DOI: 10.21088/ijfmp.0974.3383.19326.2

Indian Journal of Forensic Medicine and Pathology
Volume 19, Number 3, July-September 2026

ORIGINAL ARTICLE

Forensic Interchangeability of Live and AI-Derived Photographic Craniofacial Measurements in Cyber and Digital Forensics: A Multigenerational Study of the Indian Population

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HOW TO CITE THIS ARTICLE:

Paras Sharma, Priyanka Verma. Forensic Interchangeability of Live and AI-Derived Photographic Craniofacial Measurements in Cyber and Digital Forensics: A Multigenerational Study of the Indian Population. Indian J Forensic Med Pathol. 2026; 19(3): 292-300.

ABSTRACT

Background: In cyber and digital forensic investigations, facial measurements are commonly derived from images and video evidence rather than direct physical examination. However, forensic substitution is scientifically defensible only when photographic measurements demonstrate acceptable agreement, consistency, and interchangeability with biologically grounded reference standards.

Aim: To evaluate the forensic equivalence and interchangeability of live craniofacial anthropometry and AI-assisted photographic photo-anthropometry across three biological generations of Indian families.

Methods: A total of 216 individuals from 48 multigenerational Indian families were analyzed using fourteen standardized craniofacial landmarks. Live measurements were obtained using calibrated vernier calipers, while photographic measurements were extracted using AI-based facial landmark detection from standardized frontal images. Z-score normalization enabled cross-modal comparison. Agreement was assessed using Bland–Altman analysis, rank consistency using Spearman's correlation (ρ), and linear association using Pearson's correlation (r), with analyses stratified by generation.

Results: Population-level bias between live and photographic measurements was minimal across traits. However, substantial individual-level variability was observed. Only vertical skeletal traits, particularly N–Gn and Sn–Gn, demonstrated conditional agreement and limited interchangeability across modalities. Horizontal and soft-tissue-dominated traits exhibited poor agreement and inconsistent rank preservation.

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➢ **Received:** 04-02-2026 ➢ **Accepted:** 01-05-2026

Conclusion: Photographic craniofacial measurements cannot be universally substituted for live anthropometry in forensic applications. The findings define modality-aware operational boundaries for AI-driven facial analysis systems and reinforce the necessity of biological validation to ensure the reliability and admissibility of facial evidence in cyber and digital forensic contexts.

KEYWORDS

• Artificial Intelligence & Machine Learning • Craniofacial anthropometry • Photo-anthropometry • Forensic biometrics • Digital forensics • Facial landmarking • Measurement agreement • Bland–Altman • Cyber forensics

INTRODUCTION

Facial biometrics has become a central component of cyber and digital forensic investigations, driven by the proliferation of surveillance systems, social media imagery, mobile devices, and cloud-based data repositories.[1-4] In contemporary forensic workflows, investigators increasingly rely on facial measurements extracted from images and videos rather than direct biological examination.[5-7] While artificial intelligence and machine learning have significantly enhanced facial landmark detection and biometric profiling, the scientific admissibility of such evidence depends fundamentally on measurement validity, reliability, and biological grounding.[8-11]

Anthropometry has long served as the biological foundation of forensic facial analysis.[12-14] Traditional craniofacial measurements obtained using calibrated instruments provide high anatomical fidelity and serve as the biological gold standard for facial morphology.[27-29] However, operational forensic contexts rarely permit controlled physical examination, necessitating the use of photo-anthropometry derived from two-dimensional facial imagery.[12,16,30]

Although photo-anthropometry is widely used in forensic casework and biometric security systems,[3,5,6] its scientific defensibility depends on whether measurements derived from images can be considered interchangeable with live anthropometry. Correlation alone is insufficient for forensic substitution; agreement, bias, and individual-level variability must be explicitly quantified.[15]

The forensic literature repeatedly warns that 2D facial measurements are affected by camera geometry, pose variation, illumination, facial expression, and projection distortion.[16-19] These factors introduce systematic and random errors that may undermine biometric reliability and legal admissibility.[8,11,13,14]

Despite the increasing deployment of AI-driven facial biometrics in cybercrime investigations, digital policing, and identity verification systems,[1-4] there remains a critical gap in forensic validation studies that quantify the interchangeability of live and photographic craniofacial measurements across biologically related populations.

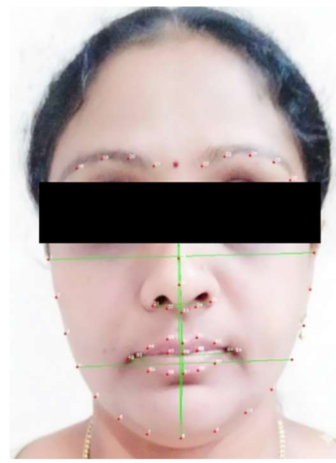
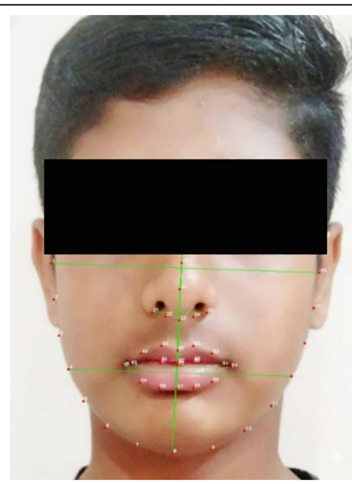
This study addresses that gap by evaluating measurement equivalence across three biological generations of Indian families using a rigorous agreement-based statistical framework anchored in forensic best practices.

This study aims to evaluate the forensic equivalence and interchangeability of live craniofacial anthropometry and AI-assisted photographic photo-anthropometry across three biological generations of Indian families. The study will assess population-level bias, consistency, and individual-level variability of facial measurements, contributing to the validation of AI-based systems in forensic applications.

MATERIALS AND METHODS

This cross-sectional family-based study involved 216 individuals from 48 Indian families, spanning three generations: grandparents (Gen 1), parents (Gen 2), and children (Gen3)[20-23] (Table 1). Inclusion criteria required confirmed biological lineage across three generations and availability of both live anthropometric measurements and standardized facial photographs. Individuals with congenital craniofacial anomalies, facial trauma, or reconstructive surgery were excluded, consistent with standard anthropometric protocols.[13,14,24]

Table 1: Distribution of participants across three biological generations

Generation		
Gen1 (Grandparents)		
Gen2 (Parents)		
Gen3 (Children)		

Age stratification followed stabilized craniofacial development phases to minimize developmental confounding.[13,25,26]

Fourteen craniofacial landmarks (Table 2) were measured using calibrated vernier calipers, ensuring precision,[12-14,25,27,28] Measurements were repeated three times to minimize intra-observer error. These landmarks were selected for their relevance in forensic anthropology.[23,27] Live anthropometry serves as the biological gold standard for facial measurement and provides empirical ground truth for validating digital and AI-based facial analysis systems.[27-29]

Table 2: Description of fourteen standardized craniofacial landmarks used in the study

Measurement Type	Landmark	Definition
Horizontal Measurements	Go-Go (Gonion)	The linear distance between the outermost points of the jawbone, defined as the gonion (Go) bilaterally.
	Al-Al (Nose Width)	The linear distance between the alare points (Al), which represent the outermost points of the nostrils.
	Ex-Ex (Outer eye corners)	The linear distance between the outer corners of the eyes, known as the exocanthions (Ex).
	En-En (Inner Eye corners)	The linear distance between the inner corners of the eyes, known as the endocanthions (En).
	Zy-Zy (Cheekbone width)	The linear distance between the zygion points (Zy), which correspond to the widest points of the cheekbones.
	Ch-Ch (Mouth width)	The linear distance between the chelion points (Ch), representing the outermost corners of the mouth.
	En-Ex (Eye Fissure length)	The horizontal width of a single eye opening.
Vertical Measurements	N-Gn (Nasion – Gnathion)	The linear distance from the nasion (N), located at the root of the nose between the eyebrows, to the gnathion (Gn), the lowest point of the chin.
	N-Sn (Nose height)	The linear distance from the nasion (N) to the subnasale (Sn), located at the junction of the columella and the upper lip.
	Sto-Gn (Stomion – Gnathion)	The linear distance from the stomion (Sto), the midpoint of the oral fissure, to the gnathion (Gn).
	Sn-Sto (Subnasale – Stomion)	The linear distance from the subnasale (Sn) to the stomion (Sto).
	N-Sto (Nasion - Stomion)	The linear distance from the nasion (N) to the stomion (Sto).
	Sn-Gn (Subnasale - Gnathion)	The linear distance from the subnasale (Sn) to the gnathion (Gn).
	Sto-Sl (Stomion – Sublabiale)	The linear distance from the stomion (Sto) to the soft tissue menton (Sl), representing the most anterior point of the chin in the midline.

Standardized frontal facial photographs were captured with controlled conditions[16,19,30] A 68-point deep learning-based facial landmark detection model (Table 1) was used to extract the measurements, which were then manually verified.[3,18,31-34] Linear distances were computed from pixel coordinates, mirroring live anthropometric measurements.[16,30]

Z-score normalization enabled comparison between live and photographic measurements.[16,17,19] Bland-Altman analysis assessed agreement[15], while Spearman's[8,35] and Pearson's correlation[36] tests evaluated consistency and linear association. Analysis was stratified by generation to assess variability across different age groups.[32,33] Statistical significance was controlled using false discovery rate correction to minimize Type I error.[27]

RESULTS

Mean bias values for all traits were centered near zero, indicating no systematic overestimation or underestimation by photographic measurements at the population level (Figure 1). This confirms the absence of directional distortion, consistent with prior photo-anthropometric validation studies.[16,17]

However, limits of agreement were wide for several traits, revealing substantial individual-level variability. Traits such as Sn–Gn and N–Gn demonstrated relatively narrow limits, indicating higher measurement precision and stability across modalities. These vertical skeletal dimensions are less affected by facial expression and camera geometry.[10,16,24]

Conversely, traits dominated by soft tissue and lateral facial width (Sto–Sl, En–En, Ch–Ch, En–Ex, Ex–Ex) exhibited very wide limits of agreement, reflecting poor individual reproducibility (Figure 1).

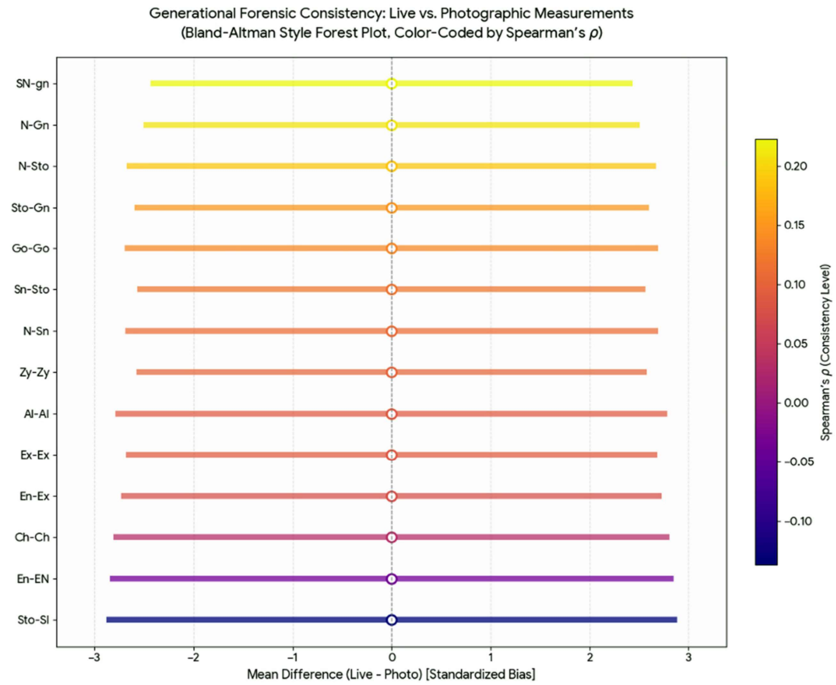


Figure 1: Bland–Altman-style forest plot showing mean bias and limits of agreement between live and photographic craniofacial measurements

These dimensions are known to be highly sensitive to pose, expression, and perspective distortion.[16,18,19]

These findings reinforce the forensic principle that low population bias alone does not justify measurement interchangeability.[15]

Vertical midline traits (Sn–Gn, N–Gn, N–Sto) exhibited statistically significant rank preservation (ρ ≈ 0.18–0.23), indicating that individuals maintain relative ordering across modalities (Figure 2). This is particularly relevant for AI-based kinship verification and resemblance modeling systems.[8, 35]

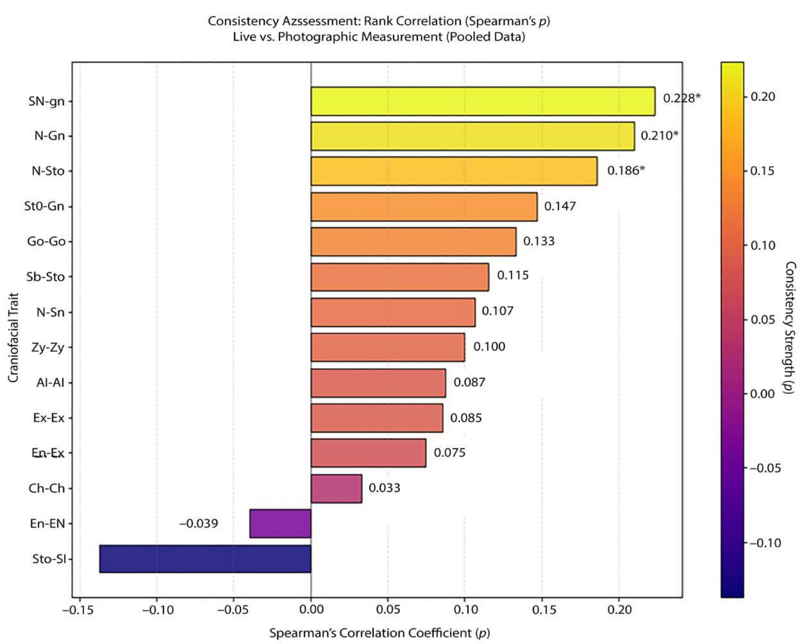


Figure 2: Rank consistency assessment using Spearman's rho across craniofacial traits

Horizontal and soft-tissue-dominated traits exhibited near-zero or negative rank correlations, confirming inconsistent ordinal behavior and undermining forensic reliability.

Pooled correlation analysis revealed that vertical skeletal traits consistently outperformed horizontal traits (Figure 3). Sn–Gn, N–Gn, and Sn–Sto exhibited the strongest agreement, consistent with findings from cephalometric–photographic validation studies.[36]

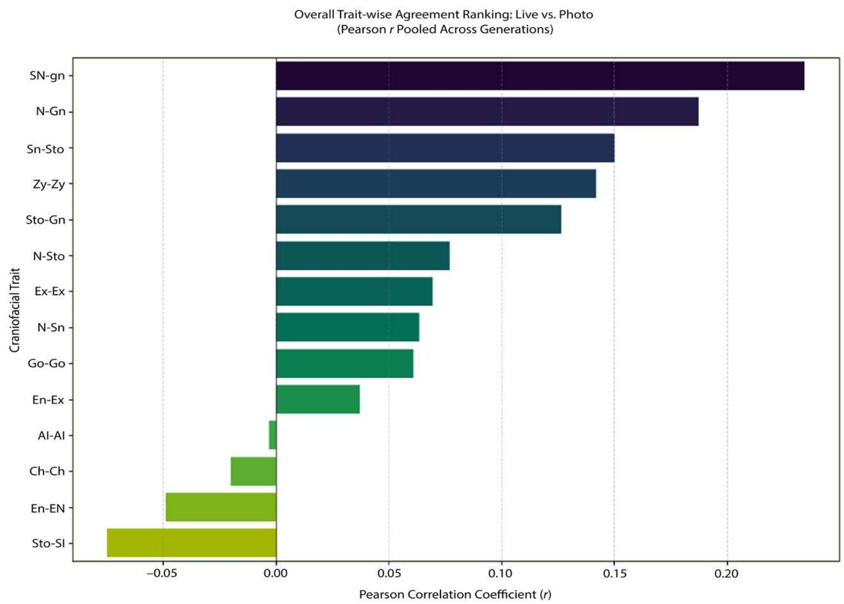


Figure 3: Trait-wise Pearson correlation coefficients comparing live and photographic measurements

However, even the highest correlations remain below thresholds typically required for biometric substitution, reinforcing that photographic measurements cannot replace live anthropometry on a one-to-one basis.

Generation 1 exhibited the highest agreement, reflecting stabilized craniofacial morphology in later adulthood[25,26] (Figure 4).

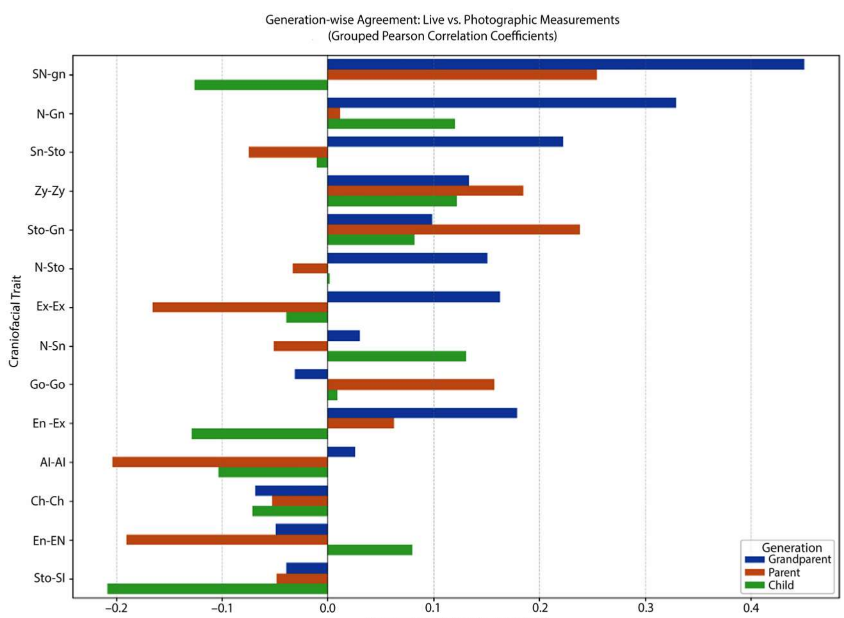


Figure 4: Generation-wise agreement of craniofacial measurements across three biological generations

Generation 3 showed the lowest agreement, consistent with ongoing growth and soft tissue remodeling, which disproportionately affects photographic capture[13,23] (Figure 4). This has direct forensic relevance when interpreting juvenile facial evidence.

DISCUSSION

The increasing reliance on facial biometrics in cybercrime investigations, digital policing, and identity verification systems demands rigorous forensic validation of measurement pipelines.[1-4] While AI-driven facial landmarking systems offer scalability and automation,[19,33,34] their outputs must remain biologically grounded and legally defensible.[8,11]

This study demonstrates that although population-level bias between live and photographic measurements is minimal, individual-level variability remains substantial. This aligns with previous studies,[1,2,32,34] which found AI-based facial landmarking systems often introduce measurement discrepancies due to factors like camera geometry and expression variability. This distinction is critical in forensic science, where identification operates at the individual level rather than the population level.[15]

Furthermore, our results echo the findings,[2,16,18,24], reported that vertical skeletal traits, like N-Gn and Sn-Gn, tend to exhibit better agreement across modalities compared to lateral soft tissue features. Importantly, biological heritability does not guarantee digital equivalence. Even highly heritable traits may be poorly captured photographically, underscoring the need for modality-aware AI systems.[8,11,19]

In contrast to studies,[3,6,7] which examined kinship verification via facial landmarks, our research underlines the necessity of considering individual variability when relying on AI for forensic identification. The findings of this research aligning with the previous work[16] suggest that while certain vertical traits are reliable for use in forensic settings, horizontal and soft tissue measurements remain susceptible to distortion, emphasizing the importance of modality-aware systems for digital forensics.

From a cyber forensic perspective, these findings establish clear operational boundaries. Photographic craniofacial measurements can support investigative intelligence but should not be treated as forensic substitutes for biological anthropometry in evidentiary contexts.[3,6,7]

CONCLUSION

This study establishes that photographic craniofacial measurements are not universally interchangeable with live anthropometry. While certain vertical skeletal traits demonstrate conditional agreement, most facial dimensions exhibit unacceptable variability for forensic substitution. These results define modality-aware admissibility boundaries for AI-driven facial biometrics and reinforce the necessity of biological validation in cyber and digital forensic systems.

DECLARATIONS

Ethics approval and consent to participate

Ethics approval for the study protocol was reviewed and discussed with the UCRD & RDC, Department of Forensic Science, Chandigarh University, Mohali, India. Informed verbal consent was obtained from all individual participants prior to data collection. Participation was voluntary, and all procedures were conducted in accordance with institutional ethical standards.

Conflict of Interest: Nil

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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