



Common Data Elements and Features of a Recommender System for People Living with Fatty Liver Disease

Samira Khademzadeh¹, Mohsen Nassiri Toosi², Esmail Mehraeen³, Arash Roshanpoor⁴ and Marjan Ghazisaeidi^{1*}

1. Department of Health Information Management, School of Allied Medical Sciences, Tehran University of Medical Sciences, Tehran, Iran

2. Liver Transplantation Research Center, Imam Khomeini Hospital Complex, Tehran University of Medical Sciences, Tehran, Iran

3. Department of Health Information Technology, Khalkhal University of Medical Sciences, Khalkhal, Iran

4. Department of Computer Science, Sama Technical and Vocational Training College, Tehran Branch (Tehran), Islamic Azad University (IAU), Tehran, Iran

* Corresponding author

Marjan Ghazisaeidi, MSc

Department of Health Information Management, Tehran University of Medical Sciences, Tehran, Iran

Fax: +98 21 8898 2905

Email: ghazimar@tums.ac.ir

Received: Jun 20 2021

Accepted: Oct 6 2021

Citation to this article:

Khademzadeh S, Nassiri Toosi M, Mehraeen E, Roshanpoor A, Ghazisaeidi M. Common Data Elements and Features of a Recommender System for People Living with Fatty Liver Disease. *J Iran Med Counc.* 2022;5(1):156-67.

Abstract

Background: Fatty liver disease is rising as the most common liver disease in recent years. One of the new approaches to manage the disease is the use of intelligent systems. The recommender system is increasingly utilized in managing chronic conditions. This study was performed to identify the common data elements and features of a recommender system for people living with fatty liver.

Methods: This study was a narrative review exploring the minimum data set for a recommender system in fatty liver disease. We aimed to review the current literature evidence to comprehend the specific requirements of the related knowledge. The search was carried out in November 2020 using PubMed, Scopus, Science Direct, and Web of Science databases. We searched the keywords including fatty liver, liver disease, nonalcoholic fatty liver disease, intelligent, smart system, recommender system, minimum data set, data element, and data requirements.

Results: A review of the articles showed that the most common data elements of the administrative category were sex/gender (n=22), age (n=22), and ethnic group/race (n=8). We also identified the clinical data elements and technical features of a recommender system for people living with fatty liver. Based on the findings of this study, “diabetes and glucose status” (n=18), “AST” (n=15), “BMI” (n=13), and “ALT” (n=13) were the most frequent data elements of clinical category. Furthermore, “predicting and identifying” (n=8) was the most common technical feature mentioned in the reviewed articles.

Conclusion: We determined the common elements and features of a recommender system in three different categories: clinical data elements, demographic data elements, and technical capabilities. Using these requirements, it is possible to structure data gathering, medication adherence, and communication with healthcare providers in a standard manner. It is suggested that appropriate policies and national grants be adopted to identify and prioritize a minimum data set to support the healthcare services of people living with chronic conditions.

Keywords: Fatty liver disease, Intelligent system, Minimum data set, Nonalcoholic fatty liver disease, Recommender system

Introduction

Nonalcoholic Fatty Liver Disease (NAFLD) is an increasing cause of chronic liver disease worldwide. Estimates suggest that about 20–30% of adults in developed countries have excess fat accumulation in the liver (1,2). Individuals with type 2 diabetes and obesity are even at higher risk of getting NAFLD (3). This disease refers to a spectrum of pathological disorders that covers simple hepatic steatosis, steatohepatitis, and cirrhosis that arise despite a lack of alcohol consumption. Moreover, there is significant morbidity and mortality with uncontrolled steatohepatitis, which may progress to advanced hepatic fibrosis, cirrhosis, and hepatocellular carcinoma (4). Therefore, the NAFLD course could follow one or more of its four clinical-pathological entities which are steatosis, nonalcoholic steatohepatitis, advanced fibrosis/cirrhosis, and hepatocellular carcinoma. NAFLD is also associated with atherosclerosis, increased cardiovascular risks as well as mortality (3).

Both genetic factors and lifestyle contribute to the pathogenesis of NAFLD. The ultimate goals of NAFLD management include early diagnosis of the disease, early prevention of further progression of the disease, regression of the disease as much as possible as well as improvement of the underlying metabolic syndrome (5). Despite pharmacological advances, healthy lifestyle changes, including dietary habits and physical activity, remain a fundamental approach for the therapeutic management of NAFLD (6). A 7–10 % weight loss results in improvements in liver enzymes and histology and can be achieved either by dietary changes or by adopting an active lifestyle⁷. However, implementing lifestyle modification is difficult for patients to achieve success in clinical settings, and maintaining such modifications consistently in daily life can be even more challenging (6,8).

Technological innovations are now commonly incorporated in designing health promotion programs (9). They can address limitations by offering low-cost, highly adaptable, and easily accessible platforms for disseminating lifestyle management interventions (10). They permit real-time data collection, and sharing is increasingly commonplace, enabling researchers to assess multiple health behaviors in various contexts and improvement of health care via non-conventional routes at unprecedented speeds (11).

Intelligent systems have recently gained increasing popularity in the promotion of healthy nutrition and physical activity, and prevention of overweight (12). Self-monitoring of dietary intake and physical activity tends to provide the user with the opportunity to set personal goals, to self-monitor their healthy behavior, and to receive tailored feedback (13). By mitigating the barriers associated with committing to repeated in-house nutrition and exercise therapy sessions, mobile apps increase the potential of expanding the reach and efficacy of lifestyle interventions (8). The objective of this study was to identify the minimum dataset for an intelligent recommender system in fatty liver disease.

Materials and Methods

Design

This study was a narrative review exploring the minimum data set for a recommender system in fatty liver disease. We aimed to review the current literature evidence to comprehend the specific requirements of the related knowledge better. A search was conducted identifying the related articles based on the inclusion and exclusion criteria. The included studies were subsequently categorized, and a summary of key points was provided.

Criteria for the selection of studies

The selection of the studies was performed by two independent researchers. We included English-written original articles published from January 1, 2010, to November 15, 2020.

The exclusion criteria were as follows:

- Different types of studies, such as reviews, abstracts, and reports
- No access to the full-text document.
- Non-English articles
- Animal studies

Search strategy

The search was carried out in November 2020 using the PubMed, Scopus, Science Direct, and Web of Science databases. We searched the keywords of fatty liver, liver disease, nonalcoholic fatty liver disease, intelligent, smart system, recommender system, minimum data set, data element, and data requirements on the following search strategy:

A. "Fatty liver" OR "Liver disease" OR "Nonalcoholic

- fatty liver disease” [Title/Abstract]
- B. ”Intelligent” OR “Smart system” OR “Recommender system” [Title/Abstract]
- C. ”Minimum data set” OR “Data element” OR “Data requirements”[Title/Abstract]
- D. [A] AND [B]
- E. [A] AND [B] AND [C]

Eligibility criteria

We included the most relevant original English studies applying the following exclusion criteria:

- 1) Non-original studies, including reviews and non-original editorials;
- 2) Pure laboratory or animal studies not conducted on humans;
- 3) Case reports and case series;
- 4) Studies not conducted on the system for people living with nonalcoholic fatty liver disease;
- 5) Studies not related to the alcoholic fatty liver disease;
- 6) Abstracts or conference abstracts, or no available full-text.

Literature selection

We screened the titles and abstracts of the retrieved papers to identify studies meeting the inclusion criteria. To analyze the identified articles included in the review, the following variables were utilized: First author, publication date, country, minimum dataset, and other findings.

The appropriate full-text articles were included, and

their results were discussed to make the final selection. After reading the full text of all the eligible papers, the researchers made the final decision for each study.

Ethics approval and consent to participate: The present study was extracted from the master thesis with code 9711450002 and code of ethics IR.TUMS.SPH.REC.1400.224 entitled “Design, and development a recommender system for people living with fatty liver disease” conducted at Tehran University of Medical Sciences in 2021. We thank the statistical population and all the participants for taking time to contribute to the study.

Consent to publication

Not applicable

Availability of data and material

The authors stated that all information provided in this article could be shared.

Using the applied systematic search strategies, 698 articles were identified and retrieved.

Results

General specifications

After an initial review of the retrieved articles, 189 duplicates were removed, and the title and abstract of the remaining 509 articles were reviewed. Applying the selection criteria, 486 articles were excluded, and only 22 articles met the inclusion criteria and were included in the final review (Figure 1).

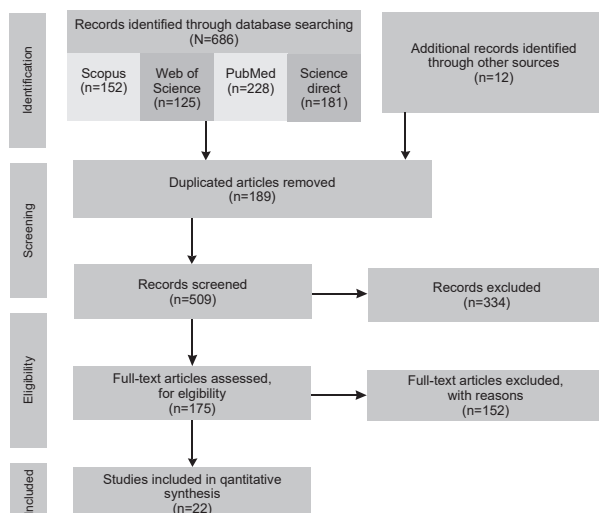


Figure 1. Flow diagram of selection process of articles identified.

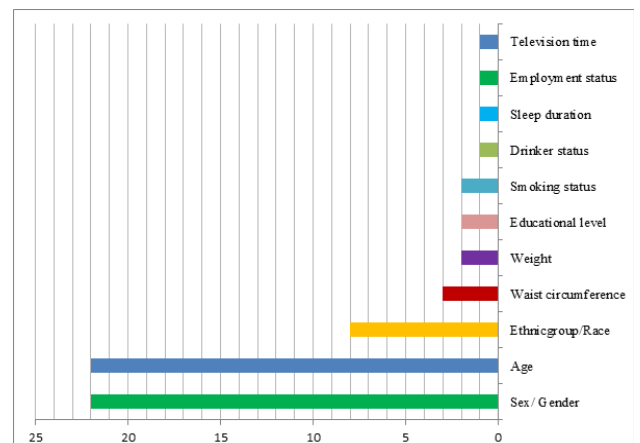


Figure 2. Frequency of the identified administrative data elements.

Identifying minimum dataset

We obtained a set of data elements and features of the intelligent recommender system for people living with fatty liver comprised of three categories: administrative data elements, clinical data elements, and technical capabilities (Table 1). A review of the articles showed that the most common data elements of the administrative category were sex/gender (n=22), age (n=22), and ethnic group/race (n=8). The frequency of the identified administrative data elements is shown in figure 2.

We also identified the clinical data elements and technical features of a recommender system for people living with fatty liver. Based on the findings of this study, “diabetes and glucose status” (n=18), “AST” (n=15), “BMI” (n=13), and “ALT” (n=13) were the most frequent data elements of the clinical category.

Furthermore, “predicting and identifying” (n=8) was the most common technical feature mentioned in the reviewed articles (Table 2).

ALT, alanine aminotransferase; AST, aspartate aminotransferase; BMI, body-mass index; HbA1c, glycated hemoglobin; HDL, high-density lipoprotein; LDL, low-density lipoprotein; PLT, platelet; type 2 DM, type 2 diabetes mellitus; A1AT, alpha 1 antitrypsin; AIH, autoimmune hepatitis; AlkPhos, alkaline phosphatase; ARLD, alcohol-related liver disease; DILI, drug-induced liver injury; HBV, hepatitis B virus infection; HCV, hepatitis C virus infection; PBC, primary biliary cholangitis; INR: international normalized ratio; eGFR: estimated glomerular filtration rate; GOT: glutamic-oxaloacetic transaminase; GPT: glutamic-pyruvic transaminase;

Table 1. Identified minimum dataset of intelligent recommender systems in fatty liver

ID	The first author (reference)	Publication date	Country	Minimum dataset		
				Administrative	Clinical	Technical features
1	Forlano, R ¹	2020	London	Age, Sex, Ethnic group	BMI, Type 2 DM, Arterial hypertension, Dyslipidemia, PLT, ALT, AST, Total cholesterol, Triglycerides, HDL, LDL, HbA1c, Ferritin	Machine Learning-Based Quantification
2	Lin, YJ ¹⁴	2020	Taiwan	Age, Sex	Albumin, Ammonia, Blood urea nitrogen, Total bilirubin, Direct bilirubin, Creatinine, C-reactive protein, eGFR, Glucose antecibus Serum GOT, Serum GPT, Hemoglobin, Potassium Sodium Platelets, PT Control, PT fibrinogen, PT international normalized ratio, Leukocyte count	Monitoring System for Predicting Mortality
3	Lim, SL ⁸	2020	Singapore	Age, Gender, Ethnicity, Waist circumference, Weight	Diabetes, Hyperlipidemia, Hypertension, BMI, ALT, AST, Systolic blood pressure, Diastolic blood pressure	Intervention by mobile technology on weight loss
4	Atabaki-Pasdar, N ¹⁵	2020	Sweden	Age, Sex, Weight, Waist circumference	BMI, SBP, DBP, HbA1c, Fasting glucose, Fasting insulin, 2-hour glucose, 2-hour insulin Triglycerides, ALT, AST, Alcohol intake, Liver fat	Predicting and elucidating by ML

ID	The first author (reference)	Publication date	Country	Minimum dataset		
				Administrative	Clinical	Technical features
5	Ioannou, GN ¹⁶	2019	USA	Age, Sex, Race/ethnicity	BMI, AUDIT-C score: No alcohol, Low-level alcohol use, Unhealthy alcohol use, Diabetes, Substance use disorder, HIV coinfection, Complications of cirrhosis, MELD score, AFP, Hemoglobin, Platelet count, Creatinine, Bilirubin, INR, Albumin, Alkaline phosphatase, FIB-4 score, AST/ALT ratio	Models estimating risk
6	Van Vleck, TT ¹⁷	2019	USA	Age, Sex, Race	Liver serology at base line: aspartate aminotransferase; alanine aminotransferase, Base line comorbidities: diabetes mellitus; hypertension; BMI	Augmented Intelligence with NLP for Identifying Patients
7	Yang, M ¹⁸	2019	China	Sex, Age	BMI , ALT, AST, AST/ALT ratio, ALP, GGT, TC, TG, HDL, LDL, apoA1, Alb, Tbil, Cholinesterase, Urea, Ferritin, Fasting glucose, PLT, Insulin, HA, PTA, PIIINP, Diabetes, Hypertension	---
8	Muthuselvan, S ¹⁹	2018	India	Age, Gender	tot bilirubin, direct bilirubin, tot proteins, albumin	--
9	Perveen, S ²⁰	2018	Pakistan	Age, Gender	Abdominal obesity, waist circumference, Lipoprotein level, HDL level, Blood pressure, Fasting Glucose (FG), Diastolic BP, Systolic BP, Unknown disease frequency, COPD frequency Dementia frequency, Depression frequency, Diabetes Mellitus frequency, Epilepsy frequency, Hypertension frequency, Osteoarthritis frequency, Parkinson's Disease frequency, Triglycerides, BMI	Diagnosis risk and progression by Machine learning
10	Wu, CC ²¹	2018	Taiwan	Age, Gender	Systolic blood pressure, Diastolic blood pressure, Abdominal Girdle, Triglyceride, HDL-C, Glucose AC, GOT-AST, GPT-ALT	Prediction using ML
11	Su, GL ²²	2018	USA	Age, Gender, Race Geographic	Hepatitis B, Cirrhosis, Cirrhosis Complication, Ascites, Hepatorenal syndrome, Spontaneous Bacterial Peritonitis, Variceal Bleed, Hepatic Encephalopathy, Hepatocellular Carcinoma, Thrombocytopenia, ALT, Bilirubin, Modified Elixhauser Comorbidity, Abdominal CT, Abdominal MRI, Abdominal Ultrasound , Esophagoduodenoscopy, Liver Biopsy Paracentesis	Virtual Consultations for Veterans with Liver Disease
12	Miller, MH ²³	2018	UK	Age, Sex	BMI, AIH, HCV, HBV, PBC, A1AT, NAFLDnofibrosis, NAFLD with fibrosis, ARLD no fibrosis, ARLD with fibrosis, Gilbert's syndrome, DILI, Isolated elevated AlkPhos, Haemochromatosis, Wilson's disease	Automated assessment

Cont Table 1

ID	The first author (reference)	Publication date	Country	Minimum dataset		
				Administrative	Clinical	Technical features
13	Trépo E ²⁴	2018	Belgium	Age, Sex	INR, bilirubin, ceratinne, Albumin	Predicts Survival of Patients
14	Zhou, XD ²⁵	2017	China	Age, Sex, Ethnicity	Cirrhosis: Alcoholic cirrhosis, number Biliary cirrhosis, number Nonalcoholic cirrhosis, number, MELD: Reweight-MELD, Del-Cr-MELD, AKI-MELD, MELD, components: Bilirubin, Creatinine, 48-hour creatinine, Cr48hours/Cr, INR, Loge MELD components: Bilirubin, Creatinine, 48-hour creatinine, Cr48hours/Cr, INR	Remodeling for Predicting Mortality Risk
15	Corey, KE ²⁶	2016	USA	Age, Gender, Ethnicity	BMI, Diabetes mellitus, Hypertension, Family history of CVD, Renal failure, LDL, HDL, Albumin, Sodium	Using an Electronic Medical Records Database to Identify NAFLD
16	Meng, G ²⁷	2016	China	Age, Sex, Physical activity, Sitting time, Smoking status, Drinker status, Sleep duration, Educational level, Employment status, Television time	BMI, ALT, Total energy intake, WC, TC, TG, LDL-C, HDL-C ,SBP, DBP, FBG	---
17	Goh, GBB ²⁸	2015	USA	Age, sex	Diabetes, Caucasian, HTN, BMI, AST, ALT, Albumin, Platelet ,Serum iron, Ferritin	Model to predict
18	Lesmana, CRA ²⁹	2015	Indonesia	Age, Sex, Smoking history	Body mass index, Systolic blood pressure, Diastolic blood pressure, Fasting blood glucose, Triglyceride levels, Total cholesterol levels, LDL-cholesterol, HDL-cholesterol, Chronic parenchymal liver disease, Serum AST levels, Serum ALT levels	---
19	Jan-PS ³⁰	2014	German	Age, Gender	AST, ALT, ALT/AST ratio, BMI, Incidence of diabetes	Non-Invasive Separation with Predictive Modeling
20	Montesi, L ³¹	2014	Italy	Age, Gender, Education, Profession, Waist circumference	Body mass index, Blood glucose Insulin, HOMA-IR, Total cholesterol, HDL-cholesterol, Triglycerides, Systolic pressure Diastolic pressure, Alanine aminotransferase, Gamma-glutamyltransferases, Diabetes, Hypertension, Treated with statins/fibrates, Kotronen index, Fatty liver index, Visceral adiposity index	---
21	Jan-Peter, S ³²	2013	Germany	Age, Gender	BMI , AST, ALT, gamma-GT, LDH, bilirubin	---
22	Sumida, Y ³³	2011	Japan	Age, Gender	BMI, Obesity, Dyslipidemia, Hypertension, Type 2 diabetes, Hemoglobin, Platelet count, AST, ALT, AST/ALT ratio, GGT, Cholinesterase, Total cholesterol, Triglyceride, Ferritin, FPG, IRI, Hyaluronic acid, Type IV collagen, Histological fibrosis	Clinical scoring system for predicting steatohepatitis in NAFLD

Table 2. Frequency of common identified clinical data elements and technical features

Category	Data element/feature	Frequency	Reference number
Clinical	1. Diabetes and glucose status	18	14,30,20,18,16,22,28,19, 31,23,15,17,20,33,20
	2. AST	15	14,16,17,18,19,20,23,24,30,31,32,33,34,35,36
	3. BMI	13	14,16,17,18,19,20,22,25,28,29,31,33,34
	4. ALT	13	14,16,17,18,19,20,23,30,31,32,34,35,36
	5. Triglycerides	8	14,17,20,23,29,31,33,35
	6. HDL	8	14,20,22,23,28,29,31,33
	7. Total bilirubin / Direct bilirubin	8	15,18,20,21,24,26,27,34,36
	8. Hypertension /Blood pressure/HTN	8	16,19,20,22,28,30,33,35
	9. Systolic blood pressure	7	16,17,22,23,29,31,33
	10. Albumin	7	15,18,20,21,36,30,28,26
	11. Diastolic blood pressure	7	16,17,22,23,29,31,33
	12. Total cholesterol	6	14,20,29,31,33,35
	13. LDL	5	14,20,28,29,31
	14. GGT	5	20,33,34,35,36
	15. HbA1c / Hemoglobin	5	14,15,17,18,22
	16. Ferritin	4	14,20,30,35
	17. Creatinine	4	15,18,26,27
	18. Platelet count	4	18,20,30,35
	19. Alkaline phosphatase	3	18,25,36
	20. Alcohol intake	2	17,18
	21. Liver fat	2	17,33
	22. Dyslipidemia	2	14,35
	23. PLT	2	14,20
	24. Hyaluronic acid	2	20,35
	25. Serum GOT	2	15,23
	26. Serum GPT	2	15,23
	27. Sodium Platelets	2	15,28
	28. INR	2	18,26
	29. Cholinesterase	2	20,35
	30. PTA	2	20,15
	31. Cirrhosis/Cirrhosis Complication	2	24,27
	32. Fatty liver index	2	17,33
Technical	1. Predicting and identifying	8	15,23,26,27,28,30,32,35
	2. Risk estimating	2	18,22
	3. Quantification	1	14
	4. Monitoring	1	15
	5. Virtual Consultations	1	24
	6. Decision support	1	36

Discussion

The general recommendations for addressing non-communicable diseases, which are responsible for two-thirds of deaths globally, are mainly related to lifestyle changes, such as diet and physical activity. Challenges with encouraging healthy diets include gathering accurate information about dietary intake and delivering interventions that can influence behavior. Internet technologies offer excellent potential for addressing these challenges (34). Increasing health information needs changes in information-seeking behavior to be observed around the globe.

According to the recent studies, 81% of U.S. adults use the Internet and 59% assert that they have looked online for health information regarding diseases, diagnoses, and different treatments. Thus, patients tend to become active participants in the decision-making process. This change in the thinking process is often referred to as patient empowerment. However, information overload and irrelevant information are major obstacles for drawing conclusions on the personal health status and taking adequate actions. Encountered a large amount of medical information on different channels (e.g., news sites, web forums, etc.), users often get lost or feel uncertain when investigating on their own. In addition, manifold and heterogeneous medical terms pose another barrier for laymen. Medical information available for patient-oriented decision making has increased drastically but is often scattered across different sites. Recommender systems (RS) suggest items of interest to users of information systems or e-business systems and have evolved in recent decades (35). Having patient demographic and health information in a medium that affords sophisticated and rapid analysis to identify tailored treatment solutions, and being able to deliver this information to the provider at the point of care, can transform treatment (36). The aim of this study was to identify the data requirements and technical capabilities of the recommender system for people with fatty liver disease. We identified a demographic category with 11 common data elements including sex/gender, age, ethnic group/race, waist circumference, weight, educational level, smoking status, drinker status, sleep duration, employment status, and television time.

According to the reviewed articles, 104 data elements were identified for the clinical category of the intelligent

recommender system for people living with fatty liver. Mehraeen *et al*, in a related study, by full-text reviewing of 9 related articles, identified and justified the elements in three main categories and 37 subcategories including clinical data elements, technical capabilities, and demographic data elements. According to the findings of this similar study, among the clinical category, 11 data elements and six data elements were selected as the demographic category by the statistical population (37). A structured and accessible clinical data set is a prerequisite for optimum information management and efficient clinical procedures in every healthcare organization(38).

Nhavato *et al*, in a developmental study, identified requirements of an intelligent system for tracking the care of patients in six categories: data acquisition requirements, telecommunications cost, privacy and data security, text message content, communication, and system scalability. The findings of this similar study showed that using this system could improve the quality of healthcare and facilitate the communication of healthcare organizations (39). According to the findings of this paper, the technical capabilities of an intelligent recommender system for people living with fatty liver need features such as predicting and identifying, quantification, monitoring, risk estimating, virtual consultations, and decision support.

The modern era of computing has stretched its reach to the intensive and efficient usage of Intelligent Techniques (ITs) in bioinformatics. Owing to the uncertainty in medical data sets, deriving comprehensible information becomes a major challenge for physicians. This challenge can lead to an erroneous diagnosis of a disease, which would further lead to improper treatment. Specifically, we can maintain that it would be favorable for patients in case medical experts cross-check their assessment with the help of some decision-making systems. These systems are developed by using intelligent techniques, which resourcefully scrutinize complex and ambiguous data sets. Implementing these ITs for liver disorders is acting as a catalyst in overcoming the overheads and problems faced by doctors. ITs effectively prevail over the inadequacies, help in obtaining better accuracies, and make the systems adaptable. ITs decrease the probability of occurrence of medical errors and reduce the cost, time, and effort needed⁴⁰. The liver resists

early detection, as it functions normally even when partially damaged, making the disease even more alarming because by then it might have suffered eternal damage. This indicates that an early diagnosis of liver disorders becomes a necessity so that in time treatment can be possible. During diagnosis, analyzing complex data set of patients stretches the decision time of doctors. To reduce this time period and effort, decision-making systems are developed using numerous intelligent techniques.

Self-management is known as a crucial key to improving the health outcomes of patients with chronic diseases including NAFLD. However, there is no instrument to measure the level of self-management for patients with NAFLD. Items of the questionnaire were generated based on the guidelines for patients with NAFLD and the Individual and Family Self-Management Theory. A six-factor was extracted from construct validation using exploratory factor analysis: lifestyle management, drinking management, sleep management, health-supplements management, medical treatment compliance, and family support. Healthcare providers should assess and evaluate the level of self-management to provide tailored interventions based on their care needs. This instrument would provide useful information for healthcare providers who assess self-management levels for individuals with NAFLD. In addition, it may be utilized as the indicator of health outcomes in this population⁴¹. Moreover, we developed a demographic category with 8 data elements including weight, marital status, gender, age, occupation, and level of education.

It is necessary that organized personal information of patients be accessible in every healthcare organization and therefore, the need to develop demographic data elements for managing the individual data is evident.

Conclusion

In this paper, we determined the common elements and features of a recommender system in three different categories: clinical data elements, demographic data elements, and technical capabilities. Using these requirements, it is possible to structure data gathering, medication adherence, and communication with healthcare providers in a standard manner. It is suggested that appropriate policies and national grants be adopted to identify and prioritize a minimum data set to support the healthcare services of people living with chronic conditions. A complementary study to identify the additional requirements such as technology infrastructures and security requirements of a recommender system for fatty liver through a semi-experimental methodology can be an appropriate route to future research on this topic.

Limitations

Given that many studies in the field of recommender system for people living with fatty liver disease were not performed, a great deal of time was spent searching for the related articles.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

References

1. Forlano R, Mullish BH, Giannakeas N, Maurice JB, Angkathunyakul N, Lloyd J, et al. High-Throughput, Machine Learning–Based Quantification of Steatosis, Inflammation, Ballooning, and Fibrosis in Biopsies From Patients With Nonalcoholic Fatty Liver Disease. *Clin Gastroenterol Hepatol* 2020 Aug;18(9):2081-90.e9.
2. Zelber-Sagi S, Salomone F, Mlynarsky L. The Mediterranean dietary pattern as the diet of choice for non-alcoholic fatty liver disease: Evidence and plausible mechanisms. *Liver Int* 2017 Jul;37(7):936-49.
3. Ahmed IA, Mikail MA, Mustafa MR, Ibrahim M, Othman R. Lifestyle interventions for non-alcoholic fatty liver disease. *Saudi J Biol Sci* 2019 Nov;26(7):1519-24.
4. McPherson S, Hardy T, Henderson E, Burt AD, Day CP, Anstee QM. Evidence of NAFLD progression from steatosis to fibrosing-steatohepatitis using paired biopsies: implications for prognosis and clinical management. *J*

Hepatol 2015 May;62(5):1148-55.

5. Zou TT, Zhang C, Zhou YF, Han YJ, Xiong JJ, Wu XX, et al. Lifestyle interventions for patients with nonalcoholic fatty liver disease: a network meta-analysis. *Eur J Gastroenterol Hepatol* 2018 Jul;30(7):747-55.

6. 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 Jan;67(1):328-57.

7. Katsagoni CN, Papatheodoridis GV, Ioannidou P, Deutsch M, Alexopoulou A, Papadopoulos N, et al. Improvements in clinical characteristics of patients with non-alcoholic fatty liver disease, after an intervention based on the Mediterranean lifestyle: a randomised controlled clinical trial. *Br J Nutr* 2018 Jul;120(2):164-75.

8. Lim SL, Johal J, Ong KW, Han CY, Chan YH, Lee YM, et al. Lifestyle Intervention Enabled by Mobile Technology on Weight Loss in Patients With Nonalcoholic Fatty Liver Disease: Randomized Controlled Trial. *JMIR Mhealth Uhealth* 2020 Apr 13;8(4):e14802.

9. Elavsky S, Smahel D, Machackova H. Who are mobile app users from healthy lifestyle websites? Analysis of patterns of app use and user characteristics. *Transl Behav Med* 2017 Dec;7(4):891-901.

10. Koot D, Goh PSC, Lim RSM, Tian Y, Yau TY, Tan NC, et al. A mobile lifestyle management program (GlycoLeap) for people with type 2 diabetes: single-arm feasibility study. *JMIR Mhealth Uhealth* 2019 May 24;7(5):e12965.

11. Cho SMJ, Lee JH, Shim J-S, Yeom H, Lee SJ, Jeon YW, et al. Effect of smartphone-based lifestyle coaching app on community-dwelling population with moderate metabolic abnormalities: Randomized controlled trial. *J Med Internet Res* 2020 Oct 9;22(10):e17435.

12. Dute DJ, Bemelmans WJE, Breda J. Using mobile apps to promote a healthy lifestyle among adolescents and students: a review of the theoretical basis and lessons learned. *JMIR Mhealth Uhealth* 2016 May 5;4(2):e39.

13. Frontini R, Sousa P, Dixe M, Ferreira R, Figueiredo M. Designing a mobile app to promote healthy behaviors and prevent obesity: analysis of adolescents' preferences. *Inform Health Soc Care* 2020 Sep;45(3):327-41.

14. Lin YJ, Chen RJ, Tang JH, Yu CS, Wu JL, Chen LC, et al. Machine-Learning Monitoring System for Predicting Mortality Among Patients With Noncancer End-Stage Liver Disease: Retrospective Study. *JMIR Med Inform* 2020 Oct 30;8(10):e24305.

15. Atabaki-Pasdar N, Ohlsson M, Viñuela A, Frau F, Pomares-Millan H, Haid M, et al. Predicting and elucidating the etiology of fatty liver disease: A machine learning modeling and validation study in the IMI DIRECT cohorts. *PLoS Med* 2020 Jun 19;17(6):e1003149.

16. Ioannou GN, Green P, Kerr KF, Berry K. Models estimating risk of hepatocellular carcinoma in patients with alcohol-related cirrhosis for risk stratification. *J Hepatol* 2019 Sep;71(3):523-33.

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 Sep;129:334-41.

18. Yang M, Jiang L, Wang Y, Li X, Zhou G, Zou Z, et al. Step layered combination of noninvasive fibrosis models improves diagnostic accuracy of advanced fibrosis in nonalcoholic fatty liver disease. *J Gastrointest Liver Dis* 2019 Sep 1;28(3)

19. Muthuselvan S, Rajapraksh S, Somasundaram K, Karthik K. Classification of Liver Patient Dataset Using Machine Learning Algorithms. *Int J Eng Technol* 2018 Sep;7(3.34):323-6.

20. Perveen S, Shahbaz M, Keshavjee K, Guergachi A. A systematic machine learning based approach for the diagnosis of non-alcoholic fatty liver disease risk and progression. *Sci Rep* 2018 Feb 1;8(1):2112.

21. Wu CC, Yeh WC, Hsu WD, Islam MM, Nguyen PAA, Poly TN, et al. Prediction of fatty liver disease using machine learning algorithms. *Comput Methods Programs Biomed* 2019 Mar;170:23-29.

22. Su GL, Glass L, Tapper EB, Van T, Waljee AK, Sales AE. Virtual Consultations Through the Veterans Administration SCAN-ECHO Project Improves Survival for Veterans With Liver Disease. *Hepatology* 2018 Dec;68(6):2317-24.
23. Miller MH, Fraser A, Leggett G, MacGilchrist A, Gibson G, Orr J, et al. Development and validation of diagnostic triage criteria for liver disease from a minimum data set enabling the 'intelligent LFT' pathway for the automated assessment of deranged liver enzymes. *Frontline Gastroenterol* 2018 Jul;9(3):175-82.
24. Trépo E, Goossens N, Fujiwara N, Song WM, Colaprico A, Marot A, et al. Combination of gene expression signature and model for end-stage liver disease score predicts survival of patients with severe alcoholic hepatitis. *Gastroenterology* 2018 Mar;154(4):965-75.
25. Zhou XD, Chen QF, Sun DQ, Zheng CF, Liang DJ, Zhou J, et al. Remodeling the model for end-stage liver disease for predicting mortality risk in critically ill patients with cirrhosis and acute kidney injury. *Hepatol Commun* 2017 Aug 1;1(8):748-56.
26. Corey KE, Kartoun U, Zheng H, Chung RT, Shaw SY. Using an electronic medical records database to identify non-traditional cardiovascular risk factors in nonalcoholic fatty liver disease. *Am J Gastroenterol* 2016 May;111(5):671-6.
27. Meng G, Liu F, Fang L, Li C, Zhang Q, Liu L, et al. The overall computer/mobile devices usage time is related to newly diagnosed non-alcoholic fatty liver disease: a population-based study. *Ann Med* 2016 Nov;48(7):568-76.
28. Goh GB, Issa D, Lopez R, Dasarathy S, Dasarathy J, Sargent R, et al. The development of a non-invasive model to predict the presence of non-alcoholic steatohepatitis in patients with non-alcoholic fatty liver disease. *Journal Gastroenterol Hepatol* 2016 May;31(5):995-1000.
29. Lesmana CRA, Pakasi LS, Inggriani S, Aidawati ML, Lesmana LA. Development of non-alcoholic fatty liver disease scoring system among adult medical check-up patients: a large cross-sectional and prospective validation study. *Diabetes Metab Syndr Obesity* 2015 Apr 23;8:213-8.
30. Sowa JP, Atmaca Ö, Kahraman A, Schlattjan M, Lindner M, Sydor S, et al. Non-invasive separation of alcoholic and non-alcoholic liver disease with predictive modeling. *PLoS One* 2014 Jul 2;9(7):e101444.
31. Montesi L, Caselli C, Centis E, Nuccitelli C, Moscattello S, Suppini A, et al. Physical activity support or weight loss counseling for nonalcoholic fatty liver disease? *World J Gastroenterol* 2014 Aug 7;20(29):10128-36.
32. Sowa JP, Heider D, Bechmann LP, Gerken G, Hoffmann D, Canbay A. Novel algorithm for non-invasive assessment of fibrosis in NAFLD. *PloS One* 2013 Apr 30;8(4):e62439.
33. Sumida Y, Yoneda M, Hyogo H, Yamaguchi K, Ono M, Fujii H, et al. A simple clinical scoring system using ferritin, fasting insulin, and type IV collagen 7S for predicting steatohepatitis in nonalcoholic fatty liver disease. *Journal Gastroenterol* 2011 Feb;46(2):257-68.
34. Zenun Franco R. Online recommender system for personalized nutrition advice. *Proceedings of the Eleventh ACM Conference on Recommender Systems* 2017 Aug 27;411-15.
35. Wiesner M, Pfeifer D. Health recommender systems: concepts, requirements, technical basics and challenges. *Int J Environ Res Public Health* 2014 Mar 3;11(3):2580-607.
36. Miller K, Mosby D, Capan M, Kowalski R, Ratwani R, Noaiseh Y, et al. Interface, information, interaction: a narrative review of design and functional requirements for clinical decision support. *J Am Med Inform Assoc* 2018 May 1;25(5):585-92.
37. Mehraeen E, Safdari R, SeyedAlinaghi S, Mohammadzadeh N, Mohraz M. Common elements and features of a mobile-based self-management system for people living with HIV. *Electron Physician* 2018 Apr 25;10(4):6655-62.
38. Abellán J, López G, De Oña J. Analysis of traffic accident severity using decision rules via decision trees. *Expert Systems with Applications*. 2013;40(15):6047-54.
39. Nhavoto JA, Grönlund Å, Chaquilla WP. SMSaúde: design, development, and implementation of a remote/mobile patient management system to improve retention in care for HIV/AIDS and tuberculosis patients. *JMIR*

Mhealth Uhealth 2015 Mar 9;3(1):e26.

40. Singh A, Pandey B. Intelligent techniques and applications in liver disorders: a survey. *Int J Biomed Eng Technol* 2014 Jan 1;16(1):27-70.

41. Jang Y, Kwon OY, Lee JY, Kim SU. PE-189: Development and Validation of the Non-Alcoholic Fatty Liver Disease Self-Management Questionnaire. *춘·추계학술대회 KASL 2020;2020(1):255-*.