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# The PCA learning effect: An emerging correlate of face memory during childhood

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ABSTRACT

Human adults implicitly learn the prototype and the principal components of the variability distinguishing faces (Gao & Wilson, 2014). Here we measured the implicit learning effect in adults and 9-year-olds, and with a modified child-friendly procedure, in 7-year-olds. All age groups showed the implicit learning effect by falsely recognizing the average (the prototype effect) and the principal component faces as having been seen (the PCA learning effect). The PCA learning effect, but not the prototype effect increased between 9 years of age and adulthood and at both ages was the better predictor of memory for the actually studied faces. In contrast, for the 7-year-olds, the better predictor of face memory was the prototype effect. The pattern suggests that there may be a developmental change between ages 7 and 9 in the mechanism underlying memory for faces. We provide the first evidence that children as young as age 7 can extract the most important dimensions of variation represented by principal components among individual faces, a key ability that grows stronger with age and comes to underlie memory for faces.


## 1. Introduction

Adults are experts in remembering faces. The processes they use to remember individual faces are more complex than simply storing them as isolated exemplars. Many previous studies demonstrated that adults represent individual faces in a multi-dimensional space that can be modeled as vectors varying in opposite directions relative to an average, or norm (Anderson & Wilson, 2005; Rhodes & Jeffery, 2006, reviewed in Valentine, Lewis, and Hills (2014)). For example, one vector might represent larger and larger foreheads in one direction and smaller and smaller foreheads in the other. Studies using multi-dimensional scaling have attempted to elucidate the details of such vectors. Usually 5–6 vectors are needed to account for most of the variance but it is not clear what each vector represents because faces at the extreme ends of a vector differ in multiple characteristics (e.g., Busey, 1998; Johnston, Milne, Williams, & Hosie, 1997; Nishimura, Maurer, & Gao, 2009).

We demonstrated recently that adults seem to use a process resembling a Principal Component Analysis (PCA) as an efficient coding mechanism for representing the differences among individual faces (Gao & Wilson, 2014). The PCA process extracts the dimensions of maximum variability among the faces to be learned, relative to their average face, with the first component representing the maximum systematic variability among the faces. We used computerized synthetic faces capturing 37 parameters in the photographs of real faces so that we could calculate the average and PCA components easily. Adults can easily recognize these synthetic faces and match them to the original photographs (Wilson, Loffler, & Wilkinson, 2002). After studying 16 individual faces, adults falsely recognized faces representing the average face (the prototype effect, Posner & Keele, 1968; Solso & McCarthy, 1981) and the first two principal components (the PCA learning effect) as having been seen at a higher rate than their correct recognition of the actually studied faces. Since the average face and the PC faces were not presented during learning, the process of learning the average and principal components is implicit. While the prototype captures the *commonality* among the studied faces, the principal components capture the *most significant dimensions of variation* among faces. It provides an efficient system for encoding individual facial identities, since fewer memory resources are needed to store the average and the individual values on several principal components compared to the storage of many details of the individual faces. In other words, it greatly simplifies the number of dimensions needed for encoding. Here we investigated the development of the PCA

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learning effect and its relationship to memory for actually studied faces.

While a typical adult can easily remember hundreds, if not thousands, of faces, it takes children a surprisingly long time to become as accurate as adults, with improvements into early adolescence (Blaney & Winograd, 1978; Carey, De Schonen, & Ellis, 1992; Flin, 1980; Goodman et al., 2007; Weigelt et al., 2014). The protracted development is not simply because children's memory is inferior to that of adults in general. This was well demonstrated in a recent study (Weigelt et al., 2014) that matched task difficulty for 10-year-olds for remembering the faces, bodies, scenes, and cars that were used. Improvements with age between 5 and 10 years were much greater for faces than for any other category, a pattern indicating that there are both domain-specific and domain-general changes in memory for faces as children grow up. The domain-specific development in children's memory for faces raises the possibility that the underlying mechanisms for remembering individual faces in children are different from those in adults.

Infants as young as 3 months show the ability to form an average representation of faces, or a face prototype. After habituation to a group of faces, infants treat their average as more familiar than a face they had actually seen (De Haan, Johnson, Maurer, & Perrett, 2001; Strauss, 1979). Between 3 and 6 years, children become more likely to falsely recognize a previously unseen average face as seen (Inn, Walden, & Solso, 1993).

However, it is unclear how children form the dimensions to differentiate individual faces. Researchers have used multi-dimensional scaling of similarity judgments to probe the nature of these dimensions. When the faces included hair, children as young as 7 appear to use the same three dimensions as adults, with those dimensions likely representing hair color, face width, and hairstyle (Pedelty, Levine, & Shevell, 1985). Without hair cues, 8-year-old children are more variable than adults and many rely on a single dimension, which may represent eye color, unlike adults who use multiple dimensions to make each judgment (Nishimura et al., 2009). Like the studies using multi-dimensional scaling with adults, these studies are limited by the need to guess what is represented on each of the dimensions identified. Here we took a quantitative approach to test whether children, like adults, implicitly learn the dimensions of most significant variation among faces as represented by principal components, that is, if they show a PCA learning effect.

Given children's inferior memory for faces compared to adults, one possibility is that children are *qualitatively* different from adults: they may not learn the principal components of variation among faces that they see. Alternatively, children may differ from adults *quantitatively*: they may learn the implicit principal components from faces that they see, but the effects may be weaker than in adults. The developmental changes, in this case, reflect only the fine-tuning of these principal components or the number of principal components that are learned in order to allow better differentiation of faces in memory encoding and retrieval.

In the current study, we investigated the implicit learning of principal components of variation among faces in 9-years old children and in a comparison group of adults tested with the same procedure, and in a group of 7-years old children tested with a more child-friendly procedure. In addition, we investigated whether children's memory for the faces, which we expected to be poorer than that of adults, was correlated with their ability to implicitly learn the principal components and the average on which they were centered. We chose to test 7- and 9-year-olds because in this age range, children's basic visual functions (e.g., acuity, contrast sensitivity) become adult-like. However, even at age 9, some high-level visual functions (e.g., matching facial identities across views; discriminating small differences in the spacing of facial features; sensitivity to biological motion) are still not adult-like (Baudouin, Gallay, Durand, & Robichon, 2010; De Heering, Rossion, & Maurer, 2012; Hadad, Maurer, & Lewis, 2011; Mondloch, Geldart, Maurer, & Le Grand, 2003). Moreover, 7- and 9-year-olds are in the age range during which there are face-specific increases in memory (Weigelt et al., 2014). These limitations are unlikely to arise from inability to form a face prototype (De Haan et al., 2001; Inn et al., 1993; Strauss, 1979). Rather, they might arise from differences in the ability to implicitly learn the most significant dimensions of variation differentiating faces.

## 2. Material and methods

### 2.1. Participants

Sixteen 7-year-olds (8 females, mean age = 7.5 ± 0.1 years), 15 9-year-olds (8 females, mean age = 9.6 ± 0.2 years), and 16 young adults (8 females, mean age = 20.3 ± 2.0 years; range = 18–24 years) participated in the current study. The number of participants was based on the finding of a PCA learning effect using the same paradigm with a sample of 10 adults in a previous study (Gao & Wilson, 2014) and the expectation of more variability in children. In the current study, the adults were undergraduate psychology students participating for course credit. Child participants were recruited from names on file of parents who volunteered their children at birth for participation in later studies. All of the participants were Caucasian to match the ethnicity of the faces from which the stimuli were derived. All of them had normal or corrected-to-normal vision (Snellen acuity of 20/20 [20/25 for the 7-year-olds] or better in each eye, fusion at near on the Worth Four dot test, and stereoacuity of at least 40 arcsec on the Titmus test). We obtained written consent from the adult participants or from a parent of the child participants, and we obtained verbal assent from the child participants. One additional 7-year-old child was tested but excluded from the final data analysis because the data were identified as an outlier according to a three-standard deviation criterion. No data from other groups were identified as outliers. The procedures were cleared by the Institutional Research Ethics Board.

### 2.2. Stimuli

We used synthetic faces derived from photographs of real faces (Wilson et al., 2002). Each synthetic face is defined by 37 parameters. Among the 37 parameters, 23 define the head shape and hairline, while the remaining 14 parameters define the locations and sizes of the facial features. For the current study, we first calculated summary statistics from a set of 41 synthetic faces of Caucasian males. Since each synthetic face is defined by 37 parameters, Principal Component Analysis on the set of 41 synthetic faces identified 37 principal components (PC). We set up a multidimensional face space, which was centered on the average of the original 41 faces, with the 37 principal components as its dimensions. We then sampled new faces from this face space that were equidistant from the average.

As shown in Fig. 1, we created 16 faces from the 37-dimensional face space as the target faces for the learning phase. Each face was defined by two dimensions in the face space with a distance from the center of the space on each dimension equivalent to that of every other face. The 16 faces were defined by one direction of the PC1 dimension (PC1+ or PC1−) of the face space in combination with one direction of a higher PC dimension (PC2, PC4, PC6, or PC8; + or − direction). For the 16 target faces, their average is the origin

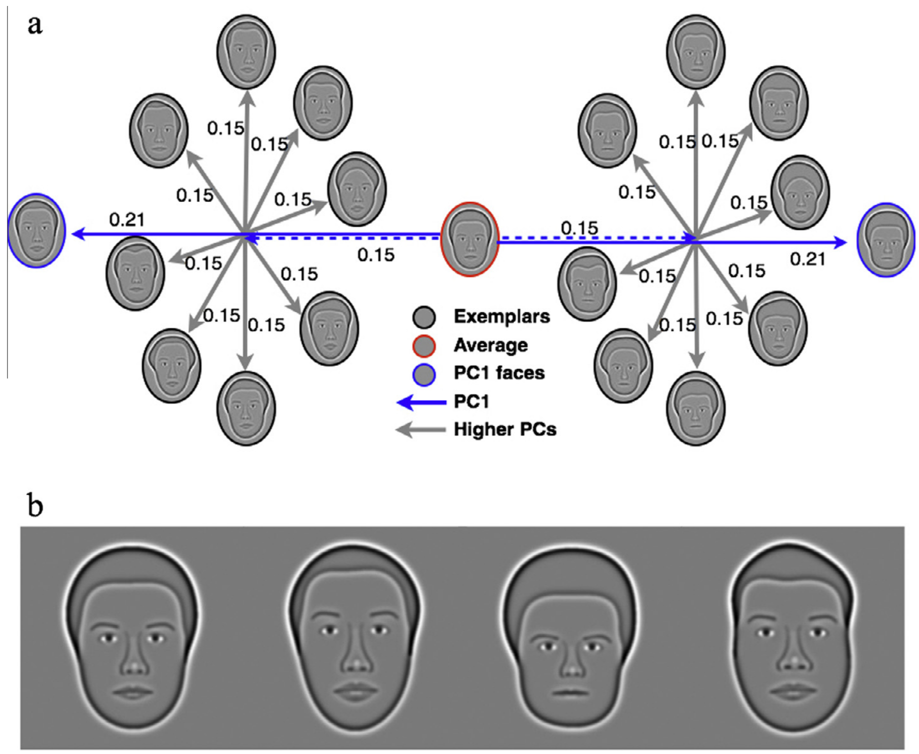


**Fig. 1.** (a) Structure of the stimulus space. Each target face (black oval) has a distance of 0.15 from the average face (red) on each of the two principal components (PC1 and a higher PC) defining a target face. Therefore, the distance from each target face to the average face is 0.21. The eigenfaces labeled PC1 faces (blue oval) have the same distance (0.21) from the average face as the target faces. Target on the left and right sides of average differ from the average face by the same distance (.15) in opposite directions on PC1. Faces within each side of the figure differ from the average face by a distance of .15 on a higher principal component. (b) Examples of the synthetic faces. From left to right: average face, PC1 face 1, PC1 face 2, one of the target faces. Each face subtended an angle of 6.9° (height) by 4.6° (width) on the screen from a viewing distance of 127 cm. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

of the face space and the PC1 dimension accounts for 50% of the variance among them.

We also sampled 16 faces as foils for the subsequent memory test from a non-overlapping and orthogonal volume of the face space relative to the faces in the learning phase. More specifically, the foil faces were defined by one direction of the PC3 dimension (PC3+ or PC3−) in combination with one direction of a higher PC dimension (PC5, PC7, PC9, or PC10; + or − direction), at a distance from the average equivalent to the target faces.

We defined distance in this face space as the Euclidean distance between two faces in the 37-dimensional face space relative to the mean head radius of the original 41 faces. By scaling to mean head radius, we eliminated the absolute head size, which varies with viewing distance. For both the target faces and foil faces, the distance from the origin (where the average lies) was 0.21 (a distance of 0.15 on each orthogonal dimension). It is worth noting that a distance of 0.21 from the origin of the face-space is greater than the mean distance of the original 41 faces, which was 0.18. Therefore, the faces used in the current study are on average more distinctive than the original faces. Besides the 16 target faces and the 16 foil faces, we created the average of the 16 target faces, which lies at the origin of the space. We also created two eigenfaces (Turk & Pentland, 1991), labeled PC1 faces in Fig. 1, which lie on the first principal component of the 16 target faces with a distance of 0.21 on either side of the origin of the space, that is, at the same distance as each target face from the origin. In total there were 35 synthetic faces used in the current experiment.

The face stimuli were grayscale and were filtered with a band-pass difference of Gaussians filter centered on 10 cycles per face width with a bandwidth of two octaves to include the most important information for facial identity (Gao & Maurer, 2011; Gold, Bennett, & Sekuler, 1999; Näsänen, 1999). They were presented on a 20-in. Sony Trinitron VGA color monitor with a mean luminance of 60 cd/m$^2$. From a viewing distance of 127 cm, each face subtended an angle of 6.9° (height) by 4.6° (width).

### 2.3. Procedures

#### 2.3.1. Learning

Before the learning phase started, we informed the participants that we would test their memory for the target faces in a subsequent session. The learning phase was separated into four blocks. Within each block, each of the 16 target faces appeared once for 10 s in a random order, for a total of 40 s of exposure across the four blocks. In between blocks, the participants took a short break if needed.

#### 2.3.2. Testing

Immediately after the learning phase, the participants performed an old/new recognition task. In this task, the trials started with a central fixation cross for 500 ms, followed by a face displayed for 500 ms. After the face disappeared, the participant pressed predefined keys to indicate whether the face was seen (old) in the learning phase or not (new). One second after the participant entered the response, the next trial started. The testing phase consisted of six blocks, with each block containing all 16 studied target faces, 16 foil faces, the average face of the 16 target faces, and two eigenfaces (at a distance of 0.21) of the first principal component of the 16 target faces. In between blocks, the participants took a short break if needed.

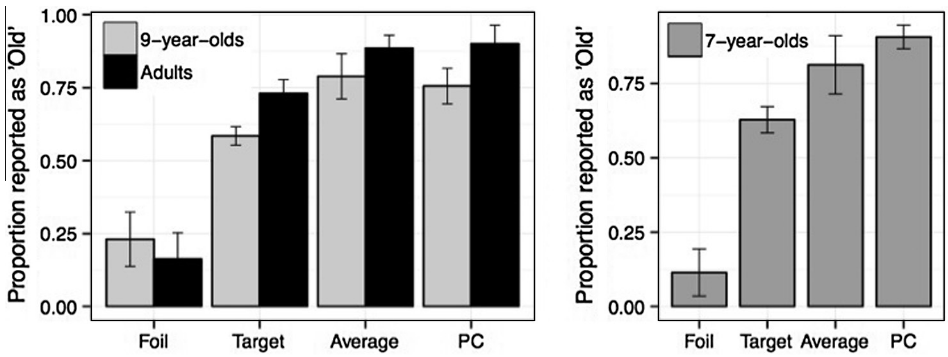


**Fig. 2.** Mean proportion reported as "old" for the target faces, the foil faces, the unseen average face and the unseen principal component faces. The error bars represent 95% confidence intervals. Data for 9-year-olds (gray bars) and adults (black bars) are shown in the left panel. Data for 7-year-olds, for whom testing trials were doubled in duration, are shown in the right panel.

To reduce the task demands for the 7-year-olds, we reduced the number of testing blocks to 4[1] and increased the test display time to 1000 ms. We also let the 7-year-olds initiate each learning and testing trial.

*2.3.3. Game context for child participants*

We introduced the task to child participants as a game in which the child was the team manager's assistant for a team of his or her favorite sport. In this game, the child is meeting the team for the first time and has to remember the team members before the team plays against a rival. In the learning session the experimenter presented each of the 16 target faces to the child. Immediately after the learning session, we introduced the testing session as a game between the child's team and a rival team. As the team manager's assistant, we emphasized that it is important for the child to be able to tell who is from his/her own team and who is not. All the children seemed to understand the game and to be engaged in playing it.

Each age group took about 30–35 min to complete the procedure.

## 3. Results

Fig. 2 shows the mean proportion reported as "old" for the target faces, the foil faces, and the unseen average face and principal component faces for the 7-year-olds, 9-year-olds, and adults. Statistical analyses were done with R (R Development Core Team, 2007). None of the measurements deviated from a normal distribution as suggested by Q–Q plot. When the equal variance assumption was violated, we used Welch's $t$-test and report adjusted degree of freedom.

Replicating our previous study (Gao & Wilson, 2014), adults showed the PCA learning effect, as their false recognition rate for the unseen PC faces was significantly higher than their correct recognition rate for the actually studied target faces ($t(15) = 4.27$, $p < 0.01$, two-tailed, *Cohen's* $d = 0.97$). The results showed for the first time that the PCA learning effect is present in children aged 7 and 9: their false recognition rates of the unseen PC faces were significantly higher that their correct recognition rate of the actually studied target faces ($t(15) = 8.21$, $p < 0.01$, two-tailed, *Cohen's* $d = 1.92$ for the 7-year-olds and $t(14) = 4.80$, $p < 0.01$, two-tailed, *Cohen's* $d = 0.98$ for the 9-year-olds). All three groups also showed a prototype effect, as their false recognition rates for the unseen average face were significantly higher that their correct recognition rate for the actually studied target faces ($t(15) = 3.24$, $p = 0.01$, two-tailed, *Cohen's* $d = 0.77$ for the 7-year-olds; $t(14) = 4.80$, $p < 0.01$, two-tailed, *Cohen's* $d = 0.97$ for the 9-year-olds; and $t(15) = 3.95$, $p < 0.01$, two-tailed, *Cohen's* $d = 1.01$ for adults). In all three groups, the strength of the prototype effect and the PCA learning effect were positively correlated ($r(14) = 0.57$, $p = 0.03$; $r(13) = 0.75$, $p < 0.01$; $r(14) = 0.67$, $p = 0.01$; for the 7-year-olds, 9-year-olds, and adults, respectively).

Because we tested the 7-year-olds with a different procedure, we did not make direct comparisons of their data to those of the two older groups. To compare the 9-year-olds and adults who were tested with the same procedure, we first calculated an unbiased measure $d'$ based on hit rate for the target faces and false alarm rate for the foil faces in the old/new recognition task. An independent sample $t$-test indicated that 9-year-old children's memory performance (mean $d' = 1.1 \pm 0.2$) was worse than that of adults (mean $d' = 1.9 \pm 0.3$) ($t(26.3) = 2.67$, $p = 0.01$, two-tailed; *Cohen's* $d = 0.95$). Adults also showed a stronger PCA learning effect (i.e., higher false recognition rate for the unseen PC face, $t(28.9) = 2.17$, $p = 0.04$, two-tailed; *Cohen's* $d = 0.78$) than the 9-year-olds. The strength of the prototype effect was not different between the 9-year-olds and adults ($t(22.3) = 1.31$, $p = 0.20$, two-tailed). With reduced task demands than the other two groups, the 7-year-olds achieved good memory performance (mean $d' = 1.7 \pm 0.8$).

We conducted a multiple regression analysis for each age group to test how well the strengths of the prototype effect and the PCA learning effect predicted memory performance ($d'$). We used the false recognition rates for the unseen average face as one predictor and the false recognition rates for the PC faces as a second predictor. For the 9-year-olds and adults, the PCA learning effect was a significant predictor of memory performance (*Beta* = 0.50, $p = 0.048$, *partial correlation* = 0.54 for the 9-year-olds; *Beta* = 0.72, $p = 0.02$, *partial correlation* = 0.60 for adults), while the contribution of the prototype effect to memory performance was not significant (*Beta* = 0.35, $p = 0.15$, *partial correlation* = 0.41 for the 9-year-olds; *Beta* = −0.01, $p = 0.96$, *partial correlation* = −0.01 for adults). We saw a different pattern for the 7-year-olds: the strength of the prototype effect was a significant predictor for memory performance (*Beta* = 0.63, $p = 0.03$, *partial correlation* = 0.58), while the contribution of the PCA learning effect to memory performance was not significant (*Beta* = 0.01, $p = 0.96$, *partial correlation* = 0.02). The results suggest that for the 9-year-olds and adults, the PCA learning effect is a strong predictor of their memory performance. However, for

[1] We assessed the potential influence of the reduction of testing blocks on the reliability of the current measurements by correlating test scores calculated with only data of the first four blocks to the scores calculated with data of all 6 blocks in 9-year-olds and adults. The correlation coefficients had a mean of 0.94 (range: 0.88–0.98) for the 9-year-olds and a mean of 0.97 (range: 0.94–.98) for adults across all the measurements. Therefore, we are confident that even with a reduced number of testing blocks, we can still obtain reliable measurements.

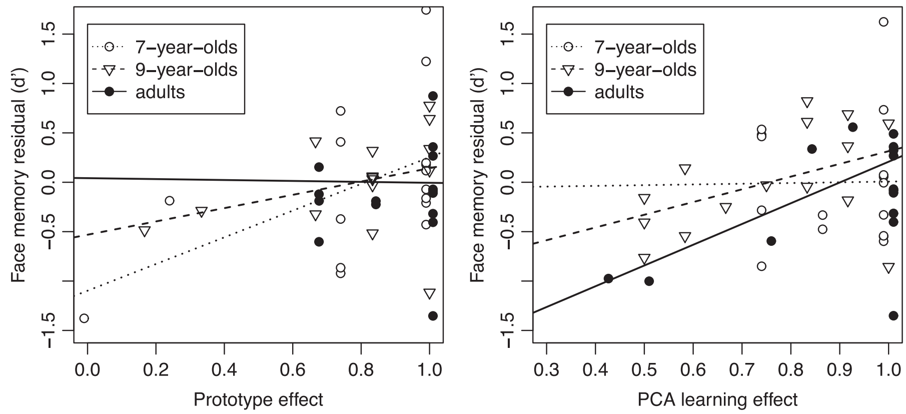


**Fig. 3.** Partial correlation between the strength of the prototype effect (left panel) and the PCA learning effect (right panel) and face memory ($d'$) in 7-year-olds (open circles, dotted lines), 9-year-olds (open triangles, dashed lines), and adults (closed circles, solid lines). The lines are linear regression lines between the prototype effect and face memory controlling for the PCA learning effect (left panel), and between the PCA learning effect and face memory controlling for the prototype effect (right panel).

the 7-year-olds, the best predictor of their face memory is the strength of the prototype effect, even though we cannot rule out the possibility that the failure to see a correlation between the PCA learning effect and face memory in the 7-year-olds might be a result of the limited range of scores observed for the 7-year-olds on the PCA learning effect with the relatively small sample size we had.

## 4. Discussion

The results for all three age groups suggest that an important ability underlying our memory for faces is the picking up of regularities in the variations among faces we encounter. The 7-year-olds, 9-year-olds, and adults all showed higher false recognition for the unseen faces representing the average and the dimensions of statistical variability (the PCA faces) than the actually studied faces. Moreover, as shown by the correlation analysis (Fig. 3), 9-year-old children and adults who had a stronger PCA learning effect were more accurate in recognizing the actually studied faces, with the (partial) correlation accounting for more than 29% of the variance at both ages. The strength of the PCA learning effect was also larger in the adults than in the 9-year-olds, paralleling their higher accuracy in recognizing the studied faces. The 7-year-olds showed a different pattern of correlation with the prototype effect accounting for much (34% based on partial correlation) of the variance in their memory for faces and no residual correlation of the PCA learning effect.

The fact that the strength of the prototype effect and strength of the PCA learning effect were highly correlated at all ages suggests that these two effects are interdependent. It is likely that the PCA learning effect depends on the prototype effect, since without an accurate prototype on which to center the dimensions, the dimensions extracted would not be the most efficient ones for encoding the variations among faces. Indeed, computation of principal components is based upon first subtracting the means from the measurements. This hypothesis is supported by the differential developmental trajectories found in the current study: the prototype effect was adult-like by age 9, whereas the PCA learning effect increased between age 9 and adulthood, as did memory for the studied faces. This hypothesis may also help to explain the finding that the prototype effect rather than the PCA learning effect correlated with face memory in the 7-year-olds. Even though the prototype effect would not have a direct influence on the memory for individual faces, since it captures the commonality among faces, it could have an indirect influence by providing an accurate center around which to extract the most significant dimensions of variation among the faces. It is possible that the 7-year-olds could not extract the prototype as well as older children and adults, at least with the limited exposure given in this experiment. As a result, the dimensions of variation they extracted may not have been as effective as those of the older groups in differentiating individual faces. It follows that the 7-year-olds who were better able to extract the average would have had a more accurate center for the dimensions of variation, leading to better memory for individual faces. It is worth noting that the implication may not be only limited to face memory. Such a face space structure is also likely to affect face perception. If a less refined prototype and/or fewer PCA dimensions were used to encode faces, it would be harder for children than adults to discriminate among faces.

These findings are consistent with the evidence for the norm-based face space hypothesis, which describes the representation of individual facial identities as points in a multidimensional space centered on a norm, or average (Valentine, 1991). Many studies have provided evidence that adults' representations of faces are centered on a norm or average face (e.g., Anderson & Wilson, 2005; Rhodes & Jeffery, 2006) and that this type of structure has emerged by 4–5 years of age (Jeffery, Read, & Rhodes, 2013; Jeffery et al., 2011). However, as summarized in the introduction, previous studies have not been satisfactory in identifying the dimensions of the face space, in part because these dimensions did not map directly to specific facial features in adults' perceptual space as revealed by Multidimensional Scaling (Busey, 1998; Johnston et al., 1997; Nishimura et al., 2009). Our results suggest that face space may be formed by extracting the average from experienced faces and the dimensions by extracting the principal components that maximally differentiate among the faces. Doing so leads to a small number of dimensions that efficiently differentiate among the faces and that, as one would expect from the literature (O'Toole, Abdi, Deffenbacher, & Valentin, 1993; Sirovich & Kirby, 1987; Turk & Pentland, 1991), do not correspond to variations in a single facial feature. Children may build this face space by first extracting an average and only later learning the most efficient dimensions of variation from the average.

Besides the fine-tuning of the face space with experience, children's memory for faces may also be limited by general cognitive abilities such as memory and attention. As demonstrated in a recent study (Weigelt et al., 2014), the long developmental trajectory for children's memory for faces seems to be face-specific. This does not mean, however, that the underlying mechanism has to be domain-specific. The development of memory for faces may involve only domain-general mechanisms that take longer to reach adult levels of accuracy for faces than for other categories because faces, unlike other categories, are highly similar to each other and need to be differentiated at the individual level. We also need to remember many more examples of faces than other categories. Therefore, more principal components may be needed in order to differentiate faces than are needed for other categories. As a result, more time may be needed to learn these extra principal components (Diamantaras & Kung, 1996). This view is consistent with evidence that infants are able to pick up not only the average of a set of faces (De Haan et al., 2001; Strauss, 1979) but also statistical regularities from different modalities in their environment (e.g., patterns in auditory sequences, Aslin, Saffran, & Newport, 1998; Saffran, Aslin, & Newport, 1996; patterns in visual sequences, Kirkham, Slemmer, & Johnson, 2002), possibly through a domain-general learning mechanism. The possibility that face space is formed through a domain general learning mechanism is supported by a biologically plausible neural network model that is able to learn the average and principal components from a set of exemplars (Diamantaras & Kung, 1996; Rubner & Schulten, 1990). Since this network model is based on Hebbian principles, it could work as well for other categories as for faces.

The current stimulus set allowed us to precisely control the physical properties of the faces. However, since more parameters (23 out of 37) were used to define the external face shape than the internal facial features, the external face shape may carry more information than the internal facial features. Therefore, children and adults may rely more on the external face shape then the internal features when learning these faces. As a result, we may have overestimated the similarity between children and adults, because previous studies suggest that children, unlike adults, have an outer face bias when processing unfamiliar adult faces (Campbell, 1999; Want, Pascalis, Coleman, & Blades, 2003).

The participants may have formed a new face space during the experiment, as the synthetic faces are different from real faces, are highly similar to each other, and were encountered in close temporal proximity. Even so, we were able to study the newly formed average and PC dimensions of a group of simplified faces. If more natural looking faces were used, participants would be more likely to incorporate them into an existing face space by modifying the existing average and PC dimensions formed from previous experience. Besides looking at that process developmentally, it would be interesting for future studies to test the PCA learning effect when the new faces are from one's own race versus a different race, as well as when there are no instructions to remember the faces. In the current study, we explicitly instructed the participants to remember the studied exemplar faces. However, in real life, we encounter many faces we do not attempt to remember. It would also be interesting for future studies to test the PCA learning effect if the exemplar faces were learned implicitly.

In summary, we demonstrated that children at age 7 and 9 are able to form a strong implicit memory for the unseen faces representing the average and the PCA dimension of major variation among studied faces. In addition, by age 9, as in adults, children who developed a stronger PCA learning effect showed better memories for the actually studied individual faces, a pattern suggesting the importance of extracting principal components for human memory.

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