

Title: Using Eye-Tracking Technology to Quantify the Effect of Experience and Education on Forensic Anthropological Analyses

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1 **ABSTRACT:** The very human interpretation of analytical outputs is a significant challenge in
2 forensic science making it vital to explore the application of protocols as we enhance our practices.
3 This study assesses decision making in forensic anthropological analyses utilizing eye-tracking
4 technology to quantify an observer's estimate of confidence and reliability. Ten individuals with
5 varying levels of education and experience were asked to score cranial morphologies for two
6 human crania. Each participants' fixation points, fixation duration, and visit count and duration
7 were assessed using Tobii™ Pro 2 eye-tracking glasses. Mid-facial morphologies capturing
8 relative widths were the quickest scored traits with an overall median time of 14.59 seconds; more
9 complex morphological assessments took longer. Using time as a proxy for confidence, Kruskal-
10 Wallis rank sum results indicate individuals with less experience differed significantly from
11 individuals with greater experience ($p = 0.01$) although differences in level of education were not
12 significant. Interestingly, intraclass correlation coefficients (ICC) indicate interobserver reliability
13 is high between observers, suggesting experience only slightly improves agreement. These
14 preliminary results suggest experience is more important than level of education. Through
15 empirical decision making studies, forensic anthropologists can improve practices—decreasing
16 participant differences by targeting confusing or problematic aspects of a data collection practice
17 and improving training protocols.

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22 **KEYWORDS:** Forensic Anthropology, Forensic Science, Subjectivity, Objectivity, Confidence,
23 Decision making, Protocol Improvement

24 Forensic anthropology is a field rooted in the visual assessment of shape, collecting and
25 recording all forms of data related to human variation with the purpose of assisting medicolegal
26 death investigators in the identification of a decedent. These visual assessments remain a large
27 component of current practice when estimating aspects of the biological profile, including age (1-
28 6), sex (7,8), and population affinity (9-13). Many of these methods utilize morphological traits to
29 estimate some part or component of the biological profile. Some of these protocols are inherently
30 subjective, requiring assessments based on both codified and tacit knowledge—for example, the
31 experience of the observer (14-16). In recent years, there have been a number of studies assessing
32 the decision making processes involved in the interpretation and analysis of skeletal remains (15-
33 18). Many of these studies focused on the effect of cognitive and contextual biases (16-18) and
34 most highlighted the need for developing a greater understanding of the decision making strategies
35 involved in the collection, assessment, and interpretation of human skeletal remains (18). In
36 forensic science, there also has been an increased engagement with—and a rapidly growing
37 evidence-base addressing—decision making and the human factors affecting interpretations in
38 forensic reconstruction approaches (19).

39 The challenges arising in human decision making have been documented in the published
40 literature (15-19, 24, 37-47). However, evaluating decision making strategies by measuring the
41 gaze patterns of the human actors making those assessments has not yet been fully evaluated (15).
42 Defining an expert in forensic science varies worldwide and is not universally agreed. Generally
43 speaking, in forensic anthropology the minimum expectation for a forensic anthropology expert
44 witness in court is a doctoral degree or equivalent forensic anthropological experience. Some
45 regions and countries (e.g. Latin America, United Kingdom, United States) establish forensic
46 anthropological professional bodies and a board certification process for forensic anthropologists

47 (20-23). Yet, empirical studies to determine the role of expertise and experience in how visually-
48 derived information is captured for sex, age, population affinity, trauma, or taphonomic protocols
49 are only moderately addressed or researched. As with many expert observations (24), the data
50 captured for forensic anthropological analyses are minutiae of visually-derived information that
51 are difficult to teach to those with limited osteology experience. Consequently, training forensic
52 anthropologists in visual processing protocols and describing the procedures used to capture these
53 visual cues is difficult. Eye-tracking research can provide greater insight into forensic
54 anthropological methods and applications. For example, we can use gaze pattern and duration to
55 identify weaknesses in the definitions of specific morphologies or in a general protocol to refine
56 definitions or to enhance training (21,26-30).

57 The aim of this paper is to demonstrate how eye-tracking technology can grant further
58 insights into the application and, in turn, education of forensic anthropological protocols. We use
59 cranial morphology to direct the participants, to test the eye-tracking technology, and to analyze
60 gaze pattern data. This approach has been tested for other regions of the skeleton and using other
61 types of data (e.g., pelvic morphology). We hypothesize that using visual methods of cranial
62 morphology would deliver similar results to the assessment on age and sex methods (15).

63 New insights into the challenges faced in the collection of morphological data can be
64 identified by studying eye gaze behavior, including shortcomings in current methods and practices.
65 Here, we use cranial morphology to identify shifts that may be necessary when teaching students
66 to assess and collect these types of data. We also identify whether there is a difference in the time
67 to score and the actual scores between individuals having different levels of experience and
68 education. This study assesses whether observers with more experience/education felt more
69 confident in their assessments than those with less experience/education. Finally, we assessed the

70 consistency between observers using eye-tracking technology to identify why some observers
71 more consistently agreed and whether those differences reflected a nuanced understanding of a
72 morphological feature, the observer's experience, or resulted from a poorly defined morphology.

73 *Eye-tracking research in the forensic sciences*

74 Eye-trackers capture eye movements and enable the collection of data related to how long
75 participants view areas of interest (15,31-33). This technology has been applied in various fields
76 to assess practitioner performance (31,33). Eye-tracking technology has generally dominated
77 psychology research, but has recently been utilized within a number of other scientific disciplines
78 for educational purposes, protocol development, proficiency testing, and cognition studies (34-
79 37). The use of eye-tracking technology as a research tool to study decision making in criminal
80 investigations and other forensic sciences has been utilized, but for only a few published studies
81 covering fields such as handwriting analysis, fingerprint examination, identifications in criminal
82 line-ups, blood spatter analysis, and general crime scene investigation (34,36,38-40). The results
83 of these studies provide insight into an experts' gaze fixations and the areas of interest when
84 evaluating evidence (34) and in the application of search strategies to process crime scenes (40)
85 As an example, studies looking at forensic document examiners demonstrate experienced
86 examiners are more accurate than lay persons; simply put they are just significantly better at
87 identifying counterfeit signatures (39,41). In one of those studies, eye-tracking technology was
88 used to record each participants' eye movements and their response times (39). The eye movement
89 and search pattern data for all subjects showed similarities in search strategy (how they looked and
90 where); however, forensic document examiners took double the amount of time to reach their final
91 decision suggesting the key to distinguishing between forgeries and disguises in signatures is in
92 some part related to a more careful inspection of the item and longer consideration of multiple

93 features in the item of interest (39). Another study used eye-tracking technology to quantify
94 consistency and variability among forensic experts, showing experts were more consistent than
95 novices when inspecting and describing the features they used for latent fingerprint analysis (38).
96 Additionally, search duration and search sequence between expert crime scene investigators and
97 inexperienced novices differed significantly; experts are much more consistent in the search
98 sequence compared to a novice group (40).

99 Only one study to date has used eye-tracking technology to study gaze pattern strategies
100 among forensic anthropologists analyzing skeletal remains (15). In that study, eye-tracking
101 technology focused on nonmetric features used in sex and age-at-death estimations. That research
102 quantified analyst gaze fixation points, fixation duration, and visit counts for the interpretation of
103 features on the skull and os coxa. Building on that research, we use cranial morphological features
104 to assess gaze patterns, gaze duration, and fixation among a sample of individuals with varying
105 levels of experience and education.

106 **Materials and Methodology**

107 *Experiment Design*

108 Cranial morphological data were collected from two human skulls by participants wearing
109 Tobii™ Pro 2 eye-tracking glasses. This wearable eye-tracking camera recorded the pattern of
110 visual attention of each participant by directing near infrared light on the eyes, identifying the
111 focus point, duration of focus, and fixation pattern for each cranial morphology on each skull for
112 each participant. Each participant was asked a series of questions to identify their level of
113 experience with cranial morphological trait data (less than or greater than 2 years) and level of
114 education (undergraduate, graduate with Master's degree, professional with PhD). The mean
115 number of years of experience with cranial morphology was two years for all participants and, as

116 such, was used as the sectioning point for experience. Individuals with master's degrees were
117 further divided according to their experience assessing cranial morphology. These demographics
118 may identify factors driving any discrepancies between observers. Each observer's level of
119 education was also collected, to evaluate the relationship between the visual collection of cranial
120 morphological data and an observer's level of education. These data should situate the visual gaze
121 pattern, the visual acuity, and the duration of an observer's gaze in a broader context to identify
122 trends.

123 Data collected from the glasses provide information on the users' eye fixation patterns.
124 This includes 1) time recorded for each morphology or morphological region, 2) the overall time
125 spent on each skull, and 3) the total duration of the analysis. In addition to these data, a visual
126 representation of gaze fixation, visualized as a heat density map, can be generated for each
127 participant and used to further assess gaze patterns and fixation.

128 *Cranial Morphological Data*

129 Seventeen morphological traits of the skull were used to assess the impact of education and
130 experience on gaze patterns (Table 1). Participants were asked to score these morphologies on two
131 different skulls. The two skulls were selected to provide variability in trait expressions (11,44,49).
132 Each participant was provided a data collection sheet with line drawings of each trait. This allowed
133 the eye-tracking glasses to capture exactly what participants were looking at in real time as they
134 made their assessments. Cranial morphological data were divided into two divisions: those
135 assessed in a single, linear direction and related to size or breadth [unidimensional] and those
136 assessed minimally in two directions that capture shape [multidimensional].

137 *[Table 1 here]*

138 *Participants and Procedures*

139 Ten participants were asked to wear the eye-tracking technology and score the individual
140 skulls. Participants with varying levels of experience were recruited. The participants ranged in
141 general levels of practical (<1-32 years) and analytical experience (0-18 years). Practical
142 experience includes all forensic anthropological experience while analytical experience only
143 considers cranial morphology. Two undergraduate students, six graduate students with Master's
144 degrees, and two individuals with doctoral degrees participated. Six individuals reported having
145 less than two years of experience collecting cranial morphology data; the remaining participants
146 had more than two years of experience. This sample represents a preliminary usability study and
147 is suitable for assessing data collection protocols and protocol efficiency (52).

148 Each participant conducted the analysis separately in a laboratory. All necessary equipment
149 was provided. The two skulls were situated on a table and presented to the participants
150 simultaneously. The mandible was present for both even though no mandibular traits were
151 considered. To minimize any potential influence on the decision making process, participants in
152 this study were not told to start the analysis on a specific skull. Instead, participants were free to
153 choose. Participants were asked to use the scoring sheet to record all answers. The scoring sheet
154 presented seventeen cranial morphological traits in alphabetical order. Each participant was asked
155 to provide their confidence for each score to quantify self-assurance in the interpretation of these
156 morphologies. No time limit was imposed on the participants.

157 *Analysis*

158 Metadata collected with eye-tracking technology provides novel information on the collection of
159 cranial morphological data. However, three questions can be addressed using the demographic
160 data. First, can we identify differences in the time to completion and the morphological scores
161 between individuals with more experience? Second, are participants with more experience always

162 more confident? And finally, regardless of confidence, are scoring procedures consistently
163 reproducible across participants?

164 To facilitate analysis, we also generated an image in a vector graphics editor to highlight
165 the area around each of the cranial morphological features or areas (Figure 1). This allowed the
166 recording of metrics and count data for each region, using the images as a baseline for reference.
167 Visualizations and metrics documented where participants were looking (gaze fixation), how long
168 they were looking (gaze duration), and if participants were going back to certain traits more than
169 once (visit counts). These data are used to generate a heat map to visualize gaze patterns.

170 *[Figure 1 here]*

171 Several measures of confidence were used to assess how each participant assessed cranial
172 morphology and whether their reported confidence matched their gaze pattern. These include: 1)
173 heat maps to visualize education/experience-level variation; 2) fixation duration as a proxy for
174 decision making measured as the overall time to completion and the amount of time spent on each
175 cranial morphology; and, 3) real-time decision making and confidence assessed through the eye
176 tracking software with ad-hoc confidence scores situating the implicit and explicit assurance in the
177 collection cranial morphological data. Finally, after data collection we calculated an intraclass
178 correlation coefficient (ICC) to quantify the association between participant scores. ICC does not
179 require a ‘correct’ score, rather ICC assesses the reliability among all individuals and within each
180 sub-group of the data (i.e., education or experience levels).

181 *Statistical Analyses*

182 Using time-to-score as a proxy to measure the observer’s level of confidence, a Kruskal-
183 Wallis rank sum test assessed differences between the various groups. Kruskal-Wallis is a non-
184 parametric multiple-comparison test approximating a chi-square distribution to compare two or

185 more groups. Summary statistics were calculated by fixation duration to understand variation
186 among confidence levels, by trait. A two-way mixed-effects model for ICC was applied to assess
187 observer agreement between the cranial morphological traits for multiple participants, and
188 assessed following Koo and Li (53). Interclass correlation coefficients can range from 0.0 to 1.0
189 (where 1 is perfect agreement between observers). To assess self-reported confidence rates,
190 observers were also asked to provide a measure of their confidence between 1 (not confident) and
191 10 (very confident) for each morphology. The medians of each trait were recorded by years of
192 experience (less than 2 years or more than 2 years).

193 **Results**

194 *Density maps*

195 Density maps were created by concatenating the fixation and duration times of all analysts.
196 These gaze patterns were combined into a single density map by individual, by education level,
197 and finally by years of experience (Figure 2) to visualize eye-tracking data. Darker areas indicate
198 higher levels of attention.

199 *[Figure 2 here]*

200 *Fixation Duration*

201 The results for the Kruskal-Wallis test indicate experience is the only variable with
202 significantly different duration times (Table 2).

203 *[Table 2 here]*

204 Participants with a master's degree were slightly faster than those with doctorate degrees
205 and both were faster than the undergraduate cohort (Figure 3). Separating the masters-level group
206 into two subgroups (one with < 2 years of experience and one with > 2 years of experience), those
207 with more experience were faster than those with less experience (Figure 4). Although these

208 differences do not reach the level of statistical significance they may indicate participants with
209 more experience arrive at a decision faster than others (Figure 5).

210 *[Figure 3 here]*

211 *[Figure 4 here]*

212 *[Figure 5 here]*

213 Next, each cranial morphological trait was analyzed individually, using time as a proxy to
214 measure confidence. Figure 6 highlights summary statistic data for each trait. The slowest trait for
215 the participants to score covers a larger area of the midfacial region and is more akin to
216 multidimensional, morphological data (NBC) compared to the fastest which captures
217 unidimensional, linear data (SNS). The median time to score was 27.97 seconds. Of the seven
218 unidimensional traits, four traits (NAW, SNS, NO, ANS) fell below the median speed and three
219 traits (PZT, MT, IOB) fell above the median. Of the ten multidimensional traits, four (NFS, OBS,
220 ZS, NAS) fell below the median speed while six traits (PS, INA, PBD, NBS, TBS, NBC) were
221 scored at a slower pace falling above the median. To most accurately capture confidence, all
222 potential outliers (identified in Figure 6) were retained as they offer great insight into the variance
223 between observers.

224 *[Figure 6 here]*

225 *Individual Confidence Ratings*

226 Self-reported confidence, divided by the median score for each cranial morphology,
227 (Figure 7), illustrates variability in various levels of experience scoring these traits. More
228 experienced participants were most confident (6.5 to 9). Those with less experience had median
229 self-reported confidence levels ranging from 5 to 8. Interestingly, participants with more
230 experience were only more confident for 14 of the 17 traits. The three traits those with less

231 experience were more or equally confident in compared to more experienced raters were
232 multidimensional traits (OBS, INA, and PBD).

233 *[Figure7 here]*

234 *Interobserver Reliability*

235 Table 3 provides the ICC data. The correlation coefficients ranged from 0.72 to 0.96.
236 (Table 3).

237 *[Table 3 here]*

238 **Discussion**

239 This study assessed eye-tracking technology as a tool to quantify how experience and
240 education influence participant decision making and to visualize their gaze patterns when assessing
241 cranial morphology. Acknowledging that participant sample sizes were limited, though
242 appropriate for protocol efficiency testing, the results of this study still demonstrate how the level
243 of experience with scoring protocols has a direct impact on fixation and duration times. The eye-
244 tracking data was used to visualize gaze fixation and to generate data for quantifying gaze fixation
245 and duration for all participants and for each cranial morphology.

246 To identify differences in the amount of time it takes to score each skull and the scores
247 each observer selected, fixation duration by group was analyzed. Individuals with more experience
248 (>2 years) elicited quicker response times and it appears experience is an important contributing
249 factor to the decision making process. Individuals with more than two years of experience were
250 overall faster than individuals with less than 2 years of experience. Assessing the overall individual
251 morphologies, median time to score all traits suggests unidimensional traits are more likely to be
252 scored faster, or more confidently. All observers took considerably longer to score traits that
253 assessed broad regions or had more complex, multidimensional morphologies, some more than 35

254 seconds longer than others (e.g. NAW and NBC). The results of the Kruskal-Wallis tests indicate
255 statistically significant differences between fixation duration and experience ($p = 0.01$).

256 The unidimensional traits are generally quicker to score. However, individuals may be
257 slower at scoring multidimensional traits, but those with less experience seem to have more
258 confidence in their scores. Three of the four traits the less experienced raters reported the highest
259 confidence are multidimensional (OBS, PBD, TPS) and yet, two of the three traits they are least
260 confident scoring are unidimensional (NO, MT). More experienced observers were most confident
261 scoring multidimensional (NFS, NBS, TPS, NBC) traits. Although, unlike less experienced
262 observers, more experienced raters were less confident scoring a number of multidimensional traits
263 (OBS, INA, PBD). These traits (OBS, INA, PBD) were the only three traits that less experienced
264 raters were equally or more confident in scoring than the more experienced raters.

265 There are two possible explanations for these differences. First, multidimensional traits
266 potentially take longer to score due to complexity (various angles or using tools). So, while they
267 take longer to score observers feel more confident having conducted a more thorough analysis.
268 Conversely, this observation may be an example of the Dunning-Kruger effect: participants with
269 less experience or knowledge do not have insights into their potential shortcomings leading to
270 more confidence than more experienced participants (54). Less experienced raters were most
271 confident in multidimensional traits that took longer for them to score. In the current context,
272 experienced raters potentially have seen more human variation giving them insight into the true
273 range of variation meaning that that the drawings for these traits potentially do not encompass the
274 true range of variation, influencing a subconscious bias that the more experienced users have when
275 scoring the regions.

276 Finally, regardless of each observer's confidence, the derived scores for all of the cranial
277 morphological traits were consistent. The ICC results indicate moderate reliability (ICC=0.72-
278 0.74), particularly when comparing individuals with similar education (ICC=0.86) or experience
279 levels (ICC= 0.86-0.92). When dividing participants into four groups based on both experience
280 *and* education, the ICC results indicate good agreement (ICC = 0.82-0.88). These results all
281 suggest experience is a key consideration for higher reliability between participants and suggests
282 increases in experience lead to more consistent visualization of cranial morphological features.

283 **Conclusion**

284 How experts make decisions, process visual cues, and interpret evidence is influenced by
285 intrinsic and extrinsic factors (55). To understand these factors we can apply modern technologies
286 like eye-tracking capabilities. Such efforts will allow us to quantify the degree of influence that
287 experience and education have on practitioners and to develop more transparent approaches for
288 forensic inference (15). New technologies are increasingly fusing the physical, digital, and
289 biological realms. This fusion is exciting and will generate novel opportunities for research
290 addressing human identification using, for example, the automated pattern analysis (56,57). In
291 forensic anthropology, machine learning, including deep learning algorithms, now facilitate
292 automated decisions on skeletal remains (58-60). However, to fully apply these technologies to the
293 improvement of procedures in forensic anthropology, we must understand the factors that play a
294 role in the interpretation process.

295 Similar to previous research using eye-tracking to assess aspects of the forensic sciences
296 (15,34,36,38-40), this study documented the usability of eye-tracking technology as a research
297 tool. That technology offers significant potential to understand the importance of certain factors
298 (like experience) when observers are collecting subjective, morphological data. Undertaking

299 further empirical research building on these data will provide insight into those factors impacting
300 the decision making and interpretative processes involved in forensic anthropological methods.

301 Future research should test these factors using a larger number of participants,
302 incorporating a broader variety of experience levels, and measuring what, if any, effect training
303 has on confidence and consistency. Beyond cranial morphology, postcranial data and dental
304 variation should be similarly treated, potentially even in combination with cranial morphological
305 approaches (10,13,61). Eye-tracking data, in relation to multiple scoring modalities will be helpful
306 to assess how scoring methods vary across different data modalities such as photos, 3D models,
307 CT scans, and other virtual data (62-66). Finally, the pedagogical implications of these results
308 require further exploration. The impact of modifying the teaching and training of forensic
309 anthropologists in visual techniques needs robust assessment and remediation.

310 Eye tracking technology is the only way to objectively record, analyse, and interpret visual
311 gaze behaviours. Without this technology, quantifying the time a researcher spends assessing a
312 particular feature, trait, or region of the skull would not be possible. With eye-tracking technology
313 we have been able to study and quantify each observer's eyes during data collection. The insight
314 these data provide into the cognitive processes underlying any forensic anthropological analysis is
315 exciting and has great potential to reveal patterns and analyst gaze behaviours heretofore
316 unconsidered and most definitely unmeasured.

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