore the generation and cognition of emotional congruence, and to deal with individual differences.

1.1 Proposed cognitive model and hypotheses

This paper attempts to explain individual differences in the generation and cognition of emotional congruence. In particular, as regards cognition, we propose a cognitive model of emotional congruence. We further relate individual differences in goodness of fit to the proposed cognitive model to psychological traits.

We created the following three hypotheses. The first one relates to the generation of emotional congruence, and the other two concern the cognition of emotional congruence.

[H.1] The distance when people put themselves and their partner in an emotional space (which hereinafter we call emotional distance) is shorter on average for more empathic individuals.

[H.2-1] Two people perceive their emotional congruence based on their emotional distance. Specifically, if their emotional distance is short, they perceive that their emotions are similar, and if it is long, they judge their emotions to be different. This is the emotional congruence cognitive model that we propose in this paper.

[H.2-2] Individual differences in the degree of fit (goodness of fit, GoF, hereafter) of H.2-1 are explained by their empathy traits.

Figure 1 illustrates the proposed model and the hypotheses.

We derived H.1 from the fact that emotional congruence is one aspect of emotional empathy, which is generated unconsciously, unlike cognitive empathy, which requires consciousness [1]. Despite this being a simple hypothesis, no studies have yet verified it directly.

For H.2-1, we applied the psychophysics-based similarity judgment approach, which was developed for lower level stimuli, such as color and shape, to emotional congruence. Specifically, we first decided to start with the dimensional theory, as a descriptor of emotional state. This means that the component dimensions for similarity judgment were determined. Therefore, when building a model of emotional congruence, it is natural to follow psychophysical approaches. Remember here that emotional categories can be mapped onto an emotional dimension space [8]. This suggests that it does not matter whether the dimensional theory or the categorical theory is employed in this study.

In the proposed model, two people’s emotional distance is first calculated, and then it is subjected to a distance-similarity conversion function $f$ (a monotone decreasing function). The output indicates the degree of perceived emotional similarity. In addition, it is assumed that a person can correctly recognize others’ emotional state, as well as his/her own emotional state exactly, namely, as a point in emotional space; we call this assumption A.1. We acknowledge that many previous studies have rejected this assumption regarding others’ emotions [11, 12] and even self emotions (e.g. for people with alexithymia [13]). Thus, the influence and alleviation of this assumption will be discussed in Section 5. As for H.2-2, since an understanding of other emotions is one aspect of empathy, we expect empathic traits to explain the individual difference in emotional congruence cognition.

1.2 Related work on mind reading

The accuracy with which people can understand others’ minds is one of the central themes in psychology. A representative example is empathic accuracy defined by Ickes et al. [11]. This scale is based on the degree of agreement between the rating value of self and the rating value (cross rating) given by another who is conversing with the target person regarding thought and/or emotion.

As mechanisms of understanding other people’s emotions, we have “simulation theory” and “theory theory” [1]. Under the simulation theory, the understanding of another’s mind creates the state of the other’s mind in the perceiver without any distinction between him/herself and the target person using the perceiver’s mirror system which involuntarily mimics the behavior of others being watched. On the other hand, the theory theory assumes that people understand another’s mind cognitively without confusing it with their own mind on the basis of their own knowledge and theory. The simulation theory is regarded as an unconscious and fast process.
(System 1 [14]), the theory theory is a conscious and slow process (System 2 [14]). There are also studies supporting both of these systems, but their hybrids have become attracted more attention in recent years [15].

The present study targets the “cognition” of “emotional congruence”, but both emotion understanding and emotional congruence are closely related to empathy. Empathy is a complex phenomenon covering multiple aspects, and it can be roughly divided into emotional empathy and cognitive empathy [1]. Emotional empathy corresponds to the above simulation theory, and emotional congruence is a state generated in the process of simulation. On the other hand, cognitive empathy corresponds to the theory theory.

Based on the above background, we predicted that the empathy measure is related to emotional congruence cognition. Baron-Cohen’s Empathizing Quotient (EQ) and Systemizing Quotient (SQ) [16] are commonly used empathy scales. EQ is an index that shows a tendency to infer the psychological state of others and respond with appropriate emotions, while SQ is an index indicating the tendency to find rules and try to build a system for things. Other empathy measures include Emotional Empathy Measure (ESCQ) [17], the Interpersonal Reactivity Index (IRI) [18], and the Autism-Spectrum Quotient (AQ) [19].

In addition to these measures based on self-evaluations, we also focused on objective measures, including the “Reading the Mind in the Eyes” test (ET) [20]. ET is the score of a test that involves understanding an internal state solely from a person’s eyes. We predicted that ET is a good measure for observing individual differences when reading others’ minds. In particular, we expect ET to be related to GoF (H.2-1).

1.3 Related work on emotional congruence

Empathic accuracy [11] is based on the degree of agreement between the rating value of self and the rating value (cross rating) given by other people to the self. In [12], the degree of agreement between two people’s self-reports was further calculated. The degree of coincidence is inversely related to our emotional distance (on the right side of Fig. 1). However, these studies did not address cognition of emotional congruence, and there has been no examination of H.2-1 or H.2-2.

One of the studies most related to emotional congruence cognition is Breithaupt’s three-person model of empathy, which explains the reactions of a third person who encounters two people in conflict; it is an extension of the conventional empathy theories assuming dyadic interactions [21]. Also, in the affective computing community, the differences between the cognition of emotional congruence between target interlocutors, outsiders inside the conversation and external observers outside the conversation have been compared [22]. Furthermore, computational models that predict emotional congruence perceived by a specific individual (an external observer) have also been proposed, e.g. [23]. However, none of these studies has analyzed the relationship between emotional congruence cognition and psychological traits to explain the individual differences. Moreover, none of them looked at similarity judgment theory as a base cognitive theory.

1.4 Objective of this study

This paper aims to contribute to the elucidation of the generation and cognition of emotional congruence by proposing a cognitive model and testing its validity. More specifically, the validity to be assessed is the criterion validity for H.1 and H.2-2, and the construct validity for H.2-1.

2. EXPERIMENT

2.1 Participants

Seventeen Japanese female college students in their early twenties participated in the experiment. We randomly assigned each participant to one of three 3-person groups or two 4-person groups, to validate the generalizability of our model in terms of group size. The members of each group were not acquainted in advance, and each group was recruited separately.

The reason for the female only experiment was to minimize gender effects. Many studies have demonstrated a gender difference in terms of empathy accuracy (in particular, differences in motivation rather than differences in ability) [15, 24] and gender differences in cognitive characteristics as regards empathy [25]. In addition, we chose multi-party conversations rather than dyadic interactions to obtain various emotional congruence ratings. In a dialogue, there is only one conversational partner. So, the emotional distance can only distribute over a narrow range (for example, when both are always in pleasant and high arousal states). This means they are always emotionally similar, and as a result only the same emotional congruence rating value can be obtained. However, if there are two or more partners, the issue can be alleviated because a variety of people tend to be involved.

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1 Strictly speaking, SQ is not a measure of empathy, but in this paper SQ is also taken as an empathy measure.
2.2 Conversation procedure

The participants conducted conversations and rating in the following procedures.

(1) Self introduction: As an ice break, they were asked to introduce themselves to each other for 2 minutes per person.

(2) Discussion: They were next asked to hold a 10-min discussion about one theme given by experimenter. The discussion was filmed for the later rating session. We used two cameras and recorded everyone so that the whole body of each was captured.

(3) Evaluation: The participants were next asked to judge their own emotional states during the discussion, and emotional congruence between all pairs in the group. Details of the evaluation method are explained in Section 2.3.

(4) Psychological questionnaires: Finally, the participants responded to various psychological questionnaires. The scales used in the present study were as follows: EQ, SQ, ET, AQ, IRI, ESCQ, Big Five [26] and University of Tokyo Egogram (TEG-II) [27]. We expected that individual’s (all or at least one of) EQ, SQ, ET and other empathy measures are related to her goodness of fit to the proposed model. Moreover, for more comprehensive tests, we also used Big Five and TEG-II, which are more general personality traits. For more detailed procedures, see [22].

2.3 Rating procedure

A movie of each group discussion was divided into non-overlapping clips every 7.5 seconds. We determined the clip length with reference to [28, 29]. The intervals were set at 15 sec and 25 sec for three- and four-person groups, respectively, due to the difference between the numbers of pairs in the groups. A computer program automatically played and paused the clips for rating. The clips were presented on a 24-inch monitor assigned to each participant. The discussion duration was slightly different for each group, and thus the resulting number of clips rated by the participants was not constant (M=92, max=106, min=80 clips).

During the intervals, each person reported her own emotion in terms of both valence and arousal dimensions on a 7-point Likert scale from -3 to +3, and made a judgment regarding the emotional congruence between each pair in the group on a 5-point Likert scale from -2: Dissimilar to +2: Similar. The participants were not provided with any further details of the empathy definition.

3. ANALYSIS

3.1 Emotional distance

This paper uses valence-arousal (v-a) space since it is one of the most commonly used emotional spaces. Therefore, according to H.2-1, the emotional distance between persons \(i\) and \(j\) is defined as the Euclidean distance between \(i\)'s emotional state \(e_i = (v_i, a_i)\) and \(j\)'s emotional state \(e_j\). There are various definitions of distance including those in nonlinear phase spaces. However, the Euclidean distance is one of the most commonly used distances in similarity judgment studies [7]. We also evaluate other Minkowski distances in Section 4.3.

Each participant provided an emotional congruence rating for all the pairs in the group. However, we only focused on the ratings given by the two people in each pair to be analyzed. This makes A.1 more valid, because the emotional congruence rater was one of the pair who assessed their own emotional state. We also report and discuss the results of the excluded data, namely the ratings given by people who were not included in the target pairs in Sections 5.2 and 5.3.

3.2 Goodness of fit with proposed model

We define goodness of fit (GoF) with the proposed model as a measure of how well the proposed model explains the obtained emotional congruence ratings. GoF was calculated independently for each person. Here, person \(i\)'s GoF was calculated as the similarity between the time series of the emotional congruence rating given by \(i\) for pair \(i-j\) (\(j\) is another person) and the corresponding time series of emotional distance for the pair; the length of both series was the number of clips for the group. Here, Pearson’s correlation coefficient was used as a similarity measure. This was done for all pairs including person \(i\), and then the correlation coefficients were averaged to eliminate the influence of the individual differences in bias and scale of rating. Finally, the mean value multiplied by -1 was taken as person \(i\)'s GoF. A higher emotional congruence rating means that the emotions of the pair were perceived to be more similar. And, a shorter emotional distance means that their emotions were actually similar. Thus, GoF increases if the rating follows the proposed model.

3.3 Correlation between GoF and psychological traits

The correlation coefficient between GoF and psychological measures obtained for each individual was then calculated to explain the individual differences (H.2-2). We distinguish this coefficient by describing it correlation

\[2 \text{ Spearman’s correlation coefficient yielded similar results. This suggests that distance-similarity conversion function } f \text{ is linear.}\]
R or simply R from other correlation coefficients (indicated by r).

3.4 Hypothesis testing

We concluded that each hypothesis was supported, if the null hypothesis was rejected at a significance level of 5% and at least small effect was found according to Cohen’s criteria [30] (e.g. .1 for correlation coefficients).

4. RESULTS

4.1 Emotional distance

Figure 2 shows the correlation between the mean emotional distance from others and psychological measures. The following three measures were correlated with emotional distance: EQ (r(15) = .74, p = .00073), “Emotional Recognition and Understanding” of ESCQ (ESCQ_RU; r(15) = .51, p = .035), and, “Communication” of the Autism Spectrum Quotient (AQ_CM, a higher score means a lower ability; r(15) = -.49, p = .047). These three also exhibited a strong cross-correlation (EQ - ESCQ_RU: r(15) = .74, p = .00077; EQ - AQ_CM: r(15) = -.66, p = .0041; ESCQ_RU - AQ_CM: r(15) = -.58, p = .015). No correlation was found between EQ, SQ and ET (EQ - SQ: r(15) = .051, p = .85; EQ - ET: r(15) = .12, p = .65; SQ - ET: r(15) = .21, p = .43). Thus, we concluded that EQ, which showed the highest correlation with emotional distance, was the main factor. Figure 3 shows a scatter plot of EQ and mean emotional distance. In summary, highly empathetic people (high EQ) tend to yield a longer emotional distance. That is, H.1 was not supported, and rather curiously the opposite result was obtained. This point is discussed in Section 5.1.

4.2 Goodness of fit (GoF) with proposed model

Figure 4 shows the distribution of GoF corresponding to H.2-1. The mean GoF of the seventeen participants was .14. There was no difference in the mean GoF between the three-person groups and the four-person groups (t(12.7) = 1.1, p = .28). However, a large individual difference was found ranging from -.16 to .52. When all the data were combined, the result showed a statistically and practically significant correlation (r(3,790) = .19, p < .001), where the element number 3,790 = # groups (the number of groups) × # pairs × 2 (people in each pair) × # clips. Therefore, H.2-1 was supported.

Now we validate the use of the Euclidean distance which is the L2 norm as a distance metric. Here, we also tested other Minkowski distances: L1 norm (Manhattan distance) and the L∞ norm (Chebyshev distance). However, the results did not differ much (L1: r(3,790) = .18, p < .001; L∞: r(3,790) = .20, p < .001).
4.3 Correlation between GoF and psychological traits

Figure 5 shows the correlation $R$ of GoF with various psychological measures, which corresponds to H.2-3. SQ ($R(15)=.50$, $p=.041$) and the lie scale of University of Tokyo Egogram (TEG_L, a scale on which to measure the honesty of the answers); $R(15)=-.54$, $p=.026$). In addition, there was no correlation between SQ and TEG_L ($r(15)=.40$, $p=.11$). The above results support H.2-2. Moreover, neither EQ nor ET was correlated with GoF ($R(15)<.23$, $p>.38$).

Figure 6 shows a scatter plot of SQ and GoF. It suggests the difference between the three-person and four-person groups. When tested separately, the three and four-person groups showed different results: the four-person groups exhibited a strong correlation ($R(15)=.886$, $p=.003$), while the three-person groups did not ($R(15)=-.057$, $p>.88$).

Again, other Minkowski distances did not change the results: $L_1$: $R(15)=.50$, $p=.041$; $L_\infty$: $R(15)=.51$, $p=.038$.

5. DISCUSSION

5.1 Opposite results to H.1

A positive correlation was observed between EQ and mean emotional distance, contrary to H.1 (Section 4.1). In simulation theory, when understanding another’s emotion, people first mimic the emotion of the other inside of the self (emotional congruence), and then understand it by correctly distinguishing it from their own emotion [1]. Experimental results suggest that people with low EQ scores are not good at self-other separation. This is because in an extreme case if person $i$ confuses his/her own emotion with imitated emotion of other person $j$, then their emotional distance is expected to be the same; in this case, both of the pair rate $j$’s emotion. Participants in this study rated their own emotional states, but not with each other, so it would be unlikely that they noticed their confusion through the rating procedure. To investigate the results more deeply, it would be necessary to ask participants to rate not only their own emotional states but also their conversational partners’, or to use their physiological data (e.g. [12]).

5.2 Correlation between GoF and psychological traits

Since emotional congruence is an aspect of empathy, we predicted that the correlation of GoF also increases with EQ, ET etc. However, only SQ and TEG_L showed such a correlation. A positive correlation with SQ would be reasonable because distance-based similarity judgment on the emotional space requires systematic thinking to some extent. A negative correlation with TEG_L (lie scale) does not contradict H.2-1.

Other empathy scales were consistently uncorrelated with GoF. We here focus on ET and SQ. First, we did expect a correlation between ET and GoF, because ET is the rate at which people can understood others’ emotions correctly and the proposed model relies on A.1, which assumes that people can correctly understand both their own and other’s emotions. This point is discussed in detail in Section 5.3.

For EQ, people with lower scores showed shorter mean emotional distances (Section 4.1). This means that they had to give ratings for a narrow range of distances, and we can expect strict rating to be more difficult than...
for people with higher EQ scores. As a result, even if people with lower EQ scores tend to follow the proposed model (although it is in the opposite direction to H.2-2), it is natural to have obtained no correlation because the two EQ effects cancelled each other out. Therefore, we here analyze emotional congruence ratings given by third persons (for example, the emotional congruence ratings given by k for pair i – j, instead of those given by i and j)\(^3\). In this case, it is unlikely that k’s EQ had a strong influence on the mean emotional distance between i and j. No correlation between EQ and GoF was observed for a third-person’s rating (r(15)=.033, p=.90). Thus, we concluded that there is no correlation between EQ and GoF.

5.3 Effects of Assumption 1 and its alleviation

The proposed model assumes that people can accurately understand their own and others’ emotional states (A.1). However, previous studies [11,12] showed the difficulty of understanding others’ emotions. Furthermore, even with regard to their own emotional states, people do not necessarily understand correctly. Therefore, here we examine the influence of this assumption and discuss the possibility of its alleviation.

First, we estimate the impact of A.1. Our analysis only used emotional congruence ratings for pairs including the rater. As mentioned in Section 3.1, A.1 is less problematic, since one of the emotional states determining emotional distance was given by herself (called person i here). On the other hand, the emotional state of the other person j should be less accurate since i could not know it directly. As mentioned in Section 1.2, it is known how often people can correctly identify others’ emotion categories, namely empathic accuracy [11]. However, little is known about how divergent their inference is as the coordinates on the emotional space. Therefore, to verify the influence of errors on understanding a partner’s emotional state, a similar analysis was performed using emotional congruence ratings given by third person(s) k, as with the analysis in Section 5.2. First, the overall GoF decreased, resulting in no practical significance (r(2,928)=.07, p<.001). Since the number of people whose emotions the emotional congruence rater (k in this case) had to understand increased from 1 to 2, the lower GoF is reasonable. However, correlation R with SQ was close to that obtained in Section 4.3 for ratings given by the target pair (R(15)=.65, p=.0047). Therefore, although the overall GoF decreased due to the errors in A.1, the individual differences in GoF were explained by SQ. These results also support our model.

Second, we discuss how A.1 can be alleviated. To preempt the discussion, we theoretically obtain the same or at least a similar correlation R if we assume that people perceive emotional state of self/other as a distribution with certain variance rather than point(s) under certain conditions.

Let us begin with the case where the emotional state of one of the pair is given as a distribution rather than a point. Here, as an example, we take a partner whose emotion is predicted by the target person as a distribution. However, the following discussion theoretically holds for the remaining case, namely the case where self’s emotion is perceived as a distribution. Now the emotional distance should be the distance between a point and a distribution. One of the most widely used definitions is Mahalanobis distance, which is the Euclidean distance divided by the covariance. If i) the distribution is a normal distribution, ii) the mean is equal to the emotional state given by the person, and iii) the covariance matrix is proportional to the identity matrix \(\alpha^2I\), then the emotional distance is \(1/\alpha\) times the emotional distance obtained by using the Euclidean distance (i.e. scaled Euclidean distance [31]). However, this constant term \(1/\alpha\) is omitted when calculating the correlation coefficient, and so the same correlation R is obtained.

Next, we extend our model by assuming that the emotional states of both of the pair are expressed as distributions. A major metric for this case is the Kullback-Leibler divergence. If we assume exactly the same conditions as assumed for the Mahalanobis distance above for the distribution, the Kullback-Leibler divergence is a half of the squared Euclidean distance\(^4\) (the proof is omitted here). It would be an interesting cognitive scientific topic to confirm whether or not a person’s cognition really follows the above conditions.

5.4 Group size effect or other potential factors

We found a strong correlation R between SQ and GoF for four-person groups, but not for three-person groups. We anticipate two reasons for this.

The first potential reason is the group size effect. In our procedure, the number of pairs to be rated increases not linearly but exponentially with respect to the group size. As the number of people increases,

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\(^3\) Note that no third person exists in dialogues, e.g. as in [4,5]. Although rating by external observers is possible, their rating differs from the third person in the conversation, as demonstrated/claimed in [14,10].

\(^4\) Squared Euclidean distances yielded similar correlation R between SQ and GoF (R(15) = .53, p = .028).
more restrictions are made on the emotional congruence rating and systematic thinking may be required in order to realize consistency in the rating. Here, we consider the emotional state of self as a known point. First, the number of unknown emotion variables to be (implicitly) predicted for each interlocutor is four for three-person groups (two-dimensional emotional state times two conversational partners), whereas the number of emotional congruence states (here, considered as known variables after the rating was given) is three. Thus, the system was underdetermined with four unknown variables and three known constants. In this case, even unsystematic cognition is unlikely to violate the geometric consistency. On the other hand, in four-person groups, the unknown emotional states are six degrees of freedom (two dimensional emotional states multiplied by three partners), and the number of pairs is also six. Therefore, the system is exactly determined. In this case, since it is possible to uniquely determine a solution except for rotation and scale uncertainty in space, unsystematic cognition is likely to violate the geometric consistency.

The second possible reason is the difference in the range of SQ scores. As shown in Fig. 6, SQ was widely distributed from 15 to 45 for four-person groups, but for three-person groups it was narrowly distributed in a 7 to 30 range. Figure 6 suggests that correlation R is better predicted using a sigmoid function that suddenly rises from an SQ of 30 and saturates at about 50. According to this assumption, it is reasonable that no correlation was seen for three-person groups. Further studies are required where people with high SQ scores are included.

5.5 Effects of rating method

In this study, the participants evaluated emotional congruence while watching a video after the end of the conversation. The rating can differ from the cognition during the conversation. Therefore, it might have induced a strong correlation with SQ instead of EQ or ET.

The processing speed of emotion in the limbic system is relatively fast compared with the processing speed of thought and judgment in the neocortex. Emotion plays a key role in providing an individual with serious information related to survival such that concerning danger and discomfort. Thus, emotion needs to be processed quickly despite the risk of making a bad decision. The cerebral neocortex plays a complementary role for judgment based on deliberation and a long-term viewpoint [14].

In real-time conversation, short-term and high-speed processing are required. Therefore, emotions processed in the limbic system are expected to dominate. On the other hand, our post rating procedure might require stronger neocortex (slower system) activity to recall the entire discussion under the weaker time constraint. If the faster limbic system and slower neocortex activities are associated with EQ and SQ, these might explain our results. To verify this hypothesis, it is likely that we need an experimental design that evaluates in real time while measuring brain activity. This is in line with recent trends in cognitive neuroscience [10]. If this assumption is true, our findings will relate specifically to post rating. Nevertheless, our findings are still important for comparing how real-time rating differs from post rating, and to predict real-time cognition from post ratings.

6. SUMMARY

This paper investigated the generation and cognition of emotional congruence including individual differences. To this end, we also proposed a cognitive model in which a person is assumed to place both their own and other’s emotions in a dimensional space, and to make a judgment based on the distance. Curiously, our experiment first demonstrated that people with lower Empathizing Quotient (EQ) scores are more likely to generate emotional congruence with others. The proposed cognitive model was supported in particular for those with higher Systematizing Quotient (SQ) scores. We acknowledge that the present study includes a number of issues that need to be addressed in future studies: for example, those mentioned in Section 5, and the lack of content validity, namely the extent to which the measured values represents all facets of emotional congruence. However, we believe that our work offers considerable novelty.

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