

CT-Derived Body Composition Assessment as a Prognostic Tool in Oncologic Patients: From Opportunistic Research to Artificial Intelligence-Based Clinical Implementation

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CT-based body composition measures are well established in research settings as prognostic markers in oncologic patients. Numerous retrospective studies have shown the role of objective measurements extracted from abdominal CT images of skeletal muscle, abdominal fat, and bone mineral density in providing more accurate assessments of frailty and cancer cachexia in comparison with traditional clinical methods. Quantitative CT-based measurements of liver fat and aortic atherosclerotic calcification have received relatively less attention in cancer care but also provide prognostic information. Patients with cancer routinely undergo serial CT examinations for staging, treatment response, and surveillance, providing the opportunity for quantitative body composition assessment to be performed as part of routine clinical care. The emergence of fully automated artificial intelligence-based segmentation and quantification tools to replace earlier time-consuming manual and semiautomated methods for body composition analysis will allow these opportunistic measures to transition from the research realm to clinical practice. With continued investigation, the measurements may ultimately be applied to achieve more precise risk stratification as a component of personalized oncologic care.

Metrics of body composition have been extensively studied and have consistently been found to serve as important prognostic markers in patients with a variety of health conditions, including cancer [1–4]. These metrics include measurements of frailty, skeletal muscle, abdominal fat, bone mineral density (BMD), and atherosclerotic calcification [1]. In 2008, motivated by the consensus that “a consensus operational definition provides an opportunity for increased research” [5], an expert group developed a standard definition of cachexia, describing it as “a complex metabolic syndrome associated with underlying illness and characterized by loss of muscle with or without loss of fat mass” [5]. Determination of the presence of cachexia in patients with cancer has traditionally relied on patient weight or BMI. Over the past decade, it has become clear that determining the presence of cachexia is complex and may instead be better performed by body composition analysis using CT images [6]. For example, one study of oncologic patients found skeletal muscle depletion and low skeletal muscle attenuation on CT to be independently associated with poor prognosis, regardless of overall body weight [7]. CT-based body composition metrics thus have the potential to help perform risk stratification for patients with cancer and to tailor decisions regarding oncologic treatment.

Traditional clinical assessments of patient frailty are not easily implemented at population scale. In comparison, body composition parameters derived from CT scans can be readily extracted in an opportunistic manner without additional testing, as oncologic patients frequently undergo serial CT examinations as part of routine care for a range of indications, including baseline staging, assessment of response to therapy, and monitoring for recurrent disease after treatment. Although research to date has primarily investigated body composition measures obtained from baseline CT examinations (e.g., initial staging examinations), such measures, as observed on successive scans, may also serve as novel prognostic indicators.

Until recently, CT-based body composition analyses required time-consuming manual or semiautomated segmentation approaches. However, fully automated artificial intelligence (AI) algorithms have emerged that rapidly perform these analyses, facilitating population-level application of body composition measures. This review describes the potential

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role of body composition measures derived from abdominal CT scans in patients with cancer. We focus on the use of abdominal CT because the most commonly studied CT-based body composition markers are extracted from the upper abdomen [1, 8–11]. Nonetheless, these principles also largely apply to thoracic CT scans. For each tissue type presented (muscle, fat, bone, liver, and vasculature), we summarize the method for CT-based quantification and discuss its relevance to oncologic imaging (Table 1 and Fig. 1).

Body Composition Measures

Skeletal Muscle Quantity and Quality

Skeletal muscle is among the most studied regions in the field of body composition analysis. Sarcopenia is an overarching generic term for muscle loss or poor muscle quality and encompasses both myopenia (i.e., a decrease in skeletal muscle bulk) and myosteatosis (i.e., the presence of excess inter- and intramuscular adipose tissue, considered as a measure of skeletal muscle quality). Both of these processes have been linked to poor outcomes in a variety of oncologic outcomes [2, 12, 7], and at times these terms are used interchangeably. Nonetheless, decreases in muscle bulk and muscle quality have shown distinct biologic implications [13], supporting the use of myopenia and myosteatosis as distinct terms. The broader term “sarcopenia” is most commonly used in the context of the loss of skeletal muscle (myopenia) that occurs with aging [2, 14, 15].

Quantitative CT-based assessment of skeletal muscle includes the cross-sectional area of skeletal muscle (expressed as square centimeters), used to measure myopenia, and the mean attenuation of skeletal muscle (expressed as Hounsfield units), used to measure myosteatosis, with both measurements typically obtained at the level of the L3 vertebral body. Use of a manual ROI results in measuring the mean attenuation from a limited volume of muscle. In comparison, the use of a semiautomated or fully automated method allows inclusion of much larger volumes of skeletal muscle in the segmentation that is used for attenuation measurement [14–16]. Automated segmentations should include all skeletal muscle found within the psoas, paraspinal, and body wall musculature at the L3 level. The cross-sectional area can be normalized by patient height to provide a skeletal muscle index. Skeletal muscle assessment can alternatively be measured at the L1 level (or other thoracolumbar levels) [17, 18], to allow quantification from chest CT scans. The use of IV contrast material has a small effect on muscle attenuation measurements; when skeletal muscle quantification is performed using contrast-enhanced scans, adjustments can be applied to facilitate comparisons with data generated from unenhanced scans [19, 20].

Variation exists in the inclusion of intermuscular adipose tissue (IMAT) within the muscle segmentation when assessing myopenia and myosteatosis. Nonetheless, inclusion of IMAT within automated segmentations results in improved agreement between manual and automated measurements [21]. The inclusion of IMAT within automated segmentation also results in more rapid decreases with age in CT-based attenuation measurements [16] (Fig. 2) and appears to increase the prognostic utility of sarcopenia measurements for a variety of oncologic and nononcologic outcomes [17, 22].

Studies across multiple cancer types have shown the prognostic utility of the presence of sarcopenia (most commonly myope-

HIGHLIGHTS

- *CT-based body composition measures of skeletal muscle, abdominal fat, and bone mineral density provide useful opportunistic information on frailty and cancer cachexia.*
- *CT-based measurements of atherosclerotic calcification and liver fat have received less attention in cancer care but may also have useful prognostic utility.*
- *Fully automated AI-based methods should transform opportunistic CT-based body composition assessment from the research realm to the clinic.*

nia). For example, patients with advanced sarcoma [23], pancreatic cancer [24, 25], colorectal cancer [26], cervical cancer [27], esophageal cancer [28], ovarian cancer [29], and prostate cancer [30] have all been shown to have lower overall survival (OS) in the presence of myopenia established by a CT scan. In a study of patients undergoing colorectal cancer surgery, Pędziwiart et al. [31] found that use of a laparoscopic (rather than open) surgical approach and an enhanced recovery after surgery (ERAS) protocol mitigated the negative impact of myopenia and myosteatosis on survival. This study illustrates a way in which knowledge of sarcopenia can be used to guide treatment approaches and improve outcomes. In addition to being a harbinger of worse survival, myopenia has been associated with a higher rate of complications from cancer treatment. This association has manifested as severe chemotherapy toxicity in patients with colon cancer and esophagogastric cancer [32, 33], increased dose-limiting toxicity from targeted tyrosine kinase inhibitor therapy in patients with renal cancer [34], increased postoperative complications after surgical resection of esophageal [28] or gastric cancer [35], and increased treatment-related mortality in patients with otherwise potentially curable hepatocellular carcinoma [36]. Finally, numerous studies have shown longitudinal changes in muscle mass during cancer treatment [37–39]; further investigation is needed to understand the prognostic implications of such changes.

TABLE 1: CT-Based Body Composition Measurements With Potential Application as Prognostic Markers in Oncologic Patients

Tissue	Measure(s)
Skeletal muscle	Muscle cross-sectional area Muscle mean attenuation
Adipose tissue	Visceral fat cross-sectional area Subcutaneous fat cross-sectional area Subcutaneous fat mean attenuation Ratio of visceral to subcutaneous fat areas
Bone	Bone mineral density
Liver	Hepatic steatosis Liver volume ^a
Abdominal aorta	Agatston calcium score Calcium mass or volume

^aNot presented in this review.

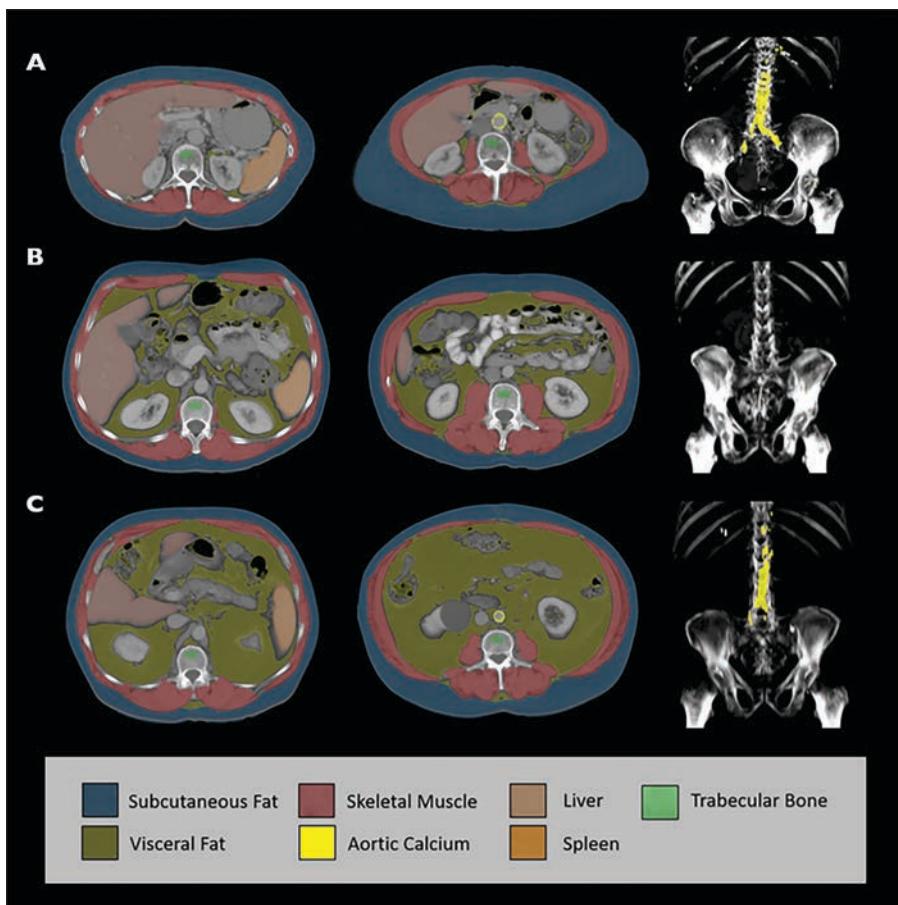


Fig. 1—Examples of baseline CT-based body composition assessment in patients with colorectal cancer.

A–C, Results of fully automated segmentation of various body tissues and organs using artificial intelligence (AI)-based algorithm for analysis of contrast-enhanced abdominal CT scans are shown for 79-year-old woman (**A**), 49-year-old man (**B**), and 63-year-old man (**C**) with colorectal cancer. Details regarding specific AI segmentation algorithms have been previously described [16, 62, 66, 86, 91]. Key species colors used to indicate segmentations of various tissues and organs. For each patient, first image in row is axial image obtained at L1 level, second image in row is axial image obtained at L3 level, and third image in row is coronal maximum-intensity-projection image showing calcified aortoiliac plaque. Quantification of segmentations of various tissues in terms of cross-sectional area, volume, or attenuation may hold prognostic value. In terms of survival risk, patient in **C** likely has worst overall combination of CT-based body composition parameters, with sarcopenic myosteatosis (muscle attenuation, 29 HU), fat distribution (subcutaneous adipose tissue [SAT], 137 cm²; visceral adipose tissue [VAT], 344 cm²; and ratio of visceral to subcutaneous adipose tissue [VSR], 2.5), and aortic calcium load (Agatston score, 10,273), compared with patient in **A** (muscle attenuation, 24 HU; SAT, 149 cm²; VAT, 7 cm²; VSR, 0.05; aortic Agatston score, 4089) and patient in **B** (muscle attenuation, 41 HU; SAT, 125 cm²; VAT, 184 cm²; VSR, 1.5; aortic Agatston score, 0). Patient in **C** did not have metastatic disease at diagnosis but died several years later, whereas patient in **A** remains alive 9 years after diagnosis and patient in **B** remains alive 4 years after diagnosis (despite having metastatic disease at presentation).

Studies have used varying criteria to define the presence of sarcopenia. Nonetheless, demographic factors such as age and sex are typically used in defining a normal skeletal muscle mass. A study by Wu et al. [40] used two different cutoffs, developed from populations from different geographic regions, for determining the presence or absence of sarcopenia based on the skeletal muscle index in a group of 146 patients with pancreatic cancer. One cutoff resulted in a baseline prevalence of sarcopenia of 66% and no significant association of sarcopenia with OS; the other cutoff resulted in a prevalence of 11% and a significant association with OS [40]. An additional study of patients with colorectal cancer found differences between men and women in terms of the association of skeletal muscle mass and mortality [41]. These studies illustrate the importance of establishing patient-specific definitions for sarcopenia as well as for other body composition measures for such measurements to become widely accepted as prognostic biomarkers. Automated quantitative tools used for determining CT-based muscle measurements in large patient cohorts will also need to consider variables such as age and sex when assessing the presence of sarcopenia.

In terms of myosteatosis, in a meta-analysis of 40 published studies, Aleixo et al. [2] found myosteatosis (i.e., decreased skeletal muscle attenuation) to be associated with shorter oncologic survival, with a 75% overall increase in mortality risk. The decrease in OS was observed in gastrointestinal, gynecologic, pancreatic, hepatic, renal, and hematologic malignancies. The parameters

used to define myosteatosis were heterogeneous across studies. Myosteatosis was most often assessed for the psoas major muscle at the level of L3. The meta-analysis also observed that a range of muscle attenuation cutoffs have been used to define myosteatosis; the most commonly applied cutoff has been less than 41 HU in the presence of a BMI of less than 25 or less than 33 HU in the presence of a BMI of 25 or more. Studies have also varied in terms of whether different cutoffs were used in men and women. In another systematic review of patients with colorectal cancer, Valle et al. [42] also showed the prognostic utility of CT-based myosteatosis assessment [42]. Measures of myosteatosis may be preferable to measures of muscle area in clinical practice given the simplicity, reproducibility, and robust prognostic utility of such measures [1, 10, 17].

The combination of increased adipose tissue and low skeletal muscle mass and/or attenuation, known as sarcopenic obesity, appears to have distinct prognostic implications. For example, Prado et al. [4] reported lower functional status and poorer survival attributes among patients with sarcopenic obesity than among those with sarcopenia without obesity. Other studies have identified sarcopenic obesity as an independent risk factor for mortality in patients with gastric cancer [43] and a predictor of worse survival in patients who have undergone pancreaticoduodenectomy [24] and patients with nonmetastatic rectal cancer [44]. Although sarcopenic obesity typically has been evaluated at baseline in oncologic populations, one study showed that in

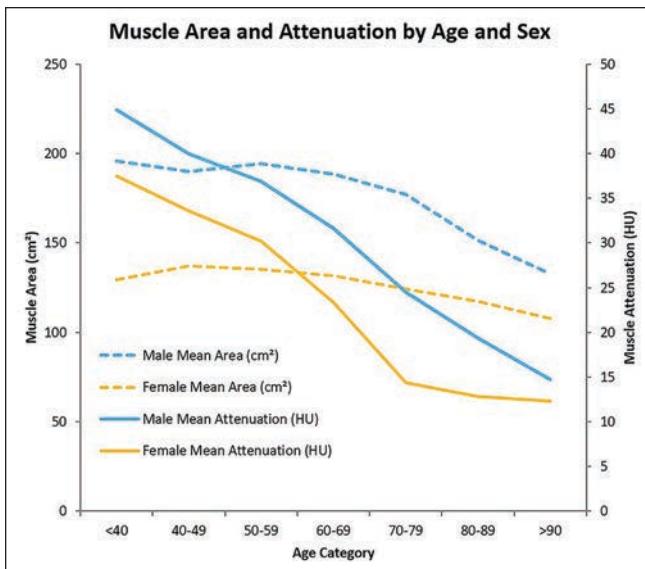


Fig. 2—Age and sex variation of automated CT-based skeletal muscle measures in adults. Graph shows data derived from cohort of asymptomatic adults using automated deep learning tool for skeletal muscle quantification at L3 level. Mean muscle cross-sectional area (dashed lines) varies less with age compared with mean muscle attenuation (solid lines), but both show overall consistent differences by sex. (Reprinted with permission from [16])

premenopausal patients with breast cancer, weight gain after adjuvant chemotherapy led to the posttreatment development of sarcopenic obesity [45].

As automated acquisition of CT-based body composition metrics becomes more widely available, sarcopenia assessment could become part of routine clinical cancer care. However, considerable work remains to standardize definitions, establish patient-specific thresholds, and show quality evidence on even larger scales than those presently available.

Abdominal Fat Volume and Distribution

As adipose tissue has an important role in physiology beyond serving as a passive store of energy, adipose tissue evaluation is a key component of body composition analysis. CT-based adipose tissue metrics may serve as more powerful markers than conventional metrics such as weight or BMI. Although methods have varied across the literature [46], visceral fat quantification in general involves the use of software to segment the intraabdominal compartment and calculate the cross-sectional area (expressed as square centimeters) of tissue having the attenuation values of fat (i.e., values of -150 to -50 HU) [47]. Measurements of fat volume performed using a single CT slice have been shown to correlate closely with fat volumes obtained from the total abdominal compartment [48]. Cross-sectional measurements have been performed at levels ranging from L1 to L4, including at the level of the umbilicus. The subcutaneous fat volume can also be quantified by segmenting a given level from the abdominal wall musculature to the skin. The visceral fat area and subcutaneous fat area can be combined to derive the total fat area [47]. Commercially available software products (e.g., FatSeg [Biomedical Imaging Group], OsiriX [Pixmeo], ImageJ [NIH], and SliceOmatic [TomoVision]) for semiautomated fat quantification appear to have ex-

cellent agreement, supporting comparisons of results from studies using these different software programs [49]. Although cutoff values have been proposed for establishing the presence of high visceral fat content [47], thresholds that can be widely applied across populations have not yet been established.

It is crucial to recognize the subcutaneous and visceral adipose tissue compartments as distinct entities with biologic differences. Subcutaneous fat purportedly represents "good" fat, whereas visceral fat purportedly represents "bad" fat. Fat quantification should thus use compartment-specific analyses, which is not possible with the use of BMI.

Increased levels of visceral adipose tissue have shown varying impacts in oncologic populations, both in terms of survival and the risk of complications. For example, increased visceral fat has been linked to reduced survival in patients with metastatic castrate-resistant prostate cancer on chemotherapy [50]; shorter distant disease-free survival in patients with breast cancer receiving neoadjuvant chemotherapy, particularly when such patients are postmenopausal [51]; and increased risk for lymph node metastases in patients who underwent resection for pancreatic adenocarcinoma as well as shortened survival among such patients who have nodal metastases [52]. However, other studies have shown increased visceral fat to be potentially beneficial or neutral. For example, one study of patients with colon cancer found an association of increased visceral adipose tissue with fewer lymph node metastases and better OS [53]. An additional large cohort study of patients with gynecologic malignancies found no significant association between visceral adiposity and patient survival [54]. In addition to its association with survival, increased visceral adiposity has been linked to treatment complications, such as those occurring after pancreatic surgery [55].

Subcutaneous adiposity has been evaluated using various metrics in oncologic patients. A study of patients with colorectal cancer found that the CT-based subcutaneous fat area, but not the visceral fat area, was independently associated with improved disease-free survival [56]. A study of patients with head and neck cancer treated with definitive chemoradiation found an association of high subcutaneous fat volume with locoregional control, metastasis-free survival, and OS [57]. Low subcutaneous fat volume was found to be associated with poor survival outcomes in patients with multiple myeloma [58]. The ratio of the visceral fat area to the subcutaneous fat area may also have prognostic utility. One study found that a high ratio of visceral fat to subcutaneous fat was an independent risk factor for surgical site infection after gastrectomy in patients with gastric cancer [59]. Finally, studies of the attenuation of subcutaneous fat have provided mixed results. In a study of men with high-risk prostate cancer who underwent radiation and androgen deprivation therapy, lower attenuation of subcutaneous fat was found to be associated with biochemical failure [60]. However, a study of patients with hepatocellular carcinoma found that increased attenuation of subcutaneous fat was negatively associated with survival [61]. Subcutaneous fat attenuation may be affected by various factors, including anasarca and the overall fat volume, possibly reducing the reliability of the metric.

Abdominal fat distribution shows clear differences, on average, between men and women. Lee et al. [62] used a fully automated tool to extract data on adiposity for a sample of 8852

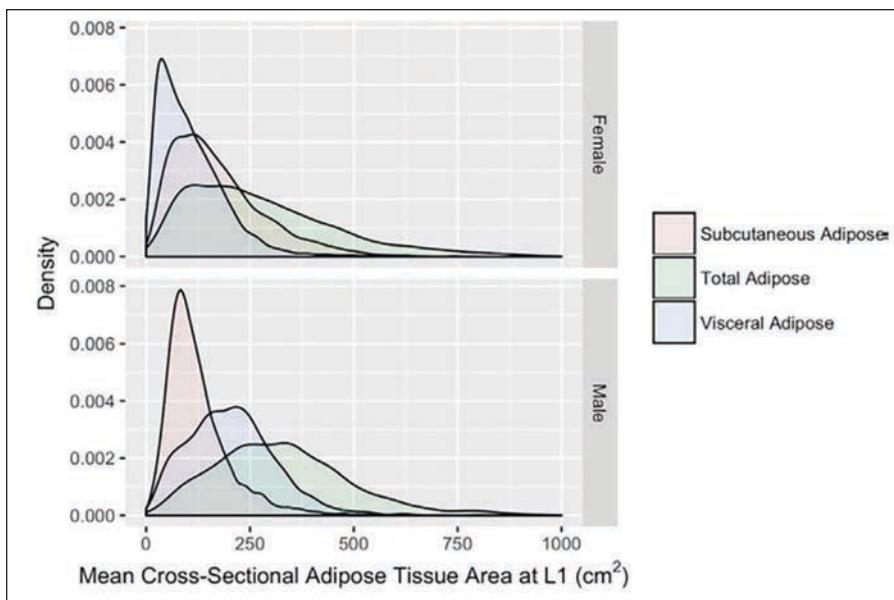


Fig. 3—Sex variation of automated CT-based subcutaneous and visceral fat in adults. Density plot compares distributions (solid lines) of subcutaneous, visceral, and total adipose tissue area at L1 vertebral level in cohort of asymptomatic adults by use of automated deep learning tool for skeletal muscle quantification at L1 level. In general, subcutaneous fat is greater in women, and visceral fat is greater in men. This distinction is obscured if measures of patient weight or body mass index are considered. (Reprinted with permission from [62].)

asymptomatic adults and found significantly higher visceral adipose levels and significantly higher ratios of visceral to subcutaneous adipose in men than in women. Specifically, the mean ratio of visceral to subcutaneous fat was three times higher in men than in women (Fig. 3).

An overweight or obese state, as measured by BMI, has traditionally been considered a negative prognostic factor in patients with cancer. However, increased survival among overweight and mildly obese patients has also been reported on the basis of BMI, leading to what has been described as an obesity paradox [63]. Nonetheless, the conclusion that a mild increase in weight may be protective could be incorrect for multiple reasons. BMI is a crude metric for assessing adiposity [64] that does not distinguish between lean muscle mass and fat [63] or take into account the adipose tissue distribution. As Lennon et al. [63] indicated, in addition to having limitations associated with the use of BMI, studies suggesting a possible favorable prognostic impact of obesity are prone to confounding, detection bias, reverse causality, and selection bias.

Bone Mineral Density

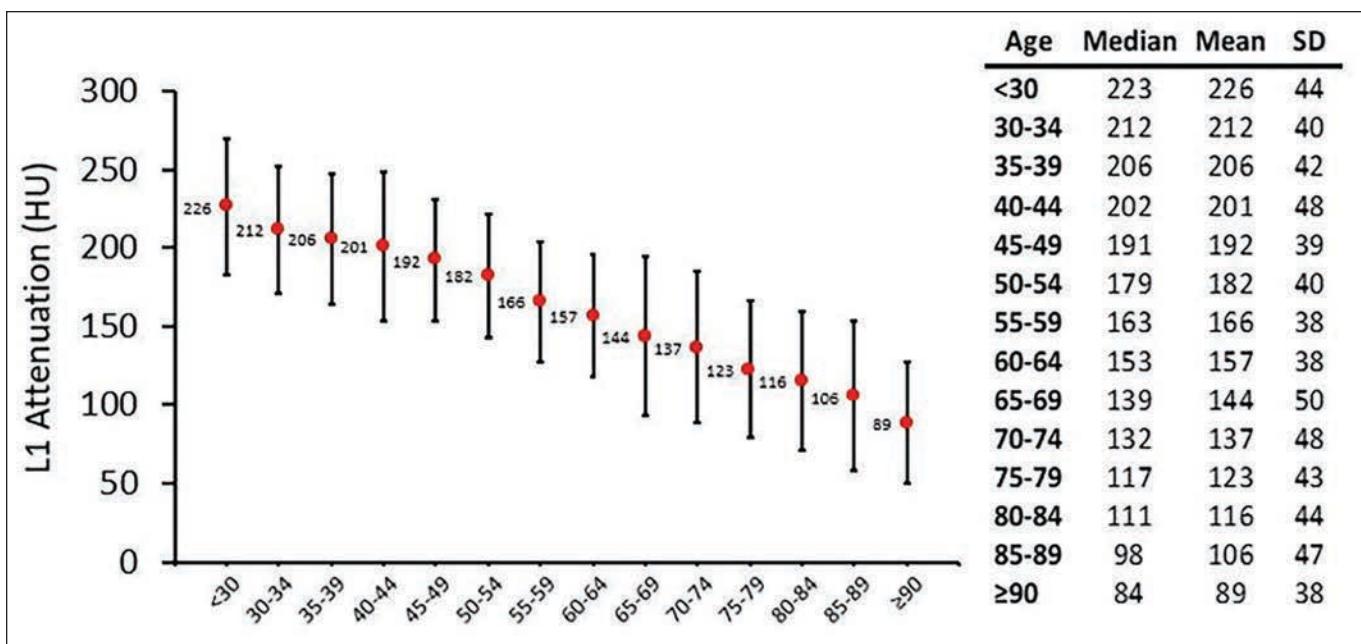
The most commonly used manual opportunistic metric for assessing BMD on CT is the mean attenuation of the trabecular bone at the level of the L1 vertebral body as assessed by ROI placement [65]. Automated tools can easily mimic this manual ROI placement in the trabecular space [66]. The attenuation value cutoffs commonly used to suggest osteoporosis range from less than 100 HU to less than 110 HU; a cutoff of less than 90 HU is associated with a significantly increased risk of prevalent and future osteoporotic fractures [67, 68]. Unlike skeletal muscle and adipose tissue measures, BMD assessment is highly sensitive to the specific kilovoltage setting [69]. Software has been developed to derive from abdominal CT scans femoral neck T scores that are equivalent to measurements obtained from dual-energy x-ray absorptiometry [70]; despite the use of software, this process may be more labor intensive than vertebral trabecular ROI placement. As with muscle attenuation, CT-based BMD measures are age dependent (Fig. 4A).

[71]. In addition, premenopausal women show slightly increased BMD compared with age-matched men, a comparison that is reversed in postmenopausal patients (Fig. 4B).

Osteoporosis, the most common metabolic disease, is characterized by a decrease in BMD. Osteoporosis is highly prevalent worldwide and predominantly affects older individuals. A recent meta-analysis found among older patients a worldwide prevalence of osteoporosis of 22% [72]. In addition to the role of BMD in indicating risk for osteoporotic fractures, evidence indicates that BMD alone and in combination with other associated body composition metrics may be useful in the assessment of patients with cancer. This metric can be easily extracted from CT scans of the thorax or abdomen that are obtained for other indications [71].

Patients who undergo screening CT examinations for lung [73, 74] or colorectal [75, 76] cancer may undergo opportunistic assessment for osteoporosis using CT images. One study in patients undergoing lung cancer screening found that BMD derived from CT, as well as the presence of vertebral fractures, independently predicts all-cause mortality [77]. Other studies using opportunistic automated body composition screening found that BMD predicted all-cause mortality in an asymptomatic screening population [22] and was equally as effective as the commonly used Fracture Risk Assessment Tool (FRAX) in predicting presymptomatic osteoporotic fractures in the general population [10]. Opportunistic BMD evaluation can also be used to assess for the development of osteoporosis and to stratify the risk of the future occurrence of fracture after cancer treatment, as shown in patients with prostate [78], gynecologic [79], and breast cancer [80].

Early research has also explored the role of osteoporosis in predicting oncologic outcomes, for example in breast cancer [81]. A decrease in BMD in combination with low skeletal muscle mass (osteosarcopenia), with or without obesity (osterosarcopenic obesity), may serve as a useful prognostic marker in oncologic patients. For example, a study of patients undergoing resection of colorectal cancer hepatic metastases found that osteosarcopenia and lymph node metastasis were independent predictors of worse OS [82].

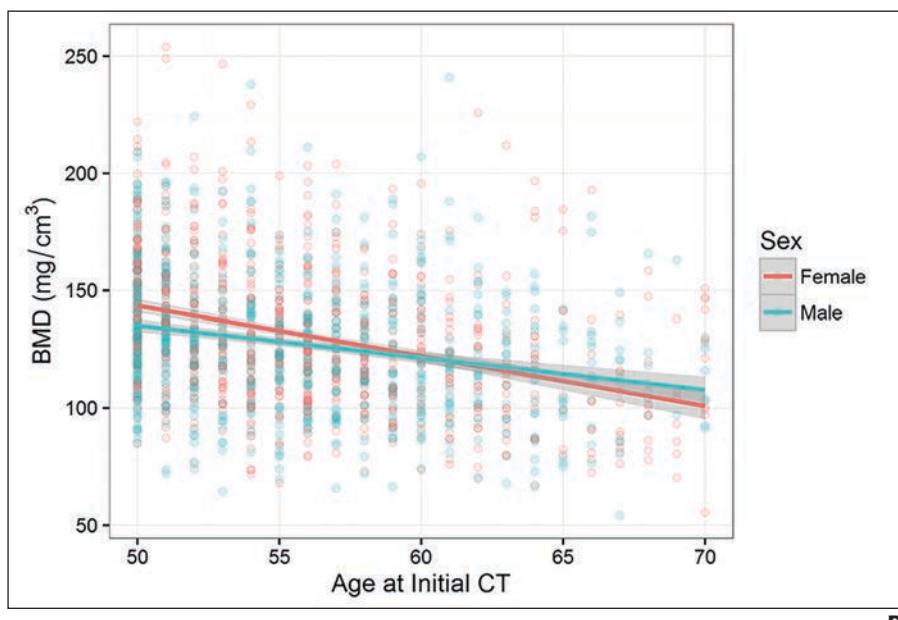


A

Fig. 4—Age and sex variation of CT-based bone mineral density (BMD) in adults.

A, Graph shows data derived from large cohort of adults by use of both manual and automated ROIs placed in anterior trabecular space of L1 vertebral body. BMD measure progressively decreases with increasing age. Circles denote mean values, and vertical lines and whiskers indicate SD. (Reprinted with permission from [71].)

B, Graph shows data derived from cohort of asymptomatic adults using automated tool for BMD measurement at L1 level. Compared with men, women show slightly higher L1 trabecular attenuation overall until approximately 1 decade after menopause, after which time measurement in women becomes slightly lower overall compared with that in men due to relatively accelerated bone loss. Circles denote individual data points, and solid lines denote best overall fit of data. (Reprinted with permission from [66].)



B

Hepatic Steatosis

CT-based body composition analysis can also be used to evaluate hepatic steatosis. Although steatosis is an important marker of metabolic disease in general, it also has potential as a marker in the oncologic setting. Some cancer-related treatments can lead to an increase in hepatic fat content, as has been shown, for example, after chemotherapy in patients with pancreatic and breast [83] cancer. Unenhanced abdominal CT scans enable straightforward assessment of liver fat content, as mean attenuation via manual parenchymal ROI placement has a linear correlation with MRI-derived proton density fat fraction, both in phantoms and in human patients [84, 85]. Automated volumetric assessment of liver attenuation on unenhanced CT, as performed using deep learn-

ing tools, provides information similar to that provided by manual assessment and can be applied at population scale [86]. Liver fat quantification on contrast-enhanced CT is less precise but generally allows accurate categoric assessment of the severity of steatosis, particularly in the setting of moderate or severe steatosis [87]. A dual-energy technique using multimaterial decomposition may facilitate liver fat quantification on contrast-enhanced CT scans [88]. Fully automated deep learning tools have also been used to guide determination of the presence of hepatomegaly [89], which may provide an adjunct to steatosis assessment.

The prognostic roles of baseline hepatic steatosis and post-therapy changes in steatosis have yet to be studied in depth in oncologic patients. The development of automated deep learn-

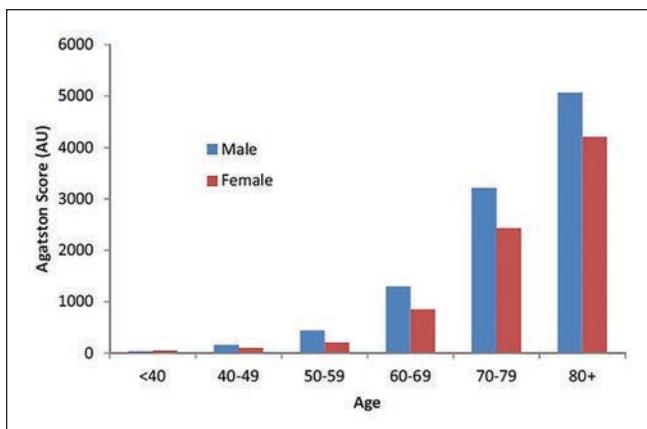


Fig. 5—Age and sex variation of automated CT-based aortic calcium load in adults. Graph shows data derived from cohort of asymptomatic adults using automated aortic calcium scoring tool. Progressive increase in load of atherosclerotic hard plaque is seen to occur with age. Women show overall trajectory similar to that shown for men, although aortic calcium load is delayed by approximately 1 decade. (Reprinted with permission from [91].)

ing tools for hepatic fat evaluation will facilitate large-scale investigations of the possible prognostic role of this marker.

Aortic Calcium

Quantification of calcified atherosclerotic plaques of the abdominal aorta can be obtained manually or by use of semiautomatic segmentation tools that have traditionally been applied for evaluation of the coronary arteries [90]. However, fully automated deep learning tools have been developed for the specific purpose of CT-based aortic calcium segmentation and quantification [91]. CT-based aortic calcium measurements can be reported using the Agatston score, a metric conventionally used for reporting coronary artery calcification, or they can be reported in terms of aortic calcium volume (expressed as milliliters) or mass (expressed as milligrams) [91]. Aortic calcium can be quantified using either unenhanced or contrast-enhanced CT scans of the abdomen [92]. As with other body composition measures, cut-off values should account for patient age and sex. In a cohort of more than 9000 adults, Graffy et al. [91] found that mean aortic calcium Agatston scores were consistently higher in men than in women (Fig. 5). In addition, overall age-specific aortic Agatston scores showed an increase of approximately 10% per year.

Semiautomated and automated assessment of aortic calcification on CT has been shown to outperform the Framingham risk score in predicting adverse cardiac events in asymptomatic adults [22, 90]. An additional study of automated opportunistic CT-based body composition metrics found that aortic calcium predicted mortality independent of the other metrics in an asymptomatic screening population [22]. The longitudinal change in the aortic calcium load on CT also appears to be a useful prognostic measure in an asymptomatic screening setting [9].

Although the prognostic utility of aortic calcium has been shown in general screening populations, it has not been as well studied in oncologic patients as have other body composition metrics. Studies have found that higher levels of abdominal aortic calcium are associated with an increased risk of anastomotic leakage after resection of colorectal cancer [93, 94]. Aortic calci-

um is also associated with higher rates of noninfectious postoperative complications after colorectal resection [95]. Serial CT examinations may also show increases in aortic calcification, which has been shown for non–small cell lung cancer after chemoradiation [96] (though it is unclear whether this development directly impacts subsequent risk of cardiac events). Regardless of any specific association of aortic calcium with oncologic survival outcomes, aortic calcium is expected to remain an important predictor of the overall risk of mortality from cardiovascular events in oncologic patients; this risk may be taken into account during treatment planning.

Conclusion

A wealth of data supports the potential prognostic utility of CT-based body composition measures in patients with cancer. Limitations of research to date include the largely retrospective nature of the investigations and the focus on baseline rather than longitudinal metrics. In addition, body composition analysis has historically required manual or semiautomated segmentation of CT images. However, technologic advances in AI have enabled development of fully automated real-time tools for CT-based body composition analysis. Publications from the past 5 years have shown the feasibility of automatically extracting quantitative CT data for muscle, fat, bone, liver, and the aorta in large cohorts [10, 16, 20, 22, 62, 66, 86, 91]. This automated approach will provide a bridge for taking CT-based body composition from serving as a research tool to serving as a standardized and routine clinical method to help refine prognoses for patients with cancer, clarify risks associated with various therapies, and guide clinical colleagues in developing customized treatments. Through the use of fully automated body composition analysis, researchers should strive to integrate the individual metrics into comprehensive predictive models that outperform clinical decision tools. Opportunistic CT-based body composition analysis will need to be evaluated at large scales to refine the methodology and thresholds before clinical deployment and adoption into patient care. Ultimately, the automated tools should be embraced as a component of personalized oncologic treatment by providing more precise risk stratification and a novel means of longitudinal patient assessment.

References

- Pickhardt PJ, Graffy PM, Perez AA, Lubner MG, Elton DC, Summers RM. Opportunistic screening at abdominal CT: use of automated body composition biomarkers for added cardiometabolic value. *RadioGraphics* 2021; 41:524–542
- Aleixo GFP, Shachar SS, Nyrop KA, Muss HB, Malpica L, Williams GR. Myosteatosis and prognosis in cancer: systematic review and meta-analysis. *Crit Rev Oncol Hematol* 2020; 145:102839
- Petrelli F, Cortellini A, Indini A, et al. Association of obesity with survival outcomes in patients with cancer: a systematic review and meta-analysis. *JAMA Netw Open* 2021; 4:e213520
- Prado CM, Lieffers JR, McCargar LJ, et al. Prevalence and clinical implications of sarcopenic obesity in patients with solid tumours of the respiratory and gastrointestinal tracts: a population-based study. *Lancet Oncol* 2008; 9:629–635
- Evans WJ, Morley JE, Argilés J, et al. Cachexia: a new definition. *Clin Nutr* 2008; 27:793–799

6. Prado CM, Birdsell LA, Baracos VE. The emerging role of computerized tomography in assessing cancer cachexia. *Curr Opin Support Palliat Care* 2009; 3:269–275
7. Martin L, Birdsell L, Macdonald N, et al. Cancer cachexia in the age of obesity: skeletal muscle depletion is a powerful prognostic factor, independent of body mass index. *J Clin Oncol* 2013; 31:1539–1547
8. Pickhardt PJ, Graffy PM, Zea R, et al. Utilizing fully automated abdominal CT-based biomarkers for opportunistic screening for metabolic syndrome in adults without symptoms. *AJR* 2021; 216:85–92
9. Graffy PM, Summers RM, Perez AA, Sandfort V, Zea R, Pickhardt PJ. Automated assessment of longitudinal biomarker changes at abdominal CT: correlation with subsequent cardiovascular events in an asymptomatic adult screening cohort. *Abdom Radiol (NY)* 2021; 46:2976–2984
10. Pickhardt PJ, Graffy PM, Zea R, et al. Automated abdominal CT imaging biomarkers for opportunistic prediction of future major osteoporotic fractures in asymptomatic adults. *Radiology* 2020; 297:64–72
11. Weston AD, Korfiatis P, Kline TL, et al. Automated abdominal segmentation of CT scans for body composition analysis using deep learning. *Radiology* 2019; 290:669–679
12. Brown JC, Caan BJ, Meyerhardt JA, et al. The deterioration of muscle mass and radiodensity is prognostic of poor survival in stage I–III colorectal cancer: a population-based cohort study (C-SCANS). *J Cachexia Sarcopenia Muscle* 2018; 9:664–672
13. Stretch C, Aubin JM, Mickiewicz B, et al. Sarcopenia and myosteatosis are accompanied by distinct biological profiles in patients with pancreatic and periampullary adenocarcinomas. *PLoS One* 2018; 13:e0196235
14. Lenchik L, Boutin RD. Sarcopenia: beyond muscle atrophy and into the new frontiers of opportunistic imaging, precision medicine, and machine learning. *Semin Musculoskelet Radiol* 2018; 22:307–322
15. Boutin RD, Lenchik L. Value-added opportunistic CT: insights into osteoporosis and sarcopenia. *AJR* 2020; 215:582–594
16. Graffy PM, Liu J, Pickhardt PJ, Burns JE, Yao J, Summers RM. Deep learning-based muscle segmentation and quantification at abdominal CT: application to a longitudinal adult screening cohort for sarcopenia assessment. *Br J Radiol* 2019; 92:20190327
17. Pickhardt PJ, Perez AA, Garrett JW, Graffy PM, Zea R, Summers RM. Fully automated deep learning tool for sarcopenia assessment on CT: L1 versus L3 vertebral level muscle measurements for opportunistic prediction of adverse clinical outcomes. *AJR* 2022; 218:124–131
18. Derstine BA, Holcombe SA, Ross BE, Wang NC, Su GL, Wang SC. Skeletal muscle cutoff values for sarcopenia diagnosis using T10 to L5 measurements in a healthy US population. *Sci Rep* 2018; 8:11369
19. Fuchs G, Chretien YR, Mario J, et al. Quantifying the effect of slice thickness, intravenous contrast and tube current on muscle segmentation: implications for body composition analysis. *Eur Radiol* 2018; 28:2455–2463
20. Perez AA, Pickhardt PJ, Elton DC, Sandfort V, Summers RM. Fully automated CT imaging biomarkers of bone, muscle, and fat: correcting for the effect of intravenous contrast. *Abdom Radiol (NY)* 2021; 46:1229–1235
21. Pickhardt PJ. Value-added opportunistic CT screening: state of the art. *Radiology* 2022; 303:241–254
22. Pickhardt PJ, Graffy PM, Zea R, et al. Automated CT biomarkers for opportunistic prediction of future cardiovascular events and mortality in an asymptomatic screening population: a retrospective cohort study. *Lancet Digit Health* 2020; 2:e192–e200
23. Strassmann D, Hensen B, Grünwald V, et al. Impact of sarcopenia in advanced and metastatic soft tissue sarcoma. *Int J Clin Oncol* 2021; 26:2151–2160
24. Peng YC, Wu CH, Tien YW, Lu TP, Wang YH, Chen BB. Preoperative sarcopenia is associated with poor overall survival in pancreatic cancer patients following pancreaticoduodenectomy. *Eur Radiol* 2021; 31:2472–2481
25. Gruber ES, Jomrich G, Tamandl D, Gnant M, Schindl M, Sahora K. Sarcope-nia and sarcopenic obesity are independent adverse prognostic factors in resectable pancreatic ductal adenocarcinoma. *PLoS One* 2019; 14:e0215915
26. Lee CS, Won DD, Oh SN, et al. Prognostic role of pre-sarcopenia and body composition with long-term outcomes in obstructive colorectal cancer: a retrospective cohort study. *World J Surg Oncol* 2020; 18:230
27. Han Q, Kim SI, Yoon SH, et al. Impact of Computed tomography-based, artificial intelligence-driven volumetric sarcopenia on survival outcomes in early cervical cancer. *Front Oncol* 2021; 11:741071
28. Fehrenbach U, Wuensch T, Gabriel P, et al. CT body composition of sarcopenia and sarcopenic obesity: predictors of postoperative complications and survival in patients with locally advanced esophageal adenocarcinoma. *Cancers (Basel)* 2021; 13:2921
29. Kim SI, Kim TM, Lee M, et al. Impact of CT-determined sarcopenia and body composition on survival outcome in patients with advanced-stage high-grade serous ovarian carcinoma. *Cancers (Basel)* 2020; 12:E559
30. Stangl-Kremser J, Suarez-Ibarrola R, Andrea D, et al. Assessment of body composition in the advanced stage of castration-resistant prostate cancer: special focus on sarcopenia. *Prostate Cancer Prostatic Dis* 2020; 23:309–315
31. Pędziwiatr M, Pisarska M, Major P, et al. Laparoscopic colorectal cancer surgery combined with enhanced recovery after surgery protocol (ERAS) reduces the negative impact of sarcopenia on short-term outcomes. *Eur J Surg Oncol* 2016; 42:779–787
32. Tan BH, Brammer K, Randhawa N, et al. Sarcopenia is associated with toxicity in patients undergoing neo-adjuvant chemotherapy for oesophago-gastric cancer. *Eur J Surg Oncol* 2015; 41:333–338
33. Barret M, Antoun S, Dalban C, et al. Sarcopenia is linked to treatment toxicity in patients with metastatic colorectal cancer. *Nutr Cancer* 2014; 66:583–589
34. Huillard O, Mir O, Peyromaure M, et al. Sarcopenia and body mass index predict sunitinib-induced early dose-limiting toxicities in renal cancer patients. *Br J Cancer* 2013; 108:1034–1041
35. Zhuang CL, Huang DD, Pang WY, et al. Sarcopenia is an independent predictor of severe postoperative complications and long-term survival after radical gastrectomy for gastric cancer: analysis from a large-scale cohort. *Medicine (Baltimore)* 2016; 95:e3164
36. Levoger S, van Vledder MG, Muslem R, et al. Sarcopenia impairs survival in patients with potentially curable hepatocellular carcinoma. *J Surg Oncol* 2015; 112:208–213
37. Yip C, Goh V, Davies A, et al. Assessment of sarcopenia and changes in body composition after neoadjuvant chemotherapy and associations with clinical outcomes in oesophageal cancer. *Eur Radiol* 2014; 24:998–1005
38. Salinas-Miranda E, Deniffel D, Dong X, et al. Prognostic value of early changes in CT-measured body composition in patients receiving chemotherapy for unresectable pancreatic cancer. *Eur Radiol* 2021; 31:8662–8670
39. Rier HN, Jager A, Sleijfer S, van Rosmalen J, Kock MCJM, Levin MD. Changes in body composition and muscle attenuation during taxane-based chemotherapy in patients with metastatic breast cancer. *Breast Cancer Res Treat* 2018; 168:95–105
40. Wu CH, Chang MC, Lyadov VK, et al. Comparing Western and Eastern criteria for sarcopenia and their association with survival in patients with pancreatic cancer. *Clin Nutr* 2019; 38:862–869
41. van Baar H, Winkels RM, Brouwer JGM, et al. Associations of abdominal skeletal muscle mass, fat mass, and mortality among men and women with stage I–III colorectal cancer. *Cancer Epidemiol Biomarkers Prev* 2020; 29:956–965
42. Valle KF, Lubner MG, Pickhardt PJ. Computed tomography assessment of sarcopenic myosteatosis for predicting overall survival in colorectal carcinoma: systematic review. *J Comput Assist Tomogr* 2022; 46:157–162

43. Kim J, Han SH, Kim HI. Detection of sarcopenic obesity and prediction of long-term survival in patients with gastric cancer using preoperative computed tomography and machine learning. *J Surg Oncol* 2021; 124:1347–1355
44. Han JS, Ryu H, Park IJ, et al. Association of body composition with long-term survival in non-metastatic rectal cancer patients. *Cancer Res Treat* 2020; 52:563–572
45. Demark-Wahnefried W, Peterson BL, Winer EP, et al. Changes in weight, body composition, and factors influencing energy balance among premenopausal breast cancer patients receiving adjuvant chemotherapy. *J Clin Oncol* 2001; 19:2381–2389
46. Tolonen A, Pakarinen T, Sassi A, et al. Methodology, clinical applications, and future directions of body composition analysis using computed tomography (CT) images: a review. *Eur J Radiol* 2021; 145:109943
47. Doyle SL, Bennett AM, Donohoe CL, et al. Establishing computed tomography-defined visceral fat area thresholds for use in obesity-related cancer research. *Nutr Res* 2013; 33:171–179
48. Faron A, Luetkens JA, Schmeel FC, Kuetting DLR, Thomas D, Sprinkart AM. Quantification of fat and skeletal muscle tissue at abdominal computed tomography: associations between single-slice measurements and total compartment volumes. *Abdom Radiol (NY)* 2019; 44:1907–1916
49. van Vugt JL, Levolger S, Gharbharan A, et al. A comparative study of software programmes for cross-sectional skeletal muscle and adipose tissue measurements on abdominal computed tomography scans of rectal cancer patients. *J Cachexia Sarcopenia Muscle* 2017; 8:285–297
50. Cushen SJ, Power DG, Murphy KP, et al. Impact of body composition parameters on clinical outcomes in patients with metastatic castrate-resistant prostate cancer treated with docetaxel. *Clin Nutr ESPEN* 2016; 13:e39–e45
51. Iwase T, Sangai T, Nagashima T, et al. Impact of body fat distribution on neoadjuvant chemotherapy outcomes in advanced breast cancer patients. *Cancer Med* 2016; 5:41–48
52. Mathur A, Hernandez J, Shaheen F, et al. Preoperative computed tomography measurements of pancreatic steatosis and visceral fat: prognostic markers for dissemination and lethality of pancreatic adenocarcinoma. *HPB (Oxford)* 2011; 13:404–410
53. Park SW, Lee HL, Doo EY, et al. Visceral obesity predicts fewer lymph node metastases and better overall survival in colon cancer. *J Gastrointest Surg* 2015; 19:1513–1521
54. Nattennmüller J, Rom J, Buckner T, et al. Visceral abdominal fat measured by computer tomography as a prognostic factor for gynecological malignancies? *Oncotarget* 2018; 9:16330–16342
55. Sandini M, Bernasconi DP, Fior D, et al. A high visceral adipose tissue-to-skeletal muscle ratio as a determinant of major complications after pancreatoduodenectomy for cancer. *Nutrition* 2016; 32:1231–1237
56. Kim JM, Chung E, Cho ES, et al. Impact of subcutaneous and visceral fat adiposity in patients with colorectal cancer. *Clin Nutr* 2021; 40:5631–5638
57. Pai PC, Chuang CC, Chuang WC, et al. Pretreatment subcutaneous adipose tissue predicts the outcomes of patients with head and neck cancer receiving definitive radiation and chemoradiation in Taiwan. *Cancer Med* 2018; 7:1630–1641
58. Takeoka Y, Sakatoku K, Miura A, et al. Prognostic effect of low subcutaneous adipose tissue on survival outcome in patients with multiple myeloma. *Clin Lymphoma Myeloma Leuk* 2016; 16:434–441
59. Kim JH, Kim J, Lee WJ, et al. A high visceral-to-subcutaneous fat ratio is an independent predictor of surgical site infection after gastrectomy. *J Clin Med* 2019; 8:E494
60. McDonald AM, Fiveash JB, Kirkland RS, et al. Subcutaneous adipose tissue characteristics and the risk of biochemical recurrence in men with high-risk prostate cancer. *Urol Oncol* 2017; 35:663.e615–663.e621
61. von Hessen L, Roumet M, Maurer MH, et al. High subcutaneous adipose tissue density correlates negatively with survival in patients with hepatocellular carcinoma. *Liver Int* 2021; 41:828–836
62. Lee SJ, Liu J, Yao J, Kanarek A, Summers RM, Pickhardt PJ. Fully automated segmentation and quantification of visceral and subcutaneous fat at abdominal CT: application to a longitudinal adult screening cohort. *Br J Radiol* 2018; 91:20170968
63. Lennon H, Sperrin M, Badrick E, Renehan AG. The obesity paradox in cancer: a review. *Curr Oncol Rep* 2016; 18:56
64. Okorodudu DO, Jumeau MF, Montori VM, et al. Diagnostic performance of body mass index to identify obesity as defined by body adiposity: a systematic review and meta-analysis. *Int J Obes* 2010; 34:791–799
65. Pickhardt PJ, Pooler BD, Lauder T, del Rio AM, Bruce RJ, Binkley N. Opportunistic screening for osteoporosis using abdominal computed tomography scans obtained for other indications. *Ann Intern Med* 2013; 158:588–595
66. Pickhardt PJ, Lee SJ, Liu J, et al. Population-based opportunistic osteoporosis screening: validation of a fully automated CT tool for assessing longitudinal BMD changes. *Br J Radiol* 2019; 92:20180726
67. Graffy PM, Lee SJ, Ziemlewicz TJ, Pickhardt PJ. Prevalence of vertebral compression fractures on routine CT scans according to L1 trabecular attenuation: determining relevant thresholds for opportunistic osteoporosis screening. *AJR* 2017; 209:491–496
68. Lee SJ, Graffy PM, Zea RD, Ziemlewicz TJ, Pickhardt PJ. Future osteoporotic fracture risk related to lumbar vertebral trabecular attenuation measured at routine body CT. *J Bone Miner Res* 2018; 33:860–867
69. Garner HW, Paturzo MM, Gaudier G, Pickhardt PJ, Wessell DE. Variation in attenuation in L1 trabecular bone at different tube voltages: caution is warranted when screening for osteoporosis with the use of opportunistic CT. *AJR* 2017; 208:165–170
70. Ziemlewicz TJ, Maciejewski A, Binkley N, Brett AD, Brown JK, Pickhardt PJ. Opportunistic quantitative CT bone mineral density measurement at the proximal femur using routine contrast-enhanced scans: direct comparison with DXA in 355 adults. *J Bone Miner Res* 2016; 31:1835–1840
71. Jang S, Graffy PM, Ziemlewicz TJ, Lee SJ, Summers RM, Pickhardt PJ. Opportunistic osteoporosis screening at routine abdominal and thoracic CT: normative L1 trabecular attenuation values in more than 20 000 adults. *Radiology* 2019; 291:360–367
72. Salari N, Darvishi N, Bartina Y, et al. Global prevalence of osteoporosis among the world older adults: a comprehensive systematic review and meta-analysis. *J Orthop Surg Res* 2021; 16:669
73. Cheng X, Zhao K, Zha X, et al; China Health Big Data (China Biobank) Project Investigators. Opportunistic screening using low-dose CT and the prevalence of osteoporosis in China: a nationwide, multicenter study. *J Bone Miner Res* 2021; 36:427–435
74. Pan Y, Shi D, Wang H, et al. Automatic opportunistic osteoporosis screening using low-dose chest computed tomography scans obtained for lung cancer screening. *Eur Radiol* 2020; 30:4107–4116
75. Fidler JL, Murthy NS, Khosla S, et al. Comprehensive assessment of osteoporosis and bone fragility with CT colonography. *Radiology* 2016; 278:172–180
76. Ziemlewicz TJ, Binkley N, Pickhardt PJ. Opportunistic osteoporosis screening: addition of quantitative CT bone mineral density evaluation to CT colonography. *J Am Coll Radiol* 2015; 12:1036–1041
77. Buckens CF, van der Graaf Y, Verkooijen HM, et al. Osteoporosis markers on low-dose lung cancer screening chest computed tomography scans predict all-cause mortality. *Eur Radiol* 2015; 25:132–139
78. McDonald AM, Yang ES, Saag KG, et al. Osteoporosis screening using computed tomography for men with prostate cancer: results of a prospective study. *Arch Osteoporos* 2020; 15:32

79. Sobecki J, Weigman B, Anderson-Carter I, et al. Opportunistic osteoporosis screening using routine computed tomography images to identify bone loss in gynecologic cancer survivors. *Int J Gynecol Cancer* 2022 Jan 31 [published online]
80. Park SH, Jeong YM, Lee HY, et al. Opportunistic use of chest CT for screening osteoporosis and predicting the risk of incidental fracture in breast cancer patients: a retrospective longitudinal study. *PLoS One* 2020; 15:e0240084
81. Zambetti A, Tartter PI. Bone mineral density is a prognostic factor for postmenopausal Caucasian women with breast cancer. *Breast J* 2013; 19:168–172
82. Furukawa K, Haruki K, Taniai T, et al. Osteosarcopenia is a potential predictor for the prognosis of patients who underwent hepatic resection for colorectal liver metastases. *Ann Gastroenterol Surg* 2021; 5:390–398
83. Inci F, Karatas F. Paclitaxel-induced hepatic steatosis in patients with breast cancer. *J BUON* 2019; 24:2355–2360
84. Guo Z, Blake GM, Li K, et al. Liver fat content measurement with quantitative CT validated against MRI proton density fat fraction: a prospective study of 400 healthy volunteers. *RadioLOGY* 2020; 294:89–97
85. Pickhardt PJ, Graffy PM, Reeder SB, Hernando D, Li K. Quantification of liver fat content with unenhanced MDCT: phantom and clinical correlation with MRI proton density fat fraction. *AJR* 2018; 211:[web]W151–W157
86. Graffy PM, Sandfort V, Summers RM, Pickhardt PJ. Automated liver fat quantification at nonenhanced abdominal CT for population-based steatosis assessment. *RadioLOGY* 2019; 293:334–342
87. Pickhardt PJ, Blake GM, Graffy PM, et al. Liver steatosis categorization on contrast-enhanced CT using a fully automated deep learning volumetric segmentation tool: evaluation in 1204 healthy adults using unenhanced CT as a reference standard. *AJR* 2021; 217:359–367
88. Corrias G, Erta M, Sini M, et al. Comparison of multimaterial decomposition fat fraction with DECT and proton density fat fraction with IDEAL IQ MRI for quantification of liver steatosis in a population exposed to chemotherapy. *Dose Response* 2021; 19:1559325820984938
89. Perez AA, Noe-Kim V, Lubner MG, et al. Deep learning CT-based quantitative visualization tool for liver volume estimation: defining normal and hepatomegaly. *RadioLOGY* 2021; 302:336–342
90. O'Connor SD, Graffy PM, Zea R, Pickhardt PJ. Does nonenhanced CT-based quantification of abdominal aortic calcification outperform the Framingham risk score in predicting cardiovascular events in asymptomatic adults? *RadioLOGY* 2019; 290:108–115
91. Graffy PM, Liu J, O'Connor S, Summers RM, Pickhardt PJ. Automated segmentation and quantification of aortic calcification at abdominal CT: application of a deep learning-based algorithm to a longitudinal screening cohort. *Abdom Radiol (NY)* 2019; 44:2921–2928
92. Summers RM, Elton DC, Lee S, et al. Atherosclerotic plaque burden on abdominal CT: automated assessment with deep learning on noncontrast and contrast-enhanced scans. *Acad Radiol* 2021; 28:1491–1499
93. Morita S, Tsuruta M, Okabayashi K, et al. Evaluation of abdominal aortic calcification by plain CT predicts anastomotic leakage in laparoscopic surgery for colorectal cancer. *Jpn J Clin Oncol* 2022; 52:122–127
94. Shen Z, An Y, Shi Y, et al. The Aortic Calcification Index is a risk factor associated with anastomotic leakage after anterior resection of rectal cancer. *Colorectal Dis* 2019; 21:1397–1404
95. Knight KA, Fei CH, Boland KF, et al. Aortic calcification is associated with non-infective rather than infective postoperative complications following colorectal cancer resection: an observational cohort study. *Eur Radiol* 2021; 31:4319–4329
96. Miki T, Miyauchi S, Miyoshi T, et al. Chemoradiation therapy for non-small cell lung cancer exacerbates thoracic aortic calcification determined by computed tomography. *Heart Vessels* 2020; 35:1401–1408

Editorial Comment: The Future Value of Automated CT-Derived Body Composition in Oncologic Patients

The ever-expanding role of imaging in the diagnosis, staging, and follow-up of patients with malignancy continues to evolve beyond the mere assessment of tumor measurements. Increasing utilization of novel treatment options that include specific tumor-targeted therapies expands the decision-making process regarding whether patients are ideally suited for surgery, radiation, chemotherapy, or other targeted therapy. This article provides a comprehensive summary of CT-derived parameters that may affect patient outcomes. These parameters include sarcopenia, body adiposity, bone density, hepatic steatosis, and atherosclerosis. Radiologists must become familiar with terms such as "sarcopenia," "myopenia," "myosteatosis," and "intermuscular adipose tissue."

Body composition measurements are not routinely performed on CT scans of oncologic patients, yet they can be easily obtained without additional acquisitions or increased radiation dose [1].

Rapid advances in artificial intelligence (AI) will enable the extraction of automated and semiautomated CT-derived body composition values from abdominal and thoracic CT scans [2]. This process moves away from manually measuring bone density, body adiposity, muscle mass, and muscle fat to provide quantitative values nearly as easily as through the use of the generation of sagittal and coronal reformatted images that are routinely included on CT scans today.

These body composition values provide prognostic information that alters the prediction of patient outcomes after surgery and chemotherapy as well as overall disease-free survival. As an exam-

ple, a study by Martin et al. [3] found that among patients with lung and gastrointestinal cancer who had a high BMI, those with poor prognostic values of muscle attenuation, muscle index, and weight loss had a survival of 8.4 months compared with survival of 28.4 months for patients with normal body composition parameters.

Further prospective studies will be forthcoming on the use of CT-derived body composition parameters generated by automated AI for assessment of outcomes in patients with cancer. Radiologists should eagerly embrace these studies.

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References

1. Boutin RD, Lenchik L. Value-added opportunistic CT: insights into osteoporosis and sarcopenia. *AJR* 2020; 215:582–594
2. Weston AD, Korfiatis P, Kline TL, et al. Automated abdominal segmentation of CT scans for body composition analysis using deep learning. *RadioLOGY* 2019; 290:669–679
3. Martin L, Birdsall L, Macdonald N, et al. Cancer cachexia in the age of obesity: skeletal muscle depletion is a powerful prognostic factor, independent of body mass index. *J Clin Oncol* 2013; 31:1539–1547