Supplementary Material S1.

The accuracy data and reaction time data obtained in speed-acuity test were analyzed separately. To determine the visual acuity threshold, a cumulative Gaussian was fitted to the proportion correct scores that were obtained for the different optotype sizes $x$ (in LogMAR):

$$P_{correct}(x) = \gamma + (1 - \gamma - \lambda) \left[ \phi \left( \frac{C - m}{w} \right) \right]$$

Eqn. s1

$$C = \phi^{-1}(0.95) - \phi^{-1}(0.05)$$

where $\phi$ is the cumulative standard normal distribution and $\phi^{-1}$ its inverse; $m$ is the inflection point of the curve; $w$ is the width parameter reflecting the difference between stimulus levels at which $\phi$ reaches 0.05 and 0.95; $\gamma$ is the guess rate at chance level performance; and $\lambda$ is the lapse rate of the subject. Fits were obtained with the psignifit toolbox for Matlab version 4.0.

Because many children did not reach 100% accuracy for the largest optotypes, the lapse rate $\lambda$ was allowed to vary between 0 and 0.1. $\gamma$ was fixed to the 0.5 chance level performance for a 2AFC task. The acuity threshold was taken at 75% correct, which is halfway between the $\gamma$=0.5 chance level performance for a 2AFC task and the 100% correct rate.

We used a well-documented model from the literature to quantify the average reaction times on the speed-acuity test as function of optotype size $x$. This model describes chronometric response functions obtained in 2AFC sensory discrimination tasks with a hyperbolic tangent function:

$$RT(x) = \begin{cases} 
\frac{A'}{k'(x-x_o)} \tanh[A'k'(x-x_o)] + t_R & \text{if } x > x_o \\
A'^2 + t_R & \text{if } x \leq x_o
\end{cases}$$

Eqn. s2

This model assumes that the brain accumulates noisy sensory evidence over time until the accumulated evidence scores reach a fixed decision bound (see Supplemental Figure 1). At that time a decision is made. The height of the decision bound for the two alternatives is assumed to be symmetric around zero. The total reaction time, RT, is considered to be the sum of this stimulus-dependent decision time and an independent residual time. The residual
time $t_R$ is thought to reflect the sum of sensory afferent delays, efferent motor delays, and other fixed delays that are unrelated to the actual stimulus discrimination process.$^{24,42,46}$

**Supplemental Figure 1.** Reaction time model for a 2AFC sensory discrimination task. After a fixed afferent delay, noisy sensory evidence in favor of one alternative over the other accumulates over time. A decision (in this case about the orientation of the Landolt-C) is made when the process reaches one of the decision bounds, internally set to a certain level ($A$). The sample paths illustrate the accumulation of evidence for different trials. Red traces are for a large optotype with its opening on the left. Cyan traces are for a smaller optotype with its opening on the right. Blue traces are for an even smaller optotype with its opening on the left. The slope of the accumulation of evidence (average decision rate) depends on the noise level ($\sigma$), the stimulus size ($x$) and the sensitivity ($k$) of the subject to the relevant stimulus features. The average time to reach the decision bound is shorter for larger optotypes. The perceptual decision becomes manifest after an additional efferent delay needed to press the corresponding button.
To obtain reliable estimates of this lower reaction time limit, we included large optotypes in our stimulus series. The height of the decision bound $A$ relative to the noise level $\sigma$ is reflected in $A' = \frac{A}{\sigma}$. The parameter $x_o$ is the optotype size at which the stimulus becomes too weak to bias the evidence scores towards either one of the two alternatives, i.e., the ‘critical optotype size’. At this level, the decision bounds are reached purely by chance after an average delay of $A'^2$ seconds\textsuperscript{24}, here referred to as the “choice delay limit”, and as a result, the chronometric function reaches its upper limit $A'^2 + t_R$. The parameter $k'$ is a measure of the sensitivity of the subject’s visual system to the relevant stimulus features, where $k' = \frac{k}{\sigma}$. Note that the signal-to-noise ratio $\frac{k(x-x_o)}{\sigma}$ of the sensory signal determines the average “decision rate”, i.e., how fast the evidence scores tend to accumulate towards the decision bound. Fit parameters for these individualized fits were determined with a Levenberg-Marquardt nonlinear least squares algorithm (fitnlm, Matlab statistical toolbox). In these fits, we fixed $x_o$ to the value of -0.43 LogMAR based on the observation that subjects approached chance-level performance at this smallest optotype size present in our stimulus set.

To assess the effect of age on the reaction times in the speed-acuity test, and to obtain prediction intervals for newly measured reaction times, we analyzed the chronometric functions with a mixed nonlinear regression model. The fixed-effect parameters in this model estimated the mean $A'$, $k'$, and $t_R$ of the population (via parameters $\beta_{A0}, \beta_{k0}, \text{and } \beta_{tR0}$) as well the average changes in these parameters with age (via parameters $\beta_{A1}, \beta_{k1}, \text{and } \beta_{tR1}$). The random-effects ($b_{A,i}, b_{k,i}, b_{tR,i}$) allowed $A'$, $k'$, and $t_R$ to vary between individual participants. Since inspection of the $A'$s and $k'$s that were found for individualized curve fits (see Fig. 4) indicated that the random effects did not follow a normal distribution, we fitted their log-transform instead. This resulted in the following definition of the parameters in Eqn. s3:

$$A'_i = \log(\beta_{A0} + \beta_{A1} \cdot Age_i + b_{A,i})$$

$$k'_i = \log(\beta_{k0} + \beta_{k1} \cdot Age_i + b_{k,i})$$ 

$$t_{R,i} = \beta_{tR0} + \beta_{tR1} \cdot Age_i + b_{tR,i}$$  \hspace{1cm} \text{Eqn. s3}
with \([b_{\lambda,i}, b_{\kappa,i}, b_{TR,i}] \sim N(0, \Psi)\) a multivariate normal distribution with zero means and covariance matrix \(\Psi\). Subscripts \(i\) refer to individual participants. \(\Psi\) was estimated from the data along with the fixed-effects and random-effects parameters (nlmefit, Matlab statistical toolbox). The continuous variable age was centered on the age of 9, the middle of the inclusion range.

To assess the effect of age on the reaction time curves (Supplemental Table 3), we pooled data from the two test sessions per subject. Confidence intervals for the fixed-effects factors were obtained by bootstrapping (\(n=2000\)). For each bootstrap trial, we resampled at the level of subjects and within subjects. The within-subject sampling generated a new set of reaction time means for each test block by sampling from the distribution of reaction times measured per optotype.

To obtain prediction intervals for the average reaction times of an individual subject on a single test block that contain 10 trials per optotype size (Figure 4), we again used a bootstrap procedure which resampled at the level of subjects and within subjects (\(n=2000\)). In this case, however, the resampled data from the 1\(^{st}\) and 2\(^{nd}\) test runs were fitted by two independent mixed models each bootstrap iteration to accommodate the fact that subjects were on average slightly faster in the second block. Individual predictions were then generated by adding randomly drawn residuals from both sets of bootstrapped models to their respective conditional responses (i.e., the model predictions which included contributions from both fixed- and random-effects predictors) such that the resulting predictions intervals span the complete range of possible observations. To ensure that any residual systematic deviation between the reaction time model and the data was accounted for in the prediction intervals, the drawing of residuals was conditioned on optotype size. The resulting reaction time predictions were also used to determine prediction intervals for the delay index (Supplement 2).