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Review Article

Artificial Intelligence in Anatomical Morphometry: A New Era for Digital Health

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Abstract

The rapid advancement of digital health technologies has accelerated the integration of artificial intelligence into medical sciences, transforming traditionally descriptive disciplines such as anatomy into data-driven and quantitative fields. Anatomical morphometry, defined as the measurement and analysis of structural characteristics of the human body, has evolved with the introduction of artificial intelligence based techniques, enabling automated, scalable, and reproducible analyses. This review explores the role of artificial intelligence in anatomical morphometry and its implications for digital health, with a particular focus on the development of digital anatomical biomarkers. Key artificial intelligence techniques, including image segmentation, feature extraction, and predictive modeling, are discussed in relation to their applications in neuroanatomy, musculoskeletal analysis, vascular imaging, and digital pathology. Additionally, ratio-based biomarkers such as the second to fourth digit ratio are examined as potential non-invasive indicators within digital health frameworks. Despite promising developments, challenges such as data heterogeneity, lack of standardization, and interpretability of artificial intelligence models remain significant barriers to clinical translation. The integration of anatomical knowledge into artificial intelligence systems and the development of explainable models are essential for enhancing clinical trust and applicability. Overall, this review highlights the emerging role of artificial intelligence driven anatomical morphometry in digital health, offering new perspectives for precision medicine and personalized healthcare.

Keywords: *Artificial intelligence, anatomical morphometry, digital health, biomarkers, 2D:4D ratio*

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1. Introduction

The rapid expansion of digital health technologies has transformed modern healthcare by integrating data-driven approaches into diagnosis, monitoring, and treatment. While digital health is often associated with wearable devices and mobile health applications, its scope encompasses advanced medical imaging, computational modeling, and artificial intelligence (AI)-driven analytics (Motahari-Nezhad et al., 2022).

Anatomy, traditionally regarded as a descriptive and foundational discipline, is increasingly being redefined as an integrative and analytical framework that links structure to function and supports hypothesis generation in biomedical research (Cortese K et al., 2025). Anatomical morphometry, defined as the quantitative assessment of anatomical structures in terms of size, shape, volume, and spatial relationships, has long been a cornerstone of both basic and clinical sciences. Historically, morphometric analyses relied on manual or semi-manual measurements, which are limited by observer variability and scalability. Machine learning techniques have enabled the transition from manual and observer-dependent measurements to data-driven analytical frameworks (Joseph TS et al., 2025). The emergence of AI has enabled automated extraction of morphometric features from medical imaging data, significantly improving reproducibility and efficiency.

Recent advances in machine learning and deep learning have facilitated applications such as segmentation, feature extraction, and predictive modeling across various anatomical domains (Liu L et al., 2021; Zhu W et al., 2019; Helms G, 2016; Yang Q et al., 2022; Yagis E et al., 2024). Traditional machine learning approaches rely on handcrafted feature extraction, whereas deep learning models enable automatic feature learning from complex anatomical data (Liu L et al., 2021). Bibliometric evidence further supports the rapid expansion of AI in anatomical research, particularly after 2020, highlighting the increasing importance of data-driven methodologies in anatomical sciences (Sivri I et al., 2026).

The integration of AI into anatomical morphometry has contributed to the emergence of digital anatomical biomarkers, defined as quantifiable structural features derived from imaging or digital datasets that can be linked to physiological or pathological processes (Obuchowski NA et al., 2015). These biomarkers enable non-invasive and reproducible assessment of anatomical variations and disease-related changes.

Despite their increasing use, digital biomarkers remain conceptually heterogeneous. A systematic mapping study identified substantial variability in their definitions, particularly regarding data type, collection methods, and intended use (Alonso AK et al., 2024). This lack of consensus highlights the need for more structured and anatomically grounded frameworks. Among candidate anatomical biomarkers, ratio-based indicators such as the 2D:4D have attracted attention due to their potential associations with biological and clinical outcomes, although findings remain inconsistent (Manning J et al., 2014; Bunevicius A, 2018; Elvan Ö et al., 2025).

Therefore, this review aims to examine the role of AI in anatomical morphometry and to explore how morphometric data can be transformed into clinically meaningful digital anatomical biomarkers within digital health.

2. Methods

This study was conducted as a narrative review. A comprehensive literature search was performed using PubMed and Web of Science databases, focusing on studies related to anatomical morphometry, AI, and digital health.

Search terms included combinations of "anatomical morphometry", "artificial intelligence", "digital health", "image segmentation", "digital biomarkers" and "2D:4D ratio".

Studies were selected based on relevance, methodological quality, and contribution to AI-driven anatomical analysis. Both original research articles and review studies were included to provide a comprehensive overview.

3. Results

3.1. AI Techniques in Anatomical Morphometry

AI-based morphometry relies on three core processes. These are "segmentation (delineation of anatomical structures)", "feature extraction (volume, thickness, shape)" and "predictive modeling (linking features to clinical outcomes)".

Machine learning techniques have enabled the transition from observer-dependent morphometric measurements to data-driven analytical frameworks. Deep learning–based architectures have significantly improved anatomical segmentation by learning hierarchical representations directly from imaging data (Liu L et al., 2021). These techniques have demonstrated high accuracy across multiple imaging modalities (Helms G, 2016; Yagis E et al., 2024). Bibliometric analyses indicate that segmentation, deep learning, and MRI-based morphometry are among the most frequently used approaches in anatomical research, with neuroanatomical structures such as the brain and hippocampus being the most extensively studied (Sivri I et al., 2026).

In addition to traditional segmentation and feature extraction methods, recent studies highlight the growing role of three-dimensional deep learning models in anatomical morphometry. Three-dimensional convolutional neural networks can analyze volumetric data and capture spatial relationships across multiple imaging planes, providing a more complete representation of anatomical structures (Thurzo A et al., 2021). These models can automatically identify relevant features without manual input and have been successfully applied to tasks such as anatomical landmark detection, biological age estimation, and structural prediction (Liu L et al., 2021; Zhu W et al., 2019).

3.2. Digital Anatomical Biomarkers

Digital anatomical biomarkers represent quantifiable structural features derived from imaging data. Macro-anatomical biomarkers include measures such as organ volumes and cortical thickness, which are widely used to assess structural variations in the human body, particularly in neuroimaging studies (Velázquez J et al., 2021). Advances in AI have further enabled automated and reproducible volumetric analyses of anatomical structures (Liu L et al., 2021).

Meso-structural biomarkers include quantitative imaging features such as tissue texture and shape irregularities, which reflect underlying structural heterogeneity and can serve as non-invasive imaging biomarkers (Yap FY et al., 2021; Bianconi F et al., 2018). These biomarkers are non-invasive, reproducible, and scalable, making them suitable for digital health applications (Montag C et al., 2021).

3.3. Ratio-Based Biomarkers

The 2D:4D is a widely investigated anatomical biomarker that has been associated with prenatal hormonal exposure. Numerous studies have explored its relationship with a range of health outcomes, including cancer and cardiometabolic risk; however, the findings remain inconsistent (Manning J et al., 2014; Bunevicius A, 2018; Elvan Ö et al., 2025; Emül TG et al., 2025). Despite these limitations, the simplicity, non-invasive nature, and ease of digitization of 2D:4D make it a promising candidate for integration into AI based analytical frameworks, although standardized automated pipelines are still lacking. While current evidence is largely correlational, these findings support the potential of 2D:4D as a scalable and accessible anatomical biomarker within digital health contexts.

3.4. Clinical Applications

Artificial intelligence driven anatomical morphometry is applied in "neuroanatomy: brain volume, cortical thickness", "musculoskeletal analysis: muscle mass, body composition", "vascular imaging: vessel structure and branching", "digital pathology: histomorphometric analysis". These applications demonstrate the versatility of morphometric data in clinical decision-making (Madabhushi A & Lee G, 2016; Yang Q et al., 2022).

4. Discussion

Artificial intelligence–driven anatomical morphometry has demonstrated substantial applications across multiple domains. In neuroanatomy, automated segmentation and quantification of brain structures support disease diagnosis and longitudinal monitoring. In musculoskeletal analysis, AI enables precise assessment of muscle mass and body composition (Yang Q et al., 2022), while in vascular imaging, deep learning models facilitate the reconstruction and analysis of complex vascular networks (Yagis E et al., 2024).

The predominance of neuroanatomical research in AI-driven morphometry, as highlighted by recent bibliometric analyses, indicates an imbalance in the field. Although brain imaging remains the primary focus, other anatomical regions, such as the musculoskeletal system, visceral organs, and peripheral structures, remain comparatively underexplored (Sivri I et al., 2026). This disparity presents a significant opportunity for future research, particularly in extending AI-based morphometric approaches beyond neuroimaging.

These developments should be interpreted within the broader transformation of anatomical sciences, where morphology is increasingly recognized not only as a descriptive discipline but also as a data-generating and hypothesis-driven framework. Morphological reasoning provides essential insights into structural organization and spatial relationships that cannot be fully captured by molecular data alone (Cortese K et al., 2025).

A key outcome of this transformation is the emergence of digital anatomical biomarkers, which enable the integration of structural data into clinical decision support systems. In this context, ratio-based anatomical biomarkers, such as the 2D:4D, represent simple yet promising indicators of biological and clinical associations (Manning J et al., 2014; Bunevicius A, 2018). However, despite these advances, several challenges persist, including the lack of standardized datasets, variability in imaging protocols, limited external validation, and the interpretability of AI models.

Explainable AI has therefore emerged as a critical approach to enhance transparency, interpretability, and clinical trust (Rundo L et al., 2024). Furthermore, the conceptual ambiguity surrounding digital biomarkers complicates their clinical integration, as inconsistencies remain in definitions related to data sources, measurement methods, and intended applications (Alonso AK et al., 2024).

Nevertheless, machine learning based digital biomarkers demonstrate considerable potential in predicting treatment response and enabling continuous patient monitoring, thereby supporting more dynamic and personalized healthcare models (Guthrie NL et al., 2019).

Within this framework, the integration of anatomical morphometric features into digital biomarker systems may provide a stable and interpretable structural dimension, thereby improving both predictive performance and clinical applicability. This is particularly important when combined with explainable AI approaches, which are essential for ensuring transparency and facilitating clinical adoption (Rundo L et al., 2024). In addition, the integration of immersive technologies, such as extended reality, further expands the scope of digital anatomy by enabling interactive environments that may serve as future platforms for both data acquisition and education (Elvan Ö et al., 2026).

5. Conclusion

Artificial intelligence is transforming anatomical morphometry into a scalable, quantitative, and clinically meaningful component of digital health, reinforcing the central role of anatomy as a data-driven and integrative discipline. By enabling automated analysis and the extraction of anatomically grounded biomarkers, AI bridges the gap between structural organization and clinical decision-making. In this context, anatomy is no longer solely descriptive but serves as a foundational framework for generating clinically actionable insights. Future research should prioritize standardization, robust validation, and the development of explainable models to ensure reliable, interpretable, and clinically safe implementation.

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Conflict of interest

The author declares no conflicts of interest.

Data availability

Details of the search strategy are provided within the manuscript. Further inquiries can be directed to the corresponding author.

Ethics approval

Ethics approval was not required for this study.

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