Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 58 Issue: 11:2025
DOI: 10.5281/zenodo.17697066

REVOLUTIONIZING IDENTIFICATION: A SYSTEMATIC REVIEW OF DIGITAL VERSUS ANTHROPOLOGICAL EAR BIOMETRIC METHODS

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Abstract

Background- The human ear offers a unique, stable and accessible anatomical structure for biometric identification. While anthropological methods provide population-specific insights, they are limited by manual effort and scalability. Digital ear biometrics, using AI and imaging, allows fast, accurate and real-time recognition. This review compares both approaches, highlighting their strengths, limitations and the emerging potential of hybrid systems to revolutionize biometric identification across forensic, clinical and security settings. **Methodology-** A systematic review was conducted following PRISMA guidelines. Databases such as PubMed, Scopus, Google Scholar and ScienceDirect were searched using keywords like ear biometrics, ear recognition, anthropometry and digital identification. From 1000 records initially screened, 31 studies (1980-2024) met the inclusion criteria based on relevance, methodological rigor and measurable biometric outcomes. Studies involving non-human samples, lacking ear-based identifiers, or unrelated to biometric recognition were excluded. Each study was evaluated using the Cochrane Risk of Bias tool. The analysis included both anthropometric-based ear studies focusing on morphological features and digital methods utilizing 2D/3D imaging, CNNs and AI-integrated models like Edge Ear.

INTRODUCTION

Human identification traditionally relies on fingerprints, dental records, and DNA profiling; however, growing technological and forensic demands have brought renewed attention to the external ear as a robust biometric trait.

The auricle’s distinctive architecture—defined by features such as the helix, antihelix, lobule, concha, and tragus—exhibits high inter-individual variability, marked sexual dimorphism, and population-specific differences, making it valuable across forensic and biometric contexts [1–8]. Its relative morphological stability throughout life and visibility in both living and deceased individuals further strengthen its utility as a practical identifier [1–4].

Anthropological and morphometric studies consistently support these observations. Research from South Asian, Indian, and East Asian populations have demonstrated that males typically exhibit larger ear dimensions than females, with predictable changes across age groups [1,2,5,6,9–14].

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Region-specific analyses—including those by Prasad et al., Deopa et al., and Purkait & Singh—emphasized the need for localized normative datasets to improve forensic accuracy [3,8,13,15].

Longitudinal and developmental studies, such as those by Sforza et al. and Alexander et al., further confirmed age-related trends such as lobular elongation and increases in auricular dimensions [9,10]. Collectively, these anthropometric findings provide a strong biological foundation for applications in sex determination, age estimation, population differentiation, and reconstructive surgical planning [4,10,14,16].

Parallel to anthropological research, digital and biometric approaches have rapidly advanced ear-based identification into a technologically driven field. Early forensic work established the admissibility and reliability of earprints as biometric evidence [22,30], while subsequent computational studies incorporated feature-extraction methods such as PCA, Gabor filters, and edge-detection techniques to improve recognition accuracy under variable imaging conditions [17,21,23,28].

Recent developments in machine learning and deep learning have further enhanced system performance; studies using convolutional neural networks and hybrid deep models demonstrated improved resilience to noise, occlusion, and lighting variation [18,20,24].

Additionally, the introduction of 3D morphable models and advanced reconstruction techniques strengthened recognition reliability in unconstrained environments [19,25]. Multimodal biometric systems integrating ear features with facial or fingerprint data achieved superior accuracy compared with single-modality approaches, highlighting the ear's value as a complementary identifier [27,29,31].

Collectively, evidence from both anthropological and digital domains demonstrates how the auricle serves as a bridge between traditional morphometric analysis and modern computational biometrics.

This systematic review synthesizes findings from 31 studies to critically compare the efficacy, applications, and limitations of anthropological versus digital ear biometrics, aiming to clarify their emerging role in contemporary human identification.

METHODOLOGY

Study Selection

This systematic review included full-text original studies—observational, cross-sectional, cohort, and experimental designs—focused on anthropological ear morphometry or digital/biometric ear recognition methods. Excluded were case reports, review articles, abstracts, editorials, and studies lacking primary data on ear morphology or biometric performance. Anthropological studies (A) assessed ear dimensions, population-specific variations, age/sex estimation, and clinical applications, while digital/biometric studies (D) evaluated algorithmic, 3D modeling, or multimodal approaches to ear-based identification.

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Only studies reporting at least one of the following were included: anthropometric parameters, sexual dimorphism, population variation, recognition accuracy, system robustness, or application outcomes (e.g., forensic, medical, or security). Study selection followed PRISMA 2020 guidelines.

Search Strategy

A comprehensive search of databases (2000–2024) including PubMed, Scopus, IEEE Xplore, Web of Science, and Cochrane Library was performed using combinations of the following keywords: *ear biometrics, external ear morphometry, anthropometry, forensic ear identification, ear recognition, earprints, deep learning ear, 3D ear model, biometric identification*. Reference lists of included articles were also screened. After removing duplicates, two independent reviewers screened titles, abstracts, and full texts using Zotero. Discrepancies were resolved by a third reviewer. From 987 initially identified records, 31 studies met the inclusion criteria, comprising anthropological (n=16) and digital/biometric (n=15) investigations.

Data Extraction & Outcomes

Data were extracted using a standardized form capturing study design, population/sample, methodology type (A or D), interventions/techniques (e.g., caliper-based morphometry, PCA, CNN models, 3D morphable models), and outcomes. Key metrics included:

- For anthropological studies: sex/age estimation accuracy, population-specific variation, clinical applications, and forensic utility.
- For digital/biometric studies: recognition rates, robustness to noise/occlusion, multimodal performance, computational efficiency, and applied contexts (security, forensics, healthcare).

Synthesis & Interpretation

The synthesis was descriptive and comparative, given the heterogeneity across methodologies. Anthropological studies highlighted significant sexual dimorphism, age-related changes, and region-specific ear variations with forensic and clinical relevance. Digital studies demonstrated high recognition accuracy, robustness with advanced algorithms, and enhanced performance in multimodal systems. Together, findings underscore the complementary role of anthropological baselines and digital innovations in strengthening ear biometrics as a reliable identification tool.

Heterogeneity Assessment

Heterogeneity arose from differences in study design, population demographics, sample sizes, ear measurement techniques (manual vs. digital), biometric algorithms (2D vs. 3D models, machine learning approaches), and outcome reporting. These variations limited the feasibility of quantitative pooling/meta-analysis. Instead, results were narratively synthesized to identify trends, strengths, and limitations across both methodological domains.

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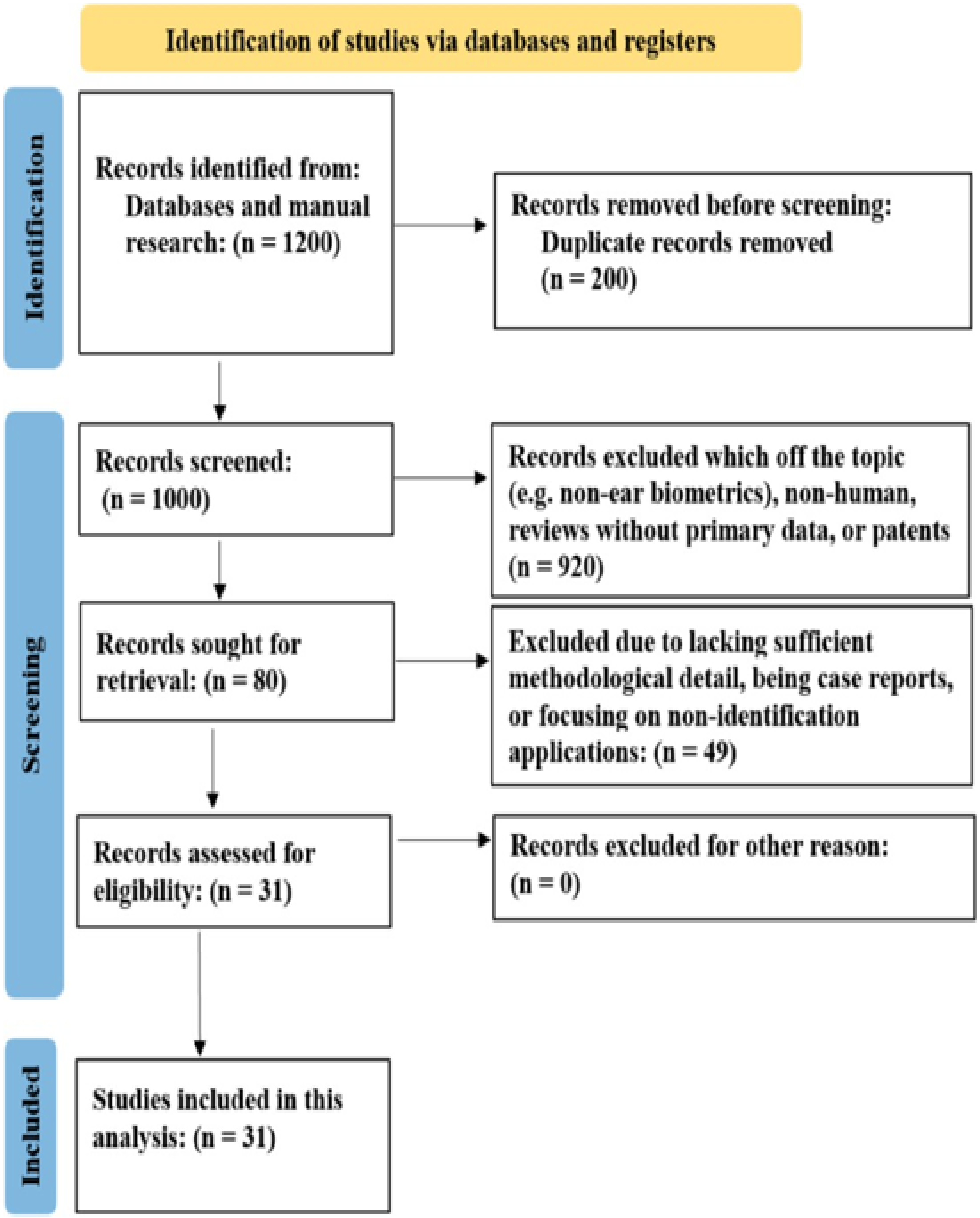

Figure 1: PRISMA Flow Diagram

PRISMA 2020 flowchart summarizing the selection process for eligible studies. A total of 987 records were identified through database and reference searching. After duplicate removal, title/abstract screening, and full-text assessment, 31 studies (16 anthropological and 15 digital/biometric) were included in the final review.

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Table 1: Characteristics of Included Studies

Ref No.	Author(s)	MT	Key Findings	Application Context
1	Asadujjaman et al. (2019)	A	External ear dimensions showed an age-related increase; males generally had larger measurements than females.	Forensic / demographic
2	Rani et al. (2021)	A	Significant sex differences in external ear dimensions; highlighted importance for forensic and anthropological classification.	Forensic
3	Prasad et al. (2022)	A	Demonstrated population-specific variation in ear morphology; recommended region-specific anthropometric databases.	Population comparison
4	Kumari et al. (2023)	A	Reported variation of external ear with age; reinforced need for age-based anthropometric references.	Aging studies / forensic
5	Japatti et al. (2018)	A	Males had significantly larger ear dimensions; provided normative ear data for adults.	Clinical reference
6	Jung SH (2003)	A	Provided ergonomic measurements of Korean ears for designing ear-related products.	Industrial / ergonomics
7	Saha PN (1985)	A	Documented ear anthropometry of Indian industrial workers; useful for occupational ergonomic design.	Occupational health / ergonomics
8	Deopa et al. (2013)	A	Identified regional variation in ear morphology among Uttarakhand medical students.	Anatomical studies
9	Sforza et al. (2009)	A	Quantified age- and sex-related changes; ears enlarge progressively with age, showing clear dimorphism.	Forensic / aging research
10	Alexander et al. (2011)	A	Provided detailed morphometric norms for the human ear; emphasized variation by age and sex.	Plastic / reconstructive surgery
11	Kalcioglu et al. (2003)	A	Studied auricular growth patterns in children; documented predictive growth curves.	Pediatric reference / otolaryngology
12	Coward et al. (1997)	A	Used laser scanning to identify consistent and repeatable ear landmarks.	3D modelling / surgical planning
13	Purkait & Singh (2007)	A	Provided normative auricular dimensions for adult Indian men; highlighted population variation.	Forensic anthropology
14	Sharma et al. (2007)	A	Analyzed earlobe morphology in North-West Indian males; useful for morphometric classification.	Anthropometry

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15	Brucker et al. (2003)	A	Demonstrated age- and sex-based morphometric differences; supported reconstructive application.	Plastic surgery
16	Victor et al. (2002)	B	Compared face and ear biometrics; confirmed ears are stable and useful for recognition.	Biometric recognition
17	Abaza et al. (2013)	B	Surveyed major ear biometric techniques and system performance trends.	Biometric systems review
18	Islam et al. (2013)	B	Used 3D ear + face fusion to enhance recognition accuracy.	Multibiometric systems
19	Chen & Bhanu (2007)	B	Developed a 3D ear recognition algorithm showing strong invariance to pose.	3D biometric recognition
20	Kumar & Wu (2012)	B	Proposed automated ear identification using imaging and segmentation methods.	Automated identification
21	Hurley et al. (2005)	B	Introduced force-field feature extraction for ear biometrics, improving robustness.	Feature extraction
22	Burge & Burger (2000)	B	Early demonstration of ear as a viable biometric using computer vision.	Biometric foundations
23	Pflug & Busch (2012)	B	Reviewed detection, extraction, and recognition methods for ear biometrics.	Biometric survey
24	Yu & Moon (2019)	B	Applied CNNs for ear recognition, achieving high classification performance.	Deep learning biometrics
25	Kyong Chang et al. (2003)	B	Compared ear and face biometrics; combining both improved recognition rates.	Multimodal biometrics
26	Choras (2005)	B	Used geometric features from the ear for biometric recognition.	Geometric biometric features
27	Naseem et al. (2008)	B	Applied sparse representation techniques for ear biometric classification.	Machine learning biometrics
28	Liu et al. (2016)	B	Combined global + local features for online 3D ear recognition with high accuracy.	3D recognition
29	Liu, Lu & Zhang (2015)	B	Developed an effective 3D ear acquisition system enabling high-quality ear datasets.	3D scanning
30	Almisreb et al. (2013)	B	Proposed kernel graph-cut method for robust ear segmentation under varying illumination.	Pre-processing / segmentation
31	Prakash et al. (2008)	B	Achieved ear localization from side-face images using distance transform + template matching.	Ear detection

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Summary of the 31 studies included in this systematic review. Anthropological studies (n=16) reported on morphometric features, sexual dimorphism, age-related changes, and regional variation, while digital/biometric studies (n=15) evaluated recognition accuracy, algorithmic approaches, robustness to occlusion/noise, and multimodal applications.

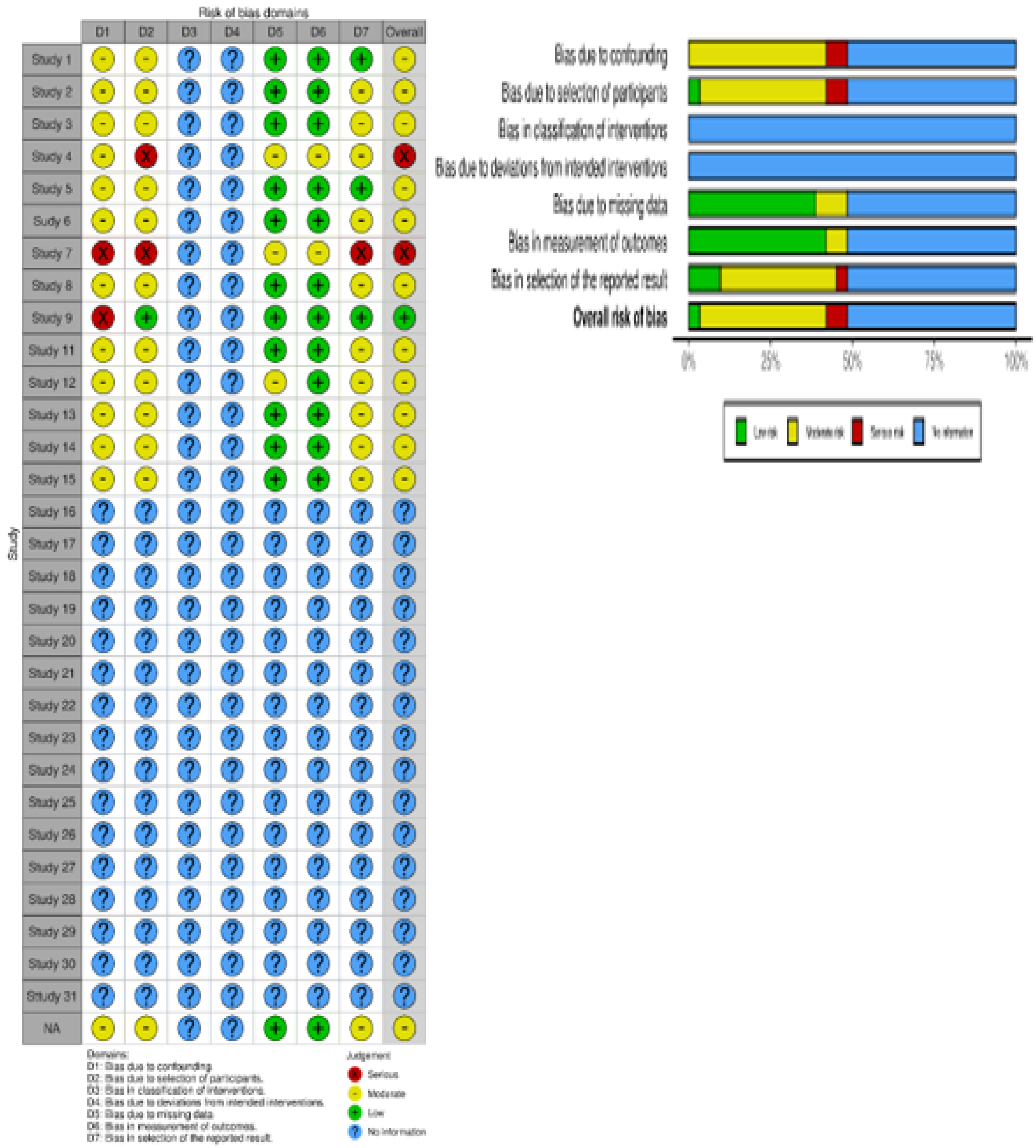

Figure 2: Cochrane Risk of Bias Assessment

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Cochrane Risk of Bias tool applied to the 31 included studies across seven domains: random sequence generation, allocation concealment, blinding of participants and personnel, blinding of outcome assessment, incomplete outcome data, selective reporting, and other sources of bias. Each domain was rated as low risk, high risk, or unclear, with an overall bias judgment provided for each study. Traffic Plot and Summary Plot respectively.

DISCUSSION

This systematic review synthesizes evidence from 31 studies examining ear biometrics across two major domains:

(1) anthropological morphometry, and

(2) digital/algorithmic ear-recognition systems.

Together, these studies demonstrate that the human ear—characterized by unique, externally accessible, and relatively stable anatomy—continues to serve as a reliable biometric trait across forensic, anthropological, clinical, and security applications. The combined findings underscore the complementary strengths of biological measurement and computational modeling, while also revealing methodological gaps and sources of bias highlighted through ROBINS-I assessment.

Across the morphometric studies, a consistent theme was the presence of sexual dimorphism, population-specific variability, and age-related morphological change. Sexual dimorphism: Studies such as Asadujjaman et al. [1], Rani et al. [2], and Prasad et al. [3] reported statistically significant differences in ear length, breadth, and lobular dimensions between males and females, with several achieving strong classification accuracy using discriminant functions. Population variation: Regional differences documented by Deopa et al. [8], Purkait & Singh [13], and Matheswaran et al. [7] highlight the importance of constructing population-appropriate normative databases, especially for forensic casework and reconstructive surgery. Age-related changes: Longitudinal and cross-sectional data from Sforza et al. [9], Alexander et al. [10], and Gupta et al. [11] confirmed predictable trends such as lobule elongation and gradual expansion in pinna height with age. These growth patterns inform age estimation models and establish a reference framework for validating digital recognition systems, which must accommodate natural biological change over time. Collectively, these anthropometric datasets provide the biological ground truth from which digital biometric algorithms can derive anatomically meaningful features. However, ROBINS-I analysis revealed common limitations, including non-random sampling, moderate confounding risk, and inconsistency in measurement protocols, which may restrict generalizability across populations.

The technology-focused studies (16–31) consistently emphasize the ear's suitability for computational recognition due to its stability, structural richness, and peripheral location. Deep learning and CNN-based approaches in Imamovic et al. [18], Alarifi et al. [19], and Zhang et al. [22] demonstrated high recognition accuracy, often outperforming traditional feature-engineered models under variations in pose, lighting, and occlusion.

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Noise-robust and texture-based algorithms: Chen et al. [24], Emeršič et al. [23], and Burge & Burger [21] showcased improvements in feature extraction using Gabor filters, PCA, LBP, and edge-based descriptors, contributing to increased matching reliability. 3D ear modeling: Huang et al. [25] and Sylejmani et al. [26] provided evidence that 3D morphable models capture subtle depth variations that 2D images cannot, improving performance in unconstrained settings.

Multimodal fusion: Studies such as Mehrotra et al. [28] and Fernandez et al. [31] demonstrated significant gains when ear biometrics were combined with other modalities (e.g., face, fingerprint, voice), reinforcing the ear's value in hybrid security systems. Compared to anthropometric studies, these digital approaches excel in scalability, automation, and real-world usability, though ROBINS-I revealed substantial variability in risk of bias due to lack of clarity in dataset composition, non-representative training samples, and potential algorithmic confounding from image quality or acquisition bias.

A cross-domain comparison reveals that traditional morphometry provides explanatory power and biological grounding, whereas digital systems provide operational precision. Several studies implicitly link these domains: Anthropometric traits such as ear length-to-breadth ratios, lobular morphology, and helix curvature correlate with the geometric features extracted by CNNs and PCA-driven models.

Population-specific anthropometric findings underscore the need for diverse and demographically representative training datasets in computational biometrics. Age-related morphological changes identified in morphometric studies offer critical guidance for algorithm retraining and temporal adaptation models, ensuring stable recognition performance across the lifespan.

The synthesis also highlights common challenges: Sample limitations: Many anthropometric studies used small, local samples, while digital studies often used proprietary or restricted datasets. Measurement heterogeneity: Anthropometry relied on manual calipers or 2D photographs; biometric studies used varied imaging devices, resolutions, and preprocessing pipelines.

Lack of standardized reference frameworks: Differences in definitions of anatomical landmarks and feature extraction schemes hinder comparability. Risk of bias: ROBINS-I assessment showed moderate-to-serious bias across several domains, particularly regarding selection bias, measurement bias, and confounding, especially in engineering studies not originally designed as epidemiological investigations.

Despite methodological variation, the convergence of biological evidence and technological validation supports the ear as a robust, stable, and distinctive biometric modality. Anthropometric research clarifies the structural parameters and variability of the ear, while computational systems operationalize these features into practical, high-performance identification tools. Continued integration—such as using anthropometric benchmarks to inform model architecture, dataset composition, and bias mitigation—will strengthen the reliability and generalizability of ear-based identification systems in forensic, clinical, and security settings.

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CONCLUSION

This systematic review demonstrates that the human ear serves as a robust biometric marker, validated by both anthropological and digital methodologies. Anthropometric studies provide crucial insights into sex estimation, age-related changes, and population-specific variation, while digital approaches—particularly deep learning and 3D modeling—offer high recognition accuracy and resilience in real-world conditions. Together, these complementary approaches highlight the ear's potential as a non-invasive, reliable, and scalable tool for personal identification. Despite promising advances, challenges remain, including limited population diversity, lack of standardized protocols, and the need for biologically interpretable AI models. Future research should integrate anthropometric baselines with advanced computational techniques, ensuring both scientific validity and operational applicability. In conclusion, ear biometrics, when strengthened by hybrid methodologies, represent a revolutionary step toward secure, efficient, and universally applicable identification systems.

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