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# Anthropometric measurements of human faces generated by artificial intelligence

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## Abstract

**Objectives:** Artificial intelligence (AI) systems are capable of detecting human faces from two-dimensional images and generating highly realistic facial representations that do not correspond to any real individuals. This study aims to quantitatively assess the anthropometric features of AI-generated virtual faces and compare these measurements with established facial anthropometric data across different human populations.

**Methods:** A total of 150 virtual faces (75 male, 75 female) were generated by an artificial intelligence system trained on the CelebAMask-HQ dataset, which consists of 30,000 high-resolution facial images of celebrities. Anthropometric distances between defined facial landmarks were measured using custom-developed software. The obtained measurements were statistically compared with anthropometric reference data from various populations reported in the literature. Statistical analysis was performed using the One-Sample t-test to assess deviations from known population means, and the Chi-square Goodness-of-Fit ($\chi^2$) test to evaluate distribution conformity. A significance level of $p<0.05$ was used for all analyses.

**Results:** Several periorbital measurements of the AI-generated male virtual faces demonstrated greater similarity to anthropometric data from East Asian populations. Additionally, morphologic face height and nasal height values in male virtual faces were most closely aligned with those reported for Thai, Azeri, and Bulgarian populations. In female virtual faces, the circumference around the eyes was found to be comparable to that of Turkish females. Although certain facial features—particularly nasal and ocular parameters—showed resemblance to those of specific ethnic groups, the overall facial composition of both male and female virtual faces did not consistently correspond to any single racial or ethnic population.

**Conclusion:** AI-generated virtual faces offer a novel and efficient alternative for establishing standardized anthropometric datasets representative of various ethnic groups. Instead of collecting data from large populations, artificial intelligence can generate virtual facial models based on existing datasets, from which reliable anthropometric measurements can be obtained. These virtual datasets can enhance diversity representation while minimizing racial bias and ethical concerns. Consequently, the anthropometric data derived from AI-generated faces may serve as a standardized reference across populations, supporting applications in forensic science, aesthetic surgery, ergonomics, and facial recognition technologies.

**Keywords:** aesthetic plastic surgery; artificial intelligence in health; facial anthropometry; generative adversarial networks; photogrammetry

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## Introduction

Artificial intelligence (AI) refers to computational systems designed to mimic human intelligence and enhance their performance through data-driven learning processes.[1] These systems encompass a wide range of capabilities, including behavioral simulation, numerical reasoning, motion analysis, logical deduction, and sound recognition.[2] Subfields of AI, such as machine learning (ML) and deep learning (DL), form the technological backbone of numerous modern applications across various domains.[3] Among these domains, healthcare has emerged as one of the most impactful areas for AI integration.[4] The field is characterized by vast and complex datasets, including patient records, surgical procedures, clinical errors, diagnostic information, and rare disease registries.[5] Leveraging these data sources, AI-driven systems support clinicians in decision-making processes related to diagnosis, treatment planning, drug discovery, and surgical precision.[6] Furthermore, the integration of AI technologies is projected to enhance the efficiency and cost-effectiveness of healthcare delivery, leading to significant systemic savings.[7]

The human face is a complex anatomical region composed of both hard and soft tissues, and it plays a critical role in individual recognition, emotional expression, and interaction with the external environment.[8,9] Facial morphology varies significantly among individuals based on factors such as sex, age, and ethnic background.

Anthropometry is the scientific discipline concerned with the measurement and proportion of the human body.[10] In facial anthropometry, specific anatomical landmarks are used to measure distances, angles, and proportions that define facial structure.[11] To ensure consistency and reproducibility across studies and clinical applications, internationally recognized reference points and standardized protocols have been established.[12–14] These standardized facial measurements are widely used in clinical disciplines including plastic and reconstructive surgery, orthodontics, craniofacial surgery, and forensic science. They are also applied in the evaluation and treatment of conditions such as cleft lip and palate, and in artistic anatomy.[12,15,16] In plastic surgery, especially aesthetic procedures, knowledge of normal facial proportions is essential for restoring anatomical harmony and achieving desirable cosmetic outcomes. Surgeons frequently reference ethnic and racial characteristics when planning procedures, often using broad categories such as Caucasian, African, or Asian, even though these classifications are not anatomically exhaustive.[17] Facial anthropometric data can serve as a foundation for creating reference models or "average faces" for specific populations, thereby informing surgical planning, enhancing symmetry, and maintaining cultural sensitivity in aesthetic procedures.

Facial morphology often exhibits notable differences across races and ethnicities; however, significant variation can also be observed within individuals of the same ethnic group residing in different geographical regions.[17,18] Understanding these variations is essential for fields such as plastic surgery, forensic science, and facial recognition technologies. This study presents a quantitative evaluation of anthropometric facial data obtained from virtual facial models generated by an AI-based web platform. Using standardized horizontal and vertical reference points from the anterior facial view, a dataset of anthropometric measurements was created. These measurements were then systematically compared with published normative data representing various racial and ethnic groups. The primary aim of the study is to investigate whether the facial anthropometric parameters of AI-generated virtual faces resemble any specific racial group or present a composite that does not correspond to any one ethnicity. The central hypothesis posits that the facial metrics of AI-generated models do not fully align with the facial characteristics of any single racial or ethnic group. This approach may provide new insights into the potential of AI in generating representative or hybrid facial morphologies that transcend traditional racial classifications.

## Materials and Methods

The dataset required for this study was obtained from a web-based platform developed by NVIDIA researchers, known as "thispersondoesnotexist".[19] This platform utilizes a type of deep learning algorithm known as Generative Adversarial Networks (GANs) to generate high-resolution, photorealistic images of non-existent human faces. Specifically, the GAN model was trained using the CelebAMask-HQ dataset, which comprises 30,000 high-quality facial images of celebrities. Following model training, the system can generate synthetic facial images at a resolution of 1024 × 1024 pixels with each iteration. These AI-generated facial images are entirely virtual and do not correspond to any real individual, thus providing an unbiased and ethically sound dataset for anthropometric analysis. The use of GAN-generated facial imagery allows for the creation of large, standardized sample sets that are free from personal identification concerns and racial bias inherent in real-world data collection.

A custom software tool was developed using the C# programming language within the Visual Studio 2019 integrated development environment to perform precise anthropometric measurements on the AI-generated facial images. The application was designed to calculate the linear distance between any two manually selected reference points on the uploaded images. As illustrated in **Figure 1**, the measurement interface allows for user-defined selection of anthropometric landmarks, after which the pixel-based distance is computed and recorded. Each virtual face image in the dataset was individually uploaded to the software, and measurements were taken consistently by the same observer to ensure methodological standardization and reduce inter-observer variability. The resulting data from each measurement session were automatically exported and stored in Microsoft Excel file format, allowing for structured data management and subsequent statistical analysis.

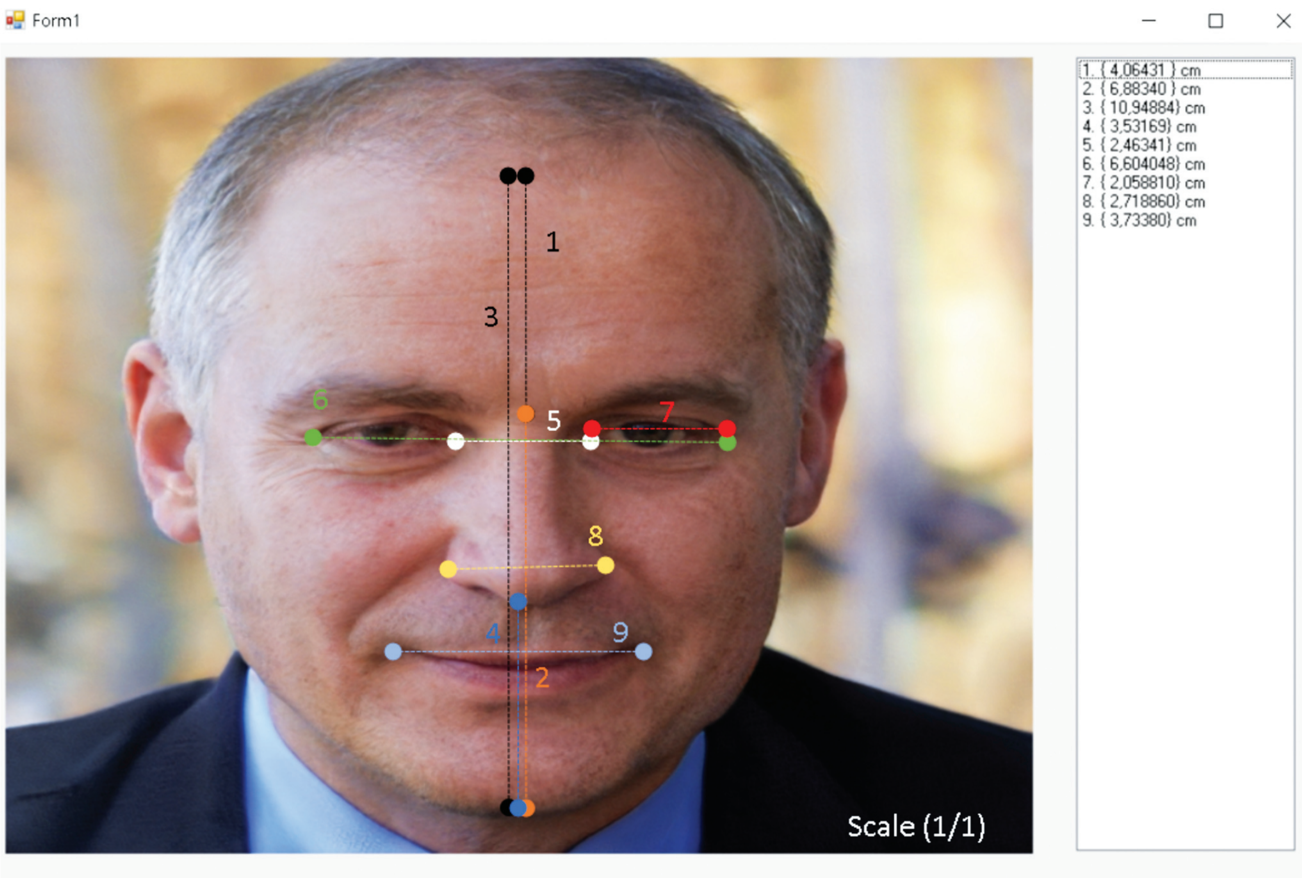


**Figure 1.** A sample analysis from the measurement software.

The dataset in this study was composed of non-realistic, artificially generated facial images obtained from the website "thispersondoesnotexist.com," which uses a Generative Adversarial Network (GAN) trained on a large-scale real image dataset (CelebAMask-HQ) to produce highly realistic, novel facial images.[19] Since each image generated by this platform is unique and disappears upon refresh, the number of images used in the study was carefully determined. A total of 150 virtual faces (75 male and 75 female) were selected based on predefined inclusion and exclusion criteria. The images selected did not represent any specific race or ethnic group, as the training data were drawn from a diverse population. Faces with overt emotional expressions (e.g., laughing, frowning, or grinning), those resembling children, or those with dark skin tones were excluded to maintain homogeneity in adult facial morphology and minimize potential measurement bias. As the images did not represent real individuals, ethical approval or informed consent was not required.

Each selected image was downloaded at full resolution and stored in a secure zip file archive. Since virtual faces have no medical background or variability due to physiological factors, they served as stable models for anthropometric analysis. The artificial intelligence system generates facial proportions at a 1:1 scale, simulating realistic human dimensions.

Standard anthropometric reference points were defined based on established literature (**Table 1**)[17–20] and 12 linear and ratio-based measurements were conducted between these points (**Table 2**). The measurement process was performed using custom-developed software, as previously described, which allowed researchers to mark two points on the image to calculate the real-world distance in millimeters. To reduce individual measurement bias, three independent researchers performed all measurements, and the mean values of their recordings were used in the final dataset. The anthropometric landmarks were applied uniformly to each image (**Figure 2**), ensuring methodological consistency throughout the analysis.

For each visual dataset, the average, minimum, and maximum values, as well as the standard deviation (SD),

**Table 1**
Reference points of the face.[17-20]

| Anthopometric point | |
|---|---|
| Trichion (tr) | The point on the hairline in the midline of the forehead |
| Nasion (n) | The point in the midline of both the nasal root and the nasofrontal suture |
| Gnathion (gn) | The lowest median landmark on the lower border of the mandible |
| Subnasale (sn) | The midpoint of the columella base at the apex of the angle where the lower border of the nasal septum and the surface of the upper lip meet |
| Endocanthion (en) | The point at the inner commissure of the eye fissure. |
| Exocanthion (ex) | The point at the outer commissure of the eye fissure |
| Alare (al) | The most lateral point on each alar contour |
| Cheilion (ch) | The point located at each labial commissure |

**Table 2**
Measurment points.[17-21]

| Abbreviation | Description |
|---|---|
| tr-n | the extended forehead height |
| tr-gn | the physiognomical face height |
| n-gn | the morphologic face height |
| sn-gn | the lower face height |
| en-en | the intercanthal distance |
| ex-en | the palpebral fissure length |
| ex-ex | the biocular diameter |
| n-sn | the nose height |
| al-al | the nose width |
| ch-ch | the mouth width |
| en-en*100/ex-ex | canthal index |
| en-en*100/al-al | intercanthal–nasal width |

were calculated separately for male and female virtual faces. The average anthropometric values from various racial groups documented in the literature[17,22–24] were also recorded for comparison. To assess the differences between the virtual faces and these established racial averages, a one sample T-test was performed using IBM SPSS Statistics Version 21 (Chicago, IL, USA). A p-value greater than 0.05 indicated no significant difference, suggesting that the anthropometric data of virtual faces were similar to those of the various racial groups.

In addition to this, the male and female data were analyzed separately and grouped according to their standard deviation (SD) relative to the North American White Young (NAW) data. The first group consisted of individuals whose measurements were within ±1 SD of the NAW mean, serving as the observed group. The second group included individuals with measurements greater than +1 SD, while the third group contained those whose measurements were smaller than -1 SD. These groups were considered the expected groups. A chi-square test was then conducted to compare the observed and expected group distributions. A p-value greater than 0.05 indicated no significant difference between the expected and observed groups, suggesting that the virtual faces did not significantly differ from the racial categories represented in the literature.

## Results

The average data for anthropometric measurements of races was taken from a 2005 study by Farkas et al.[23] It has also been compared with anthropometric data from Evereklioğlu et al.,[24] Farkas et al.[23] and Yang et al.[25]

The descriptive statistical values of 75 artificial male faces are given in **Table 3**. With data from Farkas et al.,[23] n-gn data on artificial male faces showed similarities with NAW (p=0.45), Azeri (p=0.45), Bulgarian (p=0.15), Croatian (p=0.1), Greek (p=0.19), Hungarian (p=0.19), Vietnamese (p=0.55), Zulu (p=0.12) males. The

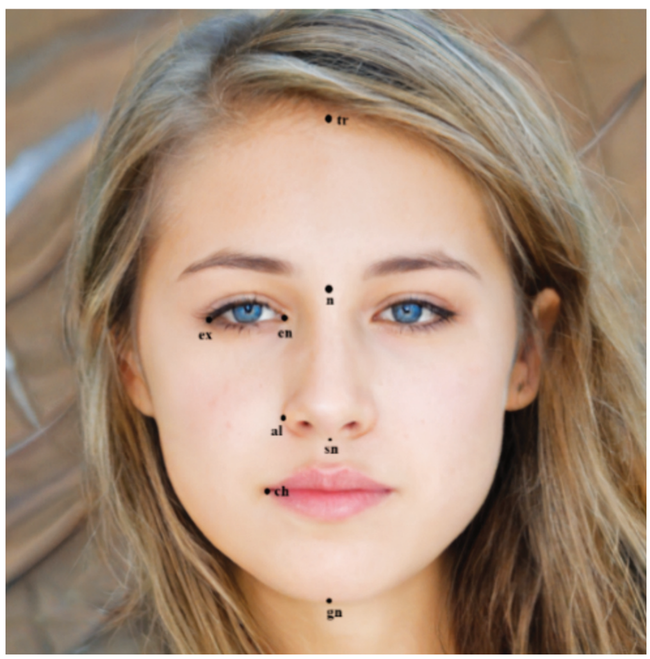


**Figure 2.** Showing the measurement points of the virtual face.

**Table 3**
Average, standard deviation, maximum and minimum values of male virtual faces.

| Measurements (mm) | Min/Max | Mean±SD | SR | p-value |
|---|---|---|---|---|
| tr-n | 5.69/9.58 | 8.09±0.87 | noSR | <0.001 |
| tr-gn | 18.19/22.33 | 20.16±1.1 | noSR | <0.001 |
| n-gn | 11.07/12.90 | 12.08±0.54 | NAW | 0.45 |
| | | | Azeri | 0.45 |
| | | | Bulgarian | 0.15 |
| | | | Croatian | 0.1 |
| | | | Greek | 0.19 |
| | | | Hungarian | 0.19 |
| | | | Vietnamese | 0.55 |
| | | | Zulu | 0.12 |
| sn-gn | 6.18/7.57 | 6.83±0.4 | Azeri | 0.16 |
| | | | Bulgarian | 0.16 |
| | | | German | 0.36 |
| | | | Polish | 0.62 |
| en-en | 3.30/4.11 | 3.70±0.25 | Thai | 0.55 |
| | | | Japanese | 0.11 |
| | | | Zulu | 0.08 |
| ex-en | 2.44/3.28 | 2.89±0.18 | Czech | 0.79 |
| | | | Vietnamese | 0.47 |
| ex-ex | 8.81/9.81 | 9.23±0.23 | Croatian | 0.59 |
| | | | Angola | 0.2 |
| n-sn | 4.49/5.98 | 5.13±0.32 | German | 0.09 |
| | | | Russian | 0.35 |
| | | | Thai | 0.68 |
| | | | AfrAm | 0.14 |
| al-al | 3.58/4.50 | 4.12±0.25 | Thai | 0.15 |
| ch-ch | 4.90/6.73 | 5.64±0.45 | Zulu | 0.27 |
| | | | Hungarian | 0.28 |
| canthal indeks | 34.45/46.69 | 40.15±3.4 | noSR | <0.001 |
| intercanthal–nasal width | 75.15/102.52 | 90.03±7.05 | noSR | <0.001 |

**AfrAm:** African American; **mm:** millimeter; **NAW:** North American white young; **noSR:** no similar data on races; **SD:** standart deviation; **SR:** similar data with races.

sn-gn data was similar in Azeri (p=0.16), Bulgarian (p=0.16), German (p=0.36), Polish (p=0.62) males. The en-en data is similar to Thai (p=0.55), Japanese (p=0.11) and Zulu (p=0.08) males. ex-en data; Czech (p=0.79) and Vietnamese (p=0.47), ex-ex data; Croatian (p=0.59) and Angola (p=0.2), n-sn data; show similarities with German (p=0.09), Russian (p=0.35), Thai (p=0.68) and African American (p=0.14) male. al-al data; Thai (p=0.15), ch-ch data are similar to Zulu (p=0.27), Hungarian (p=0.28) males (p>0.05). There was a significant difference between the generated groups with data of tr-n (p=0.000003) and n-GN (p= 0.0031) in the chi-square compatibility test. No significant differences were obtained between the other groups.

The descriptive statistical values of 75 virtual female faces are given in **Table 4**. With the data of Farkas et al.,[23] the n-gn data on artificial female faces showed similarities with Greek (p=0.07), Portuguese (p=0.18) and Turkish (p=0.07) female.[22] sn-gn data; NAW (p=0.03), Czech (p=0.92) and Iranian (p=0.77), ex-en data show similarities in Turkish (p=0.12) female. ex-ex data are similar to Portuguese (p=0.26), Turkish (p=0.21) and Japanese (p=0.36), n-sn data; German (p=0.33), Polish

**Table 4**
Average, standard deviation, maximum and minimum values of female virtual faces.

| Measurements (mm) | Min/Max | Mean±SD | SR | p-value |
|---|---|---|---|---|
| tr-n | 6.38/8.49 | 7.50±0.51 | noSR | <0.001 |
| tr-gn | 19.08/20.60 | 19.28±0.41 | noSR | <0.001 |
| n-gn | 10.72/12.70 | 11.74±0.49 | Greek<br>Portuguese<br>Turkish | 0.07<br>0.18<br>0.07 |
| sn-gn | 5.51/7.59 | 6.60±0.46 | NAW<br>Czech<br>Iranian | 0.03<br>0.92<br>0.77 |
| en-en | 3.23/4.29 | 3.83±0.19 | | |
| ex-en | 2.62/3.47 | 2.94±0.2 | Turkish | 0.12 |
| ex-ex | 8.76/9.96 | 9.35±0.25 | Portuguese<br>Turkish<br>Japanese | 0.26<br>0.21<br>0.36 |
| n-sn | 4.36/5.66 | 5.10±0.31 | German<br>Polish<br>Singapore<br>Vietnamese | 0.33<br>0.68<br>0.076<br>0.076 |
| al-al | 3.35/4.37 | 3.83±0.28 | Zulu | 0.24 |
| ch-ch | 4.17/6.71 | 5.33±0.55 | Angolan and<br>AfrAm | 0.46<br>0.72 |
| canthal indeks | 32.73/47.47 | 40.99±2.68 | noSR | <0.001 |
| intercanthal–nasal width | 82.17/114.18 | 100.27±8.26 | noSR | <0.001 |

**AfrAm:** African American; **mm:** millimeter; **NAW:** North American white young; **noSR:** no similar data on races; **SD:** standart deviation; **SR:** similar data with races.

(p=0.68), Singapore (p=0.076), and Vietnamese (p=0.076) female. al-al data Zulu (p=0.24), ch-ch data; similar to Angolan (p=0.46) and African American (p=0.72) female (p>0.05). There was no significant difference in the chi-square compatibility test among the groups created.

## Discussion

People distinguish other people from their faces and eyes.[22] The 2-D pictures are invaluable for facial surgeries, anthropology, delinquency and recognition of the individual. It can also provide research ease for forensic reconstructions.[17] The data obtained from these photographs are logged a system and provide a diagnosis of different sex and ethnic groups based on their face size. Artificial intelligence models are able to generate new faces by processing human faces in their substructures using image processing. These faces are very similar to real human faces.[18] In his work in 2019, Yang et al.[17] suggested that the face reference anthropometric ratios of one ethnic group were unsuitable for other groups of different ethnicities Artificial intelligence can be retaught with a large number of 2D photographs of different ethnicities or of the same ethnicity.

In this study, 12 measurement data were obtained to calculate the anthropometric data of artificial faces. In the data obtained, some measurements of male and female showed similarities with races. It has been concluded that virtual faces do not seem a particular race, with all features. This dissimilarity suggested that data from virtual faces could be used in surgeries without racial discrimination.

Farkas et al.[23] investigated craniofacial similarities between different populations with anthropometric parameters of NAW male. They reported that certain ethnic groups exhibited significant anthropometric convergence with NAW: Indian, Vietnamese, Thai, and Turkish male with consistent en-en distances; Thai, Vietnamese, Angolan, and Tongan male with parallel ex-ex distances; and Thai, Japanese, and African American male with parallel en-ex measurements. Farkas et al.[23] accepted values below p<0.001 representing the strictest threshold for anthropometric comparisons to determine statistical significance. We expected that the virtual data would not exactly match the data obtained from real human populations, as the virtual face generation site that formed the methodology of our study claimed that these faces were not real faces. Nevertheless, the similarity with some races in some anthropometric distances was detected. We believe this is due to the limitations of the training datasets used to train the artificial intelligence. The training data may have been limited because the dataset used was obtained from the faces of famous people who have general facial assumptions and are considered relatively beautiful. Evereklioğlu et al.[24] gave average distance values for en-en and en-ex data of Turks. When these data were compared with artificial intelligence face data, a significant difference was found between the averages. Yang et al.[17] gave canthal index and intercanthal-nasal mean data in Chinese. A significant difference was found when artificial intelligence faces were compared with these data. This shows that Turkish and Chinese face data and artificial faces are not similar. This made us think that the website from which we obtained the data in our study did not include the facial data of Turkish and Chinese celebrities while obtaining the data.

Although the virtual faces did not generally resemble the anthropometric facial data of a particular race, they showed some similarities. The measurements of the palpebral fissure length and the intercanthal distance around the eyes of our male virtual faces are more similar to those of the Far Eastern races. Measurements of nose height and width are more similar to those of Thais. The morphological face height and the lower face height are more similar to Azeri and Bulgarians. In female, the palpebral fissure length and the intercanthal distance measurements were similar to those of Turks. Although both sexes are similar to a particular race in the structure of the nose and eyes, artificial faces could not be completely likened to a race. The virtual faces did not represent the full profile of any race, suggesting that they were composed of partial characteristics of more than one group.

The main limitations of this study include the underestimation of the effect of the virtual face age factor on anthropometric measurements. Furthermore, the imbalance of ethnic representation in the training dataset of the artificial intelligence model (especially the lack of African and Middle Eastern populations) limited the morphological diversity. Another limitation is that only static facial parameters were analyzed in the study, and dynamic expressions and 3D morphometric variations were not included.

## Conclusion

This study revealed that virtual faces generated with artificial intelligence exhibit similarities with the anthropometry characteristics of some ethnic groups in certain facial parameters. For example, eye circumference measurements (en-en, ex-ex) showed convergence with Asian populations, while nose height and facial proportions showed convergence with Eastern European and Western Asian groups. However, it was revealed that the virtual facial anthropometric data generated by artificial intelligence does not accurately reflect the profile of any race. AI algorithms were able to partially capture universal patterns in human facial anthropometry. It also supports the potential for modeling anthropometric relationships between races. AI-based virtual anthropometry data can provide an important basis for creating a race-neutral dataset and using it in multidisciplinary applications (aesthetic surgery prosthesis design, forensic anthropology). Future studies should train AI models with comprehensive datasets encompassing diverse age groups, extensive ethnic diversity, and dynamic facial parameters to enhance the validity of virtual anthropometry in clinical and anthropological applications.

### Conflict of Interest

There are no conflict of interest.

### Author Contributions

ZY: project development, data collection or management, data analysis, statistical analysis, manuscript writing/editing; AAS: data analysis, statistical analysis; OC: statistical analysis, manuscript writing/editing.

### Ethics Approval

As the images did not represent real individuals, ethical approval or informed consent was not required.

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