Replication of The Self in the Mind's Eye

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Author Note

The authors made the following contributions. Wen Jiahui: Conceptualization, Introduction, Writing - Original Draft, introduction & discussion; Han Xiang: Method, Writing - Original Draft, method & results; Wu Meihui: Results, Writing - Original Draft, results; Lin Wangjing: Discussion, Writing - Original Draft, discussion.

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Abstract

The relationship between the physical self and the psychological self is a fundamental aspect of self-concept. This study aims to replicate Experiment 1 of Maister et al.'s (2021) research, which investigates the accuracy of self-portraits in reflecting participants' psychological traits and explores the influence of personality and self-esteem on these self-portraits. The findings confirm that specific facial features in the self-portraits are meaningfully associated with individual personality traits. Moreover, individuals with higher self-esteem tend to produce more accurate self-portraits, indicating a positive correlation between self-esteem and the accuracy of self-representations. While the overall replication of the effect is successful, there are slight discrepancies in certain aspects, such as the resemblance between the self-portrait and the participant and the relationship between the accuracy of self-portraits and self-reported personality traits or self-esteem, as indicated by the 95% CI, t-value, and Cohen's d. By reanalyzing and validating the data, this replication contributes to a better understanding of the generalizability and reliability of the relationship between the physical and psychological self.

Keywords: physical self, psychological self, self-portrait, replication study, personality, self-esteem.

Replication of The Self in the Mind's Eye

Introduction

In the field of self research, psychology has conducted extensive studies. The self is considered as a unique structure that influences an individual's emotions and motivations, playing an integrative role in the organization and processing of personal information (Sui, 2015). According to research, the self can be divided into two aspects: physical self and psychological self (Hu et al., 2016). The physical self refers to the ability of individuals to separate their physical existence from the external environment, and researchers can explore this aspect through tasks such as distinguishing their own face from unfamiliar faces (Gillihan & Farah, 2005; Sugiura, 2013). In contrast, the psychological self is defined by individual attributes such as personality traits, autobiographical memory, and experiences (Gillihan and Farah, 2005; Murray et al., 2012; Northoff, 2011). Hu et al. (2016) conducted a meta-analysis of neuroimaging studies related to self-face recognition and self-referential processing using activation likelihood estimation (ALE). They directly compared two key aspects of self-processing: physical self and psychological self. The research results revealed that self-face processing was primarily associated with the right-hemisphere dominant brain lateral regions, while psychological self-processing was mainly associated with activation in the cortical midline structures (specifically the anterior cingulate cortex/frontal pole).

Psychological representations of physical appearance are an important component of physical self and may be stored and retrieved in the form of pictures or descriptive information. Self-portraits can be seen as a form of physical self-representation, and some researchers believe that they reflect long-standing differences between physical and psychological self-representations (Northoff et al., 2006). Mental representations of our physical appearance have fundamental implications in social and clinical contexts. Our perception of our own physical appearance is closely related to self-esteem (Feingold, 1992) and influences a range of social behaviors, from selecting romantic partners (Feingold, 1988) to undergoing cosmetic surgery (Crerand et al., 2006). Holding distorted self-representations can lead to distress and be associated with severe clinical conditions such as body dysmorphic disorder and anorexia nervosa (Kaplan et al., 2013).

The original study's Experiment 1 focused on examining the differences between human real faces and self-portraits, aiming to explore how the physical self-representation of human faces interacts with psychological self-representations. The researchers aimed to understand if and how psychological traits affect the differences between real faces and self-portraits. Through a reverse correlation task, the researchers found that self-portraits could reflect accurate identity information but also include some biases or errors. It was influenced by the participants' psychological traits and significantly correlated with their personality and self-esteem (Maister, 2021).

To date, there has been limited research on the interaction between physical self and psychological self. Although some studies have explored the relationship between these two concepts, many aspects of how they interact and the individual differences between them remain unknown. Therefore, replicating this study is highly meaningful. The purpose of replication research is to validate the findings of the original study and further explore the field. For the interaction between physical self and psychological self, replication research can provide additional evidence and support to ensure the reliability and generalizability of the original study. Replication research also helps uncover the limitations and potential biases of the original study. Additionally, replication research promotes collaboration and communication within the scientific community. By independently verifying research results, consensus in the field could be increased and related research could be further advanced. The importance of replication research lies in strengthening the reliability and sustainability of science, ensuring the accumulation and progress of scientific knowledge.

In summary, this study aims to replicate the data analysis of Experiment 1 of Maister et al.'s (2021) to validate the results of the original study and further explore the generalizability and reliability of these findings in different samples. This study hypothesizes that physical self can reflect psychological self, and this effect may be influenced by individual psychological traits such as personality and self-esteem. Specifically, similar to the original study, we focus on the following research questions: 1.Does the self-portrait look like the participant? 2.Can external observers reliably infer personality traits from self-portraits? 3.Are self-portraits influenced by the psychological self? 4.Whether the accuracy of self-portraits relates to self-reported personality traits or self-esteem?

Methods

In the initial stage of data collection, each participant's face was photographed in passport style, and then trimmed around the hairline to remove irrelevant features. Then, the participants completed a reverse correlation task (Dotsch & Todorov, 2012), in which they chose between several pairs of randomly generated faces to create a "selfie" face that they thought looked like themselves. The reverse-correlation task was used to generate stimuli using the rcicr package in R (Version 0.3.4.1; Dotsch, 2016). This task involved creating patterns of sinusoidal noise overlaid on a "base face," resulting in unique facial images with each random noise pattern. The base face was an average composite image obtained from a pre-existing database, depending on the participant's gender. The researchers generated 500 pairs of facial images. These pairs were presented side by side to participants on a computer monitor during the experiment. In the same trial, one face is the basic face after adding random noise, and the other face is the basic face after adding the negative value of the noise. The negative value of the same kind of random noise is chosen instead of another kind of random noise in order to maximize the difference between the two presented images. The stimulus pairs were presented in random order, and the positions of faces with noise and negative noise on the screen (negative noise on the left vs. on the right) were balanced in the experiment. The selected face images for each trial were averaged to produce a final self-portrait, representing the perceptual information used for self-judgment.

At the end of the session, the participants filled out questionnaires to measure their personality traits (BFI-10) (Rammstedt & John, 2007) and state self-esteem (SSES) (Heatherton & Polivy, 1991), which includes performance self-esteem, social self-esteem, and appearance self-esteem. In addition to the personality traits, participants also rated themselves, using a Visual Analogue Scale, on attractiveness, trustworthiness, and dominance. In the second stage of data collection, 112 independent raters were shown the participants' real faces and selfie faces, and they used BFI-10 to rate their perception of each personality feature in these faces. The raters were then asked to rate these faces in the image on the facial attributes (attractiveness, trustworthiness and dominance), presented to them in the same format as for the primary participants.

The researchers answered four central research questions. First, does the self-portrait look like the participant? To test this question, they use a linear regression analysis to invesigate whether the real-face RDM significantly predicted the portrait RDM. Second, can external observers reliably infer personality traits from self-portraits? Interrater reliability scores were calculated for personality traits rated by external raters for both the self-portraits and real face photographs. Third, are self-portraits influenced by the psychological self ? To test this, they used a linear mixed-effects analysis (Baayen et al., 2008) to analyze the relationship between perceived personality features of the self-portraits and self-reported personality traits while controlling for personality features present in the participants' real faces. Fourth, which individual traits might be related to differences between participants in self-portrait accuracy? The researchers used a hierarchical multiple linear regression to investigate whether the accuracy of self-portraits relates to self-reported personality traits or self-esteem. We use the generalized linear regression model to replicate this effect. What's more, the author didn't mention why they only choose social self-esteem instead of other self-esteem dimensions as the independent variable, so we make an exploratory analysis and construct several models to compare the model effects after adding different types of self-esteem.

Results

Does the self-portrait look like the participant?

To test the question, we employed two methods. Firstly, we objectively assessed the accuracy of each participant's resulting self-portrait using a face-recognition algorithm (OpenFace; Version 2.0; Amos et al., 2016), which provided a self-specific dissimilarity score between each individual's self-portrait and a photograph of their real face. Additionally, we conducted cross-individual comparisons between each participant's self-portrait and the real faces of all other participants in the sample, resulting in non-self dissimilarity scores. The self-dissimilarity scores were found to be significantly lower than the cross-individual non-self dissimilarity scores (paired-samples $t(76) = -8.69, p < .001, Cohen'sd = -1.16$). This confirms that participants' self-portraits contained facial information that was specific to themselves. However, it is worth noting that the reported value of Cohen's d in the article was slightly different ($Cohen'sd = 0.99$.

Second, we constructed two representational dissimilarity matrices (RDMs) by calculating all pairwise dissimilarity scores between (a) each participant's self-portrait with every other participant's self-portrait and (b) each participant's real face with every other participant's real face. These RDMs were created from same-gender comparisons only, resulting in a total of 2,928 comparisons, in order to remove the potential confounding effect of same versus different genders on dissimilarity scores. Using a linear regression analysis, we found that the real-face RDM significantly predicted the portrait RDM ($Beta = 0.06, 95\%CI = [0.03, 0.08], t(2926) = 3.63, p < .001$). This demonstrates that the physical similarity structure of the real faces of the sample was represented in the self-portraits. However, it is worth noting that the reported 95% confidence interval in the article was slightly different ($95\%CI = [0.03, 0.09]$). Although the effect was highly significant, the magnitude of the effect was small ($R^2 = .004$). These findings suggest that while self-portraits contained accurate self-specific facial information, a substantial amount of variance was not accounted for by individuals' real facial features.

Besides, we also verified the accuracy of Open Face algorithm in constructing difference scores between images. A one-sample t test showed that the mean accuracy score across raters for each portrait ($M = .57, SD = .16$, $95\%CI = [.53, .61]$ was significantly higher than chance level(.50), $t(76) = 3.93, p < .001, Cohen'sd = 0.45$. For comparison, classification accuracy was also derived for the OpenFace algorithm using a simulated experiment identical to that which the human participants completed. Accuracy was numerically higher than the human accuracy scores ($M = .62, SD = .31$, $95\%CI = [.56, .69]$) and again significantly higher than chance performance, $t(76) = 3.59, p < .001, Cohen'sd = 0.41$. A bootstrapped hypothesis test across 10,000 samples showed that the difference in accuracy between the algorithm and the human participants was not significant (estimated $p = .076$).

Can external observers reliably infer personality traits from self-portraits?

Due to the lack of data, we have no idea to repeat the question.

##Are self-portraits influenced by the psychological self? We used a linear mixed-effects analysis (Baayen et al., 2008) to test these question from the perspectives of self-esteem and personality score. In this paper, we mainly introduce how we replicate this effect from the perspective of personality, and the verification from the perspective of self-esteem is similar(See the R code for details).

We used a linear mixed-effects analysis (Baayen et al., 2008) to assess whether the personality traits evident in self-portraits (as measured by the external personality ratings) were predicted by participants' self-reported personality traits (as measured using the Big Five Inventory; Rammstedt & John, 2007). We first derived an optimal null-hypothesis model containing explanatory and control variables predicting external ratings of self-portraits, including external personality ratings of the real faces ($AIC = 194.4$). Using a systematic model comparison procedure, we demonstrated that an alternative-hypothesis model (H1 model) that additionally included self-ratings of the five personality traits explained significantly more variance in external personality ratings derived from participants' self-portraits than the nullhypothesis model did (null hypothesis: AIC = 194.4, alternative hypothesis: $AIC = 192.17$), $X^2(1) = 4.23$, $p = .040$. In this winning model, the variable indexing participants' self-reported personality traits had a positive parameter estimate, $b = 0.03(SE = 0.02), t(359.6) = 2.04, F(1, 359.6) = 4.17, p = .042$ (see Fig. 2a), indicating that the higher participants rated themselves on a certain personality trait, the more facial features associated with that trait were present in their self-portrait, even when the model controlled for the actual presence of those features in participants' real faces.

Then we construct a control model, in which self-ratings on the five personality traits were randomly shuffled within each participant, performed poorly ($AIC = 196.4, X^2(1) < .001, p > .999$, and the parameter estimate of the randomly shuffled variable assessing participants' self-reported personality traits was nonsignificant, $Beta < -0.001, t(358.9) = -0.06, p = .95$. This suggests that individual personality traits were indeed meaningfully linked with specific configurations of facial features in the self-portraits.

At this question, we replicate the effect and the result is similar to the results in the paper.

Whether the accuracy of self-portraits relates to self-reported personality traits or self-esteem?

Each self-portrait contained generic facial features common to many faces, as well as self-specific content. We only focus on the accuracy of the selfspecific information contained in the self-portraits. By controlling for the similarity between each participant's selfportrait and all the other real faces in the sample, we adjusted the self-dissimilarity scores of the self-portraits to reflect accuracy of self-specific content, ensuring that the averageness of the self-portrait did not lead to biases in the self-dissimilarity scores.

First, we fellow the author's analysis idea to replicate the effect. We used a hierarchical multiple linear regression on the self-dissimilarity scores, as calculated from the face-recognition algorithm. At the first step, the mean cross-individual dissimilarity scores between each participant's selfportrait and all other same-gender real faces were entered, $Beta = .50$, $95\%CI = [0.07, 0.93]$, $t(75) = 2.30, p = .026$, the results of p value is not similar with the author reported in the article ($p = .024$). To ensure that we were analyzing self-specific accuracy as our dependent variable. At the second step, individual-difference variables of interest were added (the five personality self-ratings, to test whether selfbeliefs regarding personality were associated with selfface representation, and the three self-esteem subscales, to assess whether more attitudinal aspects of selfconcept were associated with self-representation). The winning model from the stepwise procedure included social self-esteem as a significant negative predictor of self-dissimilarity, $Beta = -0.13, 95\%CI = [-0.23, -0.03], t(74) = 2.68, p = .009$, the results of 95% CI is not similar with the author reported in the article ($95\%CI = [-0.23, -0.04]$). We also use the generalized linear model to repeat the analysis, and the results are consistent with those using the multi-level linear regression model, social self-esteem was a significant negative predictor of self-dissimilarity, $Beta = -0.13, t(74) = 2.68, p = .009$. So we came to the conclusion that the higher the participant's self-esteem with regard to social interactions, the more accurate their self-portraits were (see Fig. 2b).

The author chose social self-esteem as an independent variable to construct the model, without considering the role of other self-esteem, and did not give a reasonable explanation in the original text, so we tried to add two other self-esteem (performance self-esteem, appearance self-esteem) and build other models to investigate the role of other self-esteem on the accuracy of self-portrait. When three types of self-esteem and control variables are added to construct the model (M1a), the predictive role of each variable is not significant, $ps > .05$. We calculated the average score of self-esteem of each participaint, and constructed M1b,we found that it significantly negatively predicts the dependent variable, $Beta = -0.05, p = .009$. In M1c (which includes the control variable and performance self-esteem), performance self-esteem can't significantly predict the dependent variable.In M1d(which includes the control variable and appearance self-esteem), appearance self-esteem significantly predict the dependent variable.

However, this result could have been influenced by the attractiveness of participants' real faces. If participants tend to select the more attractive faces when performing the reverse-correlation task, by default those with more attractive real faces will generate selfportraits that gain a lower self-dissimilarity score than those who have less attractive real faces. Given that more attractive individuals may have higher self-esteem, this could explain the reported relationship between self-esteem and self-portrait accuracy. To test this alternative explanation, we conducted two further analyses. First, a correlational analysis between social self-esteem and real-face attractiveness revealed that these two variables were not significantly correlated, $r(75) = .178, p = .121$. Second, when we controlled for real facial attractiveness in the first step of the original hierarchical linear regression, the significance of social self-esteem as a predictor of self-portrait accuracy remained unchanged, $Beta = -0.13, 95\%CI = [-0.23, -0.03], t(73) = 2.55, p = .013$. Therefore, it is unlikely that the existing findings can be explained by a confounding effect of real facial attractiveness.

Another alternative explanation involves the averageness of participants' real faces. For participants with highly average real facial features, the reverse-correlation task could have generated portraits that were highly similar to their real face by chance, giving artificially low self-dissimilarity scores with the self-portrait. This could lead to a potential confound because facial averageness may be directly linked with self-rated character traits such as self-esteem. To ensure that this was not the case, we retested the key result while controlling for real-face averageness, as calculated by the mean cross-individual dissimilarity scores between the participants' real faces and all other same-gender real faces in the sample. This confirmed that the relationship between social selfesteem and self-dissimilarity remained significant even when we additionally controlled for real-face averageness, $Beta = -0.14, 95)$. The results of $95\%CI$ and the t value is not similar with the author reported in the article $(95\%CI = [-0.23, -0.04], t(73) = -2.75)$.Real-face averageness was not significantly related to self-dissimilarity in this analysis, $Beta = -0.19, 95\%CI = [-0.67, 0.29], t(74) = -0.63, p = .107$. The results of $95\%CI$ and $Beta$ value are not similar with the author reported in the article $(95\%CI = [-0.84, 0.08], Beta = -0.38)$.Furthermore, a separate analysis demonstrated that real-face averageness was not significantly related to social selfesteem, $Beta = -0.16, 95\%CI = [-1.20, 0.88], t(75) = -0.30, p = .762$. The results of 95% CI and the p value is not similar with the author reported in the article $(95\%CI = [-1.20, 0.89], p = 0.763)$.

Finally, we can draw a conclusion that the higher the participants' self-esteem in social interaction, the more accurate their self-portraits were.

Discussion

In general, the results demonstrate a meaningful relationship between individual personality traits and specific configurations of facial features in the self-portraits. These results align with Sugiura's (2013) interactive hierarchical model of self-representation.

Higher-level self-beliefs and attitudes may influence the perceived quality of self-portraits, while the perception of physical self-representation can also impact inferences about an individual's self-beliefs and attitudes.

Additionally, individuals with higher self-esteem, as indicated by their average self-esteem scores, tend to produce more accurate self-portraits that closely resemble their physical appearance. There is a positive correlation between participants' self-esteem and the accuracy of their self-portraits. individuals with higher social self-esteem tend to have more objective and accurate self-portraits. On one hand, social interactions serve as crucial sources of information about our physical appearance through feedback and social comparisons (Cash et al., 1983). Therefore, individuals with higher social self-esteem may engage in more frequent and meaningful social interactions, which provide them with more social input about their appearance, leading to more accurate self-perception. On the other hand, individuals who have a more accurate perception of their physical appearance may also experience smoother, mutually beneficial, and predictable social relationships, resulting in higher social confidence. For instance, having an accurate perception of one's attractiveness may contribute to more successful romantic interactions and a decreased likelihood of rejection by mismatched partners (Le Lec et al., 2017), thereby boosting social self-esteem.

However, it is worth noting that there are slight variations in certain aspects, such as the resemblance between the self-portrait and the participant and the relationship between the accuracy of self-portraits and self-reported personality traits or self-esteem, as indicated by the 95% confidence interval, t-value, and Cohen's d. Nonetheless, these discrepancies do not significantly impact the overall findings.

Overall, this replication study has been successful. Although the specific reasons for solely selecting social self-esteem were not explicitly provided, we further explored the potential influence of other types of self-esteem. The results indicate that appearance self-esteem significantly predicts the accuracy of self-portraits, while performance self-esteem does not. This finding is consistent with the research conducted by Moon et al. (2020). Their study aimed to visualize psychological self-representations by assessing the relationship between externally observed facial representations (e.g., unattractive vs. attractive) and various self-report measures (self-esteem, social anxiety, explicit self-evaluation, extraversion) to examine their association with self-image-related features. The results revealed that self-esteem, explicit self-evaluation, and extraversion were positively related to more positive or pleasant self-portraits, while social anxiety was associated with more negative or unpleasant self-portraits.

The combination of the three types of self-esteem did not significantly predict the accuracy of self-portraits, suggesting that specific domain-related self-esteem may interact with overall self-esteem, shaping self-perception, and subsequently influencing the accuracy of self-portraits. It is also possible that the lack of significant findings is due to the instability of state self-esteem. Future research can explore how different types of self-esteem influence the accuracy of self-portraits. Additionally, other unexplored types of self-esteem, such as trait self-esteem, may also have an impact on individuals' perception and representation of their physical selves. Furthermore, investigating potential moderating variables, such as age, gender, cultural background, or body image concerns, can provide valuable insights into the complex relationship between self-esteem and the accuracy of self-portraits. Considering that various factors can influence individuals' perception and representation of themselves in self-portraits, a comprehensive understanding of this phenomenon can be achieved.

Repeating the process of data analysis comes with its challenges. One major challenge arises from the messiness of the data code. Firstly, the disorganized data code poses difficulties in data analysis. Due to the chaotic nature of the code, we encountered some errors during the analysis process. This required us to spend additional time and effort in untangling the logic and processing of the data. This situation not only increased our workload but also impacted the efficiency and accuracy of the analysis. Therefore, we strongly urge researchers to prioritize code standardization and clarity during the data collection and organization phase to ensure smooth subsequent data analysis.Furthermore, missing data has also affected our study. Due to various reasons, we were unable to obtain data for control variables such as ICC and attractiveness. This resulted in data incompleteness. Missing data can introduce biases and inaccuracies in the results and limit our comprehensive understanding of the overall research question. Hence, we recommend particular attention to data completeness when utilizing publicly available data, along with necessary measures to minimize data gaps.

Despite our efforts to overcome these challenges and conduct effective data analysis, as well as articulate the research findings accurately, we acknowledge that these factors may impose certain limitations on the interpretation and inference of the results. To advance open science and reproducible research, it is suggested that future researchers emphasize the traceability and transparency of data during the process of data collection, organization, and analysis. Code should be well-commented and standardized to facilitate understanding and replication by others. Additionally, measures should be taken to ensure data completeness and accuracy, thereby enhancing the reliability and reproducibility of the research. Only through such practices can research better foster the sharing and advancement of scientific knowledge.

Although efforts have been made in replicating the data analysis of Maister et al.'s (2021) study, there are still limitations and constraints in this research. The obtained data is not raw data but pre-computed means. This limitation may have an impact on the reliability and generalizability of the replication study. Details regarding the specific data collection methods used in the original study are crucial for understanding the background of the research and interpreting the underlying mechanisms behind its findings. Due to the lack of original data and details, this study was unable to fully replicate the data analysis of the original study, thus limiting a comprehensive understanding of the research question.

Furthermore, this study is not a complete replication as it only involves data analysis and relies solely on existing research literature as the source of data. No actual experiments or data collection were conducted. This may also result in the influence of literature selection and publication bias on the research findings. Future research could consider employing self-designed experiments or data collection procedures to ensure a comprehensive exploration of the research question. Additionally, future studies should strive to expand the sample size, utilize multiple methods, and consider conducting actual experiments or data collection to further investigate the interaction between physical self and psychological self. Such improvements would contribute to increasing understanding in this field and driving the development of related research.

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Appendix

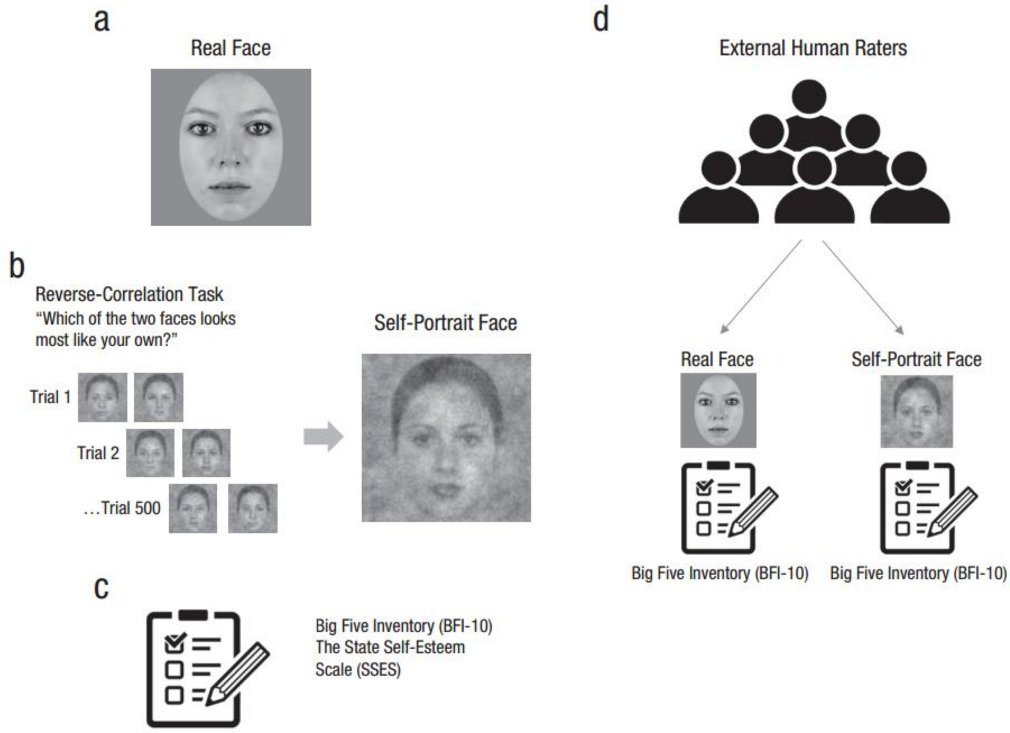

Fig. 1. the process of experiment1

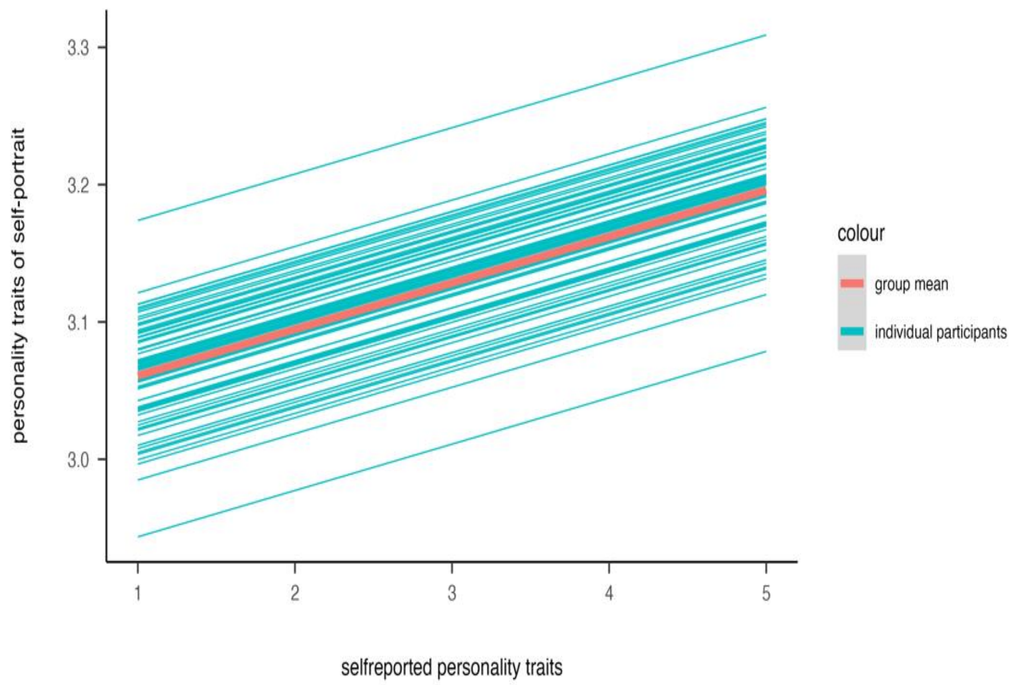

Fig. 2a. Key results from Experiment 1 (*N* = 77). Results from the linear mixed-effects models analysis (a) show the fixed effect of self-reported personality traits (as rated by participants themselves) on the intensity of the corresponding personality traits perceived in the facial features of the self-portraits (as reported by external raters). The black line indicates the population-level mean. The blue lines indicate the marginal effects for each individual participant, allowing for random variation of intercepts as dictated by the best-fitting linear mixed-effects model.

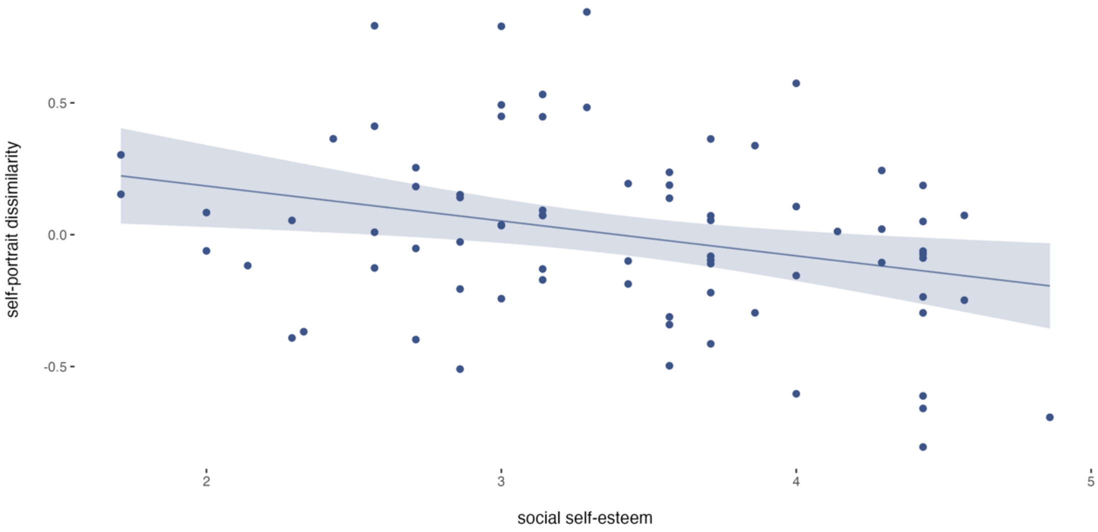

Fig. 2b. The scatterplot illustrates the relationship between individual differences in self-portrait dissimilarity (statistically controlling for the effect of non-self same-gender dissimilarity) and social self-esteem. The higher the participant's self-esteem with regard to their social interactions, the more accurate their self-portrait. The solid line shows the best-fitting regression, and the shaded region reflects the 95% confidence interval.