The Contribution of Face Recognition Ability and Other-Race Contact to Confidence and Accuracy in Cross-Race Eyewitness Identifications

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1 Exclusive Summary

The aim of this report is to find out whether face recognition abilities and contacts with other races have any impact on cross-race effects, using data presented by Dr. Jessica Gettleman. For this question, we build a linear regression model based on cross-race effects and use the ANOVA test to check each coefficient's p-value. Both CFMT scores are not statistically significant in our model. It means CFMT scores may not affect the cross-race effect in our model. Although we do not find any statistically significant factor, Adult Q3 Caucasian might be the most influential factor with a p-value of 0.074. On the other hand, we will examine the relationship between confidence and accuracy for same-race and cross-race identification based on face recognition ability and contact with other races. We build a logistic regression model and find that Adult Q7 Caucasians are statistically significant for the same race lineups and different race lineups. In the same race lineups, the p-value of Adult Q7 Caucasians is 0.012. In the different race lineups, the p-value of Adult Q7 Caucasians is extremely small, which is 0.00. Therefore, we would like to conclude that Adult Q7 Caucasians is one of the essential questions affecting final accuracy.

2 Introduction

2.1 General Background

This report aims to analyze the cross-race identification of Caucasians and Chinese. Identification of people whose race is different from their own is known as cross-race identification. Generally, people have a lower cross-race identification when asked to identify different races. According to the discussion with Dr. Jessica Gettleman, the difference in cross-race identification is equivalent to the cross-race effect. Moreover, facial recognition ability and other race contacts can affect the cross-race effect. Although most people are in the middle of prosopagnosia and super-recognizers, face recognition ability varies substantially across individuals. If some people already have low face recognition ability, adding the cross-race effect will vastly increase their difficulty. In our data set, we use Cambridge Face Memory Test (CFMT) to measure the face recognition ability of each participant. In addition, other-race contact also can affect the accuracy of cross-race identification. Some people may live in a Chinese community, although they are Caucasian. Then they may have a better cross-race identification accuracy than other Caucasians. Therefore, we must consider other-race contact as a potential effect in future analysis.

2.2 Objectives

The main objective of Dr. Jessica Gettleman's research is to determine how face recognition abilities and other-race contacts affect cross-race effects. Another aim was to examine the impact of face recognition ability and other-race contact on the confidence-accuracy relationship for same-race and cross-race identification.

2.3 Exploratory Data Analysis

Dr. Jessica Gettleman gives our data from the department of Psychology, UVA. There are 3424×43 objects and 428 participants in the data set. Each participant needs to finish four same race face recognition and four different race face recognition. The accuracy of 8 lineup face recognition is recorded in a binary column. We want to calculate each participant's cross-race effect by taking the difference of same race accuracy and different race accuracy. Then we have an 856×5 dataset with workerId, Same race, Accuracy, CFMT Caucasian, and CFMT Chinese columns.

$$\text{Cross-Race Effect (CRE)}_i = |\frac{\sum \text{same race lineups accuracy}_i}{4} - \frac{\sum \text{different race lineups accuracy}_i}{4}|$$

$$\textbf{hold for every i in} 1 \leq i \leq 428$$

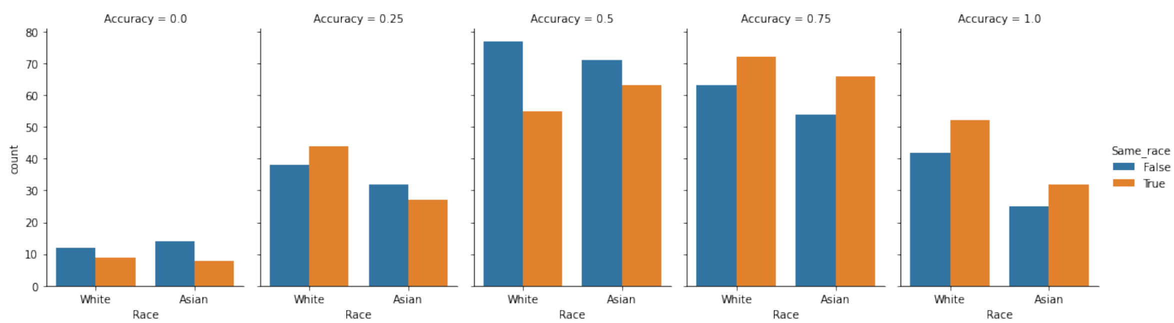

Figure 1: Frequency Plot of Accuracy

From figure 1, we find out people have a powerful face-recognition ability when they recognize the same race people. White people have 25% more accuracy to identify white people than Asian people successfully. Asian people have 33.3% more accuracy to identify Asian people than White people successfully.

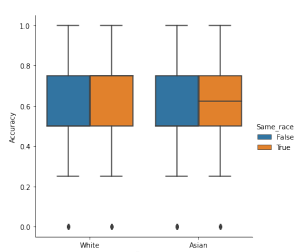

Figure 2: Box Plot of Accuracy

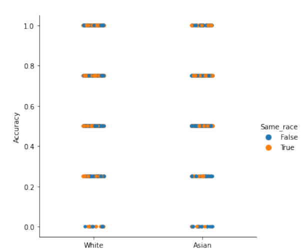

Figure 3: Dot Plot of Accuracy

Figures 2 and 3 show that the accuracy distribution of white and Asian people is similar. It may imply that race does not affect the accuracy of face recognition. Then I would like to create a new variable called "AVE CFMT" by avenging the "CFMT Caucasian" and "CFMT Chinese." Then I separate original participants into good CFMT (Average CFMT higher than the median) and bad CFMT (Average CFMT lower than the median).

Figures 4 and 5 indicate that the distribution of the Cross-Race Effect in White people is similar. It may imply good CFMT or bad CFMT may not influence the CRE. However, if Asian people have bad CFMT, they have much higher CRE than good CFMT people.

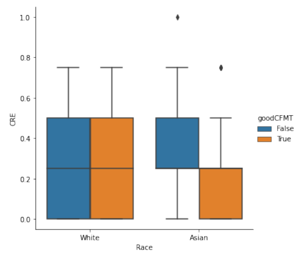

Figure 4: Box Plot of Cross-Race Effect

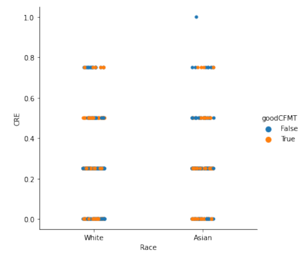

Figure 5: Dot Plot of Cross-Race Effect

3 Approach

Firstly, we determine how face recognition abilities and other-race contacts affect cross-race effects. Before we start any approach, we need to normalize the CFMT Chinese and CFMT Caucasian columns and factorize answers to 28 other-race contact questions. Then We would like to build a linear regression model on the cross-race effect. Then we can apply the ANOVA test to check the p-value of each coefficient.

$$CRE = Intercept + CFMT_{Caucasian} + CFMT_{Chinese} + Child_i + Adult_j$$

$$\begin{aligned}
\text{where:} \quad & \textbf{hold for every i in} 1 \leq i \leq 16 \\
& \textbf{hold for every j in} 1 \leq j \leq 12 \\
Child_i = & \text{ the answer of ith child other-race question} \\
Adult_j = & \text{ the answer of jth Adult other-race question}
\end{aligned}$$

Null hypothesis H(0): $\beta_k = 0$ (k = 1, 2, ..., 31).
Alternative hypothesis H(1): $\beta_k \neq 0$ (k = 1, 2, ..., 31)

	coef	std err	t	P> |t|	[0.025	0.975]
Intercept	0.2077	0.081	2.555	0.011	0.048	0.368
CFMT_Caucasian	-2.992e-05	0.103	-0.000	1.000	-0.203	0.203
CFMT_Chinese	0.0283	0.112	0.252	0.801	-0.192	0.249
Child_Q1_Asian	0.0022	0.010	0.208	0.835	-0.018	0.023
Child_Q2_Caucasian	-0.0078	0.015	-0.534	0.594	-0.037	0.021
Child_Q3_Caucasian	-0.0054	0.013	-0.412	0.681	-0.031	0.020
Child_Q4_Asian	0.0062	0.012	0.511	0.610	-0.018	0.030
Child_Q5_Asian	0.0029	0.012	0.248	0.805	-0.020	0.026
Child_Q6_Caucasian	-0.0021	0.015	-0.141	0.888	-0.032	0.028
Child_Q7_Caucasian	0.0078	0.019	0.421	0.674	-0.029	0.044
Child_Q8_Asian	0.0165	0.012	1.330	0.184	-0.008	0.041
Child_Q9_Asian	-0.0149	0.013	-1.191	0.234	-0.040	0.010
Child_Q10_Caucasian	0.0179	0.018	1.010	0.313	-0.017	0.053
Child_Q11_Asian	-0.0028	0.010	-0.282	0.778	-0.022	0.017
Child_Q12_Asian	-0.0031	0.011	-0.279	0.780	-0.025	0.019
Child_Q13_Caucasian	-0.0129	0.014	-0.954	0.341	-0.040	0.014
Child_Q14_Caucasian	0.0051	0.009	0.549	0.583	-0.013	0.023
Child_Q15_Asian	0.0148	0.012	1.267	0.206	-0.008	0.038
Child_Q16_Caucasian	-0.0077	0.009	-0.827	0.409	-0.026	0.011
Adult_Q1_Asian	-0.0014	0.010	-0.141	0.888	-0.020	0.018
Adult_Q2_Caucasian	-0.0209	0.019	-1.106	0.270	-0.058	0.016
Adult_Q3_Caucasian	-0.0320	0.018	-1.791	0.074	-0.067	0.003
Adult_Q4_Asian	-0.0012	0.009	-0.125	0.901	-0.019	0.017
Adult_Q5_Asian	0.0054	0.011	0.502	0.616	-0.016	0.026
Adult_Q6_Caucasian	-0.0023	0.010	-0.235	0.814	-0.022	0.017
Adult_Q7_Caucasian	0.0273	0.018	1.512	0.131	-0.008	0.063
Adult_Q8_Asian	0.0093	0.010	0.958	0.339	-0.010	0.028
Adult_Q9_Caucasian	-0.0020	0.015	-0.135	0.893	-0.031	0.027
Adult_Q10_Asian	0.0103	0.015	0.673	0.501	-0.020	0.041
Adult_Q11_Asian	-0.0018	0.009	-0.194	0.846	-0.020	0.017
Adult_Q12_Caucasian	-6.258e-05	0.008	-0.008	0.993	-0.015	0.015

From this table, we find out the coefficient of Adult Q3 Caucasian has the smallest p-value,0.074. Although this p-value is not statistically significant, 0.074 is close to 0.05, which indicates that there only 7.4% of the time we would see a test statistic at least as extreme as the one we found if the null hypothesis was true. It means we would likely reject the null hypothesis and accept the alternative one, and the answer of Adult Q3 Caucasian may influence the cross-race effect for our participants.

Secondly, we would like to examine the impact of face recognition ability and other-race contact on the confidence-accuracy relationship for same-race and cross-race identification. We separate the original data set into two 1712×44 data sets by same race lineups and different race lineups. Then we build a logistic regression model on accuracy. We show the detail of our same race lineups model in the following table and move different race lineups models into the appendix.

$$Accuracy = Intercept + Confidence + CFMT_{Caucasian} + CFMT_{Chinese} + Child_i + Adult_j$$

$$\begin{aligned} \text{where:}\quad & \textbf{hold for every i in} 1 \leq i \leq 16 \\ & \textbf{hold for every j in} 1 \leq j \leq 12 \\ Child_i = \ & \text{the answer of ith child other-race question} \\ Adult_j = \ & \text{the answer of jth Adult other-race question} \end{aligned}$$

Null hypothesis H(0): $\beta_k = 0$ (k = 1, 2, ..., 31).
Alternative hypothesis H(1): $\beta_k \neq 0$ (k = 1, 2, ..., 31)

For same race lineups model:

	coef	std err	z	P> |z|	[0.025	0.975]
Child_Q1_Asian	-0.0348	0.042	-0.834	0.404	-0.117	0.047
Child_Q2_Caucasian	-0.0764	0.059	-1.304	0.192	-0.191	0.038
Child_Q3_Caucasian	-0.0339	0.053	-0.640	0.522	-0.138	0.070
Child_Q4_Asian	-0.0489	0.055	-0.883	0.377	-0.157	0.060
Child_Q5_Asian	0.0443	0.053	0.839	0.401	-0.059	0.148
Child_Q6_Caucasian	0.0638	0.071	0.893	0.372	-0.076	0.204
Child_Q7_Caucasian	-0.0204	0.070	-0.293	0.770	-0.157	0.116
Child_Q8_Asian	0.0217	0.046	0.468	0.639	-0.069	0.113
Child_Q9_Asian	0.0418	0.048	0.871	0.384	-0.052	0.136
Child_Q10_Caucasian	-0.0560	0.065	-0.856	0.392	-0.184	0.072
Child_Q11_Asian	0.0583	0.049	1.187	0.235	-0.038	0.155
Child_Q12_Asian	-0.0716	0.044	-1.641	0.101	-0.157	0.014
Child_Q13_Caucasian	0.0529	0.052	1.021	0.307	-0.049	0.154
Child_Q14_Caucasian	-0.0257	0.035	-0.736	0.462	-0.094	0.043
Child_Q15_Asian	-0.0738	0.051	-1.452	0.147	-0.174	0.026
Child_Q16_Caucasian	0.0155	0.040	0.385	0.701	-0.064	0.095
Adult_Q1_Asian	0.0387	0.038	1.020	0.308	-0.036	0.113
Adult_Q2_Caucasian	0.0612	0.064	0.958	0.338	-0.064	0.186
Adult_Q3_Caucasian	0.0280	0.061	0.458	0.647	-0.092	0.148
Adult_Q4_Asian	-0.0592	0.037	-1.603	0.109	-0.131	0.013
Adult_Q5_Asian	-0.0845	0.042	-2.029	0.042	-0.166	-0.003
Adult_Q6_Caucasian	-0.0060	0.040	-0.152	0.879	-0.084	0.072
Adult_Q7_Caucasian	-0.1571	0.062	-2.526	0.012	-0.279	-0.035
Adult_Q8_Asian	0.0232	0.035	0.666	0.506	-0.045	0.092
Adult_Q9_Caucasian	0.0194	0.056	0.349	0.727	-0.090	0.129
Adult_Q10_Asian	0.0318	0.055	0.574	0.566	-0.077	0.141
Adult_Q11_Asian	-0.0106	0.039	-0.275	0.784	-0.086	0.065
Adult_Q12_Caucasian	-0.0494	0.033	-1.519	0.129	-0.113	0.014
Confidence	0.0174	0.002	9.467	0.000	0.014	0.021
CFMT_Caucasian	-0.0061	0.006	-0.942	0.346	-0.019	0.007
CFMT_Chinese	0.0081	0.008	1.071	0.284	-0.007	0.023

From the previous two tables, we find out Adult Q5 Asian (0.042), Adult Q7 Caucasian (0.012), and Confidence (0.000) are statistically significant for accuracy of same race lineups face recognition. Adult Q7 Caucasian (0.000) and Confidence (0.000) are statistically significant for accuracy of different race lineups face recognition.

4 Conclusion

Firstly, we determine how face recognition abilities and other-race contacts affect cross-race effects. After we build a linear regression model for our cross-race effect, we find out the answer of Adult Q3 Caucasian might be the most influential factor with a p-value of 0.074. In our model, neither CFMT score is statistically significant. Secondly, we examine the impact of face recognition ability and other-race contact on the confidence-accuracy relationship for same-race and cross-race identification. After we build a logistic regression model for our accuracy, we find out Adult Q7 Caucasians both are statistically significant on the same race lineups and different race lineups. Especially for different race lineups, the p-value of Adult Q7 Caucasian is 0.000, which shows the answer of Adult Q7 Caucasian will largely affect the final accuracy. As a result, Adult Q7 Caucasians is an essential question that affects final accuracy.

5 Appendix

For different race lineups model:

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Child_Q1_Asian	-0.0258	0.041	-0.636	0.524	-0.105	0.054
Child_Q2_Caucasian	-0.0644	0.057	-1.125	0.261	-0.177	0.048
Child_Q3_Caucasian	-0.0470	0.052	-0.905	0.366	-0.149	0.055
Child_Q4_Asian	-0.0473	0.054	-0.879	0.379	-0.153	0.058
Child_Q5_Asian	0.0194	0.051	0.379	0.705	-0.081	0.120
Child_Q6_Caucasian	0.0042	0.069	0.060	0.952	-0.132	0.140
Child_Q7_Caucasian	-0.0406	0.069	-0.592	0.554	-0.175	0.094
Child_Q8_Asian	0.0529	0.045	1.175	0.240	-0.035	0.141
Child_Q9_Asian	-0.0315	0.047	-0.674	0.500	-0.123	0.060
Child_Q10_Caucasian	0.0595	0.063	0.937	0.349	-0.065	0.184
Child_Q11_Asian	0.0124	0.048	0.260	0.795	-0.081	0.106
Child_Q12_Asian	0.0267	0.043	0.626	0.531	-0.057	0.110
Child_Q13_Caucasian	0.0273	0.050	0.542	0.588	-0.071	0.126
Child_Q14_Caucasian	-0.0050	0.034	-0.148	0.882	-0.072	0.062
Child_Q15_Asian	0.0198	0.050	0.397	0.691	-0.078	0.117
Child_Q16_Caucasian	0.0083	0.039	0.213	0.831	-0.069	0.085
Adult_Q1_Asian	0.0070	0.037	0.189	0.850	-0.066	0.080
Adult_Q2_Caucasian	0.1056	0.062	1.694	0.090	-0.017	0.228
Adult_Q3_Caucasian	-0.0062	0.060	-0.103	0.918	-0.123	0.111
Adult_Q4_Asian	-0.0450	0.036	-1.248	0.212	-0.116	0.026
Adult_Q5_Asian	-0.0133	0.041	-0.326	0.745	-0.093	0.067
Adult_Q6_Caucasian	-0.0166	0.039	-0.429	0.668	-0.092	0.059
Adult_Q7_Caucasian	-0.2125	0.061	-3.504	0.000	-0.331	-0.094
Adult_Q8_Asian	-0.0451	0.034	-1.330	0.184	-0.112	0.021
Adult_Q9_Caucasian	0.0332	0.054	0.613	0.540	-0.073	0.139
Adult_Q10_Asian	-0.0271	0.054	-0.503	0.615	-0.133	0.079
Adult_Q11_Asian	-0.0685	0.038	-1.816	0.069	-0.143	0.005
Adult_Q12_Caucasian	-0.0355	0.032	-1.115	0.265	-0.098	0.027
Confidence	0.0137	0.002	7.678	0.000	0.010	0.017
CFMT_Caucasian	0.0007	0.006	0.111	0.911	-0.011	0.013
CFMT_Chinese	0.0044	0.007	0.597	0.551	-0.010	0.019