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Facial age estimation at a glance: Effects of exposure duration

Janice Attard , Bryan Q.Z. Leong  and Alejandro J. Estudillo 

Department of Psychology, Faculty of Media, Science and Technology, Bournemouth University, Poole, UK

ABSTRACT

The time available to view a face affects various face processes. For example, some trait judgements (e.g., trustworthiness) can be made from an exposure duration as brief as 100 ms, and some emotional expressions (e.g., surprise) can be identified in 20 ms. While other aspects of face perception, such as face identity recognition, benefit from longer durations. The impact of exposure time on facial age estimation, however, is scarcely examined. Across two experiments, we found that age estimates that approximate true chronological age are possible even with a brief exposure duration of 100 ms, and accuracy improves slightly with longer durations (1000 and 3000 ms). However, there was large variability in performance across participants and although improvement was significant, the differences are numerically small. Therefore, it seems possible for age estimates to be made rapidly, and although there can be further refinement with additional time leading to slightly better accuracy, this improvement is not extensive.

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Age perception; face perception; age estimation; cognitive estimation; exposure duration

Evaluations based on visual information from the face can be made rapidly, often within the first 100–200 ms of exposure to the face (e.g., Du & Martinez, 2013; Rashidi et al., 2012; Todorov et al., 2009). For some types of face judgements, increased exposure time does not necessarily lead to an increase in accuracy (e.g., emotional expression recognition; Du & Martinez, 2013) or a substantial change in response (e.g., trustworthiness; Todorov et al., 2009). In other circumstances, such as in facial identity recognition, increased exposure time during encoding is associated with increased identification accuracy (e.g., Bornstein et al., 2012; Memon et al., 2003). Although the impact of exposure time to the face has been examined for several traits, examination of its influence on age estimation accuracy is scarce (Attard-Johnson et al., 2025). Thus, we will systematically examine the effect of exposure times on the numeric estimation of facial age.

The effects of exposure duration on various aspects of face processing are different. For instance, increased exposure time results in a decrease in

perceived facial attractiveness (see e.g., Rashidi et al., 2012; Sano et al., 2025). In contrast, other trait judgements (such as competence, trustworthiness, and aggressiveness) tend to be more stable with increased exposure time (see, e.g., Porter et al., 2008; Todorov et al., 2009; Willis & Todorov, 2006). Examples from behavioural rating experiments suggest that most of the information needed to make a trustworthiness judgement is obtained within the first 100 ms exposure to the face, and any judgements that are made after 167 ms have been shown not to change (Todorov et al., 2009). Consistent first impressions can be formed from some traits even under briefer viewing conditions of 39 ms, such as threat, but not intelligence (Bar et al., 2006). Further, there is also variation within a specific face dimension. For example, emotional expression recognition for happy and surprised faces can be made after being exposed to the face for only 10–20 ms, while fear, anger, sadness, and disgust require more time (70–250 ms) (Du & Martinez, 2013).

CONTACT Janice Attard  jattard@bournemouth.ac.uk  Department of Psychology, Faculty of Science and Technology, Bournemouth University, Fern Barrow, Poole BH12 5BB, UK; Department of Psychology, Faculty of Media, Science and Technology, Bournemouth University, Fern Barrow, Poole BH12 5BB, UK  Supplemental data for this article can be accessed online at <https://doi.org/10.1080/13506285.2026.2710648>.

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Within the face processing literature, faces are widely characterized as being processed as integrated perceptual wholes (Leong et al., 2023; Rossion, 2013), following a coarse-to-fine processing strategy (Goffaux et al., 2011; Jacques et al., 2007; Peters et al., 2018; Richler et al., 2011). Early stages of face processing are thought to involve rapid holistic encoding, with more fine-grained featural information extracted subsequently (i.e., featural processing). Accordingly, short exposure times of 200 ms provide less time to precisely analyse detailed facial characteristics, thereby increasing reliance on holistic processing (Jacques et al., 2007; Richler et al., 2009; but see Wang, 2019). In the case of attractiveness, faces may appear more average with shorter exposures, and thus, more attractive (see Rashidi et al., 2012). Indeed, slight shifts in attention to specific face regions have been found in a recent eye-tracking experiment (see Alfertshofer et al., 2025). Across short (1s) and long (8s) durations, the area with the most focus was the periorbital (the eye region). After that, the longer exposure led to a shift in viewing patterns of both younger and older models. Specifically, attention was directed less to the nose and cheek regions and more to areas most crucial for facial expression recognition and of most visible age-related changes in mature individuals, specifically, the perioral (area around the mouth) and forehead areas (Alfertshofer et al., 2025).

Few studies have examined the effect of exposure duration on facial age perception. In a recent experiment examining the Face Inversion Effect for an age classification task, exposure duration was also manipulated. Performance on a task requiring the classification of 14- to 21-year-old faces as being over- or under- the age of 18 was improved when given a *full* 2000ms, compared to 250 ms, to make their decision (Attard-Johnson et al., 2025). However, the exposure effect was not present if participants had *up to* 2000ms but could respond earlier if they decided sooner. Thus, it is possible that requiring participants to take more time to evaluate the face can improve accuracy, potentially by shifting focus to different face regions or shifting processing mechanisms (e.g., holistic vs. featural) (see, e.g., Özbek & Bindemann, 2011; Richler et al., 2011). However, Attard-Johnson et al. (2025) included only young adult faces, and since the task required classification (over- or under- the age of 18) rather than

precise numeric estimation, it may have not captured additional refinement of estimates that additional exposure time may have produced. Further, recent research suggests that different approaches to measuring age assessment may be linked to different cognitive processes (see Attard-Johnson et al., 2024), and therefore the effects of exposure duration in the classification task may not generalize to numeric estimation.

Presentation durations in numeric age estimation experiments often vary widely from completely self-paced (e.g., Dehon & Brédart, 2001; Ferguson & Wilkinson, 2017; George & Hole, 1995) to timed response windows of varying durations (e.g., Attard-Johnson et al., 2024; Attard-Johnson et al., 2025; Davis & Attard-Johnson, 2022; Thorley, 2021). Even when the task is self-paced, instructions on how to use this time sometimes differed, for example encouraging participants to rely on first impression (Ji et al., 2025) or encouraging participants to take as long as necessary to make an accurate judgement (George & Hole, 1995). Thus, to date, there have been no studies that have systematically examined a range of exposure times for the age assessment of photographs of individuals across the adult lifespan using a numeric estimation task. Consequently, the direct influence of exposure duration on age assessments remains unclear. Yet, age assessment is routinely performed in certain security settings, such as in immigration, evaluation of photographic evidence by specialist police teams, retail scenarios for the purchase of age-restricted items and access to venues, and eye-witness descriptions of suspects (Rahman et al., 2023; Rhodes, 2009). Thus, understanding the influence of brief and longer exposure times, as well as the impact of rapid and more deliberate decision making, on age estimation accuracy is valuable. To address the question of whether age estimation accuracy for facial images increases with exposure time, we used a numeric age estimation task and manipulated the presentation duration to be very brief (100 ms), to longer durations of 250, 1000, and 3000 ms. We expected that age estimates would approximate actual age more closely for longer presentation durations. Further, given that own-age bias is sometimes recorded in the literature (see, e.g., Moyse, 2014; Moyse et al., 2014; Willner & Rowe, 2001), we recruited participants across the lifespan and included participant age as a co-variate in all analysis to control

for the possibility that any effects are confounded by participant age.

Experiment 1

Method

Participants

110 participants (74 female, 36 male) with a mean age of 32 years ($SD = 14.8$, range = 18–73) completed the experiment using an online testing platform, Pavlovia. All participants were White, except for three Asian, two Black, four Mixed, and one Other. The target sample size was informed by previous age-perception studies (e.g., Attard-Johnson et al., 2025; George & Hole, 1995) in which samples of between 40 and 50 participants were used. We decided to increase the sample size relative to these studies to improve sensitivity to differences between the time conditions. A sensitivity power analysis indicated that the final sample size provided 80% power to detect small-to-moderate effects among the four conditions ($\eta p^2 = .03$). Participants were compensated with course credit or a small payment. The study was approved by the institution's Ethics Committee (Ethics ID: 47626) and participants provided consent electronically before taking part.

Materials

A total of 48 facial images were selected from the Minear and Park (2004) face database. To achieve an even spread of ages across the lifespan and genders, the set of faces comprised equal numbers of male and female faces across three different age subsets: 20–34, 35–49, and 50–64. The photographs presented a face set against a neutral white background cropped under the shoulders. All faces were of White ethnicity, had no external accessories (e.g., glasses) and had neutral facial expressions. The images were presented in full colour, with a width of 641 pixels and height of 480 pixels. No other manipulations were made to the images.

Procedure

The experiment was programmed in Psychopy and data collection took place via the online testing platform Pavlovia (Peirce et al., 2022). To minimize variability in stimulus size across different computer screens, participants were instructed to adjust the

height and width of a virtual card to match the dimensions of a physical debit or credit card in their possession. This calibration procedure enabled Pavlovia to calculate the pixel-to-centimetre (or inch) ratio based on the participant's input, allowing the experiment to scale stimuli to the intended size consistently.

Participants were informed that a series of faces will be displayed for a very brief duration and that their task was to provide a numeric age estimate of each face as accurately as possible after the image was removed from display. Of the 48 images, equal numbers of images (divided equally across age categories and gender) were assigned a presentation duration (100 ms, 250 ms, 1000 ms, 3000 ms). Participants only ever saw and estimated the age of any image once. To achieve full counterbalancing, there were four versions of this task, such that all images were presented in one of the duration conditions across versions.

Participants were assigned randomly to one of the four versions of the task. The task started with five practice trials using cartoon faces to prepare the participants for the different durations (100 ms, 250 ms, 1000 ms, 3000 ms). For the actual task, each trial began with a 1000 ms fixation cross, followed by the face presented in the centre of the grey display for the set duration, then the face was replaced with an entry box and participants typed in the age (e.g., 18–99). Participants pressed enter when they were satisfied with their response. There was no time pressure for their response. The task took between 10 and 15 min to complete.

Data analysis

Two standard dependent variables were calculated for age estimation error paradigms (e.g., Attard-Johnson et al., 2024; Clifford et al., 2018; Davis & Attard-Johnson, 2021; Vestlund et al., 2009; Voelkle et al., 2012). First, for *Estimation Bias* we calculated an average estimation bias score per participant for each of the exposure duration conditions. For this we subtracted the participants estimate from the actual age of the identity, such that a positive score indicates an overestimate and a negative score reflects an underestimate. We then averaged the scores for each participant. Although age estimation bias is informative for revealing systematic over- or under-estimations, inaccuracy in estimation may be

concealed if participants recorded inconsistent under- and over-estimates. Such inconsistency would lead to the estimates cancelling out each other. For this reason, a second measure is calculated, *Absolute Error*, which removes the direction of deviation. Thus, for the second dependent variable, we calculated absolute error, by taking the estimation error (i.e., participant estimate minus actual age) and using the ABS() function in RStudio on the resulting value. This turns the sign of all values into a positive value, then we calculated the average of this resulting value per participant.

Repeated measures analysis of covariance (ANCOVA) and the analogous Bayesian analysis were conducted and are reported to quantify evidence for the alternative and null hypotheses. All analysis was performed in JASP (version 19.3) using the default prior. We report Bayes Factor 10 (BF_{10}) for main effects, which represents how likely it is for the data to arise under the alternative model compared to the null model. A Bayes Factor of greater than 3 will represent substantial support for the alternative hypothesis and smaller than 0.3 will represent substantial support for the null hypothesis, and a BF in-between 0.3 and 3 represents only weak or anecdotal evidence (Jeffreys, 1961; Wetzels et al., 2011).

Outliers

Both frequentist and Bayesian analysis were initially performed on the full dataset, without excluding outliers with valid but extreme responses. In some instances, this revealed a discrepancy between the Bayes Factor demonstrating strong evidence and a non-significant result for the frequentist ANCOVA. The reason for this was outliers, since Bayesian analysis is more robust against them. We therefore decided to remove outlier participants who scored more than $\pm 3SD$ from the mean of the average for that dependent variable (i.e., estimation bias, absolute accuracy, participant age). This led to the exclusion of data from 7 participants for estimation bias, 8 outliers for absolute accuracy, and no outliers for participant age. For comparison and transparency, the analysis including all participant data is briefly included in the footnotes.

Transparency and openness

We report how we obtained our sample, all data exclusions, all measures and manipulations in the study. The datasets generated and analysed during the current study are available online and can be accessed here (https://osf.io/wnx7z/overview?view_only=ec4717bc7af14a01ba036a4c1885cfc9). Data were processed using RStudio (version 4.4.1) and the package *tidyverse*, and data were analysed using JASP (version 19.3). The study's design and its analysis were not pre-registered. The year of data collection was 2025.

Results

Estimation bias

The full distribution of scores across participants and conditions is illustrated in Figure 2. This analysis was performed on a total of 103 participants (excluding 7 outliers).¹ The mean bias across exposure conditions was similar, with an overall over-estimation of 4.6 years ($SD = 3.82$) for 100 ms, 5.2 years ($SD = 3.26$) for 250 ms, 4.9 ($SD = 2.98$) years for 1000 ms, and 5.13 years ($SD = 3.05$) for the 3000 ms condition (See Figure 1a). Next, we performed a one-way repeated measures ANCOVA with exposure duration conditions (100 ms, 250 ms, 1000 ms, 3000 ms) as the independent variable, age estimation bias as the dependent variable, and participant age as the co-variate. The analysis did not find an effect of participant age, $F(1, 101) = 0.01$, $p = 0.916$ ($BF_{10} = 0.22$). There was also no effect of exposure duration, $F(3, 303) = 0.59$, $p = 0.620$, $\eta p^2 = 0.006$ ($BF_{10} = 0.07$). This indicates that exposure duration did not systematically influence the direction of estimation bias. In other words, the results reveal that exposure duration did not lead participants to systematically over- or under-estimate durations.

Absolute error

Figure 3 illustrates the full distribution of scores across participants and conditions. This analysis was performed on a total of 102 participants (excluding

¹Analysis for estimation bias (including outlier participants): participant age, $F(1, 108) = 0.56$, $p = 0.458$ ($BF_{10} = 0.33$), exposure duration condition, $F(3, 324) = 0.20$, $p = 0.900$, $\eta p^2 = 0.009$ ($BF_{10} = 0.11$).

Analysis for absolute error (including outlier participants): participant age $F(1, 108) = 3.25$, $p = 0.074$ ($BF_{10} = 1.03$), exposure duration condition, $F(3, 324) = 3.83$, $p = 0.01$, $\eta p^2 = 0.034$ ($BF_{10} = 109.44$).

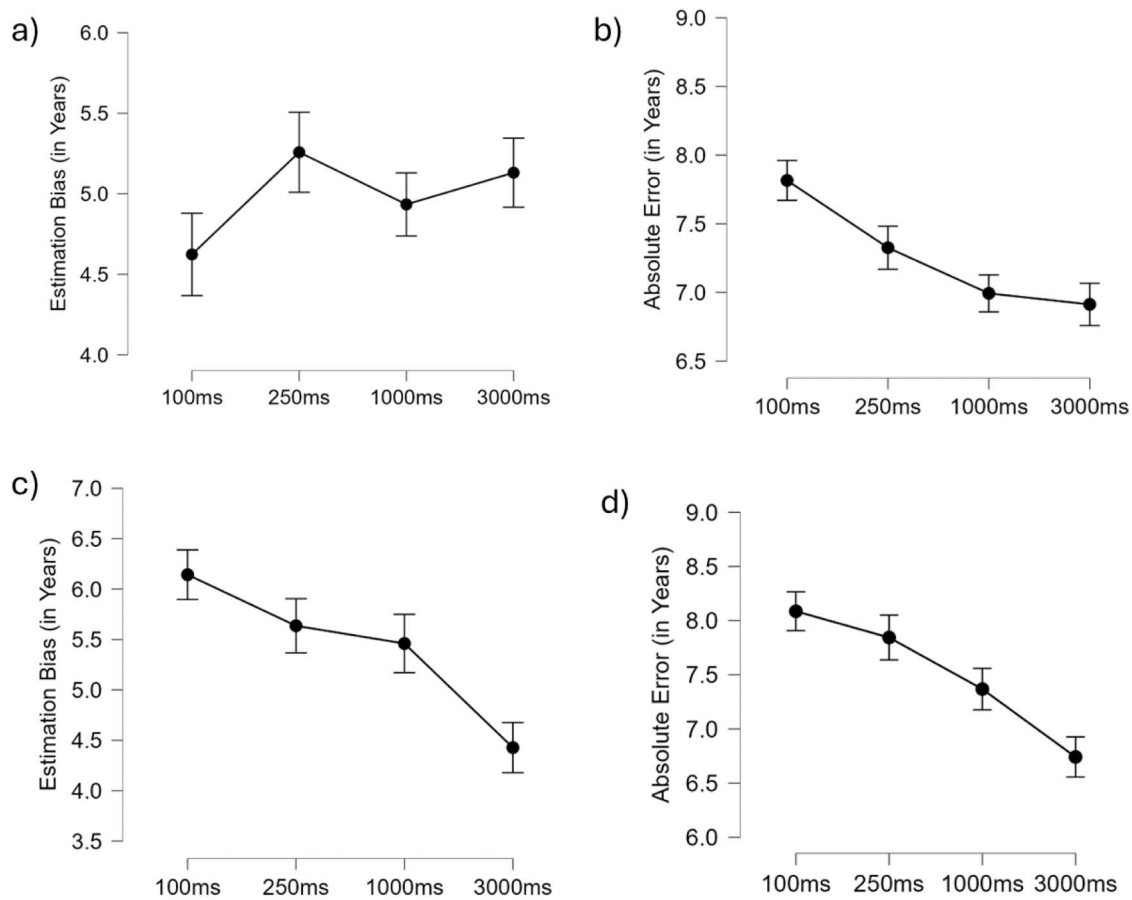


Figure 1. Graphs illustrating mean deviation from actual age across exposure duration conditions. Data excludes participant outliers. The top row represents data from Experiment 1 and Experiment 2 in the bottom row. Vertical lines represent standard error of the mean.

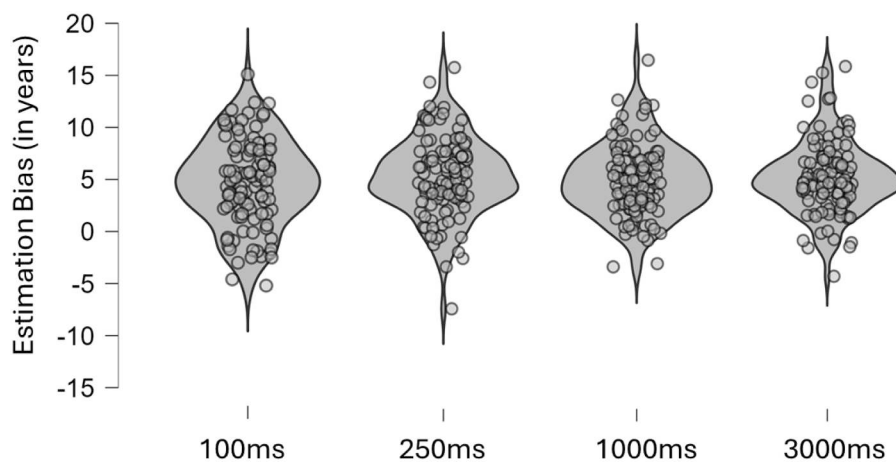


Figure 2. Violin plot with spread of individual average age estimation bias (in years), inclusive of all outliers, for the four exposure duration conditions for Experiment 1.

8 outliers)¹. The mean absolute error across exposure conditions was similar, with a deviation of 7.8 years (SD = 1.97) for 100 ms, 7.3 years (SD = 1.83) for 250 ms, 7.0 years (SD = 1.83) for 1000 ms, and 6.91

years (SD = 2.00) for the 3000 ms condition (See Figure 1b). Next, we performed a one-way repeated measures ANCOVA with exposure duration conditions (100 ms, 250 ms, 1000 ms, 3000 ms) as the

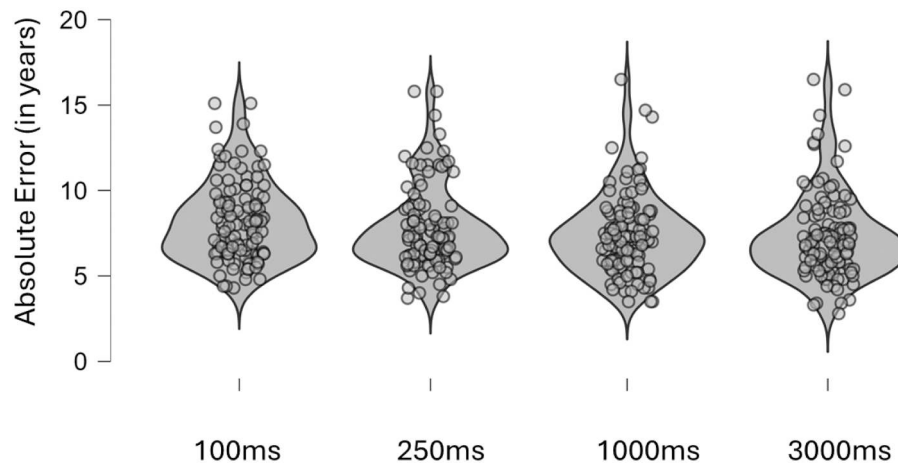


Figure 3. Violin plot with spread of individual average absolute error (in years), inclusive of all outliers, for the four exposure duration conditions for Experiment 1.

independent variable, absolute error of age estimates as the dependent variable, and participant age as the co-variate. The analysis did not find an effect of participant age, $F(1, 100) = 0.79$, $p = 0.375$ ($BF_{10} = 0.28$). There was an effect of exposure duration, $F(3, 300) = 4.58$, $p = 0.004$, $\eta p^2 = 0.04$ ($BF_{10} = 254.77$). Post-hoc t -tests with Bonferroni-adjusted p -values revealed that the mean absolute error for the shortest duration (100 ms) was higher compared to both the 1000 ms condition, $t(100) = 4.27$, $p < 0.001$, $d = 0.43$, and 3000 ms, $t(100) = 4.09$, $p < 0.001$, $d = 0.47$, but not compared to the 250 ms condition, $t(100) = 2.42$, $p = 0.105$, $d = 0.26$. All comparisons between other conditions were not significant, all $t_s \leq 1.83$, all $p_s \geq 0.423$. Thus, the shortest duration (100 ms) led to slightly, but significantly, greater error compared to the longer durations (1000 and 3000 ms), but not 250 ms.

Discussion

In Experiment 1, the different conditions did not lead to specific systematic patterns in over- or under-estimating of age. We did find a significant difference between the shortest and longer durations for absolute accuracy. However, numerically, this difference is small (less than 1 year), demonstrating only a small improvement in age estimation accuracy with additional exposure time to the face. Similar to previous research (Attard-Johnson et al., 2024; Davis & Attard-Johnson, 2022), there was also large variability in age estimation ability across participants.

The mean deviation in age estimates, even for the longer durations (around 7 years), was higher than the typically reported mean (approximately 2–4 years) (for review see Rhodes, 2009). It is possible that the brief exposures were driving this effect, even for the longer durations. Specifically, it may be that participants were primed to make rapid decisions due to the very brief durations intermixed with the longer durations leading to a reliance on a faster decision-making strategy which spilled over to all conditions. Thus, participants may have reached a decision quickly and not refined it when given additional time. This may have reduced the potential for improvement with the longer durations.

To address this, we ran a second experiment which was identical, except for one difference. Instead of randomising the exposure duration conditions, we presented them as blocks, and each block with a brief practice trial to ensure that participants knew what duration to expect and to use the full duration to make an assessment. We predicted that the same pattern would emerge, but that the difference between the shorter and longer exposure durations would be larger.

Experiment 2

Method

Participants

104 participants (72 female, 32 male) with a mean age of 31 years ($SD = 14.5$, range = 18–75) completed the experiment using an online testing platform Pavlovla.

All participants were White, except for five Asian, one Black, one Mixed, and two who selected Other/Prefer not to say. A sensitivity power analysis indicated that this sample size is sufficient to detect small-to-medium differences among the four conditions ($\eta^2 = .03$), assuming 80% power. Participants were different from those recruited in Experiment 1. Participants were compensated with course credit or a small payment. The study was approved by the institution's Ethics Committee (Ethics ID: 47626) and participants provided consent electronically before taking part.

Materials and procedure

The materials and procedure were identical to the previous experiment with one difference. The exposure conditions were presented in four blocks, the order of the presentation of the blocks was counterbalanced across participants. At the start of each block, participants were provided with a practice trial for that condition.

Data analysis

This was identical to the previous experiment. We removed outlier participants who scored more than $\pm 3SD$ from the mean of the average for that dependent variable (i.e., estimation bias, absolute accuracy, participant age). This led to the exclusion of data from 7 participants for estimation bias, 9 outliers for absolute accuracy, and an additional 1 outlier for participant age. The analysis including all participant data is briefly included in the footnotes.

Results

Estimation bias

The spread of estimates across participants and conditions is illustrated in Figure 4. A total of 8 outlier participants were excluded from this analysis with a remaining sample of 96 participants.² Overall, the shortest exposure condition of 100 ms recorded a deviation of 6.14 years ($SD = 3.82$), followed by 250 ms with 5.63 years ($SD = 3.89$), then 1000 ms with 5.46 years ($SD = 3.62$), and the shortest estimation bias of 4.43 years ($SD = 3.60$) recorded for

3000 ms duration (See Figure 1c). As before, we performed a one-way repeated measures ANCOVA with exposure duration conditions (100 ms, 250 ms, 1000 ms, 3000 ms) as the independent variable, age estimation bias as the dependent variable, and participant age as the co-variate. The analysis did not find an effect of participant age, $F(1, 94) = 0.008$, $p = 0.976$ ($BF_{10} = 0.24$). There was also no effect of exposure duration, $F(3, 282) = 2.48$, $p = 0.061$, $\eta^2 = 0.03$ ($BF_{10} = 186.20$). This indicates that exposure duration did not systematically influence the direction of estimation bias, i.e., did not lead participants to systematically over- or under-estimate durations.

Absolute error

Figure 5 illustrates the distribution of scores across participants and conditions. A total of 10 outlier participants were excluded from this analysis, leaving a remaining 94 participants². Overall, the shortest exposure condition of 100 ms recorded a deviation of 8.09 years ($SD = 2.29$), followed by 250 ms with 7.84 years ($SD = 2.28$), then 1000 ms with 7.37 years ($SD = 2.33$), and the shortest estimation bias of 6.74 years ($SD = 1.97$) recorded for 3000 ms duration (See Figure 1d).

Next, we performed a one-way repeated measures ANCOVA with exposure duration conditions (100 ms, 250 ms, 1000 ms, 3000 ms) as the independent variable, absolute error of age estimates as the dependent variable, and participant age as the co-variate. The analysis found a marginal effect of participant age, $F(1, 92) = 3.91$, $p = 0.051$ ($BF_{10} = 0.99$). An effect of exposure duration was found, $F(3, 276) = 3.27$, $p = 0.022$, $\eta^2 = 0.03$ ($BF_{10} = 3194.55$). Post-hoc t -tests with Bonferroni adjusted p -values revealed that the mean deviation of age estimates for the 100 ms duration was significantly greater than those produced in the 1000 ms condition, $t(92) = 2.74$, $p = 0.045$, $d = 0.33$, and the 3000 ms condition, $t(92) = 5.32$, $p < 0.001$, $d = 0.61$. The 250 ms condition also differed significantly from the 3000 ms duration, $t(92) = 3.91$, $p = 0.001$, $d = 0.502$. No other comparisons reached significance, all t s ≤ 2.39 , all p s ≥ 0.112 . These findings indicate that longer exposures led to an improvement

²Analysis for estimation bias (including outliers), participant age, $F(1, 102) = 0.57$, $p = 0.451$ ($BF_{10} = 0.30$) and exposure duration, $F(3, 306) = 1.65$, $p = 0.177$, $\eta^2 = 0.016$ ($BF_{10} = 11.16$).

Analysis for absolute accuracy (including outliers), participant age, $F(1, 102) = 8.68$, $p = 0.004$ ($BF_{10} = 8.044$), and exposure duration, $F(3, 306) = 2.003$, $p = 0.11$, $\eta^2 = 0.019$ ($BF_{10} = 69.28$).

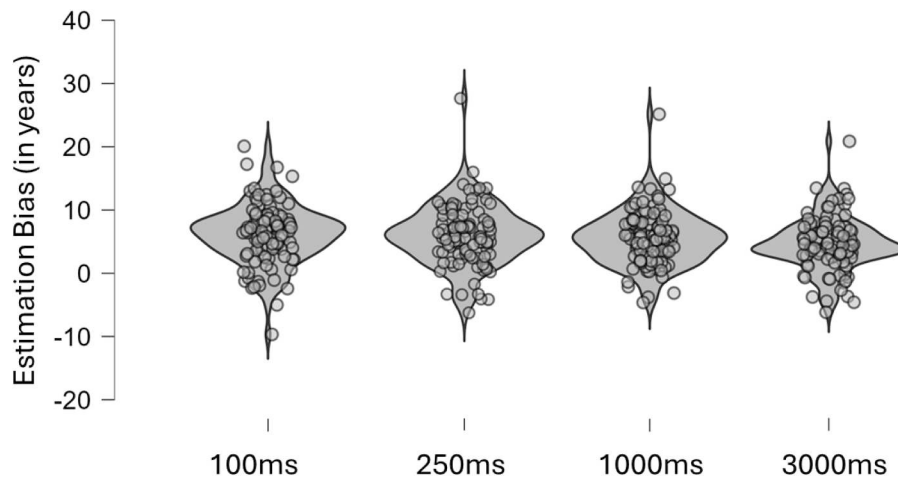


Figure 4. Violin plot showing the spread of individual average age estimation bias (in years), inclusive of all outliers, for the four exposure duration conditions in Experiment 2.

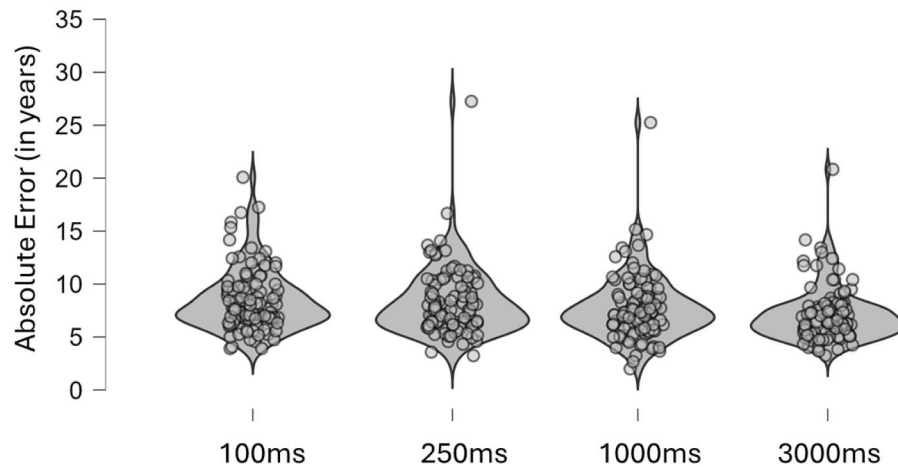


Figure 5. Violin plot showing the spread of individual average absolute error (in years), inclusive of all outliers, for the four exposure duration conditions in Experiment 2.

in accuracy of age estimates, with a maximum improvement of 1.35 years between the 100 ms and 3000 ms conditions.

Discussion

A similar pattern to the previous experiment was found, such that the different conditions did not lead to specific systematic patterns in over- or under-estimating age. However, when considering error, without direction, the mean absolute deviation from actual age became smaller as exposure time increased. As with the previous experiment, there was a significant improvement between the shortest

(100 ms) and the longest duration (3000 ms) with a difference of 1.3 years, which, although slightly greater than the difference in Experiment 1 (0.89 years), still represented only a small numerical improvement.

General discussion

There was a recorded improvement in age estimation accuracy across both experiments as exposure duration increased from 100 ms to 3000 ms. This difference was smaller in Experiment 1, likely because participants resorted to a speeded, perhaps more intuitive-based, decision-making strategy due to

being unable to predict the duration of the next trial because of intermixed duration conditions. In Experiment 2 we separated the conditions into blocks. Here we recorded a similar trend with slightly better improvement for the longer durations; however, this still offered only a small numerical advantage.

These findings inform us of primarily two things. First, age assessment decisions made in only 100 ms are not much less accurate than those made with more time. This is the first study to demonstrate that age estimates can be made rapidly, within only 100 ms of viewing a face. This suggests that at least some facial age information can be extracted quite rapidly to form an impression, similar to trait impressions (Todorov et al., 2009; Willis & Todorov, 2006). While the average deviation was found to be 7–8 years from the actual age of the target face in the 100 ms conditions, there were large individual differences across participants with mean errors ranging from 4 to 18 years. A mean group deviation ranging between 2 and 8 years is commonly reported in age estimation studies (e.g., Attard-Johnson et al., 2024; Burt & Perrett, 1995; Davis & Attard-Johnson, 2022; George & Hole, 1995; 2000; Sörqvist & Eriksson, 2007), and these experiments add to the growing body of evidence uncovering the variability in abilities on this task (e.g., Attard-Johnson et al., 2024; Davis & Attard-Johnson, 2022).

Secondly, increasing exposure time *does* improve age estimation accuracy in an incremental fashion. This suggests that with more time, participants refine their age estimates possibly by shifting their attention to more detailed facial information for a more nuanced decision. However, although significant, the improvement recorded is, perhaps surprisingly, not a dramatic increase in accuracy. This suggests that one can reach an estimate very close to their optimal ability in a very short period, and extra viewing time allows for some degree of refinement through visual processing of additional facial information. It is worth noting that across both experiments and all conditions, participants were allowed as much time as they needed to enter their decision *after* viewing the face. Therefore, this excludes the possibility that the extra duration simply led to participants having more time to engage in the higher-order processes involved in cognitive estimation (Shallice & Evans, 1978; Wagner et al., 2011), but

rather that any improvement itself was a direct result of longer visual processing of the face.

It is perhaps unsurprising that longer exposure durations only improved age estimation accuracy modestly. Holistic processing has been argued to be necessary, but not sufficient for face identification (Rossion, 2013). However, age estimation appears to place different perceptual demands, with age information extracted much earlier than identity information (Dobs et al., 2019). The present findings suggest that even brief exposures (e.g., 100 ms), which primarily reflect early holistic representations, are sufficient to approximate an accurate age estimation. Nevertheless, we also found that at longer exposure, subsequent featural processing may have contributed *additively* to performance. Longer exposure durations may have enabled observers to refine already-sufficient holistic representations with more detailed featural information, thereby modestly increasing accuracy. This is consistent with recent evidence that holistic encoding facilitates featural processing (Leong et al., 2023). This interpretation also aligns with the view that age estimation is sensitive to both holistic and featural facial information (Hole & George, 2011; Rhodes, 2009). Holistic processing enables observers to extract salient global cues of ageing such as craniofacial growth and overall skin texture (e.g., wrinkles, colour, transparency) (Burt & Perrett, 1995; Mark et al., 1980). While at the featural level, specific regions – particularly around the eyes and mouth – also convey similar age-related information (e.g., periorbital and perioral wrinkles; Alfertshofer et al., 2025; Enlow, 1982). Taken together, our findings suggest that holistic information available at early stages may be adequate for age estimation, while later featural processing refines the precision of this estimation/representation. Future studies could further investigate this switch from holistic to featural processing by limiting the number of allowed fixations to the face (see Hsiao & Cottrell, 2008).

Finally, participant age was included as a co-variate in the analysis and the effect of this variable on age estimation accuracy was absent or weak. Previous research suggests an effect of own-age bias on age estimation (Moyse, 2014; Moyse et al., 2014; Willner & Rowe, 2001); however, this effect is often inconsistent (Attard-Johnson et al., 2024; Burt & Perrett, 1995). Examining the own-age bias specifically was beyond

the scope of this study and thus we did not control for an equal distribution of ages across our participants. However, by including participant age as a co-variate, we can control for the possibility that any effects of our main variable of interest – exposure duration – are driven or confounded by participant age. Further, it is also possible to explore the effects of the age of the target faces on accuracy at different exposure durations. While this examination was beyond the scope of this study, additional exploratory analyses with stimulus age category and exposure duration as fixed factors and participant and stimuli as random effects in Linear Mixed Models are reported in the Supplementary Materials. This analysis found no interaction between stimulus age and exposure but may be informative for future research.

This study sought to understand the effect of brief and longer exposure times on age estimation accuracy. Our findings are particularly relevant given that the impact of rapid versus more deliberate decision-making on age estimation accuracy is not well understood, yet age assessments are being routinely performed in real-world contexts (Rahman et al., 2023; Rhodes, 2009). This is especially important in situations requiring estimation within a narrow age range (e.g., 16–18 years), where small errors can have meaningful consequences. For example, increased precision at longer exposure durations could improve screening accuracy in judgments of whether individuals are of legal drinking age (e.g., 16-year-olds judged as being of legal drinking age; Willner & Rowe, 2001). Taken together, the findings from this study add further evidence to challenge the longstanding notion that age estimation is easy and “relatively accurate” (Hole & Bourne, 2010) but rather that there is a large range in individual ability on this task. Despite this, it seems possible for age estimates to be made rapidly, and although additional time provides more refinement, and slightly better accuracy, this improvement is not extensive. This is the first study to systematically explore the effects of exposure time on age estimation accuracy using a range of short durations. It would be worthwhile for future research in this area to also compare estimates with even shorter (e.g., subliminal) (Jessen & Grossmann, 2020) and longer or self-paced durations to determine the saturation point at which there is no further improvement, as well as systematically manipulating specific task

instructions to induce intuitive versus more deliberate estimation strategies. Additionally, although a small set of studies have begun to explore the relationship between facial age and identity perception (see e.g., Attard-Johnson et al., 2024; Attard-Johnson, 2026), this area remains largely unexplored, and exposure duration may offer another pathway for investigating this link. For example, future research may examine whether information supporting rapid age estimation overlaps with information which is later used for identity recognition.

Author contributions

CRediT: **Janice Attard:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing; **Bryan Q.Z. Leong:** Conceptualization, Data curation, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing; **Alejandro J. Estudillo:** Conceptualization, Data curation, Investigation, Methodology, Writing – original draft, Writing – review & editing.

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ORCID

Janice Attard  <http://orcid.org/0000-0002-0563-0197>

Bryan Q. Z. Leong  <http://orcid.org/0000-0002-7394-0357>

Alejandro J. Estudillo  <http://orcid.org/0000-0002-7760-318X>

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