A Shift from Image-Based to Identity-Based Face Recognition is Enhanced by Social Significance but Mediated by Perceptual Experience

Maayan Trzewik[1], Nira Liberman[1*], and Galit Yovel[1,2*]

[1]School of Psychological Sciences, Tel Aviv University
[2]Sagol School of Brain Sciences, Tel Aviv University

*Equal contribution

Please address correspondence to Maayan Trzewik,

maayant@mail.tau.ac.il

Tel Aviv University

Abstract

Person recognition is better for familiar than unfamiliar faces. Interestingly, recognizing specific images of the face shows a reverse effect of better recognition of unfamiliar than familiar faces. This suggests a representational shift from an image-based to an identity-based representation when faces become familiar. Does this shift arise from the richer perceptual experience with familiar faces, their higher social significance, or a combination of both? Two studies (N = 172) examined how these factors influence recognition of the person and the specific image. In Study 1, learning five images per unfamiliar person, compared to one, led to better person recognition and worse image recognition, making them more akin to familiar people. Study 2 replicated this effect and showed that higher social significance improved person recognition, but only when there was sufficient perceptual experience. We conclude that perceptual experience is crucial for identity-based recognition, while social significance enhances its effect.

Keywords: face recognition, face representation, face familiarity, perceptual experience, social significance

Research Transparency Statement

General Disclosures

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Study 1 Disclosure

Preregistration: The hypotheses and analysis plan were preregistered (https://aspredicted.org/291_9QK) on 07-19-2021, prior to data collection which began on 07-26-2021. The methods were not preregistered. There were no deviations from the preregistration. Materials: All study materials are publicly available (https://osf.io/j2bg8/?view_only=5b8fd364f1d04fb3bb7e9cf993aa8f7e). Data: All primary data are publicly available (https://osf.io/j2bg8/?view_only=5b8fd364f1d04fb3bb7e9cf993aa8f7e). Analysis scripts: All analysis scripts are publicly available (https://osf.io/j2bg8/?view_only=5b8fd364f1d04fb3bb7e9cf993aa8f7e).

Study 2 Disclosure

Preregistration: The hypotheses and analysis plan were preregistered (https://aspredicted.org/FL8_4WS) on 08-29-2022, prior to data collection which began on 11-09-2022. The methods were not preregistered. There were minor deviations from the preregistration (for details see Supplementary Table S1). Materials: All study materials are publicly available (https://osf.io/j2bg8/?view_only=5b8fd364f1d04fb3bb7e9cf993aa8f7e). Data: All primary data are publicly available (https://osf.io/j2bg8/?view_only=5b8fd364f1d04fb3bb7e9cf993aa8f7e).

Analysis scripts: All analysis scripts are publicly available (https://osf.io/j2bg8/?view_only=5b8fd364f1d04fb3bb7e9cf993aa8f7e).

Introduction

When meeting a familiar person, we typically recognize them effortlessly even if they aged, changed haircut, or are standing sideways. The case with unfamiliar people, however, is markedly different, as such changes in appearance significantly hinder our ability to recognize them (e.g., Bruce, 1982; Burton et al., 2011; Keyes & Zalicks, 2016; Kramer et al., 2018; for a review see Johnston & Edmonds, 2009; Young & Burton, 2017). What explains this stark difference? Is it the richer perceptual experience that naturally comes with familiarity? Is it the fact that familiar people are more significant to us? Or perhaps both experience and significance produce this effect of familiarity on face recognition?

Depending on the task, familiarity may either enhance or impair face recognition. In a person recognition task, when answering the question "have you seen this *person* during the learning phase?", recognition is better with faces of familiar than unfamiliar people, especially when all people are presented in unlearned images. Interestingly, in an image recognition task, when answering the question "have you seen this *image* during the learning phase?", recognition is worse with faces of familiar than unfamiliar people (Armann et al., 2016). This pattern of findings is in line with the possibility that the representation of unfamiliar faces is primarily shaped by the specific perceptual features of the image (i.e. image-based representation), as this is the only information we have about them. In contrast, the representation of familiar faces is informed in addition by stored representations of their identity (i.e., identity-based representation) (Bruce & Young, 1986; Menon et al., 2015).

Identity-based representation of a familiar person has two main characteristics. First, it is perceptually richer than any specific image, simply because it contains information from multiple images, acquired over experience. This experience enables better recognition of the familiar person in previously unlearned images. Second, familiar people tend to be important to us, which may lead to greater emphasis of their identity-based representation over specific-perceptual characteristics. Consequently, the ability to recognize the person in both learned and unlearned images would improve, but the ability to recognize which exact image was learned might decline.

The contributions of perceptual experience and social significance to face recognition were typically investigated in separate lines of research. Studies on the role of perceptual experience have shown that learning faces from multiple different appearances (i.e., high-variability images) improves recognition from unlearned images, relative to learning them from a single image or from a set of relatively similar (i.e., low-variability) images (Burton et al., 2016; Ritchie & Burton, 2017). But these studies examined only the facilitative effects of experience on recognizing a learned person in unlearned images and did not address their potentially detrimental effects on recognizing which specific image of that person was learned. To substantiate the claim that learning different presentations of a person contributes to an identity-based representation (rather than, for example, enhances any memory performance with their image) we need to show that such learning enhances recognition of a person in an unlearned image, but does not enhance (and may even interfere with) recognizing a specific image among other images of the same person. Study 1 aims to do that.

As noted above, social significance may also contribute to the identity-based representation of familiar faces. Several studies have shown that assigning social significance to a person improves recognition of that person's face. For instance, people learn better faces of others whom they expect to meet (Wilson et al., 2014), who have high-, compared to low social-status (Ratcliff et al., 2011), who are members of the ingroup, compared to the outgroup (Bernstein et al., 2007), and who are relevant rather than irrelevant to their social role (van Bavel & Cunningham, 2012). However, most studies tested recognition with the same images that were presented at learning, and did not examine if the effect extends to unlearned images of learned people. Therefore, it is unclear whether social significance enhances identity-based, or only image-based recognition. Finally, because the effects of perceptual experience and social significance were examined in separate lines of research, little is known about how and whether they interact during the generation of an identity-based representation. We examine these questions in Study 2.

In summary, we examined how two aspects of familiarity – perceptual experience and social significance – contribute to two hallmarks of identity-based representation, both of which are revealed in responses to unlearned images of learned people: better performance on a person-task, and worse performance on an image-task. We adapted Armann et al.'s (2016) paradigm where participants were presented at test with the same images they have seen at learning, unlearned images of the people they have seen at learning, and images of people they have not seen at learning. At test, one group was asked to indicate whether the exact image appeared at learning (image-task), and a second group is asked to indicate whether the person appeared at learning (person-task, see Fig. 1). An identity-based representation would be manifested in better performance on the person task, but not in the image task, with unlearned images of learned people. Study 1 manipulated perceptual experience by presenting at learning faces of familiar and unfamiliar people in either one or five images per person. We expected to replicate the results of Armann et al. (2016), namely, that after learning one image of a person, performance with familiar people would be better on the person-task and worse in the image-task. We also expected to demonstrate that learning multiple images of unfamiliar people would make performance more similar to familiar people, that is, visual experience would improve performance on the person-task but impair performance on the image-task. In Study 2 we manipulated both perceptual experience and social significance. Participants learned faces of unfamiliar people from either one or five images and were told that they belong to a high-status (Physicians) or a low-status (Cleaners) group. We expected to replicate the effects of perceptual experience on person and image recognition from Study 1. We also expected to replicate past findings (Ratcliff et al., 2011; Trzewik et al., 2024) that showed better recognition of high-status, compared to low-status people for learned images. Going beyond these findings, our novel design enabled us to examine how status and perceptual experience combine. When presented with unlearned images of learned people, would performance be better in the person-task, and worse in the image-task for high-status than low-status people?

Study 1: Effect of perceptual experience on image-based and identity-based representations

Method

Participants

We recruited 96 participants for the study, with the aim of achieving at least .85 power for an effect size of $\eta^2_p = .10$ (G*Power; Faul et al., 2009) in the interaction between Task and Number of Images for unfamiliar people. This required a minimum of 76 participants, and we planned to recruit additional 20 participants to account for potential dropout. Participants were recruited via Prolific (Palan & Schitter, 2018) and completed the study online in exchange for £6 per hour. Of the 96 participants, 12 were excluded due to overall performance levels that were not significantly above chance (see Data Analysis section for details) and 5 were excluded for failing all attention checks (see Procedure for details about catch trials). The final sample included 79 participants: 40 Israeli participants (25 females, 15 males; age: M = 27.70 years, SD = 7.19) and 39 Spanish participants (20 females, 18 males, 1 other; age: M = 26.03 years, SD = 6.14). Participants were randomly assigned to one of the four experimental conditions Task (person vs. image) × Number of Images (1-image vs. 5-images).

Stimuli

We collected color face images of 72 Israeli celebrities and 72 Spanish celebrities. These images were downloaded from the internet and selected to be familiar to participants of the same nationality and unfamiliar to participants of the other nationality. Within each nationality, there were equal numbers of male and female celebrities. The mean age of the Israeli celebrities at the time of the experiment was M = 48.83, and the mean age of the Spanish celebrities was M =

48.03. We chose celebrities from various occupations (e.g., politicians, actors, singers), with a similar representation for each occupation in both nationalities. For each celebrity, we selected 6 images that showed only the head and neck, removed the backgrounds, and cropped and resized the images to 300x300 pixels each.

Procedure

Fig. 1 shows an illustration of the face recognition task. After giving their consent to participate, participants were told they would learn images of men and women, some are familiar celebrities and some are unfamiliar, and that there would be a test later. They were also informed that during the test they will be presented with these men and women either in the learned images or in unlearned images, alongside images of familiar and unfamiliar people that were not presented at learning. The participants were randomly assigned to either the Person task or the Image task. In the Person Task, they were instructed to memorize the identity of the faces presented in the learning phase such that in the test phase they would respond “learned” for both learned and unlearned images of learned people. In the Image task, they were instructed to memorize the specific images that were presented such that in the test phase they would respond “learned” for the same image that was shown during learning but “unlearned” for unlearned images of the learned people. After they read the instructions, the participants completed a practice of 6 trials. The learning phase then started during which 48 identities (24 Israeli and 24 Spanish) were presented one at a time. Each trial began with a fixation cross presented for 3000ms, and then each of the images was presented for 3000ms. Participants were further assigned to a 1-Image or 5-Images conditions. In the 1-Image condition each person was presented in a single image, whereas in the 5-Images condition the person was presented in mini-blocks of 5 different images that appeared one after the other with inter-stimuli-interval of 100ms. The assignment of identities to learning and test, the assignment of images of each identity to learning and test, and the order of images presentation in the 5-Images condition were all counterbalanced across participants. The order of the presentation of identities at study and test was random. To make sure that the participants are attentive to the task, there were 4 catch-trials that presented an animated face. The participants were instructed to press the spacebar whenever the animated face is presented.

The test phase followed the learning phase and consisted of 72 trials: 24 trials presented an unlearned image of a learned person (Unlearned-Image Learned-person condition), 24 trials presented an unlearned image of a learned person (Learned-Image Learned-person condition), and 24 trials presented an unlearned person (Unlearned-Person condition). On each trial, the image was presented until response, together with a scale ranging from 1 to 6. The levels of the scale in the person (image) condition were: 1 – certainly an unlearned person (image); 2 – probably an unlearned person (image); 3 – I guess it's an unlearned person (image); 4 – I guess it's a learned person (image); 5 – probably a learned person (image); 6 – certainly a learned person (image).

At the end of the test phase, participants were presented with a familiarity test, to find out if participants are familiar with the celebrities of the same nationality and unfamiliar with the celebrities of the other nationality. Each familiarity test trial presented an image of one of the identities, and the participants indicated by key-press whether they know anything about this person (name, occupation, etc.). The image was presented until response. If an identity failed to meet the familiarity criterion for a specific participant (a Spanish celebrity that was recognized by an Israeli participant, or was not recognized by a Spanish participant or an Israeli celebrity that was recognized by a Spanish participant, or was not recognized by an Israeli participant), it was excluded from data of that participant. Last, the participants were asked to report any distractions or difficulties they encountered while performing the task. They then provided demographic information, including their age, gender, and nationality and finally were debriefed and thanked for their participation.

Data analysis

Exclusions. As preregistered, we excluded from the analysis participants with overall accuracy rates that were not significantly above chance level (below 59%, as calculated in a binominal test). In addition, we excluded responses that were faster than 200ms or slower than 10,000ms. Overall, we excluded 17 of 96 participants, and about 1% of all trials.

Accuracy. We calculated the percent of correct responses for each experimental condition. A response was considered correct if it was between 1-3 for unlearned stimuli, and between 4-6 for learned stimuli. Namely, when answering the person task, the correct responses are 1-3 for images of unlearned people and 4-6 to learned and unlearned images of learned people. When answering the image task, the correct responses are 1-3 for unlearned people and for unlearned images of learned people, and 4-6 for learned images of learned people.

Correction for multiple comparisons. Post-hoc comparisons were corrected for false discovery rate (FDR; Benjamini & Hochberg, 1995).

Sensitivity and bias. Following Armann et al. (2016), we assessed which factors affected the sensitivity to the learned stimuli (how good the person's identity, or the image, is encoded to participants' memory), and the response bias (participant's tendency to respond that the stimuli are "learned" or "unlearned" at test). Armann et al. (2016) estimated sensitivity using d' and bias using C and found significant effects in both measures. However, recent simulations (Levi et al., 2024a; Rotello et al., 2008) and behavioral data (Levi et al., 2024b) indicate that d' is susceptible to false discovery of sensitivity differences (Type I error) when used in recognition tasks. To avoid such potential false discoveries, we planned to use the d_a index (Simpson & Fitter, 1973) to estimate participants' sensitivity and the criterion measure C_a (Macmillan & Creelman, 2004) to estimate response bias, as they have demonstrated better validity in recognition tasks (Levi et al., 2024a, 2024b).

The calculation of d_a and C_a necessitates that the data contain at least three levels of the response scale. In Study 1, out of the 79 participants, only 21 utilized more than two levels of the response scale during the test. Thus, there was insufficient data to execute this analysis in Study 1 and we therefore report only accuracy.

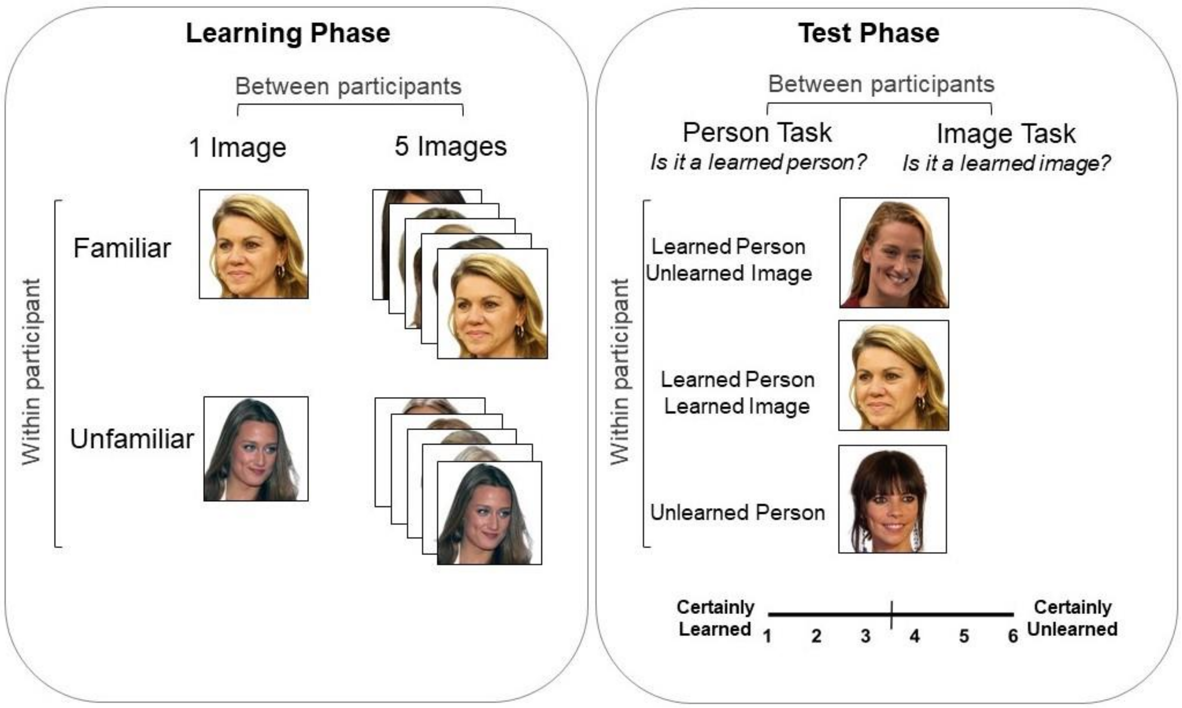

Fig. 1.

The design of the face recognition task in Study 1. During the learning phase, participants from two countries learned face images of celebrities from their own country (familiar) or from the other country (unfamiliar). Participants were presented with either a single image or five distinct images for each person. At test, participants were presented with learned and unlearned images of learned people, and images of unlearned people. Participants in the *person task* condition indicated whether they had previously seen the person depicted in each image, irrespective of the specific image presented. Participants in the *image task* condition indicated whether they had seen the exact image before, regardless of whether they have seen the person displayed in it.

Results

Replication of familiarity effects with learning a single image

We sought to replicate Armann et al., (2016), to assess whether when presented with an unlearned image of a learned person, person recognition would be better whereas image recognition would be worse in familiar, compared to unfamiliar people. Because the original study showed only one image per person, we performed the analysis on this condition of our study. We conducted the same mixed-design ANOVA as in Armann et al. (2016), with Familiarity (familiar/unfamiliar) and Test-Image (learned image/unlearned image/unlearned person) as within-participant factors, and Task (person/image) as a between-participants factor. The results were overall consistent with Armann et al. (2016), including a significant three-way interaction, $F(2,80) = 15.20$, $p < .001$, $\eta_p^2 = .28$. A full report of this ANOVA is shown in Table S2.

Similar to Armann et al., we conducted a follow-up mixed-design ANOVA on accurately responding to unlearned images of learned people (the response is "learned" in the person task and "unlearned" in the image task), with Familiarity (familiar/unfamiliar) as a within-participant factor, and Task (person/ image) as a between-participants factor (Fig. 2a and b, 1 image). This follow-up analysis was not preregistered. Consistent with the results of Armann et al. (2016), an interaction between Familiarity and Task, $F(1,75) = 33.49$, $p < .001$, $\eta_p^2 = .46$, emerged. It showed that in the person task, familiar people were recognized better in unlearned images than unfamiliar people, $t(21) = 6.93$, $p < .001$, *Cohen's d* = 1.48. In contrast, in the image task unlearned images of unfamiliar people were rejected better than those of familiar people, $t(19) = –2.24$, $p = .037$, *Cohen's d* = –0.50. A full report of this ANOVA is presented in Table S3.

The effect of perceptual experience on encoding unfamiliar people

We examined whether learning unfamiliar people from multiple images, compared to just one image, would enhance person-recognition, and impair image-recognition. In other words, we examined whether perceptual experience would produce an identity-based face recognition similar to familiar people. We conducted a two-way ANOVA on the accuracy rate of recognizing unlearned images of unfamiliar people, with Task (person/image) and Number of Images (1-image/5- images) as between-participants factors. The results pertinent to this analysis are presented in the blue bars in panels (a) and (b) in Fig. 2. In line with our prediction, an interaction between Task and Number of Images, $F(1,75) = 11.20$, $p = .001$, $\eta_p^2 = .13$, showed that learning five images of each unfamiliar person, compared to learning just one image, improved performance on the person task, $t(42) = 3.17$, $p = .003$, *Cohen's d* = .96, but had a reverse effect (albeit not significant) on the image task, $t(33) = -1.63$, $p = .114$, *Cohen's d* = –0.56. Complete report of the results of this ANOVA are shown in Table S4.

We then conducted a mixed-design ANOVA to examine whether the effect of learning five images, compared to just one, was different for familiar, compared to unfamiliar, people. There was no effect of Familiarity, $F(1,73) = 0.14$, $p = .713$, $\eta_p^2 < .01$, nor a three-way interaction between Familiarity, Task, and Number of Images, $F(1,73) = 0.06$, $p = .808$, $\eta_p^2 < .01$. Complete report of results of this ANOVA are shown in Table S5.

In summary, results reveal identity-based representation – as indicated by better performance for unlearned images of learned people on the person task and worse performance on the image task – for familiar people as well as for unfamiliar people that were learned from multiple images. In Study 2 we turn to examine how perceptual experience interacts with the social significance of the learned people.

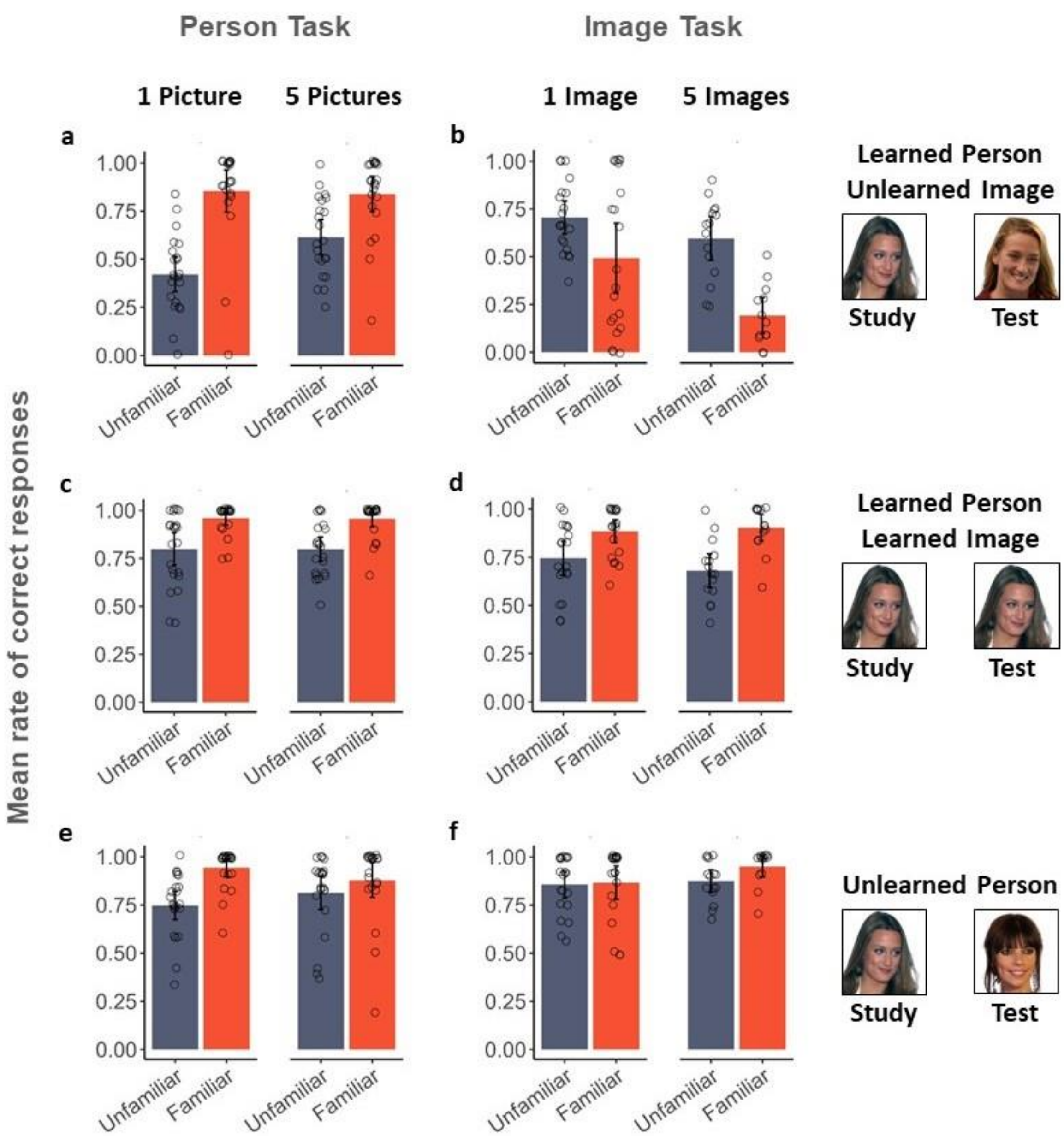

Fig. 2.
Proportion of correct responses in Study 1 in the person task (i.e., recognize a learned person regardless of the specific image presented at test, Left Panels) and the image task (i.e., recognize the specific learned image, Right Panels) for (a, b) unlearned images of learned people, (c, d) learned images of learned people, and (e, f) unlearned people. Error bars represent 95% confidences interval of the mean.

Study 2: Effects of perceptual experience and social-status on image-based and identity-based representation

Method

Participants

We sought to achieve at least .90 power for an effect size of η^2_p =.05 of the interaction between Social-Status, Task and Number of Images in recognition of learned people in unlearned images. This power required at least 100 participants, according to a power analysis conducted using G*Power (Faul et al., 2009). We planned to recruit 20 additional participants to account for potential dropout. One hundred and twenty undergraduate students from [masked] University completed the study on-line for course credit. As preregistered, we excluded from analysis one participant who did not complete the task, and 25 participants whose overall performance level was not significantly above chance (bellow 62.5% correct responses, as calculated on a binominal test), and one participant who failed more than half of the attention checks. Thus, we analyzed the data of 93 participants (80 females, 12 males, 1 other; age: M = 22.82 years, SD = 1.82).

Among the 93 participants that were included in the accuracy analysis, 40 did not use more than two levels of the response scale in the test and were therefore excluded from the sensitivity and bias analyses. Those analyses included 53 participants (45 females, 7 males, 1 other; age: M = 22.64 years, SD = 1.89). To account for the implication of the massive dropout, we conducted a sensitivity power analysis. We found that this sample provided 80% power to detect an effect size of η_p^2 = .075 or greater in a repeated-measure ANOVA with a 5% false-positive rate.

Materials

Color images of 144 European and Australian celebrities (half of them females) were downloaded from the internet. We selected celebrities that were expected to be unfamiliar to

Israeli participants. For each person, we chose 6 images that show only the head and the neck, removed the background and cropped and resized each image to 300x300 pixels.

Procedure

The procedure was identical to that of Study 1, except the following changes: all people were unfamiliar to the participants; half of them were presented with a “physician” label and half with a “cleaner” label during both learning and test. The assignment of identities to physicians and cleaners was counterbalanced across participants. Participants completed a learning phase with 48 trials and a test phase, with 72 trials; After the test, participants indicated whether they saw any familiar people, and wrote their names. Trials with familiar people were removed from the data of participants who recognized them.

Analysis

Accuracy. We calculated the proportion of correct responses for each experimental condition. A response was considered correct if it was rated between 1-3 for unlearned stimuli, and if it was rated between 4-6 for learned stimuli. Post-hoc comparisons were corrected for false discovery rate (FDR; Benjamini & Hochberg, 1995). We measured separately the accuracy for unlearned images of learned people, learned images of learned people and unlearned people.

Sensitivity and bias. We used the d_a index to estimate participants' sensitivity, as well as the criterion measure C_a to estimate response bias. Because the findings from this analysis align with the accuracy analysis and provide no additional information, we present it in the Supplementary Materials.

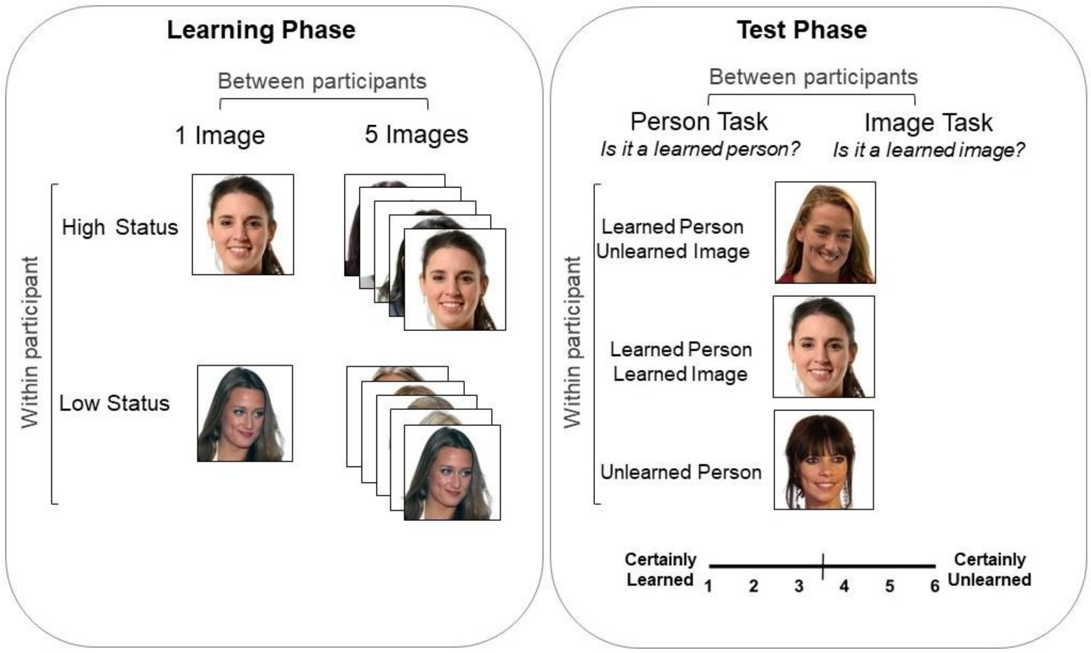

Fig. 3.

The design of the face recognition task in Study 2. Participants learned images of unfamiliar people labeled as either "Physicians" (high-status condition) or "Cleaners" (low-status condition). Participants were presented at learning with either a single image or five distinct images for each person. At test, participants were presented with learned and unlearned images of learned people, labeled with the same category as at learning, and image of unlearned people, also labeled as either "Physicians" or "Cleaners". Participants in the person task condition indicated whether they had previously seen the person depicted in each image, irrespective of the specific image presented. Participants in the image task condition indicated whether they had seen the exact image before.

Results

Replicating and extending the effect of social significance to person recognition

Previous studies that examined effects of social significance on person recognition used the person task, presented only one image at study, and presented the same image at test. We tested whether this effect would replicate, and whether it would extend to unlearned images of learned people, in both low- and high-experience conditions. The results of a repeated-measures ANOVA on the accuracy scores of the Person-task condition with Social-Status (high/low) and Test-Image (learned image/unlearned image/unlearned person) as within-participant factors, and Number of Images (1-image/5- images) as between-participants factors are presented in Table S6, and the relevant data is plotted in panels (a), (c), and (e) of Fig. 4. The three-way interaction between Test-Image, Number of Images, and Social-Status was significant, $F(2,90) = 9.52$, $p < .001$, $\eta_p^2 = .17$. Post-hoc comparisons showed a replication of the findings of Ratcliff et al. (2011): High (vs. low) status improved performance for learned images when learned from one image, $t(20) = 7.24$, $p < .001$, *Cohen's d* = 1.58. We also ensured that we replicate Ratcliff et al.'s findings when conducting the same analysis as in the original paper. The results of this unregistered analysis are presented in the supplementary materials.

But the benefit of high-status for person recognition in learned images did not emerge with ample visual experience, when participants learned five images of the person (Fig. 4c). In a follow-up ANOVA, conducted on the learned image condition, we found that Number of Images and Social-Status interacted, $F(1,45) = 21.96$, $p < .001$, $\eta_p^2 = .33$, such that learning faces from five (compared to one) images improved recognition of low-status faces, closing the gap with high-status faces, $t(25) = 0.93$, $p = .542$, *Cohen's d* = 0.18.

The benefit of high-status also did not extent to recognition of unlearned images of learned people (Fig. 4a): When learning one image of a person, high-status people were not recognized better than low-status people in unlearned images, $t(20) = 0.40$, $p = .692$, *Cohen's d* = 0.09. Rather, performance remained low in both groups.

Importantly, however, providing ample visual experience at learning improved performance with unlearned images of high-status people, but not with unlearned images of low-status people, $t(25) = 2.75$, $p = .033$, *Cohen's d* = 0.54. Finally, for unlearned people, there were no effects of Social-status, Number of Images or their interaction (all *p*'s > .152; Fig. 2e).

Together, these results show that the previously found effect of social-status is limited to previously seen images of people that are learned from a single image. Perceptual experience interacts with social-status in two interesting ways: First, it overrides the effect of social-status for previously seen images, improving performance for low-status people to the level of high-status people. Second, it extends the effect of status to unlearned images of learned people, indicating a shift from an image-based to an identity-based representation.

The joint effects of perceptual experience and social-status on person- and image-recognition for unlearned images of learned identities

As in Study 1, we examined whether learning five images, compared to one, improved performance with unlearned images of learned people in the person task but impairs performance with such images in the image task. We also examined whether these two effects depend on the social-status of the depicted person. We conducted a mixed-design ANOVA on the accuracy scores of the unlearned image condition with Social-Status (high/low) as a within-participant factor, and Task (person/ image) and Number of Images (1-image/5-images) as between-participants factors. The data pertinent to this analysis are presented in panels (a) and (b) of Fig. 4. There was a three-way interaction between Social-Status, Task and Number of Images, $F(1,89) = 4.35$, $p = .040$, $\eta_p^2 = .05$. We examined the effect of perceptual experience in two post-hoc comparisons. As in Study 1, learning each face in five images, compared to one, enhanced recognition of the person, $t(89.3) = 5.41$, $p < .001$, *Cohen's d* = 1.12, but impaired recognition of the image, $t(81.4) = –4.97$, $p < .001$, *Cohen's d* = –1.05. We then examined these effects separately for high- and low-status people and found they were significant in both (see the supplementary materials for a report of the pre-registered and post-hoc comparisons). Next, we examined the effect of social-status in two post-hoc comparisons. High-status people were remembered better than low-status people in the person task, $t(46) = 2.35$, $p = .023$, *Cohen's d* = 0.34, but not in the image task, $t(45) = 0.67$, $p = .504$, *Cohen's d* = 0.10. When examining the effect of status for each combination of Task and Number of Images separately, recognition was better for high-, compared to low-status people only in the person task when learning five images per person, $t(25) = 2.75$, $p = .044$, *Cohen's d* = 0.54. All other comparisons were not significant ($p > .314$). Complete report of the results of this ANOVA are shown in Table S7.

We also pre-registered an analysis that focuses on high-status faces: A two-way ANOVA on the recognition scores for high-status people in the unlearned-image condition with Task (person/image) and Number of Images(1- image/5- images) as between-participants factors. There was a marginally significant effect of Task, $F(1,89) = 3.29$, $p = .073$, $\eta_p^2 = .04$, showing slightly better performance in the Person, compared to the Image, task. There was no effect of Number of Images, $F(1,89) = 0.03$, $p = .866$, $\eta_p^2 < .01$. There was, however, a significant interaction, $F(1,89) = 38.17$, $p < .001$, $\eta_p^2 = .30$, that showed the hallmark of identity-based representation. Complete report of the results of this ANOVA are shown in Table S8. Two planned contrasts that were pre-registered as a part of this analysis are reported in the supplementary materials.

Together, these results show that perceptual experience improves person recognition and impairs image recognition of unfamiliar people regardless of social-status, providing further evidence for its role in the generation of identity-based representation of faces. Social-status further enhanced this effect, suggesting that high social-status contributes to identity-based representation, as opposed to image-based representation of a person.

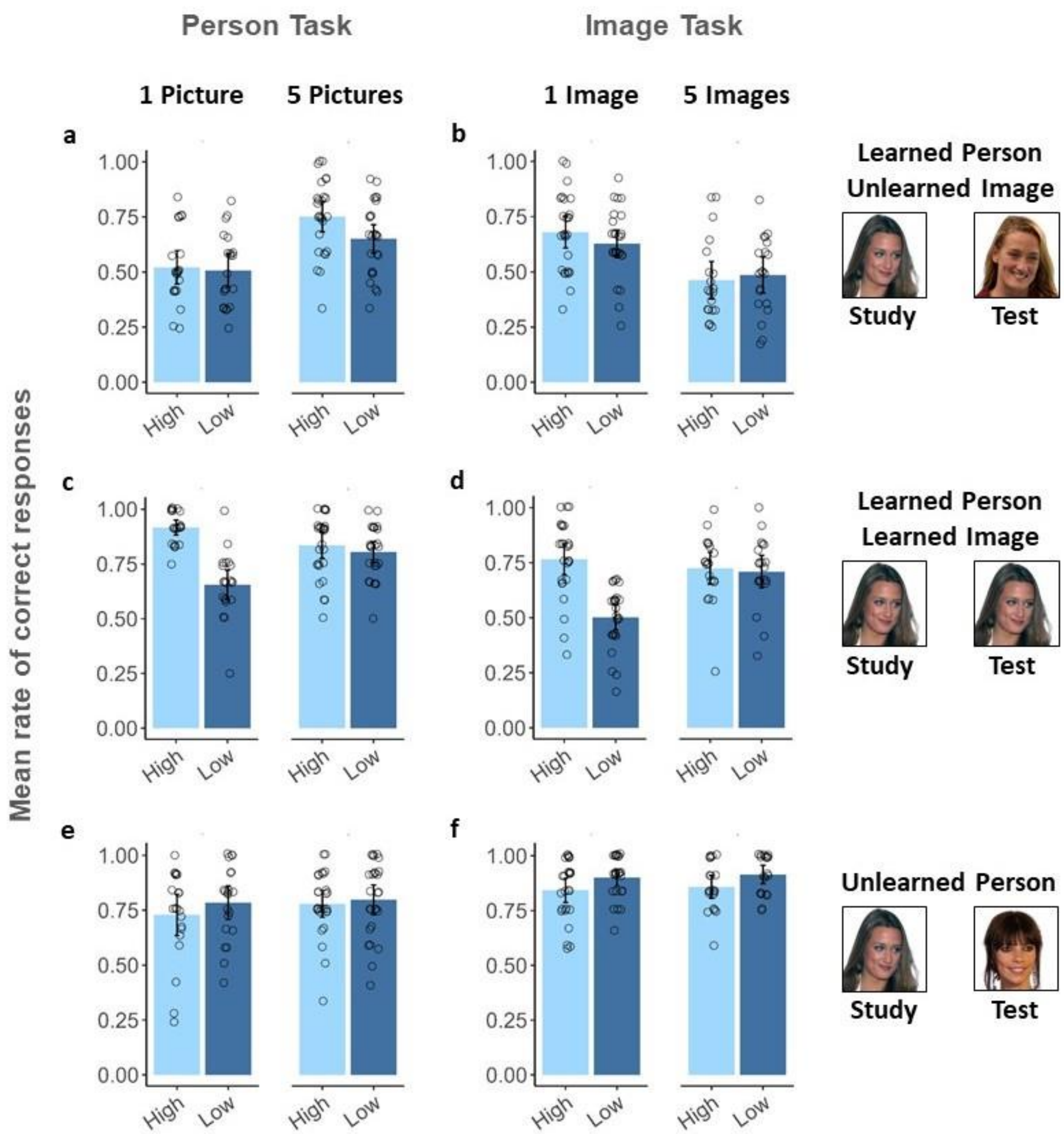

Fig. 4.
Mean proportion of correct responses in Study 2 in the person task and image task for unlearned images of learned people (a, b), learned images of learned people (c, d), and unlearned people (e, f). Error bars represent 95% confidences interval of the mean.

General Discussion

In two studies we investigated whether perceptual experience and social significance contribute to generating an identity-based representation of faces, as manifested in better person recognition and worse image recognition for unlearned images of learned people. Study 1 successfully replicated Armann et al. (2016), demonstrating that these two aspects of identity-based representation characterized recognition of familiar people more than unfamiliar people. It also found that perceptual experience (learning five images vs. one image) with an unfamiliar person mimicked the effect of familiarity: it not only improved person recognition in unlearned images, but also impaired distinction between learned and unlearned images of the same person. Study 2 found that social significance (high vs. low social-status) enhanced person recognition in unlearned images, but only when participants learned five images of each person. Recognition of learned images was better for high-status than low-status faces following one image learning, as was reported by Ratcliff et al. (2011). Interestingly, learning five images increased performance of low-status faces to the level of high-status faces for learned images. Thus, perceptual experience interacts with social-status by improving image-based recognition for low-status faces, and by enhancing person recognition for unlearned images for high-status faces. Thus, social-status contributed to the generation of identity-based representation only in conditions of high perceptual experience.

Our findings are consistent with previous studies which showed that to recognize a person in a novel image one needs to learn variable images of that person (Burton et al., 2016; Ritchie & Burton, 2017, see also Raviv et al., 2022 for the importance high variability in learning and generalization). We go beyond these findings in two ways: First we show that perceptual experience does not only enhance person recognition but also impairs image recognition. Second, we show that high (compared to low) social-status further facilitates person recognition when perceptual experience is high. Probably, in real life, both perceptual experience and social significance contribute to the ability to recognize familiar people in novel appearances. The additional finding that neither perceptual experience nor social-status reduced false image recognition of unlearned images of learned people, further establishes that experience and significance contribute to the generation of identity-based representation (rather than improving any face recognition task).

The detrimental effect of an identity-based representation on image recognition is not specific to faces but was also shown in an object recognition task. Lupyan and colleagues (2008) reported that category labeling during learning images of two categories of objects (e.g., chairs and lamps) impaired recognition of specific images of the learned categories. These authors suggested that category labeling led to a representational shift from an image-based to category-based representation. We propose that a similar representation shift occurs for familiar faces. We further found that perceptual experience with different appearances of the learned identity is required for this representational shift to occur, and that social-status further enhances identity-based recognition. We predict that a similar representational shift may occur for novel objects when provided with perceptual experiences across diverse appearances, which can be further heightened by instilling them with significant meaning (e.g., religious or cultural).

There are several limitations to the current study. First, the perceptual experience manipulation included only five still images, whereas real-life perceptual experience with familiar people is much richer and is more dynamic. Furthermore, it is possible that the manipulation of social meaning using occupation labels was not sufficiently strong. Low-status occupation, despite implying less social power, may still make the person relevant for future interactions in certain contexts. Future research could explore this issue further by manipulating social significance using more powerful manipulations.

Our findings on the effect of social-status are consistent with the notion that people of higher social-status are approached more and receive more attention (Fiske, 1993). These differences in the way we process faces of high- versus low-status people reflect and possibly maintain social stereotypes. Low-status group members are less likely to be encoded as identities, and as a result might remain undifferentiated, unrecognized, and avoided. Our findings further extend this line of research by showing that perceptual experience improved recognition of previously seen low-status people, diminishing the social-status recognition effect (Fig. 2c). Thus, frequently seeing low-status faces may contribute to identity-based encoding of their faces.

Interestingly, in social psychology, individuating a person is typically associated with concrete, piecemeal as opposed to a categorical, more abstract and stereotypic processing of information related to that person (Fiske & Neuberg, 1990). Notably, stereotypes are created at a higher level of categorization than the individual: in stereotyping, the person is the specific example, and the stereotype is the general category to which they belong (e.g., "cleaners are not influential"). The perceptual experience provided in our study enabled the formation of a detailed representation of the individual (i.e., individuation) and the high social-status further enhanced it by providing it with significant social meaning. This demonstrates the importance of studying the interactions of perceptual experience with classical effects of stereotypes (e.g., Brewer, 1999; Darley & Gross, 1983; Nosek et al., 2002), ingroup favoritism (e.g., Saucier et al., 2005; Tajfel et al., 1971), deindividuation (e.g., Kawakami et al., 2017) and dehumanization (e.g., Haslam & Loughnan, 2014) on the representational shift from image to identity and from identity to group category. Would a rich perceptual experience with outgroup members reduce discrimination? For example, would presenting employers with five different images of each job candidate reduce the tendency to discriminate against candidates from minority groups (Lippens et al., 2023)?

Taken together, our findings underscore the importance of integrating the body of knowledge on person recognition from both perception and the social domains to better understand the processes that affect performance in this central function.

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Supplementary Materials

Study 1 additional results

Supplemental results tables

Table S2

ANOVA Summary Table for Recognition Accuracy in the 1-Image Condition in Study 1, by Familiarity, Task, and Test-Image

Variables	df	Sum of squares	Mean squares	F	*p*	η^2_p
Familiarity	1.00	0.91	0.91	28.88	< .001	.42
Task	1.00	0.05	0.05	1.02	.318	.02
Test Image	2.00	2.99	1.49	37.14	< .001	.48
Familiarity × Task	1.00	1.27	1.27	39.90	< .001	.50
Test Image × Task	2.00	0.07	0.04	0.88	.417	.02
Familiarity × Test Image	2.00	0.03	0.01	0.36	.700	< .01
Familiarity × Test Image × Task	2.00	1.10	0.55	15.20	< .001	.28

Table S3

ANOVA Summary Table for Accuracy of Unlearned Images Recognition Accuracy in the 1-Image Condition in Study 1, by Familiarity and Task

Variables	df	Sum of squares	Mean squares	F	*p*	η^2_p
Familiarity	1.00	0.25	2.61	3.90	.055	.09
Task	1.00	0.03	3.11	0.40	.531	.01
Familiarity × Task	1.00	2.19	2.94	33.49	< .001	.46

Table S4

ANOVA Summary Table for Accuracy of Unlearned Images Recognition of Unfamiliar People in Study 1, by Task, and Number of Images

Variables	df	Sum of squares	Mean squares	F	*p*	η^2_p
Number of Images	1.00	0.03	0.03	0.85	.358	.01
Task	1.00	0.34	0.34	8.59	.004	.10
Number of Images × Task	1.00	0.44	0.44	11.20	.001	.13

Table S5

ANOVA Summary Table for Recognition Accuracy in the Unlearned Image Condition in Study 1, by Familiarity, Task, and Number of Images

Variables	df	Sum of squares	Mean squares	F	*p*	η^2_p
Familiarity	1.00	0.01	0.01	0.14	.713	< .01
Task	1.00	1.32	1.32	22.20	< .001	.23
Number of Images	1.00	0.15	0.15	2.43	.123	.03
Familiarity × Task	1.00	3.61	3.61	65.45	< .001	.47
Number of Images × Task	1.00	0.84	0.84	14.09	< .001	.16
Familiarity × Number of Images	1.00	0.34	0.34	6.13	.016	.08
Familiarity × Number of Images × Task	1.00	< .01	< .01	0.06	.808	< .01

Effect of participants' nationality on recognition performance

We examined whether participants' nationality (Israeli/Spanish) affected performance in Study 1. We conducted a mixed-design ANOVA on the mean accuracy scores with Nationality (Israeli/ Spanish), Task (person/image) and Number of Images (1-Image/5-Images) as between-participants factors, and Familiarity (familiar/unfamiliar) and Test Image (unlearned person/unlearned image/learned image) as within-participant factors. There was no main effect of Nationality, $F(1,68) = 2.96$, $p = .092$, $\eta_p^2 = .04$, and Nationality did not interact with any other factor of the analysis (all p's > .088).

Study 2 additional results

Supplemental results tables

Table S6

ANOVA Summary Table for Recognition Accuracy in Person task in Study 2, by Social-Status, Test Image, and Number of Images

Variables	df	Sum of squares	Mean squares	F	*p*	η^2_p
Social-Status	1.00	0.21	0.01	21.98	< .001	.33
Test Image	1.47	2.05	0.04	25.61[a]	< .001	.36
Number of Images	1.00	0.49	0.02	23.49	< .001	.34
Social-Status × Test Image	2.00	0.39	0.02	11.10	< .001	.20
Number of Images × Test Image	1.47	0.37	0.04	4.62 [a]	.022	.09
Social-Status × Number of Images	1.00	0.02	0.01	2.34	.133	.05
Social-Status × Number of Images × Test Image	2.00	0.34	0.02	9.52	< .001	.17

Note. [a] Greenhouse-Geisser correction of sphericity.

Table S7

ANOVA Summary Table for Recognition Accuracy in the Unlearned Image condition in Study 2, by Social-Status, Task, and Number of Images

Variables	df	Sum of squares	Mean squares	F	*p*	η^2_p
Social-Status	1.00	0.06	0.02	3.44	.067	.04
Task	1.00	0.09	0.04	2.28	.135	.03
Number of Images	1.00	0.00	0.04	0.02	.900	< .01
Social-Status × Task	1.00	0.02	0.02	1.23	.271	.01
Number of Images × Task	1.00	1.54	0.04	39.03	< .001	.30
Social-Status × Number of Images	1.00	0.00	0.02	0.02	.901	< .01
Social-Status × Number of Images × Task	1.00	0.07	0.02	4.35	.040	.05

Table S8

ANOVA Summary Table for Accuracy of Unlearned Images Recognition of High-Status People in Study 2, by Task, and Number of Images

Variables	df	Sum of squares	Mean squares	F	*p*	η^2_p
Number of Images	1.00	0.00	0.03	0.03	.866	< .01
Task	1.00	0.09	0.03	3.29	.073	.04
Number of Images × Task	1.00	1.14	0.03	38.17	< .001	.30

Replication of Ratcliff et al. (2011) estimated with d'

To make sure that we replicate their results, we conducted the exact same analysis as Ratcliff et al. (2011). This analysis included only the data of participants who performed the person task and learned each person from one image. We calculated d' (Tanner & Swets, 1954) based on the learned-person-learned-image and unlearned-person conditions. A paired samples t-test revealed that higher-status faces elicit higher *d'* scores, $t(20) = 2.75$, $p = .012$, *Cohen's d* = 0.60.

The effect of perceptual experience on recognition of high- and low-status people

Planned contrasts confirmed that after being learned in five images, compared to one, high-status people were recognized better in the person task $t(43.3) = 4.67$, $p < .001$, *Cohen's d* = 1.37, but worse in the image task, $t(40.4) = –4.09$, $p < .001$, *Cohen's d* = –1.22. Post-hoc comparisons revealed the same effect for low-status people in the person task, $t(42.2) = 3.03$, $p = .005$, *Cohen's d* = 0.89. and image task, $t(38.1) = –2.86$, $p = .007$, *Cohen's d* = –0.86.

Sensitivity and bias analysis

Following Armann et al. (2016), we assessed which factors affected participants' sensitivity to the learned stimuli and their response bias. Armann et al. (2016) measured sensitivity by using *d'*, however recent research (Levi et al., 2024b; Rotello et al., 2008) demonstrated that when using *d'* in recognition tasks, the probability of finding erroneous differences in sensitivity (i.e., a Type-I error) is higher than 5%, and with increasing sample size reaches levels of 100%. Hence, we planned to use d_a to estimate sensitivity (Simpson & Fitter, 1973) and C_a to estimate response bias (Macmillan & Creelman, 2004).

We calculated the mean d_a and C_a scores based on the relevant Hit and False-Alarm rates data of each task. In the person task, the Hit rate was the proportion of trials in which the participant correctly indicated that the presented person was learned, out of all the trials that actually presented a learned person (the learned-image and unlearned-image trials). The False-Alarm rate was the proportion of trials in which the participant incorrectly indicated that the presented person was learned, out of all the trials that actually presented an unlearned person (the unlearned-person trials). In the image task, the Hit rate was the proportion of trials in which the participant correctly indicated that the presented image was learned, out of all the trials that actually presented a learned image (the learned-image trials). The False-Alarm rate was the proportion of trials in which the participant incorrectly indicated that the presented image was learned, out of all the trials that actually presented an unlearned image (the unlearned-image and unlearned-person trials).

Among the 93 participants that were included in the accuracy analysis, 40 didn't use more than two levels of the response scale in the test and were therefore excluded from the sensitivity and bias analyses. Those analyses included 53 participants (45 females, 7 males, 1 other; age: M = 22.64 years, SD = 1.89).

Sensitivity. We examined whether perceptual experience and social status increase sensitivity in the two recognition tasks. In the person task, sensitivity refers to the ability to discriminate between learned and unlearned people, irrespective of the presented image at test. In the image task, sensitivity refers to the ability to distinguish between learned and unlearned images, regardless of the identities of the people displayed in them. For that aim, we conducted a mixed-design ANOVA on the mean d_a scores with Task (person/image) and Number of Images (1-image/5-images) as between-participants factors, and Social-Status (high/low) as a within-participant factor. Summary statistics are presented in Table S9. As expected, there was overall higher sensitivity to identities of high-, compared to low-status people, $F(1,49) = 8.10$, $p = .006$, $\eta_p^2 = .14$, and higher sensitivity to people who were learned in five images, as opposed to one image, $F(1,49) = 8.46$, $p = .005$, $\eta_p^2 = .15$. There was an interaction between Task and Number of Images, $F(1,49) = 5.15$, $p = .028$, $\eta_p^2 = .10$. Post-hoc comparisons showed that in the person task, learning five images of each person, compared to one image, increased sensitivity, $t(52.7) = 3.46$, $p = .002$, *Cohen's d* = 0.91. In the image task, however, learning five images compared to one image did not affect sensitivity, $t(39.5) = 0.54$, $p = .596$, *Cohen's d* = 0.15. There was no interaction between Social-Status and Task, $F(1,49) < 0.01$, $p = .953$, $\eta_p^2 < .01$, a marginally significant interaction between Social-Status and Number of Images, $F(1,49) = 3.71$, $p = .060$, $\eta_p^2 = .07$, and no three-way interaction between Social-Status, Number of Images, and Task, $F(1,49) = 2.79$, $p = .101$, $\eta_p^2 = .05$.

Table S9

Summary statistics of d_a scores in Study 2

Task and Number of Images	N	Low-Status Mean	Low-Status 95% CI Upper	Low-Status 95% CI Lower	Low-Status SD	High-Status Mean	High-Status 95% CI Upper	High-Status 95% CI Lower	High-Status SD
Person Task									
1-Image	12	0.88	1.03	0.73	0.24	1.15	1.48	0.82	0.51
5-Images	16	1.40	1.73	1.07	0.61	1.63	2.00	1.25	0.70
Image Task									
1-Image	12	0.64	0.79	0.48	0.25	1.22	1.52	0.92	0.47
5-Images	13	1.02	1.26	0.78	0.39	0.96	1.09	0.82	0.23

Note. CI = confidence interval of the mean; SD = standard deviation.

Criterion bias. We examined whether the social status of a presented person, and the number of learned images, would affect the tendency to respond “learned” or “unlearned” at test. We also examined whether this tendency would be different in different tasks. We conducted a mixed-design ANOVA on the mean C_a scores with Task (person/image) and Number of Images (1-Image/5-Images) as between-participants factors, and Social-Status (high/low) as a within-participant factor. Summary statistics are presented in Table S10. There was a main effect of Social-Status, indicating a greater tendency to respond that low-status people were “unlearned”, compared to high-status people, $F(1,49) = 20.40$, $p < .001$, $\eta_p^2 = .29$. There was no main effect of Number of Images, $F(1,49) = 2.93$, $p = .093$, $\eta_p^2 =.06$, nor a main effect of Task, $F(1,49) = 0.15$, $p = .702$, $\eta_p^2 < .01$. There were no two-way interactions (all p’s > .215), and there was no three-way interaction between Social-Status, Task, and Number of Images, $F(1,49) = 0.24$, $p = .626$, $\eta_p^2 < .01$.

Table S10

Summary statistics of C_a scores in Study 2

Task and Number of Images	N	Low-Status Mean	Low-Status 95% CI Upper	Low-Status 95% CI Lower	Low-Status SD	High-Status Mean	High-Status 95% CI Upper	High-Status 95% CI Lower	High-Status SD
Person Task									
1-Image	12	0.25	0.45	0.05	0.32	-0.01	0.26	-0.27	0.42
5-Images	16	0.10	0.30	-0.10	0.37	-0.09	0.09	-0.27	0.34
Image Task									
1-Image	12	0.25	0.41	0.09	0.25	-0.04	0.12	-0.20	0.25
5-Images	13	0.03	0.19	-0.13	0.27	-0.09	0.05	-0.24	0.24

Note. CI = confidence interval of the mean; SD = standard deviation.