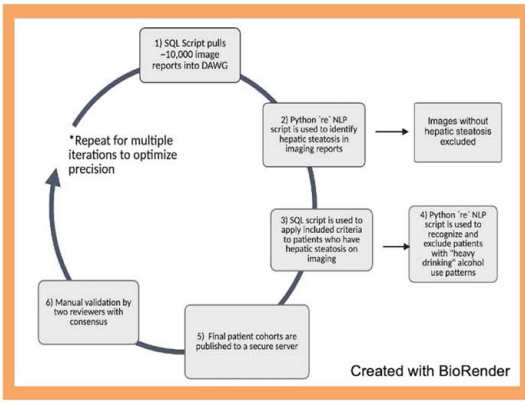
Development of an AI algorithm for early identification of MASLD in the electronic health record

VISUAL ABSTRACT

Development of an AI algorithm for early identification of MASLD in the electronic health record

Algorithm Development



The algorithm:

- Identifies patients with MASLD with positive predictive value >93%
- Excludes patients with significant alcohol use with negative predictive value ~95%

Patient Cohort

<15% had a MASLD-related ICD diagnosis

>30% received a diagnosis 4 or more months after initial imaging

AASLD Stuart, et al | *Hepatology Communications*. 2025.

Hepatology Communications

Received: 13 June 2025 | Accepted: 20 August 2025

DOI: 10.1097/HC9.0000000000000834

ORIGINAL ARTICLE

OPEN

Development of an AI algorithm for early identification of MASLD in the electronic health record

Ariana Stuart[1] | **Ashley Dotson**[1] | **Katya Swarts**[2] | **Marion Granich**[3] | **Jessica Yeung**[3] | **Arthi Thirumalai**[4] | **Manish Dhyani**[5] | **James Perkins**[6] | **Rotonya Carr**[2]

[1]Department of Medicine, University of Washington, Seattle, Washington, USA

[2]Division of Gastroenterology, University of Washington, Seattle, Washington, USA

[3]Quality and Population Health Analytics, University of Washington, Seattle, Washington, USA

[4]Division of Metabolism, Endocrinology and Nutrition, University of Washington, Seattle, Washington, USA

[5]Department of Radiology, University of Washington, Seattle, Washington, USA

[6]Division of Transplant Surgery, University of Washington, Seattle, Washington, USA

Correspondence
Rotonya Carr, Digestive Health Center, University of Washington-Montlake, Surgery Pavilion—3rd Floor, 1959 NE Pacific Street, Seattle, WA 98195, USA.
Email: rmcarr@uw.edu

Abstract

Background: Metabolic dysfunction–associated steatotic liver disease (MASLD) affects ~30% of the US adult population, and its prevalence is increasing. Early-stage disease is often missed by clinicians as it is largely asymptomatic until cirrhosis develops. Recent advances in artificial intelligence (AI) have allowed for expanded electronic health record (EHR) identification of several diseases. We aimed to develop an algorithm that utilizes AI to identify patients with MASLD via a large-scale review within the EHR.

Methods: We created a natural language processing (NLP) algorithm that identifies patients with hepatic steatosis on abdominal imaging and selects for patients meeting MASLD criteria. Validation was carried out via manual review of monthly generated cohorts. The algorithm was then utilized to retrieve a MASLD cohort for initial analysis. Demographics were summarized, and additional variables pertaining to early MASLD management were analyzed.

Results: Our algorithm identified patients with MASLD with a positive predictive value (PPV) of over 93%. The NLP component of the algorithm identified hepatic steatosis in imaging reports with a PPV of up to 99.4% and excluded patients with alcohol use with a negative predictive value of ~95%. From a cohort spanning 6 months, 957 individuals with MASLD were identified by the algorithm, of which 14.6% (n = 140) had a MASLD-related diagnosis code.

Abbreviations: AUD, alcohol use disorder; AASLD, American Association for the Study of Liver Diseases; AI, artificial intelligence; CT, computed tomography; DAWG, Data Analytics Warehouse Galaxy; EHR, electronic healthcare records; FN, false negatives; FP, false positives; GI, gastroenterology; HCV, hepatitis C virus; IRB, Institutional Review Board; LLM, Large Language Model; MASH, metabolic dysfunction–associated steatohepatitis; MASLD, metabolic dysfunction–associated steatotic liver disease; MRI, magnetic resonance imaging; NAFLD, non-alcoholic fatty liver disease; NLP, natural language processing; NPV, negative predictive value; PPV, positive predictive value; 're', python regular expression; SQL, Structured Query Language; TN, true negatives; TP, true positives; T2DM, type 2 diabetes mellitus; US, ultrasound; UWMC, University of Washington Medical Center.

Supplemental Digital Content is available for this article. Direct URL citations are provided in the HTML and PDF versions of this article on the journal's website, www.hepcommjournal.com.

Conclusions: We developed an AI algorithm that can perform a large-scale review of electronic health records to identify patients with MASLD with >93% accuracy. Our initial analysis suggests that a substantial proportion of individuals meeting MASLD criteria do not yet carry a MASLD-related diagnosis. Our work can be adapted by other institutions to enhance the detection of MASLD and alcohol use patterns, allowing for targeted interventions to prevent disease progression and improve outcomes.

Keywords: diagnosis, iterative refinement, liver disease, machine learning, natural language processing

BACKGROUND

Metabolic dysfunction–associated steatotic liver disease (MASLD) is the leading driver of chronic liver disease in the United States and globally. With an estimated prevalence of 31% and 18% in North American adults and adolescents, MASLD is associated with increased risk of progression to end-stage liver disease. It now ranks as the primary contributor to liver-related mortalities and has become a common indication for liver transplantation.[1–5] The economic burden of MASLD has also increased over time, paralleling its rising prevalence. Recent data estimates healthcare costs exceeding over $100 billion per year in the United States alone.[6] This substantial economic strain is largely attributed to the costs of liver transplantation, including immunosuppressive medications and long-term disease management. Despite the significant health and economic burden of MASLD, there exists no comprehensive population-based strategy to curtail this growing epidemic.

Previously termed non-alcoholic fatty liver disease (NAFLD), MASLD is the new nomenclature for the subset of steatotic liver diseases in individuals with cardiometabolic risk factors.[7,8] MASLD represents a spectrum of steatotic liver conditions that range from isolated fat accumulation in hepatocytes (hepatic steatosis) to severe metabolic dysfunction–associated steatohepatitis (MASH), which is distinguished by active hepatocyte ballooning with lobular and portal inflammation and/or fibrosis. MASH can progress to cirrhosis with complications resulting from end-stage liver disease and hepatocellular carcinoma. Patients with MASH also have an increased risk of developing several extrahepatic conditions, including cardiovascular disease, chronic kidney disease, and non-hepatic cancers.[9,10] In its early stages, MASLD is largely asymptomatic or minimally symptomatic, yet reversible, making early-stage disease a prime target for screening and management with dietary, medical, and/or surgical metabolic dysfunction-directed interventions.[11]

Under the revised criteria, the diagnosis of MASLD was simplified from the prior criteria for NAFLD, now requiring only radiographic or histologic evidence of steatosis alongside the presence of at least 1 of 5 cardiometabolic risk factors, including dysglycemia (type 2 diabetes mellitus, impaired fasting glucose, or impaired glucose tolerance), clinical obesity [either elevated BMI of $\geq$25 kg/m^2 in patients not of Asian ethnicity or $\geq$23 kg/m^2 in Asian patients or elevated waist circumference of 94 cm (male) or 80 cm (female), ethnically adjusted], elevated blood pressure (BP $\geq$130/85 or on antihypertensive therapy), hypertriglyceridemia (triglycerides >150 mg/dL), low HDL-cholesterol (HDL $\leq$40 mg/dL in males or $\leq$50 mg/dL in females), or lipid-lowering therapy, in the absence of alternative causes of steatotic liver disease.[7,11] Nonetheless, from a clinical perspective, the diagnosis and management of MASLD remain challenging.

Steatosis is frequently detected incidentally during abdominal ultrasound (US), computed tomography (CT), or magnetic resonance imaging (MRI) performed for other reasons. Of these incidentally discovered cases, 10%–26% arise from studies performed in the emergency department.[12–16] Although this information is typically noted in the radiology report, it frequently fails to be incorporated into subsequent clinical documentation.[17] A retrospective chart review study at the London Health Science Center's emergency department revealed that among the 450 patients who underwent abdominal CT imaging performed for non-hepatic indications, 10.7% had incidental findings of hepatic steatosis. However, none of these patients received any follow-up within a year.[15] Moreover, the asymptomatic nature of early-stage disease results in many cases remaining undiagnosed until advanced liver disease develops.[18] One study in the emergency department found that up to 66% of patients with incidentally diagnosed MASLD cirrhosis had no prior

MASLD diagnosis,[18] and, in primary care settings, MASLD is frequently underdiagnosed.[19,20]

The underutilization of ICD codes for both NAFLD and MASLD within electronic healthcare records (EHR) adversely affects EHR population-based strategies aimed at early diagnosis and management.[21,22] Reviewing radiologic imaging, regardless of the initial indication, serves as a potential screening method to identify MASLD within the general population, thereby enabling the timely implementation of appropriate management strategies to mitigate disease progression in asymptomatic or unrecognized individuals.[23–25] However, radiology alone is insufficient for a confident diagnosis of MASLD.

To facilitate early identification of patients with MASLD using current diagnostic criteria and to address the limitations of ICD-based population health strategies, we developed an artificial intelligence (AI)–based algorithm that can be implemented across diverse healthcare systems. AI or machine learning offers powerful tools for large-scale analysis of EHRs, enabling automated practices that can address gaps in clinical care within hepatology.[26] Notably, the development of natural language processing (NLP) software has improved the identification of disease populations by accommodating nuanced variations in clinical documentation. In the context of MASLD, several studies have applied data science methodologies to improve patient identification and care optimization.[27–36] However, many of these studies have examined metabolic liver disease under previous definitions (ie, NAFLD), potentially leaving a gap in recognizing and characterizing patients who meet the new MASLD definition. In this context, we developed an NLP algorithm to identify patients who meet the new diagnostic criteria for MASLD within our EHR and have made our source code publicly available to support adoption by other institutions.

METHODS

Data source

The algorithm was developed utilizing patient records within the University of Washington Medical Center (UWMC) health system, which encompasses 4 primary hospitals and over 300 outpatient locations, including 14 primary care clinics.[37] UWMC also has a comprehensive liver transplant program with over 2000 liver transplants performed to date.[38] UWMC utilizes the Epic EHR system, and patient charts include all imaging and laboratory data obtained and reviewed at any UWMC locations, as well as access to select information from outside health systems via the Care Everywhere sharing system. Our project was reviewed by the UWMC Institutional Review Board (IRB) and determined to be exempt. All research was conducted in accordance with both the Declarations of Helsinki and Istanbul.

Study population: definition of MASLD

The goal of the algorithm was to identify all patients within the UWMC health system meeting criteria for MASLD as defined by the recent American Association for the Study of Liver Diseases (AASLD) nomenclature change.[8] Our definition encompassed any patient $\geq$18 years old with imaging findings of hepatic steatosis (US, CT, or MRI) and meeting at least 1 of the following metabolic criteria: BMI $\geq$25 kg/m^2 ($\geq$23 kg/m^2 if Asian race), hemoglobin A1c $\geq$5.7% or diagnosis of type 2 diabetes mellitus (T2DM), 2 readings showing blood pressure $\geq$130/85, plasma triglycerides $\geq$150 mg/dL, plasma HDL-cholesterol $\leq$40 mg/dL for males and $\leq$50 mg/dL for females. Individuals with imaging evidence of hepatic steatosis were excluded from the MASLD definition if they had other non-metabolic causes of liver disease or heavy alcohol use [defined as $\geq$14 standard drinks/week for females and $\geq$21 standard drinks/week for males, alcohol use disorder (AUD)–related diagnosis, or natural language noting a history of or current heavy alcohol use]. Of note, we did not include the entirety of the revised AASLD MASLD criteria (ie, use of blood pressure or lipid-lowering medication) but favored maintaining a broader definition to attempt to capture the majority of the MASLD population. In addition, we did not include ALT in our definition of MASLD as we wanted to emphasize the intention of the new nomenclature to classify diseases based on metabolic components.

Development of a natural language processing algorithm to recognize MASLD

A Structured Query Language (SQL) program script was employed in the UWMC Data Analytics Warehouse Galaxy (DAWG) program, which allows for data retrieval from the UWMC Epic EHR. The script pulled ~10,000 imaging interpretation reports from relevant US, CT, and MRI studies performed within the UWMC system. A sample of these initial reports was reviewed manually to create a label set and generate a pattern search list. This list was then used to process unlabeled imaging reports through the Python 're' (regular expression) text processing program (Python 3.11.9), leveraging pattern-recognition techniques to identify relevant findings. Reports were scored as negative or positive by the processing script based on the presence or absence of hepatic steatosis (Supplement 1, http://links.lww.com/HC9/C190). Patient

charts that received a positive imaging score were reintegrated into the DAWG program, where an algorithm utilizing SQL programming to select for patients who met at least one metabolic criterion was applied to their entire electronic health record. Patients with significant alcohol use were excluded via 2 methods: (1) ICD-10 codes for alcohol-associated liver disease (K70 and related codes) and alcohol use and complications of alcohol use (F10 and related codes) were identified using SQL programming within the DAWG interface and (2) the Python 're' text processing program was used to characterize natural language terms found in any note type into "non-drinking" and "heavy drinking" patterns. "Non-drinking" patterns included references to infrequent or no alcohol use, while "heavy drinking" patterns included references to a history of heavy alcohol use, number of drinks per week, counseling to decrease alcohol use, and documented consequences of alcohol use (Supplement 2, http://links.lww.com/HC9/C191). The NLP was refined to include or exclude various text strings throughout multiple iterations based on feedback from manual validation (Figure 1).

Manual validation and iterative refinement

The final patient list was published to a secure server for manual validation, which was conducted by 2 independent physicians or physician trainees trained in the new AASLD MASLD criteria. An attending physician hepatologist then reviewed the patient list for accuracy. Each patient entry was then manually assessed in Epic and classified as either meeting or not meeting the MASLD criteria. Entries that did not meet criteria were then further classified by error type: imaging interpretation, inclusion criteria, or exclusion criteria. Initial validation demonstrated that alcohol use was the most challenging exclusion criterion for the algorithm to accurately capture, leading to its designation as a separate error category. Any discrepancies between the 2 reviewers were resolved through consensus and attending physician review. An error analysis was performed on the scored results and informed subsequent algorithm refinements. This process was repeated for multiple iterations until the algorithm consistently achieved a previously defined precision rate of $>88\%$, in line with acceptable standards from the literature (Figure 1).[39–43]

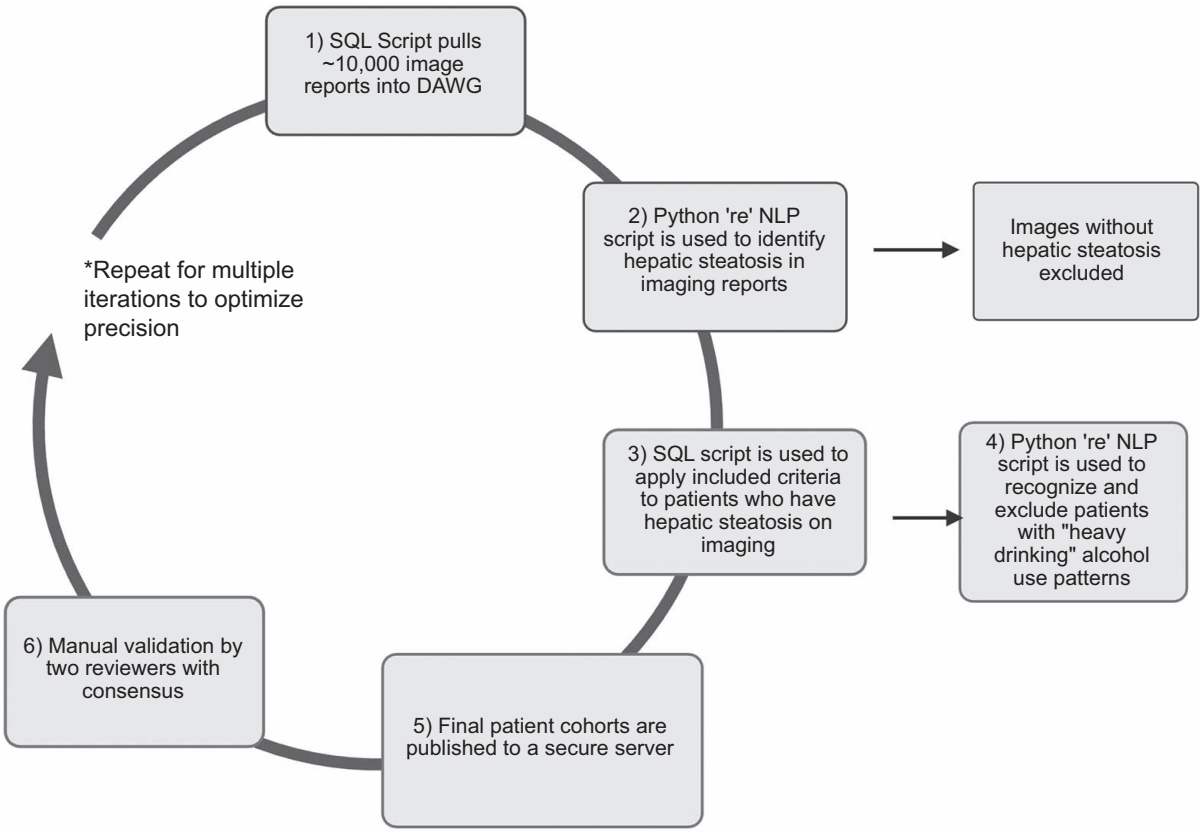


FIGURE 1 Diagram depicting the iterative refinement process utilized to develop the MASLD algorithm. Abbreviations: DAWG, Data Analytics Warehouse Galaxy; MASLD, metabolic dysfunction–associated steatotic liver disease; NLP, natural language processing; 're', regular expressions; SQL, Structured Query Language.

Initial analysis of MASLD

Once the MASLD algorithm was demonstrated to perform at a level surpassing the above precision rate, it was used to generate a cohort of patients meeting MASLD criteria between December 1, 2023, and May 31, 2024. In addition to the above inclusion criteria, patient demographic information, including age, sex, race, and ethnicity, was collected. Other collected variables were the presence or absence of MASLD-related ICD-9/ICD-10 diagnosis code (including all codes related to NAFLD, NASH, and fatty liver), date, and type of any Epic encounter with a gastroenterology (GI) or hepatology specialty location within the UWMC medical system. We also collected data on the presence or absence of any hepatitis C virus (HCV) antibody or quantitative PCR lab result as a surrogate measure of initial MASLD management and preventive hepatology care, given the guidelines for testing in all adult patients.

Validation and statistical methods

Precision of the algorithm was evaluated based on positive predictive value (PPV), which was calculated as the total number of accurate identifications (as determined by manual validation) of patients with MASLD out of the total number of patients identified by the algorithm in each iterative cohort [true positives/(true positives + false positives)]. PPV of the algorithm to accurately interpret imaging and all inclusion criteria were also evaluated. Negative predictive value (NPV) for exclusion of alcohol use was also collected and calculated as the total number of patients not meeting the alcohol use criteria (as determined by manual validation) out of the total number of patients identified as having MASLD by the algorithm in each iterative cohort [true negatives/(true negatives + false negatives)]. Median and interquartile ranges (IQR) were calculated for the descriptive characteristics of the generated cohort. Comparative statistics were calculated using the Mann–Whitney *U* test for comparative variables and the Pearson chi-squared test for categorical variables. Statistics were calculated using R/R Studio (R Foundation, version 2024.12.1+563) and Graphpad Prism (Version 10.4.2).

RESULTS

Iterative refinement of the MASLD algorithm

The initial algorithm identified patients with MASLD with a PPV of ~83% (less than our goal of >88%), with 95.1% PPV for identification of hepatic steatosis on radiologic interpretation using NLP, and 97.5% accuracy of the algorithm when filtering for patients who met metabolic inclusion criteria. Changes were made to the algorithm throughout multiple iterations to reach a maximum PPV of 93.4%. Refinement of the NLP used to identify hepatic steatosis resulted in a maximum PPV of 99.4%, and alterations to the script used to filter for inclusion criteria resulted in ~100% accuracy over the final 2 iterations. Extensive refinement of the NLP used to exclude patients with significant alcohol use was required, with improvement to a maximum NPV of ~95% (Table 1).

MASLD cohort

Among patients who underwent hepatic imaging between December 1, 2023, and May 31, 2024, the MASLD algorithm identified 957 patients as meeting MASLD criteria. Our primary objective in developing the algorithm was to enhance the identification of patients with MASLD according to the new AASLD nomenclature. Consequently, we assessed the proportion of patients who had already been recognized as having MASLD based on MASLD-related ICD codes, which we observed in only 14.6% of AI-identified MASLD patients.

For the total cohort, median age was 52 years (IQR 38–63 y). A total of 56% of patients were male, 68% of

TABLE 1 Metabolic dysfunction–associated steatotic liver disease algorithm iterative refinement outcomes

Iteration	N	Total PPV [TP/(TP +FP), %]	Imaging PPV [TP/(TP +FP), %]	Inclusion PPV [TP/(TP +FP), %]	Alcohol NPV [TN/(TN +FN], %]
1	81	67/81 (82.7%)	77/81 (95.1%)	79/81 (97.5%)	76/81 (93.8%)
2	188	163/188 (86.7%)	185/188 (98.4%)	186/188 (98.9%)	169/188 (89.9%)
3	151	141/151 (93.4%)	150/151 (99.4%)	151/151 (100%)	143/151 (94.7%)
4	182	161/181 (89.0%)	180/182 (98.9%)	181/182 (99.4%)	165/182 (91.2%)

Note: Results of manual validation for 4 iterations of the MASLD algorithm, evaluating the total PPV of the cohort, as well as the PPV of the algorithm to identify hepatic steatosis in imaging reports (Imaging PPV), the PPV of the algorithm to accurately apply inclusion criteria (Inclusion PPV) and the NPV of the algorithm to exclude patients with significant alcohol use (Alcohol NPV).

Abbreviations: FN, false negatives; FP, false positives; MASLD, metabolic dysfunction–associated steatotic liver disease; NPV, negative predictive value; PPV, positive predictive value; TN, true negatives; TP, true positives.

patients were White, 16% were Asian, 6% were Black or African-American, 2% were American Indian or Alaska Native, and 1% were Native Hawaiian or other Pacific Islander. In addition, 12% were Hispanic or Latino/a/x. Metabolic markers were also evaluated, with a total cohort median BMI of 31.3 mg/dL and median hemoglobin A1c of 5.7%. Baseline characteristics and metabolic criteria were also evaluated for the proportion of patients with MASLD-related ICD codes, as this cohort most likely represents the classically studied MASLD population. No significant difference was found between this group and the total cohort.

To assess initial MASLD management and general hepatology care, we also explored screening for HCV and interaction with a specialist. HCV screening was conducted in 57.1% and 65.7% of the total and ICD-diagnosed cohort, respectively, with a non-significant trend toward higher screening in the ICD-diagnosed cohort. A significantly higher proportion of ICD-diagnosed patients interacted with GI/hepatology than that of the total cohort (55% compared with 25.6%, respectively, $p < 0.0001$) (Table 2).

Baseline characteristics of patients in the total MASLD cohort obtained between December 1, 2023, and May 31, 2024 (total cohort, n = 957) and the patients with MASLD-related ICD-9/ICD-10 diagnostic code (ICD Dx cohort, n = 140). *p-value obtained from the Mann–Whitney U test for continuous variables and the Pearson chi-squared test for categorical variables. All continuous variables were non-normally distributed.

For all patients with a MASLD-related ICD-9/ICD-10 code, the mean time from imaging to diagnosis was 33 days, with a range of 0–145 days. Among those who had at least 4 months since initial imaging showing steatosis, we identified 26 patients who had initial imaging in December 2023 with a median time to diagnosis of 38 days (IQR 19–99 d). In all, 30.8% of patients received a diagnosis 4 months or more after initial imaging (Figure 2).

DISCUSSION

Our initial results demonstrate the utility of utilizing machine learning techniques—specifically NLP—in identifying patients who meet criteria for MASLD under the new AASLD nomenclature within the EHR. Through iterative refinement, we increased the PPV of our

TABLE 2 Demographics of metabolic dysfunction–associated steatotic liver disease patient cohort

Characteristic	Total cohort (n = 957)	ICD Dx cohort (n = 140)	p[a]
	Percent of total	14.6%	
Demographics			
Age, median (IQR)	52 (38–63)	54.5 (43–65)	0.07
Male, n (%)	417 (43.6%)	63 (45%)	0.82
Hispanic or Latino/a or Latinx, n (%)	117 (12.2%)	13 (9.3%)	0.4
American Indian or Native Alaskan, n (%)	17 (1.8%)	1 (0.7%)	0.57
Asian, n (%)	152 (15.9%)	30 (21.4%)	0.12
Black or African-American, n (%)	57 (6.0%)	4 (2.9%)	0.19
Native Hawaiian or Pacific Islander, n (%)	9 (1.0%)	2 (1.4%)	0.93
White, n (%)	654 (68.3%)	92 (65.7%)	0.59
MASLD criteria	n = 932	n = 137	
BMI (kg/m^2), median (IQR)	31.3 (27.3–36.8)	31.8 (27.9–38.4)	0.23
	n = 651	n = 107	
Hemoglobin A1c (%), mean (SD)	5.7 (5.4–6.6)	5.9 (5.4–7.1)	0.33
	n = 711	n = 123	
Triglyceride (mg/dL), median (IQR)	207 (133–309)	209 (149–298)	0.42
	n = 692	n = 119	
HDL (mg/dL), median (IQR)	51 (43–62)	51 (42–61)	0.54
MASLD management	n = 957	n = 140	
HCV ab measured, n (%)	546 (57.1%)	92 (65.7%)	0.065
	n = 957	n = 140	
Interaction with GI/hepatology, n (%)	245 (25.6%)	77 (55.0%)	< 0.0001

Note: Baseline characteristics of patients in the total metabolic dysfunction–associated steatotic liver disease (MASLD) cohort obtained between December 1, 2023, and May 31, 2024 (total cohort, n = 957) and the patients with MASLD-related ICD-9/ICD-10 diagnostic code (ICD Dx cohort, n = 140).

[a]p-value obtained from the Mann–Whitney U test for continuous variables and the Pearson chi-squared test for categorical variables. All continuous variables were non-normally distributed.

Abbreviations: ab, antibody; BMI, body mass index; Dx, diagnosis; GI, gastroenterology; ICD, International Classification of Diseases.

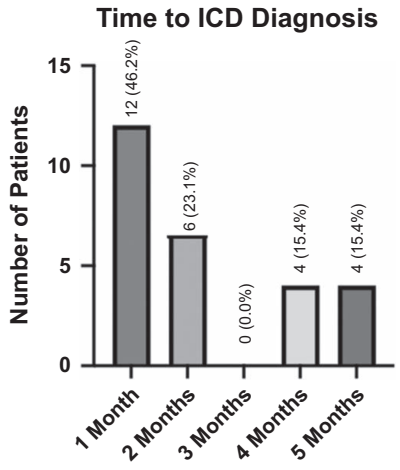


FIGURE 2 Number of patients [n (%)] with initial imaging showing hepatic steatosis in December 2023 who received a MASLD ICD diagnostic code 1–5 months from initial image date (n = 26 patients, median = 38 days, IQR 19–99 d). Abbreviations: ICD, International Classification of Diseases; MASLD, metabolic dysfunction–associated steatotic liver disease.

algorithm to consistently exceed > 90% in identifying patients meeting MASLD criteria. Notably, the NLP component of the algorithm used to detect hepatic steatosis in imaging reports achieved a PPV as high as 99.4%. This level of nuanced language capture would not be possible with traditional, non-machine learning approaches that rely on standardized, discrete variables.

A key example of the need for flexible language recognition was evident in refining our algorithm to exclude patients with significant alcohol use. Manual chart review revealed that alcohol use was frequently documented in non-standardized ways, with providers often noting "heavy alcohol use" or "history of alcohol use disorder" in note text rather than through structured data fields such as problem list diagnosis or quantified weekly alcohol intake. With successive improvements to our NLP script, we were able to increase the NPV for excluding patients with significant alcohol use to over 94% (Table 1).

Once the overall accuracy of the algorithm exceeded 88%, we used it to generate a cohort of MASLD patients for preliminary analysis. Strikingly, fewer than 25% of patients identified had a MASLD-related ICD-9 or ICD-10 code, suggesting substantial underdiagnosis within our health system. This is consistent with prior observations that MASLD-related ICD diagnostic codes are underutilized and that MASLD itself is underrecognized in primary care settings.[19–22] Contributing factors may include challenges in symptom recognition, limited provider awareness of MASLD and practice guidelines, dearth of approved pharmacologic treatments, and a lack of consensus on diagnostic screening strategies.[19,20,44–46]

Given the importance of early diagnosis and risk stratification to prevent progression to end-stage liver disease,[11] it is concerning that such a small proportion of patients with AI-diagnosed MASLD received a formal diagnosis. Furthermore, we found that approximately one-third of patients were not diagnosed via ICD code until more than 3 months after imaging first documented hepatic steatosis (Figure 2). While we acknowledge that a 3-month delay between imaging and clinical MASLD diagnosis may not in and of itself be meaningful for individuals with asymptomatic disease, further research is warranted to determine if this lack of early recognition impacts risk stratification and likelihood of disease recognition only at advanced stages. In addition, fewer than 75% of patients diagnosed with MASLD received HCV screening, potentially reflecting gaps in primary care understanding of MASLD management and general preventative hepatology care. This is particularly concerning given the U.S. Preventive Services Task Force Grade B recommendation that all adults receive HCV screening at least once in their lifetime.[47] Prior studies have shown that nearly half (47%) of primary care physicians are unaware of clinical practice guidelines for the diagnosis and management of MASH.[48] Moreover, only ~25% of MASLD patients had documented interaction with GI/hepatology specialty care. Unsurprisingly, patients with MASLD ICD diagnosis had significantly higher rates of specialist involvement (Table 2). These findings underscore the need for increased education within the primary care setting on initial risk stratification and management of patients with MASLD.

The underdiagnosis of MASLD also has significant implications for population-based research. It is standard practice for researchers to identify patients based on disease-specific ICD codes, including in hepatology.[17,19,49] However, if only a small proportion of the total MASLD population carries an ICD code, we question if those study cohorts are truly representative. While baseline characteristics between our total MASLD population and those with an ICD diagnosis did not differ significantly (Table 2), our initial cohort was relatively small, and comparison on a larger scale is warranted. In addition, ICD codes themselves are imperfect proxies for disease, with studies showing PPV of < 92% for MASLD,[22,50] less than the maximum PPV for our algorithm. These discrepancies provide further support for medical researchers to deploy machine-learning–based tools such as our algorithm to recognize patients based on objective diagnostic criteria rather than administrative coding.

Limitations and strengths

While we were able to manually review of patients identified by the algorithm as meeting MASLD criteria, allowing us to determine the algorithm's positive predictive value, the algorithm's design did not capture patients who did not

meet MASLD criteria (those with hepatic steatosis on imaging who did not meet inclusion criteria or had significant alcohol use) or patients who could have met MASLD criteria but had missing data and were not recognized by the algorithm. Therefore, we were not able to determine the negative predictive value, sensitivity, or specificity of our algorithm. As a result, we cannot account for the proportion of patients meeting the MASLD diagnosis in the UWMC population who were inaccurately excluded by the algorithm. In addition, our decision to use objective blood pressure and lipid measurements in the algorithm's inclusion criteria (rather than incorporating blood pressure- or lipid-lowering medications) may have inadvertently excluded patients with MASLD whose values appear normal due to treatment. We believe this impact was minimal, as we collected data across all available records for each patient. This choice was also made to simplify the algorithm, given the challenges of capturing prescription data in our tertiary referral center, where many patients receive medications from outside providers. However, this aspect of the algorithm could be modified in future iterations or by other institutions adapting our approach to include medication data. Although we achieved our target level of precision, the variation in the PPV and NPV between the final 2 iterations (Table 1) highlights the need for continued refinement. It is also important to note that we were unable to capture clinical data obtained outside our health system, which may have led to an underestimation of screening rates for markers such as HCV ab (antibody) testing.

Our primary intention in the publication of this methodology is to demonstrate a model for the integration of machine learning in the form of natural language processing into existing database structures. While different institutions may utilize various EHRs or databases, the language utilized to describe both hepatic steatosis within imaging reports and patient alcohol use likely shares universal terminology. Therefore, we have shared our Python 're' scripts so that other institutions may, with the application of a similar iterative refinement process, integrate them into their own database systems. We feel this is a novel and accessible approach to facilitate the incorporation of machine learning techniques into existing healthcare systems.

While many researchers are understandably turning to Large Language Models (LLMs) for nuanced capture of diagnoses, we feel there is still a role for NLP models such as ours. Many institutions are better situated to integrate smaller NLP code like the one we created using Python 're' into their existing databases. This format also allows for more seamless addition of inclusion and exclusion criteria, enabling capture of large sets of data in a format that is more consistent with that previously utilized in research and patient registries. However, as these models become more easily integrated with established institutional databases, we hope to adapt our model to LLM formats.

Future directions

Our algorithm has the potential to aid in the early identification of MASLD, allowing for targeted interventions to prevent disease progression and improve patient outcomes. We plan to leverage this tool in an educational quality improvement intervention aimed at increasing recognition and early management of MASLD in the primary care setting. We also anticipate a role for integration of the algorithm within the EHR, allowing for automation of this care. In addition, this tool will also be instrumental in generating future MASLD research cohorts, minimizing the need for laborious manual chart review and reliance on administrative ICD codes for identification of disease populations.

CONCLUSIONS

Our algorithm utilized NLP techniques to accurately identify patients meeting the new AASLD MASLD criteria. We also demonstrated underdiagnosis of MASLD at our medical center and highlighted the need for further evaluation to expand the characterization and management of this population. This augmented intelligence represents a new frontier in hepatology disease management.

ACKNOWLEDGMENTS

Stuart A, Swarts K, Granich M, Yeung J, Thirumalai A, Dhyani M, Perkins J, Carr R. Artificial Intelligence for Early MASLD Identification in the Electronic Medical Record. Hepatology. October 2024; 80(S1):S1140.

FUNDING INFORMATION

US Department of Health and Human Services, National Institutes of Health, National Institute on Alcohol Abuse and Alcoholism. Grant number: R01 AA026302 NIH/NIAAA.

CONFLICTS OF INTEREST

For Rotonya Carr: Merck, Inc., grant support; Intercept, consulting and prior grant support; Novo Nordisk Inc., consulting; Madrigal, consulting. For Arthi Thirumalai: Novo Nordisk, Inc., consulting; Fractyl Health, research support.

ORCID

Arthi Thirumalai https://orcid.org/0000–0003–1239–2614
James Perkins https://orcid.org/0000–0002–6935–0012
Rotonya Carr https://orcid.org/0000–0003–0235–6994

REFERENCES

1. Younossi ZM, Golabi P, Paik JM, Henry A, Van Dongen C, Henry L. The global epidemiology of nonalcoholic fatty liver disease

(NAFLD) and nonalcoholic steatohepatitis (NASH): A systematic review. Hepatology. 2023;77:1335–47.
2. Le P, Tatar M, Dasarathy S, Alkhouri N, Herman WH, Taksler GB, et al. Estimated burden of metabolic dysfunction–associated steatotic liver disease in US adults, 2020 to 2050. JAMA Network Open. 2025;8:e2454707.
3. Anderson EL, Howe LD, Jones HE, Higgins JPT, Lawlor DA, Fraser A. The prevalence of non-alcoholic fatty liver disease in children and adolescents: A systematic review and meta-analysis. PLoS One. 2015;10:e0140908.
4. Arshad T, Paik JM, Biswas R, Alqahtani SA, Henry L, Younossi ZM. Nonalcoholic fatty liver disease prevalence trends among adolescents and young adults in the United States, 2007–2016. Hepatol Commun. 2021;5:1676–88.
5. Noureddin M, Vipani A, Bresee C, Todo T, Kim IK, Alkhouri N, et al. NASH leading cause of liver transplant in women: Updated analysis of indications for liver transplant and ethnic and gender variances. Am J Gastroenterol. 2018;113:1649–59.
6. Miao L, Targher G, Byrne CD, Cao YY, Zheng MH. Current status and future trends of the global burden of MASLD. Trends Endocrinol Metab. 2024;35:697–707.
7. Kanwal F, Neuschwander-Tetri BA, Loomba R, Rinella ME. Metabolic dysfunction–associated steatotic liver disease: Update and impact of new nomenclature on the American Association for the Study of Liver Diseases practice guidance on nonalcoholic fatty liver disease. Hepatology. 2024;79:1212–9.
8. Rinella ME, Lazarus JV, Ratziu V, Francque SM, Sanyal AJ, Kanwal F, et al. A multisociety Delphi consensus statement on new fatty liver disease nomenclature. Hepatology. 2023;78: 1966–86.
9. Mantovani A, Lonardo A, Stefan N, Targher G. Metabolic dysfunction–associated steatotic liver disease and extrahepatic gastrointestinal cancers. Metabolism. 2024;160:156014.
10. Chan KE, Ong EYH, Chung CH, Ong CEY, Koh B, Tan DJH, et al. Longitudinal outcomes associated with metabolic dysfunction–associated steatotic liver disease: A meta-analysis of 129 studies. Clin Gastroenterol Hepatol. 2024;22:488–498.e14.
11. Rinella ME, Neuschwander-Tetri BA, Siddiqui MS, Abdelmalek MF, Caldwell S, Barb D, et al. AASLD Practice Guidance on the clinical assessment and management of nonalcoholic fatty liver disease. Hepatology. 2023;77:1797–835.
12. Kontrick AV, VanWagner LB, Yeh C, Courtney DM. Hepatic steatosis: An incidental finding that deserves attention. Acad Emerg Med. 2020;28:578–581.
13. Cleveland ER, Ning H, Vos MB, Lewis CE, Rinella ME, Carr JJ, et al. Low awareness of nonalcoholic fatty liver disease in a population-based cohort sample: The CARDIA study. J Gen Intern Med. 2019;34:2772–2778.
14. Kontrick AV, Alinger JB, Goins EC, Mollo AF, Cruz DS, McCarthy DM. Documentation of incidentally noted hepatic steatosis to emergency department patients: A retrospective study. Acad Emergency Med. 2025;32:284–291.
15. Wells MM, Li Z, Addeman B, McKenzie CA, Mujoomdar A, Beaton M, et al. Computed tomography measurement of hepatic steatosis: Prevalence of hepatic steatosis in a Canadian population. Can J Gastroenterol Hepatol. 2016; 2016:4930987.
16. Nagra N, Penna R, La Selva D, Coy D, Siddique A, Burman B. Tagging incidental finding of fatty liver on ultrasound: A novel intervention to improve early detection of liver fibrosis. J Clin Transl Res. 2021;7:641–7.
17. Van Vleck TT, Chan L, Coca SG, Craven CK, Do R, Ellis SB, et al. Augmented intelligence with natural language processing applied to electronic health records for identifying patients with non-alcoholic fatty liver disease at risk for disease progression. Int J Med Inform. 2019;129:334–41.
18. Bertot LC, Jeffrey GP, Wallace M, MacQuillan G, Garas G, Ching HL, et al. Nonalcoholic fatty liver disease-related cirrhosis is commonly unrecognized and associated with hepatocellular carcinoma. Hepatol Commun. 2017;1:53–60.
19. Blais P, Husain N, Kramer JR, Kowalkowski M, El-Serag H, Kanwal F. Nonalcoholic fatty liver disease is underrecognized in the primary care setting. Am J Gastroenterol. 2015;110:10–4.
20. Patel KM, Zhang J, Marsden J, Bays C, Mauldin PD, Schreiner AD. Missed and delayed diagnoses of chronic liver disease in primary care patients with cirrhosis. Dig Dis Sci. 2024;69:3721–8.
21. Hagström H, Adams LA, Allen AM, Byrne CD, Chang Y, Grønbæk H, et al. Administrative coding in electronic health care record-based research of NAFLD: An expert panel consensus statement. Hepatology. 2021;74:474–82.
22. Hayward KL, Johnson AL, Horsfall LU, Moser C, Valery PC, Powell EE. Detecting non-alcoholic fatty liver disease and risk factors in health databases: accuracy and limitations of the ICD-10-AM. BMJ Open Gastroenterol. 2021;8:e000572.
23. Schonfeld E, Kierans AS, Fox R, Brandman D. Using incidental radiologic findings of hepatic steatosis to improve the diagnosis of metabolic dysfunction–associated steatotic liver disease. J Am Coll Radiol. 2025;22:358–65.
24. Penna R, Lim J, Williams BL, Blackmore CC, Coy DL. Opportunistic screening of patients for hepatic steatosis: Clinical follow-up and diagnostic yield. J Am Coll Radiol. 2021;18: 1423–1429.
25. Kutaiba N, Richmond D, Morey M, Brennan D, Rotella JA, Ardalan Z, et al. Incidental hepatic steatosis on unenhanced computed tomography performed for suspected renal colic: Gaps in reporting and documentation. J Med Imaging Radiat Oncol. 2019;63: 431–438.
26. Schattenberg JM, Chalasani N, Alkhouri N. Artificial intelligence applications in hepatology. Clin Gastroenterol Hepatol. 2023;21: 2015–25.
27. Kalapala R, Rughwani H, Reddy DN. Artificial intelligence in hepatology—Ready for the primetime. J Clin Exp Hepatol. 2023; 13:149–61.
28. Zhang L, Mao Y. Artificial intelligence in NAFLD: Will liver biopsy still be necessary in the future. Healthcare. 2022;11:117.
29. Dinani AM, Kowdley KV, Noureddin M. Application of artificial intelligence for diagnosis and risk stratification in NAFLD and NASH: The state of the art. Hepatology. 2021;74:2233–40.
30. Schneider CV, Li T, Zhang D, Mezina AI, Rattan P, Huang H, et al. Large-scale identification of undiagnosed hepatic steatosis using natural language processing. EClinicalMedicine. 2023;62: 102149.
31. Chen R, Petrazzini BO, Nadkarni G, Rocheleau G, Bansal M, Do R. Machine learning enables single-score assessment of MASLD presence and severity. medRxiv [Preprint], 2023;25:2023.
32. John BV, Bastaich D, Mezzacappa C, Ferreira RD, Hentschel A, Samos A, et al. Identifying metabolic dysfunction–associated steatotic liver disease using natural language processing in a US national cohort. Am J Gastroenterol. 2025;120:2583–2591.
33. Liu J, Liu Z, Liu C, Sun H, Li X, Yang Y. Integrating artificial intelligence in the diagnosis and management of metabolic syndrome: A comprehensive review. Diabetes/Metab Res Rev. 2025;41:e70039.
34. Sherman MS, Challa PK, Przybyszewski EM, Wilechansky RM, Uche-Anya EN, Ott AT, et al. A natural language processing algorithm accurately classifies steatotic liver disease pathology to estimate the risk of cirrhosis. Hepatol Commun. 2024;8:e0403.
35. Torgersen J, Skanderson M, Kidwai-Khan F, Carbonari DM, Tate JP, Park LS, et al. Identification of hepatic steatosis among persons with and without HIV using natural language processing. Hepatol Commun. 2024;8:e0468.
36. Boullion J, Husein A, Agrawal A, Xing D, Hossain MI, Bhuiyan MS, et al. Machine learning-based biomarker identification for early diagnosis of metabolic dysfunction–associated steatotic liver disease. J Clin Endocrinol Metab. 2025;110:e3866–e3877.

37. UW Medicine, University of Washington. The UW Medicine Family; 2025. Accessed June 1, 2025. https://www.uwmedicine.org/about/the-uwmedicine-family
38. UW Medicine, University of Washington. Liver Transplant; 2025. Accessed June 1, 2025. https://www.uwmedicine.org/specialties/transplant/liver-transplant
39. Dashti M, Azimi T, Khosraviani F, Azimian S, Bahanan L, Zahmatkesh H, et al. Systematic review and meta-analysis on the accuracy of artificial intelligence algorithms in individuals gender detection using orthopantomograms. Int Dent J. 2025;75:2157–2168.
40. Mc Entee PD, Boland PA, Cahill RA. AUGUR-AIM: Clinical validation of an artificial intelligence indocyanine green fluorescence angiography expert representer. Colorectal Dis. 2025;27:e70097.
41. Mahmood MA, Jamel L, Alturki N, Tawfeek MA. Leveraging artificial intelligence for diagnosis of children autism through facial expressions. Sci Rep. 2025;15:11945.
42. Kurniawan A, Saelung M, Rizky BN, Chusida A, Prakoeswa BFWR, Nefertari G, et al. Dental age estimation using a convolutional neural network algorithm on panoramic radiographs: A pilot study in Indonesia. Imaging Sci Dent. 2025;55:28.
43. Hong EK, Ham J, Roh B, Gu J, Park B, Kang S, et al. Diagnostic accuracy and clinical value of a domain-specific multimodal generative AI model for chest radiograph report generation. Radiology. 2025;314:e241476.
44. Younossi ZM, Wong VWS, Anstee QM, Romero-Gomez M, Trauner MH, Harrison SA, et al. Fatigue and pruritus in patients with advanced fibrosis due to nonalcoholic steatohepatitis: The impact on patient-reported outcomes. Hepatol Commun. 2020;4:1637–50.
45. Chalasani N, Younossi Z, Lavine JE, Charlton M, Cusi K, Rinella M, et al. The diagnosis and management of nonalcoholic fatty liver disease: Practice guidance from the American Association for the Study of Liver Diseases. Hepatology. 2018;67:328–57.
46. Berzigotti A, Tsochatzis E, Boursier J, Castera L, Cazzagon N, Friedrich-Rust M, et al. EASL Clinical Practice Guidelines on non-invasive tests for evaluation of liver disease severity and prognosis—2021 update. J Hepatol. 2021;75:659–89.
47. Owens DK, Davidson KW, Krist AH, Barry MJ, Cabana M, Caughey AB, et al. USPSTF recommendation: Screening for hepatitis C virus infection in adolescents and adults. JAMA. 2020;323:970–975.
48. Nadolsky K, Cryer DR, Articolo A, Fisher T, Schneider J, Rinella M. Nonalcoholic steatohepatitis diagnosis and treatment from the perspective of patients and primary care physicians: A cross-sectional survey. Ann Med. 2023;55:2211349.
49. Dahiya M, Eboreime E, Hyde A, Rahman S, Sebastianski M, Carbonneau M, et al. International classification of diseases codes are useful in identifying cirrhosis in administrative databases. Dig Dis Sci. 2022;67:2107–2122.
50. Åström H, Wester A, Hagström H. Administrative coding for non-alcoholic fatty liver disease is accurate in Swedish patients. Scand J Gastroenterol. 2023;58:931–936.

How to cite this article: Stuart A, Dotson A, Swarts K, Granich M, Yeung J, Thirumalai A, et al. Development of an AI algorithm for early identification of MASLD in the electronic health record. Hepatol Commun. 2025;9:e0834. https://doi.org/10.1097/HC9.0000000000000834