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# Automated Deep Learning Detection of Hepatic Steatosis on Noncontrast Computed Tomography Scans and Discrepancy With Scan Reports

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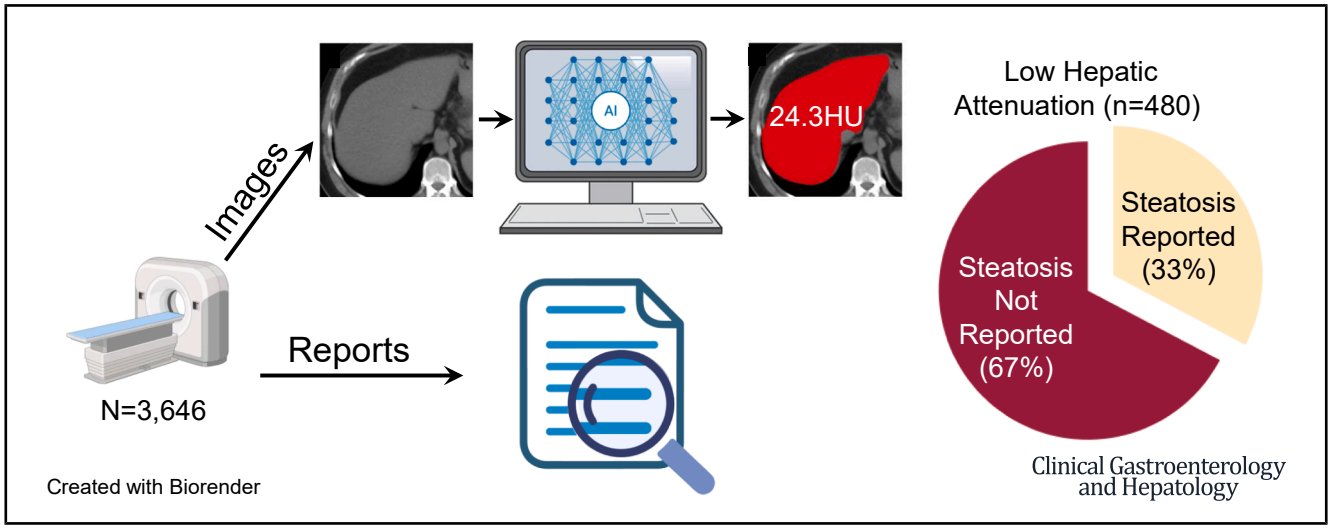


**BACKGROUND & AIMS:** **Metabolic dysfunction–associated steatotic liver disease is a major cause of liver disease that is growing in prevalence. Typically asymptomatic, is often undiagnosed. Imaging studies, including noncontrast computed tomography (CT) scans, can detect hepatic steatosis opportunistically, but the reporting rate is unknown. We hypothesized that incidental finding of steatosis on noncontrast CT is often not reported if not specifically sought in the imaging request.**

**METHODS:** **This study was a retrospective, cross-sectional, single-center analysis of abdominal noncontrast CT scans performed between 2012 and 2020 for any indication in adult subjects. Images were analyzed using an automated deep learning liver segmentation and attenuation assessment algorithm to obtain a mean volumetric liver attenuation value. Image-based**

*Abbreviations used in this paper:* AI, artificial intelligence; BMI, body mass index; CT, computed tomography; ED, emergency department; HU, Hounsfield units; IQR, interquartile range; MASH, metabolic dysfunction–associated steatohepatitis; MASLD, metabolic dysfunction–associated steatotic liver disease; MRI, magnetic resonance imaging; MRI-PDFF, magnetic resonance imaging–based proton density fat fraction; NCCT, noncontrast computed tomography; NIH, National Institutes of Health; ROI, region of interest.



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**steatosis was defined as mean hepatic attenuation <40 HU and compared with textual radiology reports. Manual review of a random subset of scans and reports was used to verify results.**

**RESULTS:** **A total of 3646 noncontrast CT scans from 2710 adult patients were analyzed. The mean liver attenuation derived from the deep-learning algorithm was 50.4 ± 11.8 HU. Image-based steatosis was found in 480 (13.1%) scans, with a mean liver attenuation of 29.8 ± 14 HU. Radiologists reported steatosis in only 157 (32.7%) of these low-attenuation scans. Predictors of unreported steatosis included higher average liver attenuation (even if < 40 HU), high variability of fat distribution in the liver and low body mass index.**

**CONCLUSIONS:** **We found that incidental hepatic steatosis in noncontrast CT is reported in a minority of scans. Incorporating artificial intelligence-based hepatic attenuation measurement in computed tomography scan reading may increase reporting rates.**

*Keywords:* Attenuation; Computerized Tomography; Deep Learning; Radiology; Steatosis.

Metabolic dysfunction–associated steatotic liver disease (MASLD) is a major cause of liver disease that is growing in prevalence.[1,2] It is currently estimated that in Western and industrialized countries the prevalence of MASLD may exceed 40% of the population, especially in adult men with obesity, diabetes, and other features of the metabolic syndrome.[3–5] MASLD encompasses a spectrum of disease ranging from steatosis to steatohepatitis, which can ultimately lead to liver cirrhosis and the development of hepatocellular carcinoma.[6,7]

Despite the potentially severe outcomes of MASLD and the increased global prevalence of the disease, studies suggest it remains relatively underdiagnosed.[8–10] Although several surrogate markers have been suggested, such as the Fatty Liver Index,[11] these are mostly applicable in epidemiologic studies and have limited accuracy when applied to specific subpopulations.[12] Clinical diagnosis still requires imaging to detect hepatic steatosis. Thus, at-risk patients with features of the metabolic syndrome may remain undiagnosed until an abdominal ultrasound or cross-sectional imaging via computed tomography (CT) or magnetic resonance imaging (MRI) are performed. Although MRI-based scans have excellent performance in detection and quantification of steatosis,[13,14] they are less widely available than CT scans. Previous studies have shown noncontrast CT (NCCT) scans can detect steatosis comparably to MRI–based proton density fat fraction (MRI-PDFF), even if not fully quantitatively, and thus, their wide use can allow opportunistic screening for MASLD.[15–17] Typically, hepatic steatosis is identified on NCCT scans via measurement of attenuation at a manually selected region of interest (ROI) of the liver. Attenuation below 40 Hounsfield units (HU) or a liver-spleen attenuation difference greater than 20 HU are considered indicative of at least moderate hepatic steatosis.[15]

CT scans are often performed for indications other than liver disease. How often an incidental finding of steatosis is reported in that context is unclear and, as of yet, there are no clear hepatology or radiology society guidelines clarifying when incidental steatosis should be reported.[18,19] We hypothesized that steatosis on CT scans is frequently not reported when not specifically sought and aimed to test this hypothesis in a large dataset using a validated automated image analysis tool.[20]

## Materials and Methods

### Study Population

This was a retrospective, cross-sectional, single-center analysis of deidentified abdominal CT scans. Of 73,692 abdominal CT scans performed between 2012 and 2020 for any indication, we randomly selected 13,234 scans. Downscaling was performed for technical and computational feasibility, and block randomization was applied across calendric months to ensure equal temporal spread. All subjects participated in 1 or more clinical research studies at the National Institutes of Health (NIH) Clinical Center after signing an informed consent for participation. Data were deidentified, and potential identifiers were redacted from scans and radiology reports. The use of deidentified data was exempted from obtaining informed consent by the NIH Office of Human Subjects Research Protections.

Scans were excluded if they did not contain a noncontrast series, if there was incomplete visualization of the liver (for example, scans done in the context of an interventional procedure), if the standard deviation of liver attenuation (see below) was >98th percentile, or if the subject age was <18 years, as the segmentation algorithm was validated in an adult cohort.

### Data Sources and Image Analysis

Clinical parameters including demographics, anthropometric data, images, and radiology reports were

retrieved from the electronic medical record through the NIH clinical research repository, Biomedical Translational Research Information System. The clinical indication for each CT scan was extracted and searched for a liver-specific request using the key terms: "liver," "hepatic," "hepato," "biliary," "fatty liver," and "steatosis." Indications unrelated to the liver were classified as urologic, general abdominal (ie, abdominal pain, bowel obstruction, bleeding), chest and pulmonary (ie, pneumothorax, pneumonia, dyspnea), cancer staging, evaluation of weight loss or weakness, suspected infection (ie, sepsis, abscess, endocarditis), hematologic evaluation (ie, leukemia, lymphoma, myeloma), neuroendocrine tumor evaluation, and scans for research purposes for clinical research studies performed at the NIH Clinical Center.

Images were analyzed using an automated deep learning liver segmentation and attenuation assessment algorithm to obtain the mean volumetric liver attenuation and its standard deviation (Figure 1).[20,21] A detailed description of the liver segmentation method and acquisition of liver attenuation by the segmentation algorithm was previously published and validated.[21–23] Attenuation measured using the automated algorithm was previously shown to closely agree with manual measurements with a mean difference of 2.7 HU.[20] Scans in which the standard deviation of attenuation values within the liver was extremely high (top 2%) were excluded, as these were likely to reflect the presence of large liver lesions, a metallic object artefact, or an error in segmentation. The list of scanners used and the kVp settings are provided in Supplementary Table 1.

### What You Need to Know

#### Background

Hepatic steatosis is highly prevalent and is often undiagnosed. Abdominal computed tomography for any indication offers an opportunity to incidentally detect hepatic steatosis. Rates of reporting on the presence of steatosis in computed tomography are unknown.

#### Findings

Automated deep learning tool allows for identification of hepatic steatosis in large-scale imaging datasets. The presence of steatosis is often not reported if not explicitly sought.

#### Implications for patient care

Standardization of reporting policy for incidentally detected steatosis is needed. Incorporation of artificial intelligence tools may improve reporting rates for the presence of steatosis.

### *Definition of Outcomes*

Our aim was to compare rates of steatosis evident on imaging (image-based steatosis) to steatosis noted in the radiology report of a scan (report-based steatosis).

Image-based steatosis was defined as mean hepatic attenuation $<40$ HU, irrespective of report language.

Report-based steatosis was defined based on the textual radiologic report attached to the original scan. The text of the original radiology report was scanned for the terms: "hepatic steatosis," "liver steatosis," "fatty infiltration," "fatty change," "fatty liver," "fatty attenuation," and "extremely fatty," Reports containing any of these terms were considered to meet the outcome. Reports of steatosis that also contained the term "focal fat" were manually reviewed. If focal fatty infiltration near the falciform ligament was the only finding, the scan was considered negative for steatosis.

The text scanning approach was assessed and calibrated in a subset of 120 randomly selected radiology reports that were reviewed by an experienced hepatologist, to determine whether steatosis was reported or not. Manual review was concordant with the text scanning in 98.3% of cases for report-based steatosis. A second manual review of all reports with reported steatosis and of a random set of reports without steatosis were manually reviewed by a hepatologist to establish the sensitivity and specificity of text scanning. Both reviewers were blinded to the text-scanning results and to liver attenuation.

### *Validation of Outcome Detection*

To determine whether the machine learning–based attenuation properly detects steatosis, we randomly selected 113 scans for manual review. Randomization aimed for a balanced presence of steatotic and nonsteatotic scans and reports. Scans were reviewed by a radiologist, blinded to indication, the original report, and to the algorithm-derived liver attenuation value. The radiologist had access to additional contrast series, if available, and performed a clinical assessment of the scans to determine whether steatosis is present by clinical criteria. The criteria used were liver attenuation $<40$ HU on noncontrast series using manually placed ROIs or liver attenuation $>10$ HU less than the spleen on portal venous phase scans.

### *Statistical Analysis*

Subject characteristics were described using frequencies for categorical variables and means for continuous variables. Univariate comparisons were made using the $\chi^2$-test or Fisher exact test for categorical variables and the Student $t$ test or Mann–Whitney $U$ test for quantitative variables, as appropriate. Multivariable analyses were performed using multiple logistic regression for parameters significant on univariate

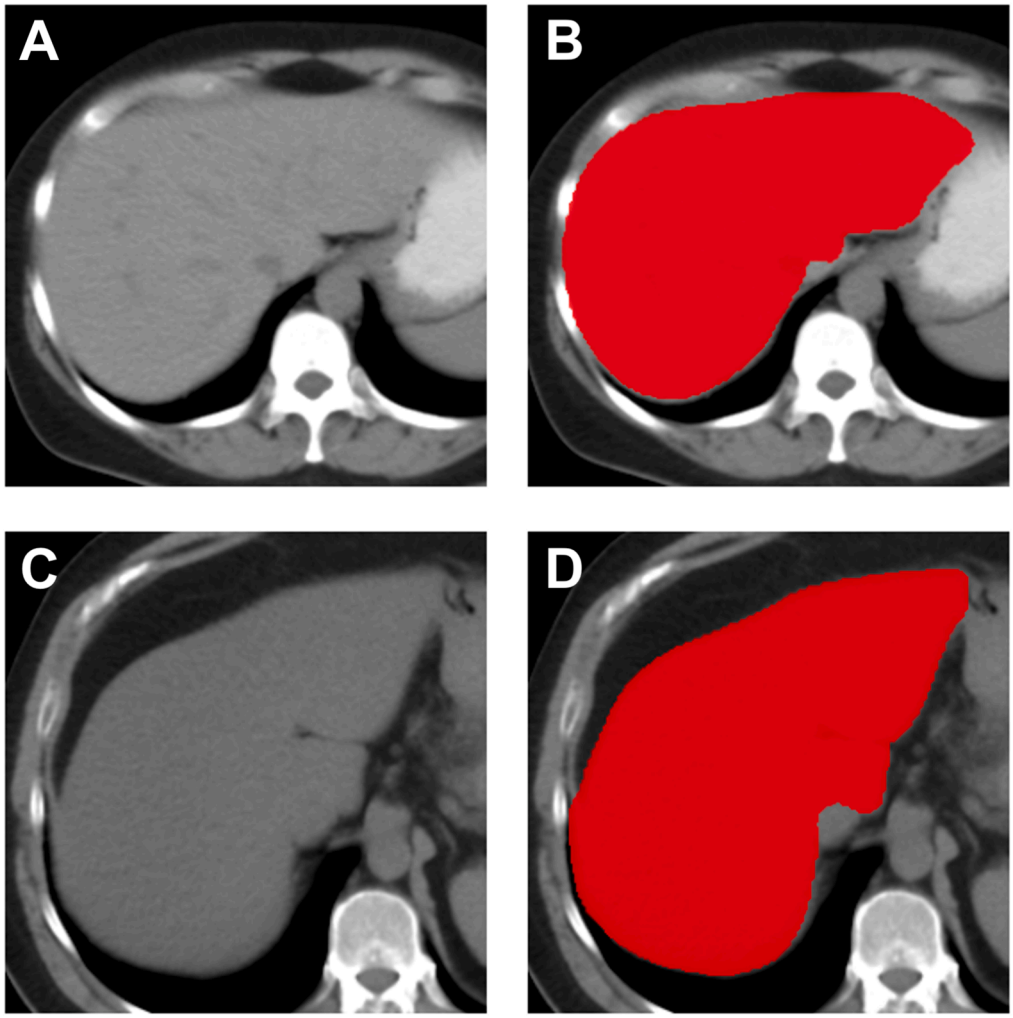


**Figure 1.** Examples of automated segmentation. (*A*) A slice from an NCCT scan of a subject without steatosis and (*B*) the corresponding automated segmentation. The mean volumetric whole liver attenuation was 71.0 ± 19.8 HU. (*C*) A slice from an NCCT scan of a subject with steatosis and (*D*) the corresponding automated segmentation. The mean volumetric whole liver attenuation was 24.3 ± 13.8 HU.

analyses. Statistical significance was defined as $\alpha \leq .05$ (2-sided). GraphPad PRISM version 10.2 was used for statistical analysis.

## Results

### *Study Population*

We randomly selected 13,234 abdominal CT scans, performed for any indication between 2012 and 2020. Of these, 9588 scans were excluded due to lack of a noncontrast phase, incomplete visualization of the liver, excessively high standard deviation, or pediatric subjects (Supplementary Figure 1). The final cohort was composed of 3646 scans from 2710 unique subjects (Table 1). Overall, 1288 subjects (47.5%) were female, and the majority (71.7%) were White, with a mean age of 51.7 ± 15 years and a mean body mass index (BMI) of 27.9 ± 6.5 kg/m$^2$. The indication for the scan explicitly referred to the hepatobiliary system in 260 scans (7.1%), typically encompassing evaluation of abnormal liver tests, seeking or assessing liver lesions, postoperative monitoring, or determining response to

**Table 1.** Patient Characteristics

| Characteristics | Total (N = 2710) |
|---|---|
| Male | 1422 (52.4) |
| Ethnicity | |
| White | 1945 (71.7) |
| African | 374 (13.8) |
| Asian | 163 (6) |
| Native American/Alaska | 12 (0.4) |
| Hawaiian/Pacific Islander | 9 (0.3) |
| Multiracial | 42 (1.5) |
| Unknown | 164 (6) |
| Age, *y* | 51.7 ± 15 |
| BMI, *kg/m*$^{2a}$ | 27.9 ± 6.5 |
| BMI category, *kg/m*$^{2a}$ | |
| <25 | 943 (35.9) |
| 25–30 | 843 (32.1) |
| 30–40 | 703 (26.8) |
| >40 | 132 (5) |

NOTE. Data are presented as number (%) or mean ± standard deviation.
BMI, body mass index.
[a]BMI available for 2621 subjects.

intervention (Supplementary Table 2). Of the scans, 1194 were from an NCCT examination, whereas in 2452, we analyzed the noncontrast series of a scan that also included contrast-enhanced series.

### *Image-Based Steatosis*

The mean liver attenuation across all scans, as derived from the deep-learning algorithm, was 50.4 ± 11.8 HU (Table 2). Image-based steatosis (<40 HU) was found in 480 of 3646 scans (13.1%) and in 377 of 2710 subjects (13.9%). Factors associated with image-based steatosis were male sex, BMI >30 kg/m$^2$, and White race (Table 2). In subjects with a liver-related indication for the scan, steatosis was found in 31 scans (12%) with a mean liver attenuation of 34.4 HU (interquartile range [IQR], 32.1–38.6 HU).

### *Attenuation vs Radiology Reports*

Steatosis was noted in the radiology report in 205 of 3646 scans (5.6%). There were 371 scans (10% of all scans) in which there was a discordance between image-based steatosis (<40 HU) and the radiology report. These include 323 scans where steatosis was suggested by attenuation but not reported, and 48 where it was reported in the presence of higher attenuation.

Of the 480 scans with image-based steatosis, the report mentioned steatosis in only 157 scans (32.7%) (Table 2). Among those 480 scans (all with liver attenuation <40 HU) the liver attenuation was markedly lower in the 157 scans where steatosis was reported compared with the 323 scans where it was not noted (24.6 ± 11.4 vs 32.4 ± 14.5 HU; $P < .001$) (Figure 2*A*). To determine if the likelihood of reporting is related to the attenuation threshold used to define steatosis, we assessed the impact of alternative thresholds (Figure 2*B*). Even when thresholds lower than 40 HU are applied to define steatosis, it was often not reported. A 50% reporting rate of steatosis was reached at a threshold of 34.2 HU and did not increase above 80% for any threshold.

In addition to lower liver attenuation, we found that reporting of steatosis in scans with liver attenuation <40 HU was also associated with lower standard deviation of attenuation within the liver, higher BMI, a younger age, and being female (Table 3). On multivariate regression, liver attenuation, standard deviation of liver attenuation, and BMI remained as significant and independent predictors, whereas sex and age were no longer significant (Table 4). When the analysis was limited to a

**Table 2.** Characteristics of Scans With and Without Image-Based Steatosis

| Characteristics | All scans (N = 3646) | Liver attenuation <40 HU (n = 480) | Liver attenuation ≥40 HU (n = 3166) | *P* value |
|---|---|---|---|---|
| Liver attenuation, HU | 50.4 ± 11.8 | 29.8 ± 14 | 53.5 ± 7.3 | <.001 |
| Male sex | 1948 (53.4) | 286 (59.6) | 1662 (52.5) | .004 |
| BMI, *kg/m$^2$*[a] | 28 ± 6.5 | 31.9 ± 7.8 | 27.4 ± 5.6 | <.001 |
| BMI category, *kg/m$^2$*[a] | | | | <.001 |
| <25 | 1230 (34.6) | 85 (17.7) | 1144 (37) | |
| 25–30 | 1174 (33) | 115 (24) | 1061 (34.4) | |
| 30–40 | 973 (27.3) | 206 (43) | 768 (24.9) | |
| >40 | 176 (5) | 64 (13.5) | 114 (3.7) | |
| Age, *y* | | | | .08 |
| ≤40 | 836 (23) | 95 (19.8) | 741 (23.4) | |
| >40 | 2810 (77) | 385 (80.2) | 2425 (76.6) | |
| Race | | | | .02 |
| White | 2607 (71.5) | 364 (75.8) | 2243 (70.8) | |
| African | 512 (14) | 49 (10.2) | 463 (14.6) | |
| Asian | 227 (6.2) | 25 (5.2) | 202 (6.3) | |
| Native American/Alaska | 17 (0.5) | 2 (0.4) | 15 (0.4) | |
| Hawaiian/Pacific Islander | 12 (0.3) | 4 (0.8) | 8 (0.2) | |
| Multiracial | 56 (1.5) | 8 (1.6) | 48 (1.5) | |
| Unknown | 214 (5.8) | 28 (5.8) | 187 (5.9) | |
| Steatosis noted in radiology report | 205 (5.6) | 157 (32.7) | 48 (1.5) | <.001 |

NOTE. Data are presented as number (%) or mean ± standard deviation.
BMI, body mass index.
[a]BMI available for 3553 scans.

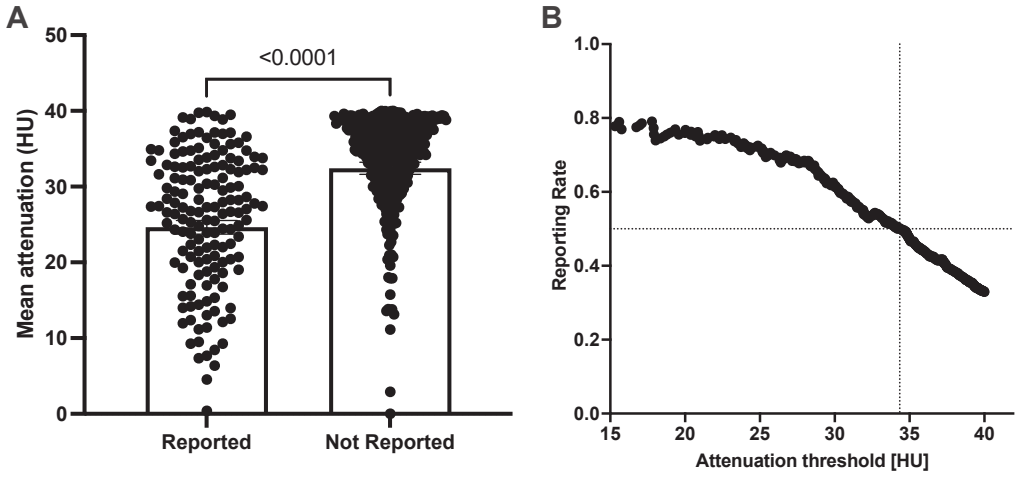


**Figure 2.** Steatosis reporting by liver attenuation. (*A*) The mean volumetric hepatic attenuation of scans meeting radiologic criterion for steatosis (attenuation <40 HU) by mention of steatosis in the radiology report. Bars denote the mean. *P* value from Mann–Whitney *U* test. (*B*) The proportion of scans with hypoattenuation in which steatosis is reported according to attenuation threshold. Dotted lines denote 50%. N = 480.

single (first) scan per patient, univariate and multivariate predictors were overall similar (Supplementary Tables 3 and 4).

Reporting rates were not higher for scans performed for a hepatobiliary indication (Supplementary Table 2).

There were 48 scans with liver attenuation >40 HU (mean attenuation 47.6 ± 6 HU) in which steatosis was reported, likely reflecting additional information obtained from contrast-enhanced series that were not included in our automated analysis.

### *Validation*

To confirm the accuracy of the text-scanning approach, we manually reviewed all reports that were found by text-scanning to mention steatosis (n = 205) and a random subset (n = 200) where no steatosis was reported. Review was performed by a hepatologist, blinded to the images, attenuation measurement, and to the results of the text-scanning function. Of the 205 reports identified as mentioning steatosis by text scanning, 18 (8.8%) were found on manual review to not report steatosis, mostly reflecting nonstandard phrases to report focal fat. In contrast, manual review confirmed no mention of steatosis in the 200 reports where text scanning determined it was absent. Overall, the text scanning approach has a specificity of 0.92 (95% confidence interval, 0.88–0.95) and sensitivity of 1 (95% confidence interval, 1-1).

We randomly selected 113 scans, with intentional over-representation of scans with low attenuation and discordance, to be manually reviewed by a resident radiologist, blinded to indication, report, and measured attenuation and asked to specifically comment on steatosis. Of 57 reviewed scans with mean liver attenuation <40 HU, the reviewing radiologist reported steatosis in 35 (61.4%). Of these 35 scans, the original radiology report noted steatosis in only 19 (54.3%), whereas in 16 (45.7%), steatosis was noted on manual review but was not initially reported. Scans where the original report did not identify steatosis had a trend towards higher liver attenuation (32.8 ± 4.9 vs 27.7 ± 8.8 HU; $P = .09$) (Supplementary Figure 2*A*).

There were 22 scans with attenuation <40 HU in which the reviewing radiologist did not report steatosis. These trended to have higher attenuation (33.4 ± 8.1 vs 30 ± 7.6 HU; $P = .056$) (Supplementary Figure 2*B*) and higher standard deviation within the liver (18.9 ± 5.9 vs 13.7 ± 4 HU; $P < .001$) (Supplementary Figure 2*C*). This suggests that, in scans with high spatial variability of attenuation, manual ROI selection to measure attenuation likely yielded different values (>40 HU) than the automated whole-liver averaging approach.

There were 56 manually reviewed scans with liver attenuation >40 HU in which the reviewing radiologist identified 9 with steatosis; all were also noted in the original radiology report.

### *Temporal Pattern of Steatosis Reporting*

To determine whether increased awareness of MASLD over time affected reporting rates, we assessed the percentage of steatosis reported in scans with liver attenuation <40 HU in 2-year intervals starting from 2012. There was no clear trend of change in steatosis reporting rates over time (Figure 3).

### *Steatosis Reporting by Radiologists*

To understand reporting patterns at the provider level, we analyzed the rates of steatosis reporting in low-attenuation scans by the coded identity of the reporting radiologist, limiting the analysis to radiologists who read >15 low-attenuation scans (range, 17–71). Reporting rates varied widely, with individual radiologists noting steatosis in 5.9% to 65% (mean, 31.1%) of scans with liver attenuation <40 HU. There was no association of reporting rates with the number of scans read or with the average liver attenuation.

**Table 3.** Characteristics of Scans With a Liver Attenuation <40 HU by Report Status

| Characteristics | All scans (N = 480) | Steatosis reported (n = 157) | Steatosis not reported (n = 323) | *P* value |
|---|---|---|---|---|
| Average liver attenuation, *HU* | 29.8 ± 14 | 24.6 ± 11.4 | 32.4 ± 14.5 | <.001 |
| Standard deviation of liver attenuation, *HU* | 15.4 ± 5.5 | 13.8 ± 3.8 | 16.2 ± 6.0 | <.001 |
| BMI, $kg/m^2$[a] | 31.9 ± 7.5 | 33.8 ± 7.5 | 30.9 ± 7.3 | <.001 |
| Male sex | 286 (59.5) | 83 (52.9) | 203 (62.9) | .04 |
| Age | 53.9 ± 13.4 | 52.1 ± 12.9 | 54.8 ± 13.6 | .03 |
| Race | | | | .08 |
| White | 364 (75.8) | 122 (77.7) | 242 (74.9) | |
| African | 49 (10.2) | 10 (6.4) | 39 (12.1) | |
| Asian | 25 (5.2) | 6 (3.8) | 19 (5.9) | |
| Native American/Alaska | 2 (0.4) | 1 (0.6) | 1 (0.3) | |
| Hawaiian/Pacific Islander | 4 (0.8) | 1 (0.6) | 3 (0.9) | |
| Multiracial | 8 (1.6) | 3 (1.9) | 5 (1.5) | |
| Unknown | 28 (5.8) | 14 (8.9) | 14 (4.3) | |

NOTE. Data are presented as number (%) or mean ± standard deviation.
BMI, body mass index.
[a]BMI available for 464 scans.

## Discussion

In this study, we found that incidental presence of hepatic steatosis in abdominal CT scans is frequently not reported. Steatosis was reported in fewer than a third of scans where an automated algorithm identified liver hypoattenuation, generally accepted as a feature of steatosis. A manual reread of a random subset of scans with a specific question of steatosis nearly doubled the reporting rate, confirming our main finding that incidental steatosis is often not reported.

We identified several independent predictors of lower likelihood of reporting steatosis. Hepatic hypoattenuation is a marker of steatosis, and reporting rates were lower for livers with only mild hypoattenuation. A higher standard deviation of attenuation within the liver, marking spatial heterogeneity, was associated with lower reporting rates, and this was also evident in the manual read validation. This likely reflects difference between manually placed ROIs and whole liver measurement. The association of BMI with steatosis reporting, independently of attenuation, likely reflects obesity as a visible trait on cross-sectional imaging, where its presence may increase attention to other metabolic features that would not necessarily be sought otherwise. We also found variability in reporting rates from individual radiologists. As the identity of the reading radiologist was coded, we are unable to associate these rates with training, specialization, or other individual characteristics.

**Table 4.** Multivariate Logistic Regression for Predictors of Reporting Steatosis in Scans With Liver Attenuation <40 HU

| Predictor | Odds ratio (95% confidence interval) | *P* value |
|---|---|---|
| Average liver attenuation, *HU* | 0.94 (0.92–0.96) | <.0001 |
| Standard deviation of liver attenuation, *HU* | 0.88 (0.83–0.93) | <.0001 |
| BMI, $kg/m^2$ | 1.04 (1.008–1.069) | .01 |
| Male sex | 0.76 (0.49–1.17) | .21 |
| Age, *y* | 0.99 (0.978–1.01) | .47 |

BMI, body mass index.

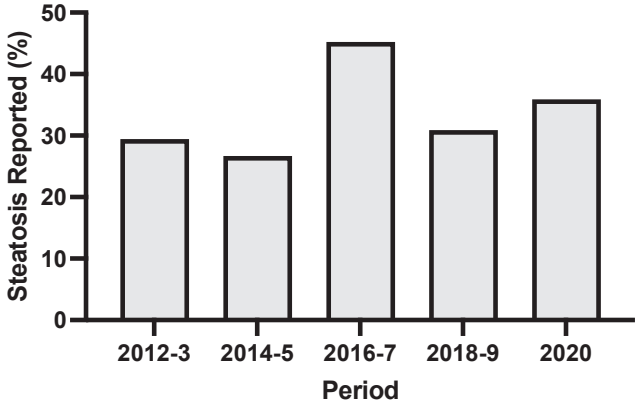


**Figure 3.** Steatosis reporting by year. The proportion of scans with hepatic hypoattenuation (<40 HU) reported to have steatosis according to year of the study.

Our study has several important clinical implications. First, although screening for MASLD is not currently advocated,[18,24] incidental identification of steatosis has multiple clinical implications, especially since the recent approval of medications for steatohepatitis.[25,26] Opportunistic detection can occur in the emergency department (ED)[27] or other clinical settings,[28] but requires both identification and reporting. Our findings suggest that no mention of hepatic steatosis does not equate ruling it out, and that the negative predictive value of CT for steatosis is affected by reporting patterns in addition to technical characteristics. Similarly to the application of artificial intelligence (AI) in other aspects of medicine,[29,30] incorporation of an automated segmentation and attenuation measurement tool may aid radiologists in detecting steatosis in borderline cases and incidental context.

Wells et al[31] manually reviewed 405 CT scans from a single ED over a 6-month period and found that, although 100 cases met criteria for steatosis, it was only reported in 40 (40%). Similarly, Garg et al[32] found that steatosis was reported in 63% of cases meeting criteria for moderate-to-severe steatosis, but only 11% of those with mild steatosis. In a pediatric population, reporting rate for steatosis was only 28% of cases meeting radiologic criteria.[33] These studies, albeit much smaller, show incidental steatosis reporting rates that are overall similar to the 32.7% rate that we found. Of note, even when incidental steatosis is documented in radiology reports, it is often not mentioned in discharge notes.[34]

The reporting of incidental findings on cross-sectional imaging is a topic of active discussion. Guidance documents have mainly discussed mass lesions ("incidentalomas")[35,36] and focused on recommendations for further workup, not on whether findings should be reported at all. Even in the ED setting, where time constraints and workload may impact level of detailed reporting and communication, a recent multidisciplinary consensus statement recommended that all actionable incidental findings should be included in radiology reports.[37] With the clear association of hepatic steatosis with clinical outcomes and mortality[38] and with medical therapy approved for metabolic dysfunction–associated steatohepatitis (MASH),[25,26] we believe the presence of steatosis meets the criteria for an actionable incidental finding and merits reporting. The American College of Radiology is currently developing guidance regarding incidentally discovered fatty liver,[39] which we eagerly anticipate.

Our study has several strengths. First, an automated deep learning approach allowed us to review a large dataset, markedly larger than previous cohorts, and obtain robust data on steatosis reporting rates. Second, we systematically identified factors that are associated with reporting rates, and these findings can drive guidance, quality improvement, and further research. Third, we have studied a cohort combining inpatients, outpatients, and healthy volunteers who were imaged for many indications. This demonstrates the usefulness of CT scans to opportunistically detect steatosis across a wide spectrum of clinical scenarios. Finally, we were able to validate our findings with blinded reviews by independent radiologists and hepatologists.

Our study has several important limitations. We have focused only on liver attenuation, although additional radiologic criteria for steatosis exist. However, in NCCT, liver attenuation is considered the strongest predictor of steatosis.[15,17] Second, the literature suggests various attenuation thresholds to define steatosis. We chose a threshold of 40 HU, estimated to correspond to 15% liver fat by MRI-PDFF[16] or 30% of hepatocytes by histology[40] as a conservative approach for enhanced specificity. Importantly, this threshold has limited sensitivity for mild steatosis; thus, we are plausibly overestimating true reporting rates. However, 15% liver fat has also been suggested to be a useful threshold for detection of MASH or fibrotic MASH,[41–43] making this a clinically relevant cutoff. Moreover, although the 40-HU attenuation cutoff is widely used, variability due to CT vendor, scanning protocols, and x-ray energy does occur. CT scanners are calibrated daily to ensure consistency of attenuation values, and fixed CT attenuation thresholds are widely used in the practice of radiology (for example, in classifying renal cystic lesions and adrenal nodules). Nevertheless, attenuation measurements are approximate despite routine calibration. Additionally, no calibration specific to the application of assessing liver fat was performed, and we are not aware of a commercially available phantom for doing such a calibration. Third, we cannot rule out possible errors in the automated measurements due to incorrect segmentation or the presence of large hypointense liver lesions (eg, cysts), which can reduce the mean attenuation of the liver. Moreover, the automated segmentation includes the whole liver, including blood vessels, which are difficult to separate on noncontrast imaging. However, vessels comprise $<5\%$ of the total liver volume[44] and, with typical intravascular blood attenuation of 35 to 45 HU, are unlikely to markedly affect the average attenuation of the total liver. Similarly, focal steatosis could lower the total average attenuation of the liver but typically occupies only a small proportion of the organ. Fourth, there are potential causes for hepatic parenchymal hypoattenuation beyond steatosis (eg, amyloidosis or infiltration) as well as an increase of attenuation (eg, amiodarone therapy and severe iron overload) masking steatosis. A fifth limitation is the retrospective and deidentified design of our study, which did not allow us to assess clinical and laboratory parameters, cardiometabolic risk factors, and alcohol consumption. As such, our findings apply to steatotic liver disease (SLD) in general; we cannot classify the subjects to the specific subtypes of SLD, nor can we assess liver disease severity. Finally, as the cohort was derived from a single specialized research center serving a distinct population of patients undergoing treatment and evaluation in

clinical research studies, local radiology reporting patterns and expertise regarding awareness to the importance of hepatic steatosis as well as population-specific factors may limit the generalizability of our findings to other settings and centers.

## Conclusions

In conclusion, in this cross-sectional retrospective analysis of abdominal CT scans for multiple indications we show that the presence of hepatic steatosis is often not reported. We demonstrate how an AI tool can be applied to large imaging datasets in epidemiologic studies and suggest that incorporating AI-based tools to provide hepatic attenuation values in CT scans may improve the radiologist workflow and lead to higher steatosis reporting rates. Finally, clinicians should not interpret a report that does not mention steatosis as one that rules out its presence.

## Supplementary Material

Note: To access the supplementary material accompanying this article, visit the online version of *Clinical Gastroenterology and Hepatology* at www.cghjournal.org, and at https://doi.org/10.1016/j.cgh.2026.07.009.

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**Conflicts of interest**
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**Data Availability**
Aggregate data will be made available upon request. Individual participant data will not be shared.