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# From compartments to dynamic physiology: toward actionable body composition

Karl E. Friedl[1]✉, Adam W. Potter[1], Jennifer L. Miles-Chan[2], Yosuke Yamada[3,4], John A. Shepherd[5], Leigh C. Ward[6], Dympna Gallagher[7] and Steven B. Heymsfield[8]

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The 12th International Symposium on In Vivo Body Composition Studies (ISBCR 2025) highlighted a fundamental transition from estimating static tissue compartments to dynamic physiological phenotyping, actionable interpretation, and demonstrable value for clinical decision-making, health prediction, and human performance assessment. This represents an evolution in technological capability and conceptual framing, as an extension of the Functional Body Composition concept. Classical multicompartment models and established methods such as dual-energy X-ray absorptiometry, isotope dilution, bioimpedance, computed tomography, and magnetic resonance imaging remain foundational; however, emerging approaches increasingly integrate advanced imaging, artificial intelligence, bioimpedance spectroscopy, stable isotope methods, wearable sensing, and multidimensional phenotyping. Several themes were prominent at ISBCR 2025, including expansion of imaging beyond traditional DXA paradigms, increasing emphasis on muscle quality and fluid compartments, greater attention to visceral and ectopic adipose tissue, clinical applications in oncology and critical illness, the evaluation of obesity pharmacotherapy, the importance of generalizability to individuals across sex and ethnicity, and data governance. This perspective proposes a framework for future research in which body composition measurements become integral components of predictive models of health, performance, and physiological resilience. Future body composition assessment practices must include demonstrated added value over previous methods, and the greatest advances will come from technologies that bring physiologically meaningful assessment to large populations. The success of future technologies should be judged less by how precisely they estimate tissue compartments than by how effectively they improve physiological understanding, prediction, and decision-making.

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## INTRODUCTION: AN INFLECTION POINT FOR BODY COMPOSITION SCIENCE

For more than a century, body composition science has asked a deceptively simple question of "what is the human body made of?" Early approaches relied on anthropometry, densitometry, and dilution methods to estimate fat mass, fat-free mass, water, mineral, and protein. These methods established the core conceptual framework of the field and enabled modern research in nutrition, metabolism, obesity, aging, and disease. The development of multicompartment models, later formalized through the five-level model of body composition organization, provided a powerful way to connect measurement technology with biological structure [1, 2] (Fig. 1).

The field is now confronting a different question, "not only what tissues are present, but what physiological state they are in, how they are changing, and what those changes imply for health and function?" This conceptual transition builds on the framework of Functional Body Composition articulated by Muller and colleagues, which emphasized that body components should be interpreted in relation to their physiological functions, regulatory systems, and metabolic consequences rather than as isolated anatomical compartments [3, 4]. The current evolution extends that framework through technologies capable of characterizing tissue quality, metabolic activity, fluid distribution, and longitudinal adaptation.

Body composition science is evolving toward dynamic physiological phenotyping through the convergence of advances in biology, physics, engineering, and computational science [3, 5]. Emerging technologies including advanced imaging, bioimpedance spectroscopy, stable isotope methods, wearable sensing, and artificial intelligence are expanding assessment beyond the quantification of tissue compartments to characterize tissue function, adaptation, and physiological state [6]. The future state-of-the-art will emerge from integrating structural measurements with physiological interpretation and computational prediction. In this framework, dynamic body composition is defined by the integration of structural measurements with physiological, temporal, or contextual information that improves interpretation

[1]U.S. Army Research Institute of Environmental Medicine, Natick, MA, USA. [2]Human Nutrition Unit, School of Biological Sciences, University of Auckland, Auckland, New Zealand. [3]Graduate School of Biomedical Engineering, Tohoku University, Sendai, Japan. [4]Department of Medicine and Science in Sports and Exercise, Graduate School of Medicine, Tohoku University, Sendai, Japan. [5]University of Hawaii Cancer Center, University of Hawaii- Manoa, Honolulu, HI, USA. [6]Department of Health Sciences, Faculty of Medicine, Health and Human Sciences, Macquarie University, Sydney, NSW, Australia. [7]Division of Endocrinology, New York Nutrition Obesity Research Center, Columbia University, New York, NY, USA. [8]Pennington Biomedical Research Center, Louisiana State University System, Baton Rouge, LA, USA. ✉email: karl.e.friedl3.civ@health.mil

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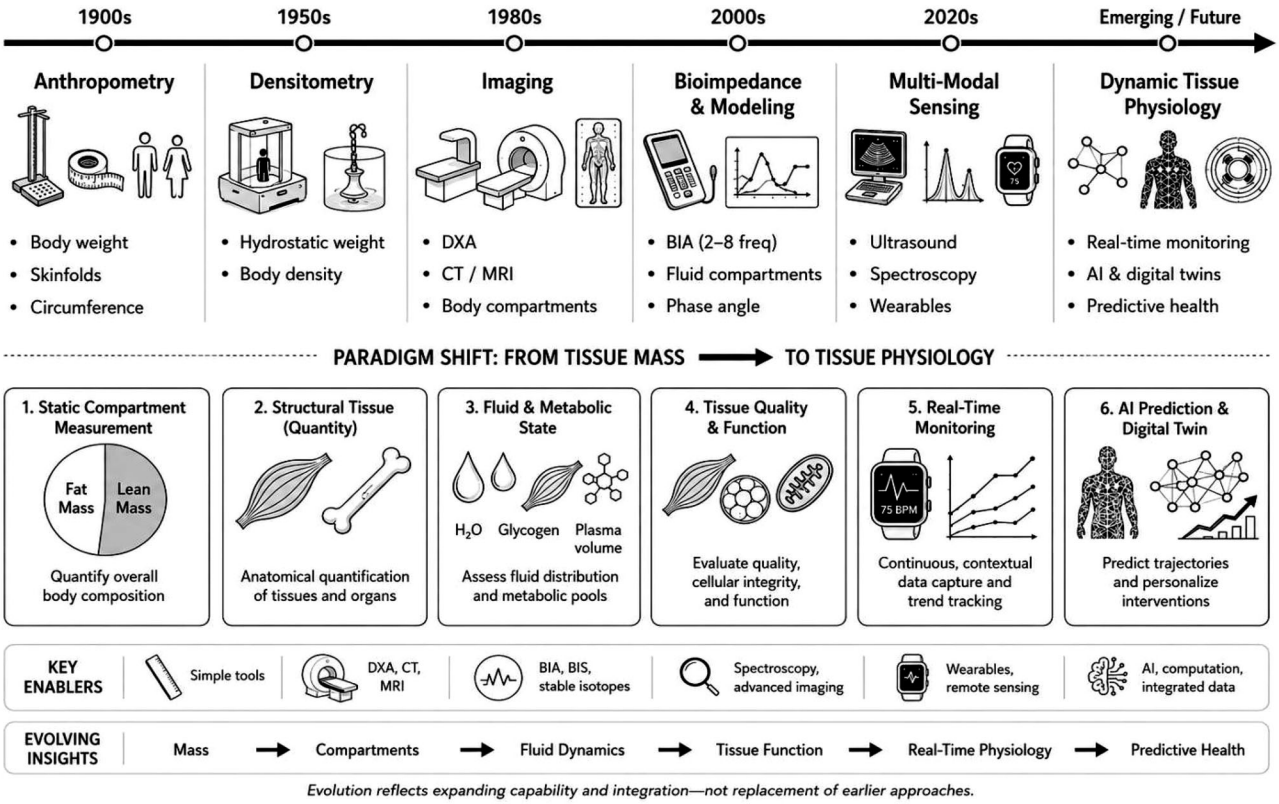



**Fig. 1 Evolution of body composition science from anthropometric estimation to dynamic physiological modeling.** Early approaches relied on anthropometry and densitometry to estimate body fat. Mid-twentieth-century advances introduced chemical and multicompartment models incorporating water, mineral, and protein. Imaging technologies such as DXA, CT, and MRI enabled regional tissue characterization. Emerging approaches integrate imaging, bioimpedance spectroscopy, isotope methodologies, wearable sensors, and artificial intelligence to support dynamic physiological models capable of predicting tissue adaptation and health outcomes. This figure was prepared using AI tools.

of tissue function or prediction of future state. The defining feature of dynamic body composition is not the adoption of new technologies per se, but the ability to provide physiologically meaningful information that improves prediction, interpretation, and ultimately clinical or performance decision-making.

## POWER AND LIMITS OF STATIC MODELS

Traditional body composition models conceptualize the body as a hierarchy of compartments. The two-compartment model divided body mass into fat mass and fat-free mass. Predictions from two-compartment models applied to density measurements reached practical limits in the 1980s with an appreciation for the high variability that could exist between individuals in the density of the fat-free mass, especially from the bone mineral and water components. Three- and four-compartment models incorporating water, bone mineral, and protein improved accuracy and reduced assumptions [7, 8]. The five-level model, articulated by Wang and colleagues, organized body composition from atomic to molecular, cellular, tissue-system, and whole-body levels [1]. This framework remains foundational because it clarifies that each level measures only certain aspects of biological structure. These models provided the methodological foundation for modern body composition research and technologies including DXA, isotope dilution, CT, MRI, air-displacement plethysmography, neutron activation analysis, and bioelectrical impedance. Recent efforts to formalize definitions of the components at each level further advance standardization of measurement terminology and methods [9, 10].

These static models remain foundational, but emerging technologies increasingly extend their physiological interpretation. Two individuals with the same appendicular lean mass can differ in strength, mitochondrial function, lipid infiltration, cellular hydration, and metabolic health. Two individuals with the same total fat mass can differ markedly in visceral adipose tissue, hepatic fat, intermuscular fat, and cardiometabolic risk. A DXA-derived change in lean soft tissue may reflect true muscle remodeling or glycogen and water shifts, edema, or changes in extracellular fluid. Therefore, the next phase of the field must address not simply "how much tissue?" but "how is it clinically meaningful?"

Several presentations at ISBCR 2025 illustrate this transition from increasingly precise compartment measurement toward physiologically informative and potentially actionable phenotyping (Table 1). These examples shift the central question from whether a new method can measure a body component more accurately to whether the additional information improves biological interpretation, prediction, or clinical and performance decision-making.

## THE EVOLUTION OF FUNCTIONAL BODY COMPOSITION: FROM TISSUE QUANTITY TO TISSUE PHYSIOLOGY

### Adipose tissue: from total fat to regional biology

The world is most familiar with three terms in body composition because of the emphasis in public health for BMI, waist circumference, and percent body fat. For several decades, percent body fat has functioned as a metonym for body composition in both clinical and lay discussion, despite representing only one dimension of a far more complex physiological system [11]. This component could be readily estimated from anthropometry and impedance [12–14]. Traditional assessments of total adiposity remain useful because of their simplicity, accessibility, and extensive outcome data, but regional methods can provide

**Table 1.** From body composition measurement to physiological phenotyping: emerging directions illustrated at the 12th ISBCR meeting.

| Emerging direction | Conventional approach | Illustrative examples from ISBCR 2025 | Potential added value | Key question |
|---|---|---|---|---|
| From total adiposity to depot-specific risk | BMI, waist circumference, total fat mass, percent body fat | Visceral adipose tissue in relation to metabolic syndrome, insulin resistance, and prediabetes; high interindividual VAT variation at higher levels of adiposity | Identifies biologically important differences in fat distribution that may be obscured by similar BMI, waist circumference, or percent body fat | Does accurately predicted VAT improve individual risk stratification, treatment or monitoring beyond simpler anthropometric measures? |
| From lean mass to tissue-specific skeletal muscle | DXA lean soft tissue or BIA-derived fat-free/lean mass as proxies for muscle | $D_3$-creatine dilution examined in relation to body composition and muscle strength | Assessment of skeletal muscle may distinguish actual quantity from other components of lean tissue and improve associations with function | Does a muscle-specific measure provide clinically or functionally meaningful information beyond DXA lean mass or BIA estimates? |
| From static composition to dynamic tissue response | Cross-sectional assessment of body weight and tissue masses | Changes with physical inactivity/sedentary behavior from space science and clinical research; changes in maternal adipose depots during pregnancy | Treat body composition as a responsive physiological phenotype that changes with behavior, environment, and life stage | Do trajectories and rates of tissue change predict physiological adaptation or health outcomes better than a single measurement? |
| From weight loss to quality of weight loss | Treatment success defined primarily by kilograms or percentage of body weight lost | Muscle and bone loss during anti-obesity pharmacotherapy, including GLP-1 receptor agonist treatment | Determines what is being lost rather than simply how much, potentially identifying undesirable loss of muscle or bone during otherwise successful treatment | Does measurement of tissue-specific change alter exercise, nutrition, drug treatment, or monitoring decisions during weight loss? |
| From tissue quantity to tissue quality and function | Amount of fat-free mass, lean mass, or skeletal muscle | Relationships between muscle-specific measures and strength; BIA measures including phase angle and raw impedance parameters | May identify differences in functional capacity or physiological condition among individuals with similar tissue mass | Which measures of tissue quality provide information about strength, metabolic health, resilience, or clinical outcome beyond tissue quantity alone? |
| From prediction equations to physiological bioimpedance | BIA used principally to predict fat mass, fat-free mass, skeletal muscle mass, or other reference method outputs | "Have we reached peak impedance?"; studies of BIS, raw bioelectrical parameters, diurnal variation, and water redistribution | Shifts emphasis from reproducing DXA-derived compartments to exploiting impedance for information on fluid distribution and tissue electrical properties | Can raw impedance, spectroscopy, or derived physiological characteristics provide useful information not obtained simply by improving body composition equations? |
| From conventional imaging to quantitative phenotyping | CT, MRI, or DXA used primarily for tissue segmentation and quantification | AI in body-composition research and emerging spectral photon-counting CT | Automated and potentially richer characterization of tissue amount, distribution, composition, and quality from existing or next-generation images | Can AI or advanced imaging extract phenotypes that improve prediction, diagnosis, or treatment beyond conventional tissue area, volume, or mass? |
| From measurement accuracy to actionable information | New methods judged predominantly against a reference method using bias, precision, agreement, or correlation | Collectively illustrated by the Auckland presentations on VAT, muscle, pharmacologic weight loss, AI, imaging, and impedance | Reframes validation around whether a measurement improves understanding, prediction, decision-making, or outcomes | Does the new measurement change what we know, predict, or do? |

Examples are drawn from presentations and abstracts at the 12th International Symposium on In Vivo Body Composition Research (ISBCR), Auckland, New Zealand, 2025. They are intended to illustrate emerging directions rather than provide a comprehensive summary of the meeting.
*BIA* bioelectrical impedance analysis, *BIS* bioimpedance spectroscopy, *CT* computed tomography, *DXA* dual-energy X-ray absorptiometry, *VAT* visceral adipose tissue.

additional information on adipose tissue distribution that is not captured by total fat mass alone. Multifrequency BIA and DXA-derived VAT estimates are examples of increasingly practical approaches to regional adiposity assessment. Nevertheless, some simple measures have continuing usefulness. Mid-upper-arm circumference remains a practical clinical marker of malnutrition and cachexia, particularly when depletion of fat stores is accompanied by loss of muscle mass [15].

Total body fat is a crude predictor of metabolic risk because adipose tissue depots differ in physiology. Visceral adipose tissue is strongly associated with insulin resistance, dyslipidemia, hepatic steatosis, inflammation, and cardiometabolic disease, whereas subcutaneous adipose tissue may have more heterogeneous or even protective roles depending on location and context [16–18]. The Auckland program included work on visceral adipose tissue thresholds, adipose tissue depot changes during pregnancy, MRI-derived adipose phenotypes in UK Biobank, and South Asian body composition phenotypes associated with cardiometabolic risk [19–21]. These themes point toward regional and depot-specific phenotyping as the future standard.

Imaging methods such as CT, MRI, and DXA have long been able to quantify regional tissues, but manual segmentation limited scalability. Artificial intelligence now changes the equation. Automated segmentation can identify VAT, SAT, skeletal muscle, liver fat, muscle attenuation, and organ volumes rapidly and reproducibly across large datasets. This transforms imaging from a specialized research method into a scalable phenotyping engine [22].

Opportunistic body composition analysis is a particularly promising application. Clinical CT and MRI scans are already acquired for many indications.

### Skeletal muscle: from mass to quality

Skeletal muscle is a leading example of the field's conceptual transition. Traditional methods quantify muscle mass or lean soft tissue, but muscle quantity alone does not adequately explain strength, mobility, metabolic function, or resilience [23]. The decline in strength with aging often exceeds the decline in muscle mass, implying changes in tissue quality, neuromuscular activation, fat infiltration, and cellular physiology [24, 25]. At ISBCR 2025, muscle assessment was a major theme. Plenary and short oral sessions included assessment of muscle in clinical settings, bedside muscle assessment during critical illness, ultrasound validation against MRI, D3-creatine dilution, and muscle quality in relation to physical performance [26, 27]. This concentration reflects a broader field-wide recognition that "lean mass" is not synonymous with healthy, functional muscle.

At a predecessor meeting of the ISBCR series, the 1959 Conference on Techniques for Measuring Body Composition, Francis Moore described the clinical use of tracer monitoring of body fluid compartments and the concept of body cell mass [28]. Pierson invoked this seminal work of Moore at the 4$^{th}$ ISBCR, describing this use of body composition measurements to "assess failures in homeostasis (e.g., ratios of extracellular water to intracellular water) that may signal failing cell membranes" and provide early warning of disease [29]. Advances in bioimpedance technologies may now permit practical realization of many of these concepts.

Bioimpedance spectroscopy (BIS) and multifrequency BIA contribute to this shift by estimating intracellular water and extracellular water. ICW is closely related to body cell mass and muscle cellularity, while expansion of ECW relative to ICW may reflect edema, inflammation, disuse, or declining cellular integrity. Phase angle, derived from reactance and resistance, reflects the capacitive properties of cell membranes and has been associated with nutrition status, muscle strength, frailty, and survival [30]. Rather than predicting fat-free mass, the future value of BIS may be in providing physiological information on fluid distribution, membrane integrity, and tissue quality. Indeed, Ward has argued that prediction of mass from impedance may be approaching practical limits. Yamada's work in aging emphasizes ICW/ECW balance, segmental impedance, and the relationship between muscle composition and function [31]. These approaches extend muscle assessment from morphology toward cellular physiology.

This direction aligns with clinical imaging work by Prado and colleagues, who have shown that muscle radiodensity, adipose infiltration, and sarcopenic obesity can predict clinical outcomes beyond body weight or total fat-free mass [32]. When combined, imaging and BIS provide complementary perspectives; imaging defines tissue location, quantity, and morphology, whereas BIS provides complementary information on fluid compartments and electrical tissue properties. AI-enabled opportunistic analysis of routine clinical imaging may allow population-scale assessment of sarcopenia, myosteatosis, visceral adiposity, and organ fat without additional patient burden [32].

## THE ENABLERS: TECHNOLOGIES DRIVING THE NEW STATE-OF-THE-ART

### AI-enabled imaging

AI-enabled imaging is likely the most transformative near-term advance. It enables scale, standardization, reproducibility, and discovery. AI augments but does not replace expert interpretation and established imaging methodologies. Automated analysis can convert images into quantitative phenotypes based on muscle area and density, VAT volume, SAT distribution, liver fat, organ size, bone structure, and regional asymmetry [33]. With population-scale datasets such as UK Biobank and routine clinical imaging archives, AI can reveal phenotype-outcome associations that were previously inaccessible [34]. AI methods may improve segmentation, cross-calibration, artifact detection, and integration with MRI/CT reference datasets [35, 36].

Despite its transformative potential, AI should be viewed as an enabling technology, not an endpoint. AI-derived measurements require rigorous external validation across diverse populations, transparency in algorithm development, and appropriate regulatory oversight before clinical implementation. Particular attention must be given to explainability, reproducibility, and automation bias. Ultimately, the success of AI will be determined by its ability to generate physiological insights that improve clinical decision-making and health outcomes.

### Bioimpedance spectroscopy and distributed sensing

BIS and multifrequency BIA have moved beyond fat-free mass prediction. Although considerable methodological challenges remain, the emphasis is increasingly shifting from estimating body compartments to characterizing tissue physiology. Segmental devices, raw impedance vectors, phase angle, and ICW/ECW estimates can provide information about cellular hydration, extracellular expansion, and tissue integrity [37]. Emerging electrode arrays and wearable impedance devices may eventually permit regional or repeated monitoring of fluid shifts in clinical, athletic, and operational settings. The broader principle is that distributed sensing may make body composition more frequent, contextual, and practical. However, physiological interpretation of BIS remains constrained by inter-device variability, electrode configuration, posture and hydration effects, model assumptions, and the absence of widely accepted clinical decision thresholds; harmonized acquisition and reporting standards will therefore be essential for broader clinical application [10].

### Spectroscopy and tissue chemistry

Spectroscopic approaches provide an emerging means of extending body composition assessment from tissue quantity toward tissue chemistry and metabolism. Near-infrared spectroscopy can characterize skeletal-muscle oxygenation and oxidative metabolism, while proton magnetic resonance spectroscopy

enables non-invasive quantification of ectopic lipid in liver and skeletal muscle. Phosphorus magnetic resonance spectroscopy provides complementary information on muscle bioenergetics and mitochondrial oxidative capacity, and Raman-based approaches can characterize adipose tissue lipid composition and molecular phenotype [38–41]. Their potential contribution is to connect structural body composition with tissue chemistry and metabolism.

### Wearables and contextual monitoring

Wearable sensors provide temporal context for interpreting body composition changes by capturing activity, sleep, environmental exposures, physiological strain, and recovery. Emerging wearable impedance technologies may eventually support longitudinal monitoring of fluid compartments outside the laboratory [42, 43].

### Digital physiological models

The integrative endpoint is a digital physiological model, or "digital twin," in which imaging, fluid compartments, biomarkers, wearables, and environmental context are combined to predict tissue trajectories [37, 44, 45]. This is where body composition science moves from description to prediction. The next advance is not simply better measurement; it is the ability to forecast how tissues will respond to diet, training, obesity pharmacotherapy, disease, immobilization, aging, or operational stress.

## FROM MEASUREMENT TO PREDICTION: DYNAMIC BODY COMPOSITION

Although body composition is often represented as a static state measured at a single point in time, biological tissues exist in continuous flux. Every tissue compartment reflects the balance between ongoing anabolic and catabolic processes that are modified by environmental and physiological influences. Accordingly, dynamic body composition can be conceptualized as a time-dependent state in which tissue quantity and quality evolve continuously in response to internal regulation and external perturbations.

This concept can be represented schematically as:

$$X(t+1) = X(t) + A(t) - C(t) + E(t) + R(t)$$

where **X(t)** represents the current physiological state of a tissue or body composition phenotype, **A** represents anabolic or accretion processes (e.g., protein synthesis, tissue growth, cellular hydration), **C** represents catabolic losses (e.g., proteolysis, lipolysis, inflammation, disuse, aging), **E** represents external and environmental drivers including nutrition, physical activity, sleep, medications, environmental stressors, illness, and psychosocial stress, and **R** represents intrinsic regulatory and adaptive responses that modify tissue remodeling, recovery, and homeostasis over time.

Each term in the equation represents multiple interacting physiological processes rather than a single measurable variable. The model is therefore intended as a conceptual framework illustrating that body composition reflects a dynamic equilibrium between tissue accretion, tissue loss, environmental inputs, and adaptive regulation. Different tissues, including adipose tissue, skeletal muscle, bone, and body water, may be characterized by distinct values for these components and operate over different biological time scales, ranging from hours for fluid shifts to months or years for structural remodeling. This framework clarifies why static measurements may be physiologically incomplete. Early weight loss may reflect glycogen and water depletion more than true fat loss. Apparent fat-free mass gain during training may include extracellular fluid expansion before true hypertrophy [46]. Rapid loss of DXA lean soft tissue during illness may reflect fluid shifts, muscle catabolism, or both. Dynamic models help distinguish tissue remodeling from transient fluid changes.

This approach is especially relevant for new anti-obesity pharmacotherapies. At ISBCR 2025, the quality of weight loss with novel anti-obesity pharmacotherapy was a hot-topic session. The key question is not simply whether fat-free mass declines during weight loss, but whether observed changes reflect loss of functional muscle, reductions in organ mass, water shifts, or appropriate changes predicted by baseline body composition. Normalization, control populations, and physiological interpretation are critical [47, 48]. Viewed this way, body composition becomes more than simply a measurement of tissue quantity but a dynamic physiological phenotype whose future trajectory reflects the integration of biological adaptation, environmental exposure, and time.

## GENERALIZABLE AND INCLUSIVE MODELS

ISBCR 2025 emphasized indigenous data sovereignty, population-specific interpretation, and the meeting explicitly highlighted communities and researchers underrepresented because of geography, ethnicity, culture, or gender. This theme has direct implications for body composition modeling. Race and sex variables often function as imperfect proxies for underlying physiological variation and may reduce model generalizability when direct biological measures are available [49].

Future models should use direct physiological measurements whenever possible, quantifying tissue distribution, bone size, organ volume, ICW/ECW, limb proportions, hormonal state, and environmental exposure. The goal is not to ignore biological variation but to measure it more accurately and ethically. This is where AI requires special caution. Algorithms trained on biased datasets can reproduce inequities, while models based on physiological variables and transparent validation may improve fairness.

## APPLICATIONS: CLINICAL MEDICINE, POPULATION HEALTH, AND PERFORMANCE

In clinical medicine, dynamic body composition could improve early detection of deterioration. Phase angle and ECW/ICW provide information about cellular and fluid-compartment characteristics associated with frailty, muscle strength, and physical function that is not captured by muscle mass alone [30, 31]. CT-derived muscle radiodensity may identify myosteatosis and treatment vulnerability in cancer. Calcium isotopes may detect skeletal imbalance before BMD changes. Opportunistic imaging could embed body composition into routine clinical workflows [50].

In population health, regional phenotyping may improve risk stratification beyond BMI and waist circumference. VAT, liver fat, muscle quality, and ectopic lipid better explain metabolic heterogeneity than total body mass. Scalable imaging and AI may allow population-level mapping of these phenotypes, especially when combined with direct physiological measures and attention to equity.

In human performance, dynamic models may improve monitoring of adaptation and resilience. Athletes, military personnel, and physically stressed workers experience rapid changes in hydration, glycogen, muscle damage, inflammation, and recovery. Measures of muscle quality, fluid distribution, and contextual workload could provide earlier information than body mass or fat-free mass alone. Future applications will increasingly integrate physiological monitoring, shifting body composition assessment from periodic snapshots toward characterization of dynamic and longitudinal change (Fig. 2).

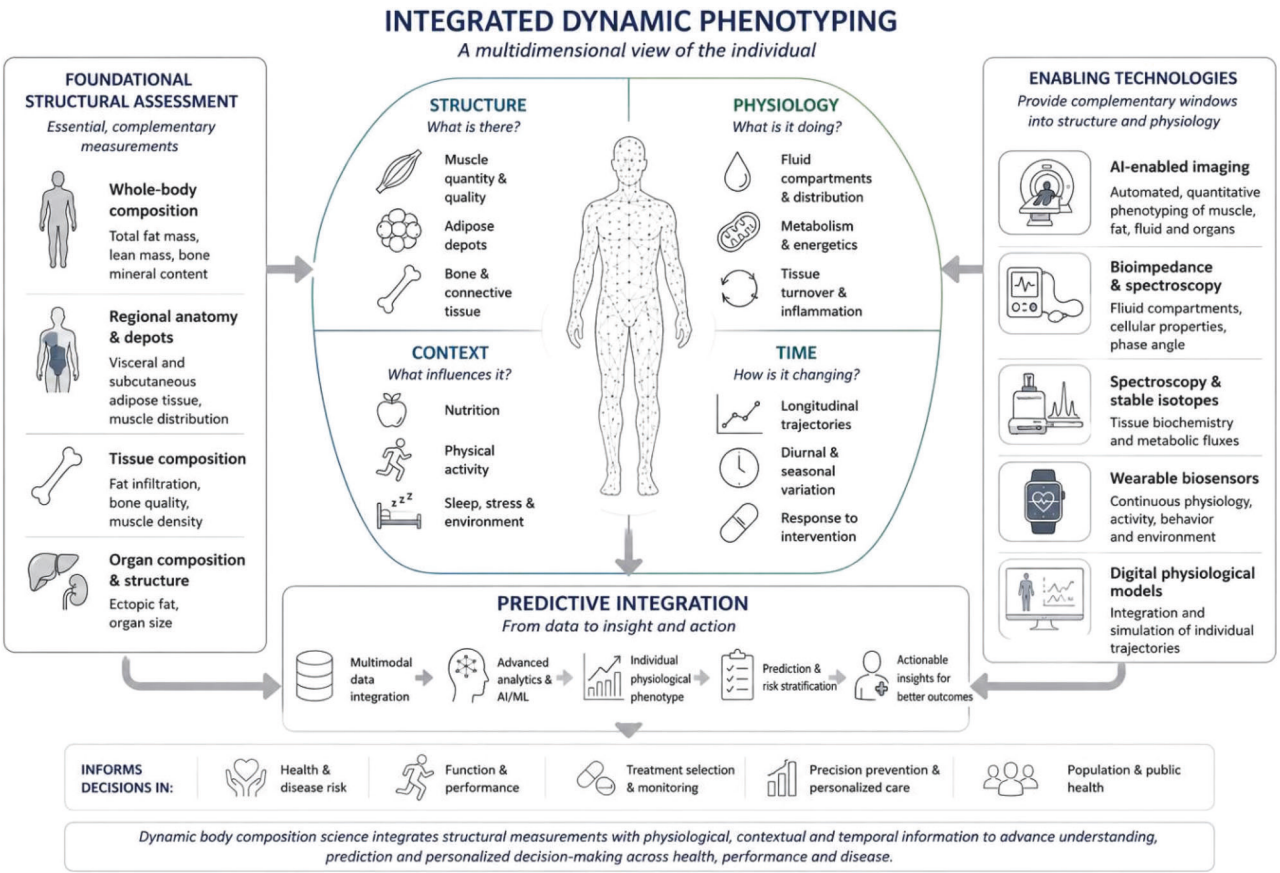



**Fig. 2 Conceptual framework for integrated dynamic body composition phenotyping.** Foundational structural assessments of whole-body composition, regional anatomy, tissue composition, and organ structure remain essential but are extended by measurements that characterize four complementary dimensions of the individual: structure (what is there), physiology (what it is doing), context (what influences it), and time (how it is changing). Emerging technologies provide additional information across these dimensions. Integration of multimodal data may generate individualized physiological phenotypes and longitudinal trajectories that improve prediction, risk stratification, and actionable decision-making for health, disease, treatment, and human performance. Dynamic physiological phenotyping complements established body composition measurements with added value from improved physiological interpretation, prediction, or decision-making. This figure was prepared using AI tools.

## PRIORITIES FOR THE NEXT DECADE

Insights emerging from ISBCR 2025 suggest several priorities that may shape the future development of body composition science. These priorities reflect both technological advances and evolving conceptual frameworks emphasizing physiological interpretation and integrative modeling.

### Build generalizable physiological models

Historically, many prediction equations incorporated demographic variables such as race or sex as proxies for physiological variation. Future models should emphasize direct measurement of physiological attributes to improve both biological accuracy and generalizability across populations.

### Move beyond tissue quantity toward tissue physiology

Future research should prioritize measurements that capture physiological properties of tissues. Indicators of cellular hydration, tissue lipid infiltration, metabolic activity, and tissue remodeling can provide earlier and more informative markers of health and performance status than mass measurements.

### Integrate structural and functional measurements

Advances in imaging, bioimpedance spectroscopy, stable isotope methodologies, and metabolic spectroscopy provide complementary insights into tissue composition and physiology. Integrating these modalities will allow investigators to characterize tissues across multiple biological scales, linking anatomical structure with metabolic and cellular processes.

### Develop longitudinal monitoring frameworks

Body composition is not static but continuously influenced by nutrition, physical activity, aging, disease, and environmental stress. Future approaches should emphasize repeated or continuous monitoring capable of capturing dynamic physiological adaptation over time rather than relying solely on single-point assessments.

### Integrate body composition into systems-level physiological modeling

Advances in computational modeling and AI enable integration of imaging data, physiological measurements, behavioral information, and environmental context to support individualized prediction of health trajectories, responses to therapeutic interventions, and adaptation to physiological stressors.

### Develop practical and scalable assessment tools

For body composition science to achieve broad clinical and public health impact, future methods must balance physiological sophistication with practicality, cost, and accessibility. Future innovation should therefore emphasize approaches that are rapid, low-burden, inexpensive, fieldable, and compatible with clinical workflows. The greatest advances will likely come from

technologies that bring physiologically meaningful assessment to large populations.

These priorities reflect an evolving view of body composition not simply as a structural description of the body but as an integrative framework for understanding human physiology.

## CHALLENGES

The new paradigm also faces substantial challenges. Validation remains essential.

Emerging methods must be tested against appropriate reference standards and, where no perfect standard exists, against physiologically meaningful outcomes. Standardization is equally important. Device differences, protocols, posture, hydration, timing, and software versions can all affect interpretation [51].

Interpretability is a major challenge for AI. A model that predicts risk without explaining which tissues or mechanisms drive risk may have limited scientific value. Accessibility is another concern. The future of the field cannot be limited to wealthy institutions with advanced imaging. Fieldable, affordable, and globally applicable technologies remain essential, consistent with the ISBCR emphasis on low- and middle-income country capacity and global participation.

An important challenge identified by several investigators at ISBCR 2025 is that advances in body composition assessment must ultimately demonstrate added value beyond existing approaches. Future progress should be evaluated not only by improvements in measurement precision but also by whether new measurements alter clinical decisions, improve risk stratification, or enhance prediction of meaningful outcomes. The field has developed increasingly sophisticated methods for assessing adipose tissue distribution, skeletal muscle quality, liver fat, and fluid compartments; however, consensus frameworks linking these measurements to specific clinical and research decisions remain underdeveloped. Future work should therefore focus on defining actionable body composition phenotypes and establishing decision algorithms that demonstrate clear value beyond conventional measures such as BMI, waist circumference, and body weight [23].

## CONCLUSION

Body composition science has historically focused on quantifying structural compartments: fat, fat-free mass, water, mineral, and protein. Those measurements remain foundational. However, themes emerging from ISBCR 2025 suggest that the field is entering a new phase in which tissues are increasingly understood as dynamic physiological systems. The state-of-the-art now includes AI-enabled imaging for regional phenotyping, bioimpedance spectroscopy for fluid compartments and cellular integrity, stable isotope methods for turnover, spectroscopy for tissue chemistry, and wearables for real-world context. The future lies in integrating these methods into predictive models that explain why tissues change and forecast what they will become. The dynamic physiological framework proposed here should be viewed as a natural extension of the Functional Body Composition paradigm articulated by Muller and Bosy-Westphal, in which tissues are interpreted through their physiological roles, regulatory interactions, and adaptive responses. This defines the next generation of body composition research and its applications in clinical medicine, population health, and human performance.

Across all emerging technologies, future success will depend on demonstrating reproducibility, standardization, physiological interpretability, and measured improvements in clinical and research decision-making.

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## AUTHOR CONTRIBUTIONS

All authors were involved in all aspects of the conception of this work and the information synthesis. KEF, AWP, and JM-C supervised the work; KEF, AWP, JM-C, YY, JAS, LCW, DG, and SBH participated in writing and approval of the final version of the paper.

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## COMPETING INTERESTS

The authors declare the following potential competing interests: SB Heymsfield and Y Yamada have consulted for Tanita, LC Ward provides consulting services to ImpediMed Ltd, and JA Shepherd has received industry-sponsored grants from Tanita, Samsung, InBody, served on a scientific advisory board for Styku, and is a manufacturer of body composition phantoms as co-owner of Precision Composition, LLC. No other conflicts of interest are declared.

## ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable to this mini-review.

## ADDITIONAL INFORMATION

**Correspondence** and requests for materials should be addressed to Karl E. Friedl.

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