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Opportunistic Imaging-based Assessment of Sarcopenia and Visceral Adiposity using Routine Abdominal CT: Clinical Applications and Implications for Personalized Patient Management

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ABSTRACT:

Background: Many millions of CT scans are performed around the world every year, yet much of the skeletal muscle and abdominal fat data contained in these scans goes unreported. By harnessing this body composition information, opportunistic screening for sarcopenia, myosteatosis, and visceral fat may be possible, without additional radiation dose, cost, or patient visits.

Methods: A systematic search of the literature from 2020–2025 was performed on Pub Med using synonyms of CT-derived muscle/fat metrics, automated segmentation, reference values and clinical outcomes. Twenty peer-reviewed studies and reviews were selected and their quantitative results were abstracted into evidence tables.

Results: Deep-learning-based pipelines can segment skeletal muscle, visceral adipose tissue (VAT), and subcutaneous adipose tissue (SAT) with Dice coefficients ranging from 0.87 to 0.98. A meta-analysis has found a pooled DICE coefficient of 0.941 for muscle segmentation. Cutoffs at L3 of a standardized L3 level corresponding to T-score of 2 at the L3 level have been defined (36.3 cm2/m2 in men, 27.5 cm2/m2 in women)1. In a sample of 9,223 asymptomatic adults, muscle attenuation was associated with better mortality prediction compared to a clinical risk score, with five-year area under the curve (AUC) of 0.721 vs. 0.688 for L3 attenuation and the Framingham score, respectively; BMI had an AUC of 0.499. Several measures of sarcopenia and adiposity have been associated with prognosis in those with cancer, spinal metastases, COVID-19, cardiogenic shock, and acute pancreatitis, although effect sizes and best metrics differ among clinical contexts.
Conclusions: Opportunistic body composition evaluation is regarded as sophisticated and clinically relevant. The barriers for its widespread implementation are its harmonized thresholds, validation in different populations and using different scanners, and the demonstration that interventions based on the results can be translated to better clinical outcomes. It is suggested to establish a pragmatic body composition reporting and care-pathway model for personalized management of patients.

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1. INTRODUCTION

The clinical marker of adiposity as reported by the body mass index (BMI) remains unchanged; yet, the limitations of BMI to distinguish muscles and fat or visceral vs. subcutaneous deposits are well recognized. Patients with identical BMIs can have vastly different metabolic and survival outcomes, with the prevalence of systematic misclassification being high for sarcopenic obesity (Pekar et al., 2025). Cross-sectional imaging for tissue quantification of tissue compartments can address these limitations by using the individual images' existing study (opportunistic imaging concept), which typically has been performed for another indication (Linder et al., 2024).

Until recently, the limiting factor in applying this technique on a large scale was the long analysis time for manual segmentation (15-20 min per patient on a single slice), which made population scale application nonviable (Pekar et al., 2025). With recent progress in deep learning techniques, analysis time has been reduced to seconds, enabling the development of fully automated quality-controlled analysis pipelines (Nowak et al., 2022; Bedrikovetski et al., 2022). Simultaneously, analysis in large screening cohorts with long-term follow-up showed that CT-derived measures of muscle and fat were predictive of fracture, cardiovascular events, diabetes and death (Lee et al., 2025; Pickhardt et al., 2022).

With these recent improvements, three roadblocks hold the promise of making these findings a regular part of radiologic report. What the quantification and cutoffs radiologists should report is needed? How reproducible and generalizable are these automated methods between scanners, phases of contrast, and among patients? When in the clinical workup does this information change management? This review attempts to answer these questions by summarizing recent data, providing quantitative comparisons as tabular and figure representations, and suggesting a framework between opportunistic CT finding and individualized management.

2. METHODS

2.1 Search Strategy

In November 2026 a formal search was performed through Pub Med to identify all published articles from 1 January 2020 to 31 December 2025. Search blocks were based on a combination of controlled vocabulary and free text: (1) opportunistic CT in context of sarcopenia and skeletal muscle at L3 (2) visceral adipose tissue in context of opportunistic CT screening and outcome (3) deep-learning based automated segmentation of body composition in context of muscle and fat and (4) relationship between sarcopenia and survival in cancer as defined by CT scans, including meta-analyses.

2.2 Selection and data extraction

Screening was performed at the level of the title and abstract. Studies were included if they 1) provided a quantitative computer tomography (CT)-based measure of muscle and/or fat, or values thereof, 2) validated an automated segmentation, 3) demonstrated a relationship between a CT-based measure and a clinical outcome, 4) provided a CT measure related to a published quantitative measure (for meta-analyses of quantitative research only), 5) published a reference CT value, 6) in a pediatric or pediatric-outcome study, or 7) was at the thigh or hip level when such information was necessary for the technical generalizability of the data. Twenty publications met our inclusion criteria. For all publications, the design, number of subjects, level of measurement, metrics, and main numerical results were extracted exactly as they were reported by the authors. No results were re-estimated or pooled; all figures and tables below merely reproduce published numbers.

This work is a narrative review with structured searching rather than a systematic review with risk-of-bias scoring, and one database was used; these methodological considerations are outlined in the Limitations section.

3. TECHNICAL FOUNDATIONS OF OPPORTUNISTIC BODY-COMPOSITION ANALYSIS

3.1 Landmarks and Metrics for Measurement

The lumbar vertebrae 3 (L3) has been the conventional level used when evaluating sarcopenia as one axial slice at L3 is reflective of whole-body muscle and fat. This becomes problematic when using chest CT or scans of the pelvis, where L3 is often not included in the image (Pickhardt et al, 2022). Several papers have demonstrated that attenuation at L1, which can be captured on both chest and abdominal CT, as well as measures of muscle attenuation at L1, may be predictive of outcomes (Pickhardt et al, 2022). Zannoni et al (2020) found a significant correlation between attenuation of the psoas at L3 and hip musculature ($r = 0.491$-0.754) in a series of 50 patients. A summary of the most common metrics used is included in Table 1.

Table 1. Principal CT body-composition metrics used in opportunistic assessment

Metric	Definition	Clinical interpretation (as used in the reviewed studies)
Skeletal muscle index (SMI)	Muscle cross-sectional area at a landmark slice divided by height squared (cm^2/m^2)	Low values indicate myopenia/sarcopenia; sex-specific thresholds are required (Bongers et al., 2022; Ju et al., 2025)
Skeletal muscle density (SMD) / attenuation	Mean CT attenuation of muscle (Hounsfield units, HU)	Low values indicate fatty infiltration (myosteatosis); strong predictor of death and fracture (Pickhardt et al., 2022)
Visceral adipose tissue (VAT) area	Intra-abdominal fat area on the landmark slice (cm^2)	Higher values linked to cardiometabolic risk and adverse outcomes in acute illness (Lee et al., 2025; Salam et al., 2023)
Subcutaneous adipose tissue (SAT) area	Fat area beneath the skin on the same slice	Association with mortality may be U-shaped (Lee et al., 2025)
Visceral-to-subcutaneous ratio (VSR)	VAT area divided by SAT area	Marker of fat distribution; high values predict death, cardiovascular events and diabetes (Lee et al., 2025)
Intermuscular adipose tissue (IMAT)	Fat between muscle groups	Associated with ICU admission or death in COVID-19 (Bunnell et al., 2021)
Liver attenuation	Mean attenuation of liver parenchyma (HU)	Low values reflect hepatic steatosis; adds mortality information (Lee et al., 2025)

Definitions follow the cited studies. SMI = skeletal muscle index; HU = Hounsfield units.

3.2 Automation and quality control

Contemporary pipelines move through several stages, including target slice auto registration, tissue-class segmentation, measurements, and autoregistration quality control. (Fig. 6, Section 6) Nowak et al. (2022) built a 2-network pipeline in which a slice-extraction network is followed by a segmentation network, with machine-learning quality control used to predict the segmentation Dice score. Dabiri et al. (2020) found an average slice-localization error of 0.87 +− 2.54 in 1,748 CT volumes. The value of quality control is highlighted by the consequences of failures, especially in cases with metallic implants: In the study of Nowak et al. (2022), a strict quality-control setting excluded 39 of 364 patients, including eight patients with implants.

4. RESULTS

4.1 Segmentation accuracy

Studies have consistently shown high accuracy in the deep-learning segmentation of muscle and fat on CT. Evidence can be seen in Table 2 and Figure 1. A systematic review and meta-analysis of 24 studies (15 of which were included in the quantitative analysis) revealed pooled Dice coefficients of 0.941, 0.963, and 0.967 for skeletal muscle, VAT, and subcutaneous adipose tissue (SAT), respectively. However, significant heterogeneity and publication bias was found in muscle studies (Bedrikovetski et al., 2022). Interestingly, VAT proved to be the most difficult in some studies, with a lower Dice coefficient of 0.87 for contrast-enhanced CT than for non-contrast CT (0.92) by Shen et al. (2023). Meanwhile, muscle achieved high Dice coefficient values (0.95-0.96) across both modalities.

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Table 2. Performance of automated CT body-composition segmentation tools

Study	Population / scan type	Key performance results
Nowak et al. (2022)	Dual-centre, abdominal CT (n = 364 for end-to-end test)	Dice: muscle 0.95, VAT 0.98, SAT 0.97; mean relative area deviation 3.3% (muscle), 3.0% (VAT), 2.7% (SAT)
Dabiri et al. (2020)	Cancer patients, 1,748 volumes for L3 localization	Slice error 0.87 ± 2.54; Jaccard 97% (muscle, VAT), 98% (SAT), 83% (IMAT)
Shen et al. (2023)	Lung-cancer cohort; enhanced and plain CT at L3	Dice enhanced/plain: SAT 0.93/0.90; muscle 0.96/0.95; VAT 0.87/0.92
Zopfs et al. (2020)	Spectral detector CT; test–retest (n = 48) and BIA comparison (n = 39)	Slice classification accuracy 98.7%; concordance 0.99 (muscle, SAT) and 0.98 (VAT)
Bedrikovetski et al. (2022)	Meta-analysis: 24 studies, 15 pooled	Pooled Dice: muscle 0.941, SAT 0.967, VAT 0.963, bone 0.970
Jung et al. (2024)	Gastroesophageal adenocarcinoma staging CT	Dice ≥ 0.94 ± 0.06 for muscle and fat compartments
Lee et al. (2022)	Pediatric whole-body CT (transfer learning)	Average Dice 99.28% after transfer learning; little effect of age, sex or BMI
Yoo et al. (2022)	Thigh CT vs DXA (n = 100)	CT–DXA correlation R = 0.813–0.98; DXA overestimated thigh lean mass by about 10%

BIA = bioelectrical impedance analysis; DXA = dual-energy X-ray absorptiometry. Values are reproduced from the cited publications.

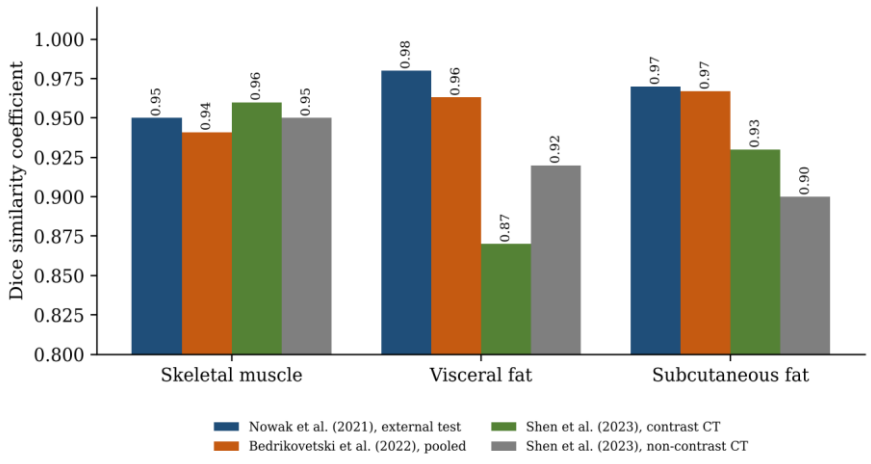


Figure 1. Dice similarity coefficients of automated segmentation for three tissue compartments in studies reporting Dice values (Nowak et al., 2022; Bedrikovetski et al., 2022; Shen et al., 2023).

Other reference methods have also been used to validate automated tools. Zopfs et al. (2020) showed almost perfect repeatability in patients who were examined twice. In addition, Yoo et al. (2022) confirmed a good correlation between segmentation of the thigh by CT and DXA; however, DXA was found to systematically overestimate lean mass, further supporting the idea that CT is the more specific technique anatomically. These findings overall imply that the accuracy of

segmentation is no longer a limitation in muscle and subcutaneous fat assessment, yet visceral fat on contrast-enhanced images is likely to be a key weakness and must be validated at the study site.

4.2 Reference values and thresholds

Another common issue cited with CT sarcopenia research is the lack of standardized cutoffs based on population, tool, and outcome. Ju et al. (2025) were able to solve this issue by performing a meta-analysis of 14 studies comprising 16,958 healthy, young adult (~18-45 years old) individuals and derived T-score-style references: 2 SD below the mean of healthy young adults. The values are displayed in Table 3 and in Figure 2. There was also significant heterogeneity in all studies for every measure so these cutoffs are meant to serve as a harmonized baseline rather than a definitive cutoff.

Table 3. Reference means and T-score −2 cutoffs for L3 CT muscle metrics in healthy young adults (Ju et al., 2025)

Metric	Men: mean	Men: cutoff	Women: mean	Women: cutoff
Skeletal muscle index (cm^2/m^2)	54.6	36.3	42.4	27.5
Skeletal muscle density (HU)	47.4	36.4	43.6	28.1
Interstudy SD, SMI	5.4	–	4.3	–
Interstudy SD, SMD (HU)	1.9	–	3.2	–
Individuals contributing (SMI)	11,819	–	5,139	–

SMI data: 14 studies; SMD data: 7 studies (11,175 individuals). Cutoff = T-score of −2.

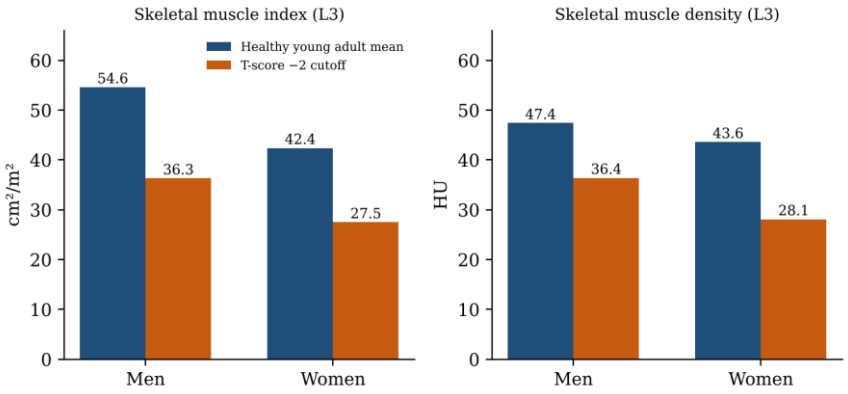


Figure 2. Healthy young-adult reference means and T-score −2 cutoffs for skeletal muscle index and density at L3 (data from Ju et al., 2025).

A prominent feature of this is its conceptual similarity to bone densitometry; patients are benchmarked with a young healthy reference subject, classified by distance from the mean in a wellknown way to clinicians and may make reporting less complicated. It is important to emphasize that the previous disease-specific cutoffs (for example the cut-offs of 52.4 cm2/m2 for men and 38.5 cm2/m2 for women used by Bongers et al (2022) in oncology) were created for prognostic purposes for cancer, and should not be confused with population reference values.

4.3 Prognostic Value in Screening Populations

The strongest data consists of a cohort of 9223 asymptomatic adults (mean age 57 years) who had previously undergone computed tomographic colonography screening and then were followed for 8.8 – 9 years on median (Lee et al., 2025; Pickhardt et al., 2022). Hip fracture was observed in 219 patients (2.4%) and death was reported in 549 patients (6.0%). Table 4 and Figures 3-4 summarize.

Table 4. Prognostic performance of CT-derived measures in the asymptomatic screening cohort (n = 9,223)

Predictor	Outcome	Discrimination (5-year AUC)	Hazard ratio (threshold)
L1 muscle attenuation	Hip fracture	0.717	2.20 (lowest quartile)
L3 muscle attenuation	Hip fracture	0.709	2.45 (lowest quartile)
FRAX score	Hip fracture	0.708	2.53 (highest quartile)
L1 muscle attenuation	Death	0.737	3.25 (lowest quartile)
L3 muscle attenuation	Death	0.721	3.58 (lowest quartile)
Framingham risk score	Death	0.688	2.82
Visceral-to-subcutaneous ratio	Death	0.661	3.1 (VSR > 1.53)
BMI	Death	0.499	–
Muscle attenuation < 15 HU	Death	–	5.4
Liver attenuation < 45 HU	Death	–	2.3

Note. Data from Pickhardt et al. (2022) and Lee et al. (2025). Muscle cross-sectional area at L1 and L3 was less predictive (5-year AUC ≤ 0.571; HR ≤ 1.56).

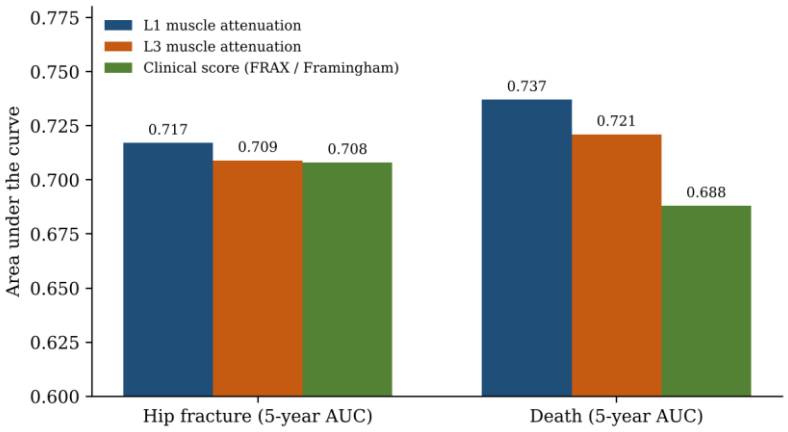


Figure 3. Five-year discrimination (AUC) of CT muscle attenuation at L1 and L3 compared with established clinical risk scores (Pickhardt et al., 2022).

Three important inferences can be made:

1. Muscle quality (attenuation) was a better predictor of adverse events than muscle quantity (CSFI), which supports reporting density in addition to SMI.
2. An automated CT index was as good or better than validated clinical scores.
3. BMI was almost useless as a predictor for death in the same sample (AUC 0.499), emphasizing the importance of compartment-specific measures (Lee et al., 2025).

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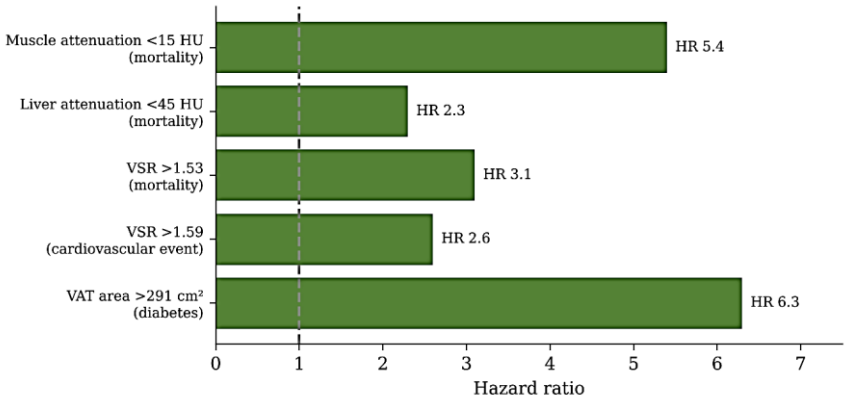


Figure 4. Hazard ratios for mortality and cardio-metabolic outcomes by CT-derived fat and muscle thresholds in the screening cohort (Lee et al., 2025).

4.4 Fat Distribution and Its Distinct Information

There are markedly different implications for metabolic health with regard to fat distribution. In relation to cardiovascular events and diabetes, increased visceral-to-subcutaneous fat ratio (VSR) and larger visceral adipose tissue (VAT) area were associated with a hazard ratio of 2.6 for VSR >1.59 and 6.3 for VAT area >291cm2 (Lee et al., 2025). Although subcutaneous adipose tissue (SAT) displayed a U-shaped association with mortality, with very low and high values leading to increased risk; this would again be unlikely to be captured on a single-slice AI report.

4.5 Prognostic Value in Disease-Specific Cohorts

Beyond screening, opportunistic assessments have also been studied among acutely ill and cancer populations (Table 5,Figure 5). For these conditions, association direction and strength varied by disease; for example, for cardiogenic shock and COVID-19, higher VAT or VAT/SAT were associated with worse outcomes, whereas for cancer and orthopedic oncology, lower muscle mass was the more consistent indicator of worse prognosis.

Table 5. Disease-specific studies of CT-derived body composition and outcomes

Study	Population (n)	Landmark	Principal findings
Salam et al. (2023)	Cardiogenic shock (152)	L3/L4	30-day mortality 59.2%. VAT area HR 1.004 (95% CI 1.002–1.007) and SM area HR 0.987 (0.975–0.999) were independent predictors
Bunnell et al. (2021)	COVID-19 inpatients (124)	Abdominal CT	VAT/SAT ratio HR 1.30 (1.04–1.62) and IMAT HR 1.44 (1.10–1.89) per SD for ICU admission or death, adjusted for BMI and comorbidity
Bongers et al. (2022)	Spinal metastases surgery (196)	L4	1-year mortality 66% with vs 41% without sarcopenia; HR 1.68 (1.08–2.61); HR 1.58 after adjusting for modified Bauer score
Twining et al. (2022)	Long-bone metastasis surgery (212)	L4	Higher VAT area and lower muscle attenuation associated with longer hospital stay; no association with 30-day complications

Study	Population (n)	Landmark	Principal findings
Jung et al. (2024)	Gastroesophageal adenocarcinoma (299)	Routine staging CT	Baseline measures not associated with survival; VAT loss > 70% at 6–12 months: mortality HR 1.99 (1.18–3.34), DFS HR 1.73 (1.01–2.95)
Roberto et al. (2024)	Breast cancer meta-analysis (16 studies, 6,130)	CT SMI / DXA	Sarcopenia prevalence 33%; higher risk of death (33%) and progression (29%); grade 3–4 toxicity OR 3.58 (2.11–6.06)
Tan et al. (2023)	Acute pancreatitis, systematic review (15 studies)	Abdominal CT	10 studies found a positive correlation between VAT and severity; 5 found none

HR = hazard ratio; CI = confidence interval; DFS = disease-free survival; IMAT = intermuscular adipose tissue.

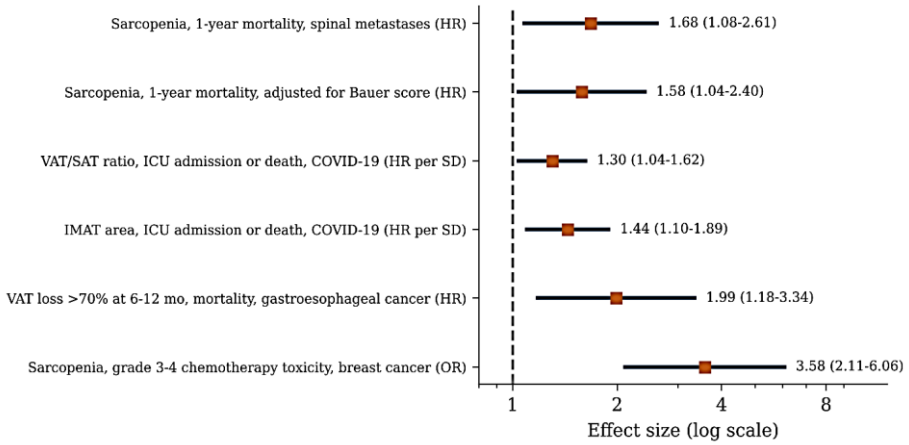


Figure 5. Effect sizes with 95% confidence intervals for selected disease-specific associations (data from Bongers et al., 2022; Bunnell et al., 2021; Jung et al., 2024; Roberto et al., 2024). The x-axis is logarithmic.

Two findings deserve specific comment. First, change over time may be informative in a way a baseline scan cannot reveal. In patients with gastroesophageal adenocarcinoma, baseline body composition was not prognostic; however, a drop in visceral adipose tissue (VAT) following surgery identified those patients with a higher rate of death and recurrence (Jung et al., 2024). Second, sarcopenia in breast cancer appeared to have a sizeable influence on the severity of chemotherapy toxicity (Roberto et al., 2024), a direct indicator of the potential use of body composition scanning in treatment planning. The evidence related to acute pancreatitis was mixed, leading the review authors to conclude that CT-quantified VAT is a "potentially useful but as yet unvalidated prognostic factor" (Tan et al., 2023).

4.5 Alternative Landmarks and Modalities

Extending assessment beyond the L3 slice maximises the opportunistic yield. Attenuation measured at L1 was comparable to L3 in 9,223 adults (Pickhardt et al., 2022), which allows the chest CT to be conducted, while muscle measurements at the hip level correlated with psoas measurements at L3, albeit requiring 2 minutes 12 seconds versus 41 seconds for the psoas at L3, thus L3 is rapidly becoming desirable for orthopaedic planning when body composition is important (Zannoni et al., 2020). A transfer learning applied model achieved a Dice coefficient of 99.28% on whole-body CT in paediatric patients, so an application in paediatrics looks to be technically possible (Lee et al., 2022).

5. DISCUSSION:

5.1 From Measurement to Decision

The data provided in Section 4 indicates that opportunistic CT can provide two unique types of risk information, first muscle quantity and quality (sarcopenia and myosteatosis) and second fat distribution (VAT, visceral to subcutaneous fat ratio, liver fat). But how do these results translate into a decision? It is suggested that the results should be reported along with the standard imaging reports, perhaps as a small structured block, with the measurements reported as a percentage of the sex-specific reference values shown in Table 3 with a clear statement of what tool and landmark was used.

5.2 Areas of application

- Oncology: Higher mortality and recurrence, as well as more severe chemo toxicity, has been found with sarcopenia among those with breast cancer (Roberto et al., 2024), along with 1-year mortality following surgery for those with spinal metastases (Bongers et al., 2022). Potential implementation could involve examination of dose adjustments, prehabilitation, nutrition, and shared decision-making for surgical procedures.

- Surgery and Orthopedics: Body composition has been associated with length of stay after long-bone metastasis surgery (Twining et al., 2022) and has potential to assist perioperative risk assessment if muscle metrics at L3 or the hip are accessible (Zannoni et al., 2020).

- Infection & Critical Care: VAT, skeletal muscle area and fat ratios are predictors of death or ICU admission in cardiogenic shock and COVID19 (Salam et al., 2023; Bunnell et al., 2021) where routine CT is readily available at admission.

- Preventive Medicine: In adults without symptoms, muscle attenuation, visceral-to-subcutaneous fat ratio, and liver attenuation were already predicting for all-cause mortality, fractures, CVD events, and diabetes (Lee et al., 2025; Pickhardt et al., 2022), thus screening-CT populations are already primed for potential lifestyle or metabolic field intervention.

- Gastroenterology and Pancreatology VAT could be of value to evaluate severity of acute pancreatitis but the data are conflicting (Tan et al., 2023).

5.3 Proposed model of Personalized Pathways

Table 6 provides a tiered framework based on the results and recommendations to this effect. This synthesis, utilizing the above three references, is to be treated as a hypothesis for future evaluation.

Table 6. Proposed tiered framework linking opportunistic CT findings to management actions (author synthesis)

CT finding	Suggested interpretation	Candidate actions to evaluate
SMI below sex-specific T-score −2 cutoff (Table 3)	Probable sarcopenia (myopenia)	Confirm with strength and function tests; dietitian referral; resistance-exercise programme; review in oncology or surgical planning
Low muscle attenuation (myosteatosis)	Elevated fracture and mortality risk independent of muscle size	Bone-health and falls assessment; cardiometabolic review; consider bone densitometry
High VAT area or high VSR	Increased cardiometabolic risk, not reflected by BMI	Screen for diabetes and hypertension; lifestyle and weight-management counselling
Low liver attenuation	Probable hepatic steatosis	Liver-risk assessment; metabolic evaluation

CT finding	Suggested interpretation	Candidate actions to evaluate
Marked decline in VAT or muscle on serial CT in cancer	Possible cachexia or disease progression	Early nutritional and oncological review (Jung et al., 2024)
Normal metrics	Low body-composition-related risk	No action; avoid false reassurance when BMI and metrics disagree

Actions are candidate interventions for prospective testing. No outcome benefit of acting on opportunistic findings was demonstrated in the reviewed studies.

6. IMPLEMENTATION CONSIDERATIONS

Implementation Requirements

For automated reporting to be incorporated into the clinical workflow without requiring significant extra effort, a generic pipeline is presented in Figure 6 that is compatible with all the tools discussed: automatic slice selection, segmentation, quality control (review of flagged cases by a human), reference comparison and reporting. QC is hard to envisage being dropped, as just the Bonn pipeline would have omitted 10.7% of cases (39/364) with stringent settings in order to remain accurate, as identified by Nowak et al. (2022). Other practical difficulties include the management of contrast enhanced scans (Shen et al., 2023 suggest VAT segmentation is less accurate on enhanced scans) versus non-contrast; the management of implants, truncated fields of view, and conversion thresholds to scanner noise floor that need to be adapted to local scanner protocols. Equity is a concern, with reference values based on healthy young adults perhaps not representative of all ethnic groups, and the heterogeneity in Ju et al. (2025) research further suggests population effects are considerable. Finally, communication with the patient is especially important; the reporting of findings like sarcopenia in patients without symptoms causes a duty to have a pathway defined, and health systems should generate those pathways before automated reporting is used.

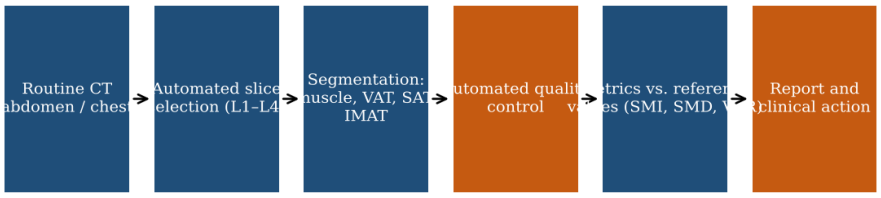


Figure 6. Proposed workflow for automated opportunistic body-composition reporting. Orange boxes indicate steps that require clinician oversight or action.

7. LIMITATIONS

This review has several shortcomings. The analysis was limited to one database, potentially missing relevant studies in other sources. No blinding during the selection of studies and no formal risk of bias analysis have been done. Studies published are diverse in design, landmark, instruments used, and definition of outcomes. All these factors prevented pooling in meta-analysis. A number of disease-specific cohorts have been small, retrospective, and single-center investigations. Some of the results of screens also come from single large cohorts with predominantly asymptomatic population (Lee et al., 2025; Pickhardt et al., 2022). The most important issue is that these studies show relationships and prediction, but no interaction of opportunistic findings translated into better patient outcomes.

Future Directions

Further prospective trials are required to demonstrate whether opportunistically initiated interventions (exercise, nutrition and metabolic treatment) will improve outcomes. Further multi-center, multi-vendor validation of automated tools is indicated, especially with regard to contrast phase effects and visceral fat segmentation. Multiracial, multi-ethnic, harmonized reference values as well as consensus cutoff values for dichotomization (according to Ju et al. 2025) are also indicated. Further development of longitudinal models based on serial scans is indicated, motivated by the prognostic usefulness of the change in visceral adipose tissue (Jung et al. 2024). Further application to chest CT (by lumbar measurements) and to the paediatric cohort (Lee et al. 2022, Pickhardt et al. 2022) could be beneficial.

8. CONCLUSIONS

In the context of routine CT imaging, opportunistic determination of sarcopenia and visceral adiposity using technical aspects of an accurate method amenable to automation yields prognostic information that adds to BMI and, in some analyses, clinical scores. Indicators of muscle attenuation and distribution of fat seem most promising. Currently, the field is moving from feasibility to implementation, with efforts directed at regular reporting to shared reference values, sound quality control, and, above all, prospective evidence that actionable findings lead to changes that benefit patients.

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