Modeling the dynamics of observational behaviors base on observers' personality traits using hidden Markov Models

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***Abstract*—Previous studies indicated that how people look at others' faces depends on observers' characteristics. A vast majority of these studies used aggregated data, treating gaze data in a static manner and often neglected dynamics of observational behaviors. The present study, on the other hand, examined the relationship between observers' personality traits and observational behaviors (i.e., which areas of face were looked at) using time-series eye movement data. In particular, we collected gaze data using a smile judgments task, asking participants to judge whether smiley faces were genuine or not. Observational behaviors were analyzed using a hidden Markov model. The results showed that participants with different patterns of personality traits exhibited different transition patterns. In addition, there were also significant interactions between personality traits and the number of hidden states each participant had. Furthermore, there were significant relationships between participants' personality traits and the result of judgments.**

I. Introduction

How people look at the faces of others attracted much interest, and a wide variety of research has been conducted. Among them, studies that used observer's gaze provided quantitatively sound and interesting results. For example, a study that examined cultural differences in observational behaviors while looking at others' faces found that Westerners tended to focus on the eyes and mouth, while Easterners tended to look mainly at the nose [1]. Another study examining the effects of gender, task, and stimulus types on gaze during face observation showed that observational behaviors differed depending on gender and (difficulty and type of) tasks, and these effects were independent of the type of stimuli [2]. According to one study, individual participants had their own scan paths when looking at the faces of others [3], and a different study that recorded observational behaviors over a period of 18 months confirmed that this type of behavior was stable with almost no significant deviations [4]. Furthermore, in a study that examined the relationship between observers' gaze and personality traits, observers with different personality traits exhibited different observational behaviors, and these behaviors were so robust, showing similar behaviors even if their gazes were manipulated [5].

The above studies used the gaze data in an aggregated manner so that their analyses were based on static observational behaviors. Simply using the frequencies of attention alone may not be sufficient. In response to this potential problem, some researchers began using raw gaze data and analyzed dynamics of observational behavior using, for example, hidden Markov models [6][7][8]. For example, the results of a study that examined cultural differences found three patterns (center of the face, left eye leaning and right eye leaning) common to both Westerners and Easterners [6]. This result suggested that eye movement patterns may be essentially similar independent of cultures. Another empirical result showed that observational behavior was also influenced by the age of the observer [7]. Older people tended to focus more on the center of the face than younger people whose gaze shifted more frequently. Furthermore, differences in gaze shifts were also observed when judging whether or not the other person was lying or not [8].

As mentioned above, dynamic analysis of the observers' observational behaviors may provide much richer information than static analysis. However, a majority of studies still analyze gaze data in a static manner, and thus a little is known about the dynamic relationship between observational behavior and observer characteristics. In particular, no single study examined the influence of observer personality traits on the dynamics of eye movements. While previous studies have found robust relationships between observational behavior and personality traits using aggregated (static) gaze data, it is unclear whether this relationship also exists in raw eye movement data. In order to clarify this question, we conduct a smile judgment experiment to examine relationships between observers' personality traits and observational behavior using raw eye movement data.

A smile is a means of expressing emotion for humans and is also a means of communicating with others. There are several types of smiles, and researchers have tried to classify them depending on their functions and purposes [9][10][11][12][13][14]. One type of smile that is often used to promote smoother inter-personal communication in real life is a "presented" smile (i.e., non-Duchenne smile). The ability to discriminate Duchenne (i.e., genuine smile) from non-Duchenne smiles particularly has attracted scientific interests among various types of smiles. Duchenne smiles and non-Duchenne smiles are known to be triggered by different muscle movements, but the results of the previous study showed that it is very difficult to distinguish them. Although several previous studies confirmed the difficulty of distinguishing a Duchenne from a non-Duchenne smile, a little was discussed why it was difficult. In addition to investigating relationships between observers' personality traits and observational behavior using raw eye movement data, the present research also investigate why it is so difficult to distinguish a Duchenne from a non-Duchenne smile.

II. Experiment

A. Participants

Twenty-three students from Chiba University participated in the experiment. Among them, there were 12 male and 11 female participants. Their mean age was 21.35 (sd = 1.229).

B. Materials

Twenty actors (13 males and seven females) provided pictures of both Duchenne and non-Duchenne smiles. Each actor was asked to come to a photo shooting session with at least one of his or her friends. For each actor, we first asked him or her to show a non-Duchenne smile and took a picture of the actor. We then asked the actor to have a chat with his or her friend(s). All actors were instructed to look into a camera throughout their chatting. While chatting, we took some pictures of the actor when he or she exhibited smiles or laughs. After taking these pictures, we showed them to the actor to confirm whether (or which pictures of) his or her smiles were Duchenne. We randomly selected one self-confirmed Duchenne smile picture for each actor. All pictures were taken from the front. The brightness of the pictures was corrected with Photoshop.

C. Apparatus

We used Tobii T120 eye-tracker to present stimuli and collect data on eye movements. The entire experiment was controlled by PsychoPy. The distance between the monitor and participant's heads was fixed at 65cm, and the visual angle was set at 13-degree to imitate a real interpersonal communication scene. We used a jaw stand to keep the heads of participants from moving.

D. Procedure

Before starting the experiment, we calibrated the eye-tracker for each participant. After calibration, the experiment was started according to each participant's timing. There was a total of 40 sessions (20 Duchenne and 20 non-Duchenne smiles) in the experiment. Each session began with a task statement asking participants to judge a picture they were about to see would be a Duchenne or non-Duchenne smile. When the participant pushed the space-key, a fixation marker (i.e., "+") was presented at the center of the monitor for 500 milliseconds, followed by a randomly selected smile picture (either Duchenne or non-Duchenne smile). The observational duration was not fixed, and thus participants could look at the pictures as long as they would like. When participants made a judgment, then the picture disappeared, and the next session started. After completing the judgment task, participants were asked to complete the Japanese version of Ten Item Personality Inventory (TIPI) to collect their five personality traits, namely Agreeableness, Conscientiousness, Extraversion, Neuroticism, and Openness to experience [15].

The present experiment with human participants was approved by the Internal Review Board of the Faculty of Letters, Chiba University.

E. Data preprocessing

First, we divided the data recorded by the eye tracker into increments of 10 Hz. This was done to ensure sufficiently long time-series data while imputing missing measurements. A Gaussian filter (sd = 10) was then applied to the segmented data, and relative attention weight information was added. Next, we applied individualized facial area masks (pre-made for each stimulus) to the facial images to extract data corresponding to each facial area. The facial area mask includes the eyes, nose, mouth, corners of the eyes, corners of the mouth, and cheeks. We used these areas because they were said to be important in determining and/or distinguishing smiles in previous studies. The area with the highest relative attention weight (relative to the size of the areas) was considered to be the representative behavior at this time. Figure 1 shows examples of the preprocessed data, showing two participants' observational behaviors to the nose for three different facial stimuli.

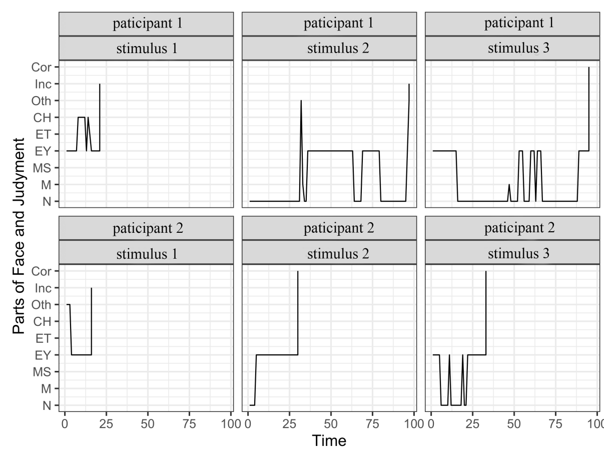

Fig. 1. An example of the preprocessed data, showing two participants' observational behaviors for three different facial stimuli. N: nose; M: mouth; MS: corners of the mouth; EY: eyes; ET: corners of the eyes; CH: cheek; Oth: other; Inc: incorrect; Cor: correct.

F. Analysis

1) Estimation of hidden states: We constructed Hidden Markov Model (HMM) to model relationships (transition) among observational behavior as well as relationships between observational behaviors and smile judgments using hidden states. The HMM is a model that estimates the transition probability due to hidden states. An example of HMM for this study is shown in Fig. 2 The formulation of the model is given in Eq. (1) and (2).

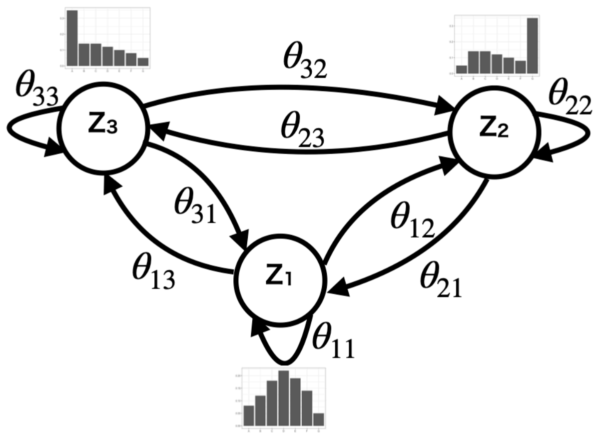

Fig. 2. Example of the Hidden Markov model.

The state model included time T and first-order Markov chain $z_t \in 1..., K$ whose transition probabilities were given by $p(z_t|z_{t-1})$. The observation model was governed by $p(y_t|z_t)$, where y_t indicate the observational behaviors (the area that participants looked at) and the result of judgment (i.e., either correct or incorrect) at time t. The corresponding joint probability distribution was given as follows:

$$p(z_{1:T}, y_{1:T}) = [p(z_1)\prod_{t=2}^{T} p(z_1|z_{t-1})][\prod_{t=1}^{T} p(y_t|z_t)] \quad (1)$$

$$p(y_t|z_t = k, \theta) \sim Categorical(y_t|\theta_k) \quad (2)$$

The maximum number of hidden states was set at 10 (K = 10).

2) Relationship between the number of hidden states and personality traits: As shown in Fig. 3, the distribution of hidden states is best explained by a categorical distribution, so we constructed multinomial logistic regression to model the relationships between the number of hidden states and personality traits. The model was formulated as in Eq. (3), where βs represent the fixed effect and k for the numbers of the hidden states. Given that multinomial logistic regression requires the base or reference category, we used "two hidden states" as the reference category. This means that βs in the model represent how likely or unlikely other (non-reference categories) numbers of hidden states are presented in a particular participant-stimuli pair while judging smile is genuine or not.

$$k \sim Categorical(\alpha + \beta_a Agr + \beta_c Con + \beta_e Ext + \beta_n Neu + \beta_o Ope) \quad (3)$$

3) Effects of hidden states and personality traits on the transition probabilities: We constructed linear regression to model the relationships between the transition probabilities from hidden state to observational behavior and the numbers of the hidden state as well as their interactions. The model was formulated as in Eq. (4), where βs indicate the fixed effect of personality traits and the number of hidden states. The objective variable y indicates the transition probabilities from hidden states to observed areas (plus the result of judgment). In particular, y was the maximum value of the transition probabilities from the hidden states to each facial area and judgment, representing the hidden states that are most associated with observed behaviors (observed areas and judgment).

$$y \sim Normal(\alpha + \sum_{p=1}^{11} \beta_p X_p, \sigma) \quad (4)$$

$$X_p = K + Agr + Con + Ext + Neu + Ope + K \times Agr + K \times Con + K \times Ext + K \times Neu + K \times Ope \quad (5)$$

We used Rstan [16][17][18][19] for Bayesian parameter estimations. The uniform prior was used for fixed effects, and weakly informative prior (gamma with α = 10, β = 10). We used Rstan's default settings for MCMC sampling. For each model, there were four chains, each of which had 1000 warmup steps, 2000 iterations and thin factor being one. Thus there were a total of 4000 MCMC samples for each model.

To verify whether MCMC samplings had converged, we checked $\hat{R}$ values. $\hat{R}$ values for all coefficients were less than 1.1, which is a typically used criterion, and we considered that our MCMC sampling had converged.

We used the Highest Density Interval (HDI) as a method to determine the "significance" of the estimation results. If the 95% HDI does not contain 0, we consider the estimation result to be "significant." The HDI indicates which points of a distribution are most credible. Thus, the HDI specifies an interval that spans most of the distribution such that every point inside the interval has higher credibility than any point outside the interval.

III. Results

The overall judgment accuracy was 37.5%, and only one out of 23 subjects performed better than the chance level, confirming previous research that it is very difficult to distinguish Duchenne and non-Duchenne smiles with a single source of visual information. Even though the judgment accuracy was low, we examined the relationships between participants' personality traits, observational behaviors, and the results of judgments using the raw eye movement data.

A. The optimal number of hidden states

In order to verify the optimal number of hidden states for each participant-stimuli pair, we used the WAICs for models containing a different number of hidden states. Fig. 3 shows the optimal number (i.e., best WAICS) of the hidden states among 685 (we removed the low sampling-rates data sets) time series.

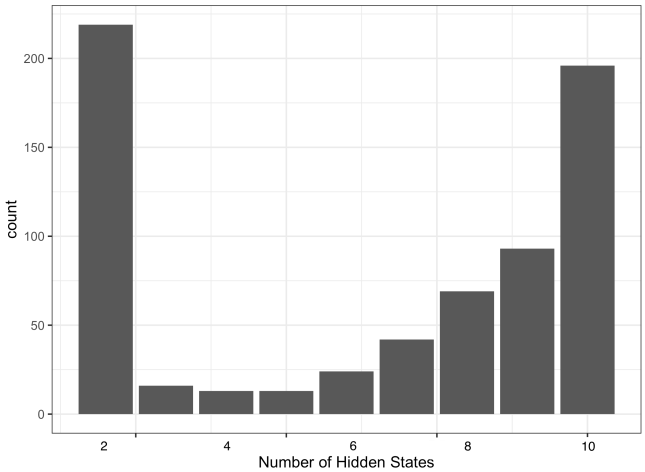

Fig. 3. The optimal number of hidden states among 685 time series.

The Fig. 4(a) shows the relationship between numbers of hidden states and reaction time. The Fig. 4(b) shows the relationship between the numbers of observational behaviors' type (the number of areas of interest actually looked at during the task) and numbers of hidden states. They show that as the number of hidden states increased, the reaction time and the number of observed areas increased.

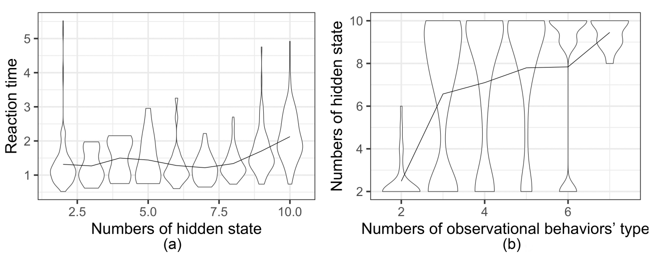

Fig. 4. (a) Relationship between the numbers of hidden states and reaction time. (b) relationship between the numbers of hidden states and the numbers of type of observational behaviors.

B. Relationship between hidden states and personality traits

Based on the results from the optimal number of hidden states model, the relationship between personality traits and the number of hidden states was examined. Fig. 5 shows the 95% HDI of the effects of participants' personality traits on the number of hidden states. Among them, the significant effects are shown in Table I. We considered an effect was significant if the 95% HDI interval did not contain zero. Participants with low levels of conscientiousness tended to have four hidden states compared to two hidden states. High openness participants tended to have higher numbers of hidden states (e.g., seven and 10 being positively significant while six, eight, and nine states being marginally significant) compared to 2 hidden states. On the other hand, participants with high levels of neuroticism have smaller numbers of hidden states (e.g., nine and 10 being negatively significant and eight being marginally significant) compared to two hidden states.

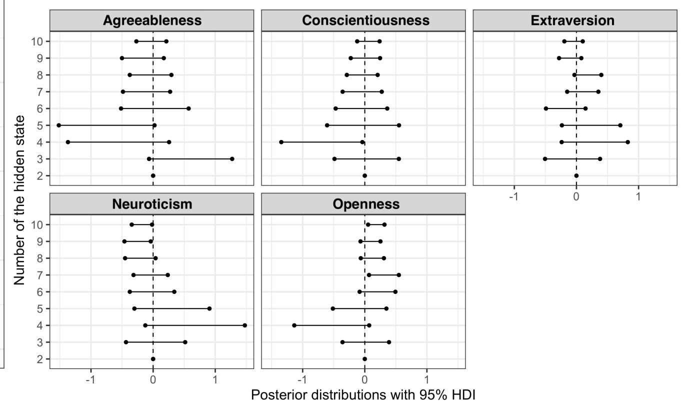

Fig. 5. The 95% HDI of the effects of participants' personality traits on the numbers of hidden state.

TABLE I
PERSONALITY AND HIDDEN STATES

State	Personality traits	Mean	95%HDI
4	Conscientiousness	-0.692	-1.387 ∽ -0.062
7	Openness	0.3191	0.073 ∽ 0.579
9	Neuroticism	-0.2461	-0.460 ∽ -0.028
10	Neuroticism	-0.165	-0.334 ∽ -0.001
	Openness	0.182	0.046 ∽ 0.309

1) Effects of hidden states and personality traits on the transition probabilities: Table II shows the results of the significant effects of the number of hidden states, personality traits, and their interaction on observational behaviors (i.e., observed areas and results of judgments). The results can be summarized as follows:

The higher the number of hidden states (K), the less likely participants were to look at the nose or mouth.

The higher conscientious participants were, the less likely they were to look at the nose. But, they tended to look at the eyes more. When the interaction between conscientiousness and the number of hidden states was considered, the result was reversed. The higher conscientiousness and the higher numbers of hidden states, the less likely participants were to look at the eyes. Likewise, participants with lesser levels of conscientiousness with lower numbers of hidden states tended to look at the eyes more (Fig. 6).

The higher extravert participants were, the less likely they were to look at the mouth. But, they tended to look at the cheek more. When the interaction between extraversion and numbers of hidden states was considered, the result was reversed. Participants with higher levels of extraversion and higher numbers of hidden states tended to look at the mouth but not at the cheek.

The higher neuroticism participants were, the less likely they were to look at the eyes and nose. When interactions with the number of hidden states were considered, the result was reversed. Participants with a higher level of neuroticism and the higher numbers of hidden states tended to look at the eyes and nose more often.

Participants with higher levels of openness tended not to look at the mouth. But, they tended to look at the eyes. When interaction with the number of hidden states was considered, the result was reversed. Participants with a higher level of openness and higher numbers of hidden states tended not to look at the eyes, while those with a lesser level of openness and smaller numbers of hidden states tended to look at the eyes.

The above results are summarized in Fig. 6. The rectangles with filled background represent the main effects of participants' personality traits. The rectangles with solid and dotted lines with white background show the interactions between participants' personality traits and the number of hidden states (solid for positive and dotted for negative interaction). The interaction between the number of hidden states and personality traits can be partition into four types of factors that influence the probability of transition from hidden states to looking at different areas of the faces. They are: a high personality trait score with a high number of hidden states; a low personality trait score with a high number of hidden states; high personality trait low score and a low number of hidden states; and a low personality trait score with a low number of hidden states.

TABLE II
PERSONALITY AND HIDDEN STATES EFFECT ON PROABLITY

Face parts	Parameters	Mean	95%HDI
Eye	Conscientiousnes	0.032	0.007 ∽ 0.056
	Neuroticism	-0.049	-0.069 ∽ -0.029
	Openness	0.032	0.014 ∽ -0.050
	K × Conscientiousnes	-0.003	-0.006 ∽ -0.001
	K × Neuroticism	0.005	0.002 ∽ 0.007
	K × Openness	-0.003	-0.005 ∽ -0.001
Nose	K	-0.050	-0.084 ∽ -0.018
	Conscientiousnes	-0.030	-0.054 ∽ -0.005
	Neuroticism	-0.027	-0.047 ∽ -0.007
	K × Neuroticism	0.005	0.001 ∽ 0.007
Mouth	K	-0.031	-0.061 ∽ -0.002
	Extraversion	-0.028	-0.046 ∽ -0.011
	Openness	-0.026	-0.043 ∽ -0.011
	K × Extraversion	0.003	0.001 ∽ 0.005
Cheek	Extraversion	0.034	0.009 ∽ 0.057
	K × Extraversion	-0.003	-0.006 ∽ -0.001

Table III shows the significant effects of the number of hidden states and personality traits on the smile judgment task. The results can be summarized as follows:

The probability of being correct was positively correlated with extraversion. That means the higher extravert participants were, the more likely they were to correctly judge if the face exhibited a genuine smile or not.

The probability of being correct was negatively correlated with neuroticism. That means the higher neuroticism participants were, the more likely they were to incorrectly judge if the face exhibited a genuine smile or not.

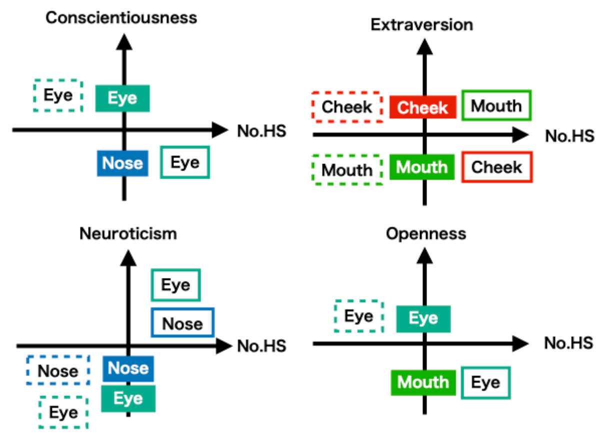

Fig. 6. Hidden states and personality traits on the transfer probability of observational behavior.

TABLE III
TABLE TYPE STYLES

Respond	Parameters	Mean	95%HDI
Correct	Extraversion	0.009	0.001 ∽ 0.017
Incorrect	Neuroticism	-0.009	-0.015 ∽ -0.003

In order to examine potentially important hidden states, we extracted (A) the hidden states that were most strongly associated, in terms of transition probabilities, with correct or incorrect judgments, and (B) the hidden states that were most strongly associated with the hidden states identified in (A) for each participant-stimulus pair. Our rationales are as follows: (A) the manifested behaviors (i.e., facial areas that were looked at) that were associated with the hidden states that were also most strongly associated with correct (incorrect) judgments were the areas that were important for correct judgments (well call this type of hidden states as Judgment States or JSs); and (B) the manifested behaviors that were associated with the hidden states that were also associated with JSs were the areas that were most likely to look at just before making judgments (we call this type of hidden states as Pre-judgment States or PSs). For both JS and PS, there were two types, namely JS that were associated with either correct or incorrect judgments, and PS that were associated with either correct JS or incorrect JS. We then extracted the transition probabilities from JSs and PSs to each facial area. We have done this for each optimal number of states separately (Fig. 3).

Fig. 7a shows the distributions of transition probabilities from JS to each area when judgments were correct and Fig. 7b for incorrect judgments. Overall, the distributions of transitions probabilities from JSs to each area for correct and incorrect judgments were similar to each other within a given number of hidden states. However, there were some differences as well. When the number of hidden states was small, participants who judged correctly were more likely to look at the cheek than those who misjudged. Likewise, when the number of hidden states was large, those who judged correctly were less likely to look at areas outside AOI. On the other hand, when the number of hidden states was two, misjudged participants tended to look at the corners of the eyes and mouth than those who judged correctly, indicating misjudged participants might have been deceived by these particular areas.

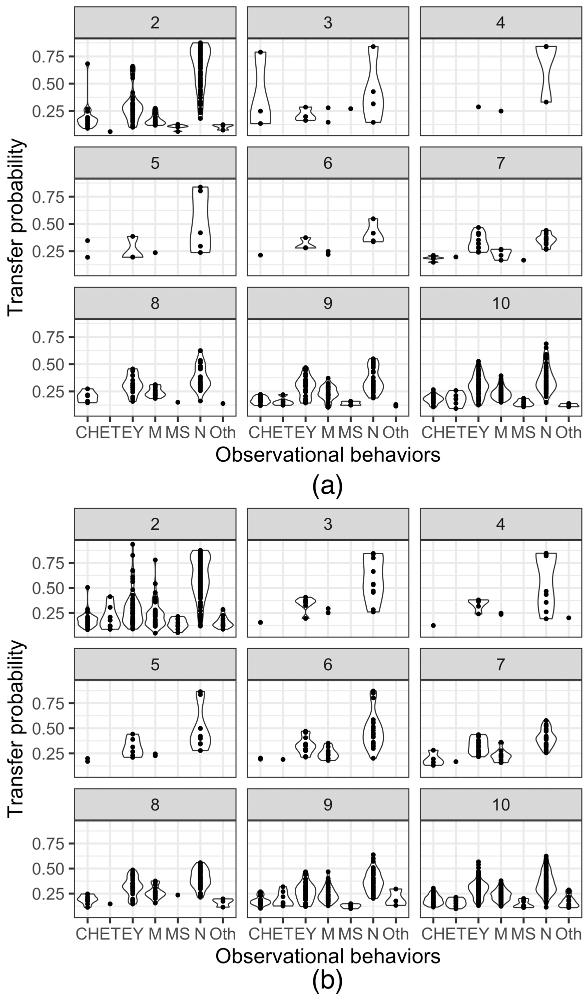

Fig. 7. The distributions of the transition probabilities from "Judgment States" to each facial area, (a) for correct, and (b) for incorrect judgments.

Fig. 8 shows the distributions of transition probabilities from Pre-judgment States (PSs) to each facial area. Fig. 8a shows the results for PS that were associated with Judgement States (JSs) that were associated with correct judgments. Fig. 8b shows the results for PS associated with incorrect JS. As in analyses in JS, the overall distributions for both types of PSs were similar to each other within a given number of hidden states. In addition, the distributions for the correct JSs and corresponding PSs were also similar to each other within a given number of hidden states. We conducted Tukey's range test to compare transition probabilities (from hidden states to each facial area) between (a) correct JSs and incorrect JSs, (b) correct JSs and PSs that were associated with correct JSs, and (c) incorrect JSs and PSs that were associated with incorrect JS wherever applicable. However, there was no significant difference in those transition probabilities.

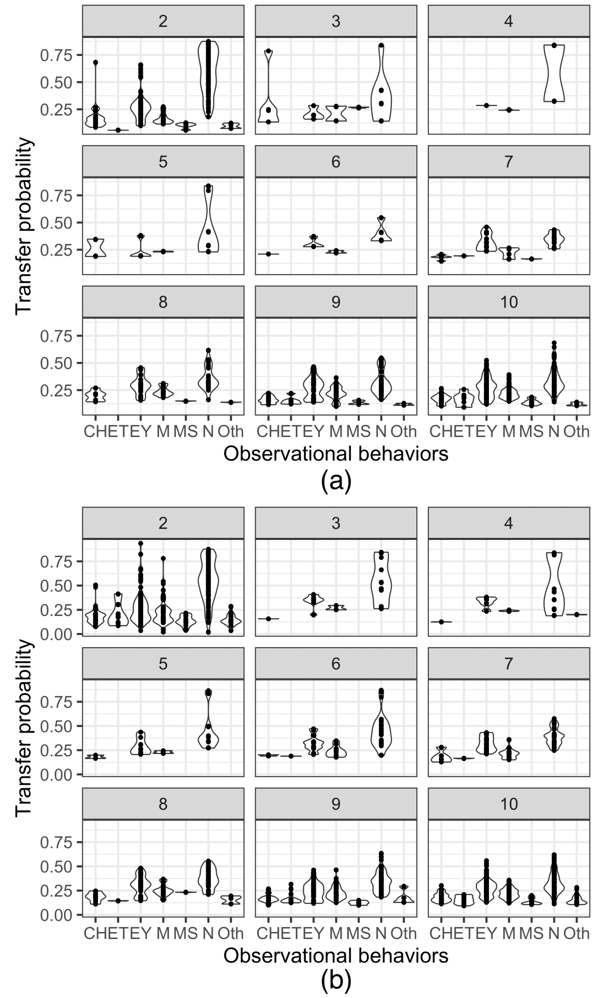

Fig. 8. The distributions of the transition probabilities from "Pre-judgment States" or PS to each facial area. (a) Distribution of transition probabilities for PS that were associated with the correct Judgement States, and (b) for the incorrect Judgment States.

IV. Discussion and Conclusions

The present study conducted a smile judgment experiment to examine the relationships between observers' eye movement trajectories and personality traits. In our analyses, we, first, used hidden Markov models to detect the optimal number of hidden states for each participants-stimulus image pair independently. The resulted optimal numbers of hidden states were then examined for their relationship with personality traits using a multinomial logistic regression model. Finally, we examined the effects of the number of hidden states and personality traits on the transition probabilities from the hidden states to each area of the face, as well as the results of judgments.

The results showed that the optimal numbers of hidden states were mostly concentrated on two and 10, and the distributions from three to ten showed an upward trend. Note that this study only used a maximum of ten hidden states, but it was possible that there might have been more than ten states. However, since our aims in the present study were not to find the optimal number of hidden states per se, we truncated the number of states that were more than ten states and counted them as ten states.

One important finding of this study is that the interaction between the observer's personality traits and the number of hidden states leads to different observational behaviors (transition probabilities from the hidden state to each area of the face). Although each personality trait was significantly correlated with the observed behavior, the effects were all reversed when the effect of the number of hidden states was added. As the number of hidden states increased, participants began to pay more attention to the areas on the face that we did not originally focus on, or vice versa. The results provide us some insights and better understandings about relationships between personality traits and observational behaviors that were previously difficult to interpret. For example, suppose a person with a high level of neuroticism looks at the eyes frequently, contrary to the general behavior of this type of person who tends not to look at the eyes. One possible explanation is that this neurotic person's observational behavior of faces might contain many hidden states. Based on this result, we believe that personality traits can have both ”positive aspects” and ”negative aspects” depending on the number of hidden states that particular individuals have in their observational behaviors.

Other significant relationships were found between personality traits and the optimal number of hidden states. In particular, openness and neuroticism were found to have opposite effects. This result is similar to previous studies based on aggregated data and statical models of observational behaviors and personality traits. In other words, the attributes of the personality traits themselves may be reflected in the hidden state.

The effect of personality traits in the judgment results was also found. People with a high level of extroversion were more likely to correctly judge whether smiles were genuine or not, while people with a high level of neuroticism were more likely to judge incorrectly. Considering this result in terms of observational behavior characteristics, people who are highly extroverted are more likely to judge correctly because they look at the face extensively and have access to more materials and information that lead to correct judgments. However, people with high levels of neuroticism with lower numbers of hidden states look at the face more intensively (looking at a smaller number of areas), not having enough material and information, thus resulting in incorrect judgments.

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