1	Title: Novel urinary protein panels for NAFLD and fibrosis stages diagnosis
2	
3	Short Title: Urinary NITs for NAFLD diagnosis
4	Authors:
5	Gong Feng <sup>1, 2*</sup> , MD; Xiaoxun Zhang <sup>3, 4, 5*</sup> , MD; Liangjun Zhang <sup>3, 4, 5</sup> , MD; Wen-Yue Liu <sup>6</sup> ,
6	MD; Shi Geng <sup>7</sup> , MD; Hai-Yang Yuan <sup>8</sup> , MD; Jun-Cheng Sha <sup>9</sup> , MD; Xiao-Dong Wang <sup>10</sup> ,
7	MD; Dan-Qin Sun <sup>11</sup> , MD; Giovanni Targher <sup>12</sup> , MD; Christopher D. Byrne <sup>13</sup> , MD; Tian-
8	Lei Zheng <sup>7,14</sup> , MD; Feng Ye <sup>1</sup> , MD; Ming-Hua Zheng <sup>8,10#</sup> , MD; Jin Chai <sup>3, 4, 5#</sup> , MD on
9	behalf of CHESS-MAFLD consortium
10	
11	<sup>1</sup> The First Affiliated Hospital of Xi'an Jiaotong University, Xi'an 710061, China;
12	<sup>2</sup> Xi'an Medical University, Xi'an 710021, China;
13	<sup>3</sup> Department of Gastroenterology, Southwest Hospital, Third Military Medical
14	University (Army Medical University), Chongqing 400038, China;
15	<sup>4</sup> Institute of Digestive Diseases of PLA, Southwest Hospital, Third Military Medical
16	University (Army Medical University), Chongqing 400038, China;

- <sup>5</sup>Cholestatic Liver Diseases Center and Center for Metabolic Associated Fatty Liver
- 18 Disease, Southwest Hospital, Third Military Medical University (Army Medical
- 19 University), Chongqing 400038, China;
- <sup>6</sup>Department of Endocrinology, The First Affiliated Hospital of Wenzhou Medical
- 21 University, Wenzhou 325000, China;

22	<sup>7</sup> Artificial Intelligence Unit, Department of Medical Equipment Management,
23	Affiliated Hospital of Xuzhou Medical University, Xuzhou 221004, China;
24	<sup>8</sup> MAFLD Research Center, Department of Hepatology, the First Affiliated Hospital of
25	Wenzhou Medical University, Wenzhou 325000, China;
26	<sup>9</sup> Interventional radiology, Affiliated Hospital of Xuzhou Medical University, Xuzhou
27	221004, China;
28	<sup>10</sup> Key Laboratory of Diagnosis and Treatment for The Development of Chronic Liver
29	Disease in Zhejiang Province, Wenzhou, Zhejiang 325000, China;
30	<sup>11</sup> Department of Nephrology, the Affiliated Wuxi No.2 People's Hospital of Nanjing
31	Medical University, Wuxi, Jiangsu Province 214001, China;
32	<sup>12</sup> Section of Endocrinology, Diabetes and Metabolism, Department of Medicine,
33	University and Azienda Ospedaliera Universitaria Integrata of Verona, Verona, Italy;
34	<sup>13</sup> Southampton National Institute for Health and Care Research Biomedical Research
35	Centre, University Hospital Southampton, Southampton General Hospital,
36	Southampton, UK;
37	<sup>14</sup> School of Information and Control Engineering, China University of Mining and
38	Technology, Xuzhou 221116, China.
39	
40	*These authors contributed equally to this study.

44	<b>Contact</b>	Information:	,
----	----------------	--------------	---

- <sup>45</sup> <sup>#</sup>Ming-Hua Zheng, M.D., Ph.D., MAFLD Research Center, Department of
- 46 Hepatology, the First Affiliated Hospital of Wenzhou Medical University, Wenzhou,
- 47 China. Tel: 86-577-55579611; Fax: 86-577-55578522; E-mail:
- 48 <u>zhengmh@wmu.edu.cn</u>
- <sup>49</sup> <sup>#</sup>Jin Chai, M.D., Ph.D., Professor of Gastroenterology and Hepatology in Chongqing
- 50 University School of Medicine and Third Military Medical University. Address:
- 51 Center for Metabolic Liver Diseases and Center for Cholestatic Liver Diseases,
- 52 Department of Gastroenterology, The First Affiliated Hospital (Southwest Hospital),
- 53 Third Military Medical University (Army Medical University) Chongqing, 400038,
- 54 China; Tel: 86-23-68765331; Fax: 86-23-65410853; E-mail: jin.chai@cldcsw.org

55

- 56 **Total word count:** 4060 words
- 57 Number of figures/supplementary figures: 4/5
- 58 Number of tables/supplementary tables: 1/7
- 59

# 60 Author contributions to this manuscript:

- 61 Ming-Hua Zheng, Jin Chai, and Gong Feng conceived and designed the study; Gong
- 62 Feng, Xiaoxun Zhang, Wen-Yue Liu, and Liangjun Zhang performed the study; Hai-
- 63 Yang Yuan collected the data; Xiao-Dong Wang analyzed the pathology; Gong Feng,

64	Tian-Lei Zheng, Shi Geng, and Jun-Cheng Sha performed the statistical analysis;
65	Xiaoxun Zhang and Liangjun Zhang contributed to reagents/analysis tools; Ming-Hua
66	Zheng, Jin Chai, and Gong Feng wrote the draft of the manuscript; Giovanni Targher,
67	Christopher D. Byrne, Dan-Qin Sun and Feng Ye gave their critical revision.
68	
69	Grants Support:
70	This work was supported by grants from the National Natural Science Foundation of
71	China (81922012 and 82070588), the Outstanding Youth Foundation of Chongqing
72	(cstc2021jcyj-jqX0005), and the Project of Chongqing University Innovation
73	Research Group (2021cqspt01). GT is supported in part by grants from the School of
74	Medicine, University of Verona, Verona, Italy. CDB is supported in part by the
75	Southampton NIHR Biomedical Research Centre (IS-BRC-20004), UK.
76	
77	Conflicts of Interest
78	The authors disclose no conflicts of interest.
79	
80	Abbreviation list: AUC, area under the curve; ELISA, enzyme-linked immunosorbent
81	assay; LASSO, least absolute shrinkage and selector operation; Limma, linear models
82	for microarray data; NAFLD, non-alcoholic fatty liver disease; NAS, NAFLD activity
83	score; NASH, non-alcoholic steatohepatitis; ROC, receiver operator characteristic;
84	OPLS-DA, orthogonal partial least square discriminant analysis; UPLC-MS/MS,
85	ultra-performance liquid chromatography-mass spectrometry.

87 Abstract

Background & Aims: There is an unmet clinical need for simple non-invasive tests 88 to diagnose nonalcoholic fatty liver disease (NAFLD) and fibrosis stages. We aimed 89 to test whether urine samples could be used to diagnose NAFLD, NAFLD with 90 fibrosis (fibrosis stage F $\geq$ 1), and NAFLD with significant fibrosis (fibrosis stage F $\geq$ 2). 91 **Methods:** We collected urine samples from 100 patients with biopsy-proven NAFLD 92 and 40 healthy volunteers and proteomics and bioinformatics analyses were 93 performed in this derivation cohort. Diagnostic models were developed for detecting 94 95 NAFLD (UP<sub>NAFLD</sub> model), NAFLD with fibrosis (UP<sub>fibrosis</sub> model), or NAFLD with significant fibrosis (UP<sub>significant fibrosis</sub> model). Subsequently, the derivation cohort was 96 divided into training and testing sets to evaluate the diagnostic efficacy of these 97 98 diagnostic models. In a separate independent validation cohort of 100 patients with biopsy-proven NAFLD and 45 healthy controls, urinary enzyme-linked 99 immunosorbent assay (ELISA) analyses were undertaken to validate the accuracy of 100 101 these newly developed diagnostic models. 102 **Results:** The UP<sub>fibrosis</sub> model and the UP<sub>significant fibrosis</sub> model showed an AUROC of 0.863 (95% CI: 0.725-1.000) and 0.858 (95% CI: 0.712-1.000) in the training set; 103 0.837 (95% CI: 0.711-0.963) and 0.916 (95% CI: 0.825-1.000) in the testing set. The 104 UP<sub>NAFLD</sub> model showed excellent diagnostic performance and the area under the 105 receiver operator characteristic curve (AUROC) exceeded 0.90 in the derivation 106 cohort. In the independent validation cohort, the AUROC for all three of the above 107 diagnostic models exceeded 0.80. 108

```
5
```

- 109 **Conclusions:** Our newly developed models constructed from urine protein
- 110 biomarkers have good accuracy for non-invasively diagnosing early liver fibrosis in
- 111 NAFLD.
- 112
- 113 Keywords: Fibrosis, NAFLD, Urinary proteomics, Diagnosis, Liver biopsy

### 115 Introduction

135

Nonalcoholic fatty liver disease (NAFLD) has become the most common chronic 116 liver disease, affecting up to  $\sim 30\%$  of the world's population.<sup>1,2</sup> NAFLD includes a 117 spectrum of progressive liver conditions ranging from nonalcoholic fatty liver (NAFL) 118 to nonalcoholic steatohepatitis (NASH), cirrhosis and hepatocellular carcinoma.<sup>3-5</sup> 119 Patients with NAFLD may develop varying amounts of liver fibrosis, and previous 120 studies have shown that the severity of liver fibrosis is the strongest histologic risk 121 factor of liver-related complications and mortality.<sup>6,7</sup> Recent studies have also shown 122 that even NAFLD with fibrosis (fibrosis stage  $F \ge 1$ ) or NAFLD with significant 123 fibrosis (fibrosis stage  $F \ge 2$ ) is a predictor of overall and liver-related mortality in 124 patients with NAFLD.<sup>8-11</sup> The assessment of liver fibrosis extends beyond the realm 125 of NAFLD and holds significance in terms of evaluating cardiovascular risk.<sup>12</sup> 126 Noninvasive assessment of hepatic fibrosis may predict cardiovascular events and 127 overall mortality in patients with NAFLD.<sup>12</sup> While the diagnostic performance of 128 traditional non- invasive tests are satisfactory for ruling out advanced fibrosis (fibrosis 129 stage  $F \ge 3$ ), their performance is not adequate for diagnosing fibrosis or significant 130 liver fibrosis.<sup>13,14</sup> Therefore, the detection of NAFLD with fibrosis and NAFLD with 131 significant fibrosis can facilitate a more accurate assessment of the patient's condition, 132 treatment response, and prognostic outcomes. 133 134

disease in NAFLD. However, liver biopsy is an invasive method that is expensive,

To date, liver biopsy remains the 'gold standard' for staging the severity of liver

137	potentially risky, has possible sampling errors, and patients may not be available to
138	undergoing repeated liver biopsies over time for a benign condition. <sup>13,15,16</sup>
139	Consequently, it is essential to find pragmatic, less expensive and safer non-invasive
140	methods for diagnosis, staging and monitoring liver fibrosis. Non-invasive diagnosis
141	of each of the stages of NAFLD has been an unmet clinical need. <sup>17,18</sup> Urine tests are
142	simple and also more easily accessible than blood tests; thus, urine has been proposed
143	as a source of potential biomarkers for diagnosis of human diseases in several
144	research fields. <sup>19</sup> Moreover, urine changes may reflect dynamic changes in disease
145	status, which is potentially important for liver disease in NAFLD, especially when
146	clinicians need to know whether the disease is improving or not with a pharmacologic
147	treatment. <sup>20</sup>

Recently, proteomic analyses of liver tissue and blood have been used to discover new 149 biomarkers and therapeutic targets in NAFLD.<sup>21,22</sup> Urine proteomics has also become 150 a focus of research in other chronic diseases, such as diabetic nephropathy, type 1 151 diabetes, and adult-onset Still's disease.<sup>23,24,25</sup> To date, however, proteomic studies on 152 urine in individuals with NAFLD are scarce, and there is still a lack of any relevant 153 evidence as to whether urine can be used to diagnose NAFLD and the severity of liver 154 fibrosis. Thus, the aim of our study was to explore the urinary protein panels to 155 diagnose NAFLD, NAFLD with fibrosis, and NAFLD with significant fibrosis in a 156 liver biopsy-based derivation cohort of patients with NAFLD. 157

158

#### 159 Methods

### 160 Patients and Urine Sample Collection

Patients with NAFLD were diagnosed at the First Affiliated Hospital of Wenzhou 161 Medical University from December 2016 to December 2018, as part of the 162 Prospective Epidemiologic Study of Significantly Characterized Non-Alcoholic 163 Steatohepatitis (PERSONS) cohort study.<sup>14</sup> The inclusion criteria for the study were 164 as follows: (1) individuals aged 18-75 years; (2) individuals with fatty liver diagnosed 165 by imaging and/or elevated serum liver enzymes who were willing to undergo a liver 166 167 biopsy; (3) individuals with availability of urine samples for protein quantification using label-free quantitative proteomics technology; and (4) individuals who were 168 willing to provide written informed consent. We excluded from the study: (1) 169 170 individuals with significant alcohol consumption ( $\geq 140$  g/week in men or  $\geq 70$  g/week in women); (2) those who were taking potentially hepatotoxic medications; (3) 171 individuals with viral hepatitis, autoimmune hepatitis, or other known chronic liver 172 diseases; (4) those with pathological liver biopsy suggesting fat content < 5%; and (5) 173 those with incomplete data. Since urine values can vary considerably during a 24-h 174 period, the first-morning urine samples were collected for all participants. Healthy 175 controls were derived from a physical examination population, who was free of fatty 176 liver, as confirmed by ultrasonography. Finally, in the derivation cohort, we obtained 177 100 patients with biopsy-confirmed NAFLD who had completed urine proteomic 178 abundance measurements from the Wenzhou center and 40 non-steatotic healthy 179 controls from the Southwest Hospital of the Army Medical University, who also 180

181	completed urine proteomic abundance measurements. The derivation cohort was then
182	divided into a training set and a testing set (in a 1:1 ratio) to examine the diagnostic
183	efficacy of early patterns diagnosis models for NAFLD. In a separate and independent
184	validation cohort, we included 45 healthy controls from the Southwest Hospital of the
185	Army Medical University and 100 patients with biopsy-confirmed NAFLD from the
186	First Affiliated Hospital of Wenzhou Medical University. The flowchart of the study is
187	summarized in Figure 1. We undertook proteomics and bioinformatics analyses to
188	uncover potential diagnostic biomarkers and develop diagnostic models for
189	identifying NAFLD (UP <sub>NAFLD</sub> model), NAFLD with fibrosis stage F $\geq$ 1 (UP <sub>fibrosis</sub>
190	model), or NAFLD with significant fibrosis stage F $\geq$ 2 (UP <sub>significant fibrosis</sub> model),
191	respectively in the derivation cohort. Furthermore, we also validated the diagnostic
192	efficacy of urinary diagnostic panels utilizing enzyme-linked immunosorbent assay
193	(ELISA) in an external validation cohort of patients with biopsy-confirmed NAFLD.
194	The study was conducted in accordance with the ethical guidelines of the Declaration
195	of Helsinki and the International Conference on Harmonization Guidelines for Good
196	Clinical Practice. Written informed consent was obtained from all participants.
197	

# 198 Liver histology

Ultrasound-guided percutaneous liver biopsy was performed using a 16-gauge
Hepafix needle. Liver biopsy samples were stained with hematoxylin, Masson's
trichrome as well as eosin and subsequently assessed by an experienced liver
pathologist, who was blinded to patients' clinical and laboratory data. Liver biopsy

203	specimens were required to be $>1$ cm and the number of portal areas was $>6$ . The
204	histological scoring of NAFLD was assessed by using the NAFLD activity score
205	(NAS), as proposed by the NASH Clinical Research Network. <sup>26</sup> The NAS score
206	includes three histologic features including the presence of steatosis, lobular
207	inflammation and hepatocellular ballooning. Liver fibrosis was staged from zero to 4
208	as follows: $0 = no$ fibrosis, $1 = perisinusoidal or portal fibrosis; 2 = perisinusoidal and$
209	portal/periportal fibrosis; 3 = bridging fibrosis; and 4 = highly suspicious or definite
210	cirrhosis, respectively. The presence of liver fibrosis was defined as fibrosis stage $\geq F1$ ,
211	while significant fibrosis was defined as fibrosis stage $\geq$ F2, which is clinically
212	relevant for prognostic liver-related outcomes. <sup>27</sup>

# 214 Label-free quantitative proteomics technology

Label-free proteomic quantification was based on the use of the ultra-performance 215 liquid chromatography-mass spectrometry (UPLC-MS/MS). Mass spectrometry can 216 obtain the mass-to-charge ratio and the signal intensity of peptides in a sample, as 217 well as the mass-to-charge ratio and the signal intensity of fragment ions after peptide 218 fragmentation.<sup>28</sup> Usually, the information at the peptide level is referred to as a first-219 level spectrum and the peptide fragment ion information a second-level spectrum. The 220 information contained in the spectra is very complex, and a database is created to 221 resolve the peptide sequences contained in the spectra. Before searching the database, 222 a theoretical secondary spectrum database is constructed from the protein sequences 223 in the database. Then the secondary spectrum generated by mass spectrometry is 224

225	analysed and compared with the theoretical secondary spectrum, and the correct
226	matching theoretical peptide sequences obtained after algorithm scoring and filtering.
227	The protein information contained can be identified by the protein-specific peptides
228	identified. The secondary mass spectrometry data in this experiment was searched
229	using Maxquant (v1.6.15.0). <sup>29</sup> To obtain high-quality data , the search library analysis
230	results required further data filtering. We set the false discovery rate at 1% for the
231	three levels of the spectrum, peptide and protein identification; and the identified
232	proteins had to contain at least one specific (unique) peptide.
233	
234	Measurement of specific protein levels in urine samples
235	The levels of ACE2 (CAT#F10272-A), CILP2 (CAT#F111328-A), ENPP7
236	(CAT#F111336-A), MPST (CAT#F111323-A), OGFOD3 (CAT#F111319-A), P2RX4
237	(CAT#F111332-A), TMEM256 (CAT#F111315-A), TMEM25 (CAT#F111311-A), or
238	ICAM-1/CD54 (CAT#F0034-A) proteins in the urine samples from patients (n=45 for
239	healthy volunteers and n=100 for biopsy-proven NAFLD patients) were quantified
240	using the corresponding commercial ELISA Kit (Fankew, Shanghai FANKEL
241	Industrial Co., Ltd, Shanghai, China), according to their manufacturer's instructions.
242	
243	Statistical analysis
244	Reporting of clinical data was according to the most frequently obtained data from
245	each participant, with the mean $\pm$ SD presented for normal continuous variables and
246	the median (interquartile range) for non-normal continuous variables. Otherwise, the

247	frequency was used for categorical variables. For proteomic abundances, proteins
248	with a missing value ratio higher than 50% in all samples were removed, and the k-
249	nearest neighbor algorithm was used to fill protein abundances, and log2
250	transformation was performed for data at the same time. The methods for screening
251	differential proteins include orthogonal partial least square discriminant analysis
252	(OPLS-DA) or linear models for microarray data (limma). OPLS-DA has been widely
253	used in the multi-omics analysis, including proteomic analysis and metabolomics
254	analysis. <sup>30,31</sup> Limma is a differential expression screening method based on
255	generalized linear equations. The R software package limma (version 3.40.6) was
256	used for differential analysis to obtain the differential proteins among different groups.
257	This method has also been used in proteomic analysis. <sup>32,33</sup> Furthermore, we used
258	LASSO regression to pick out the more important proteins. <sup>34</sup> The R package glmnet
259	was used for the LASSO regression analysis and the 10 folds cross-validation method
260	was used to filter the lambda. <sup>35,36</sup> The cross-validation method divided the data into
261	10 equal parts, first fitting the full data to generate the lambda sequence, then
262	excluding one part of the data at a time and using the remaining 9 parts for validation.
263	The mean and standard deviation of the errors obtained from the 10 validations were
264	calculated. The diagnostic efficacy of each key protein was assessed by the area under
265	the receiver operating characteristics curves (AUROC). The top four ranked proteins
266	of AUROC were considered for inclusion in the pooled analysis of the indicators. The
267	Variance inflation factor (VIF) was calculated to detect the presence of
268	multicollinearity between identified proteins. A cut-off value of 5 was used when

269	applying the VIF in the study. <sup>37</sup> We used a stepwise algorithm to find the best
270	combined model including key proteins, which was based on the Akaike information
271	criterion (AIC) principle that involves removing the variables that were not
272	statistically significant.
273	
274	Results
275	Characteristics of NAFLD patients and urine proteomes in the derivation cohort
276	Patients with NAFLD were divided into two subgroups: patients with liver fibrosis
277	(defined as stage $\geq$ F1; n=81) and those without fibrosis (n=19) or, alternatively,
278	patients with significant liver fibrosis (defined as stage $\geq$ F2; n=16) and those without
279	significant fibrosis (n=84). Figure 2 shows the workflow in the derivation cohort.
280	Baseline characteristics of patients with NAFLD and different fibrosis stages in the
281	derivation cohort are presented in Table 1 and Supplementary Table 1. Label-free
282	proteomic analyses identified a total of 4206 proteins among healthy controls and
283	NAFLD patients with different fibrosis stages.
284	
285	Proteomic biomarkers for non-invasive identification of NAFLD in the derivation
286	cohort
287	The OPLS-DA method is more sensitive to variables with lower levels of correlation
288	and helps maximize the difference between NAFLD patients and healthy controls
289	based on differential proteins compared with PCA and PLS-DA (Figure 2e and
290	Supplementary Figure 1). The R2Y represents the interpretation rate of the model to

291	the Y matrix, and the Q2 represents the prediction ability of the model. The closer
292	these three indexes are to 1, the more stable and reliable the model is. Generally, the
293	model is considered effective with a Q2 value above 0.5. In our modeling results, the
294	parameters of R2Y and Q2 were 0.956 and 0.775, respectively, thereby suggesting
295	that the model is reliable and has good prediction ability, and there was also no
296	overfitting in our model (Supplementary Figure 2). The OPLS-DA S-plot clearly
297	shows the distribution of all urinary proteins based on their variable importance in
298	projection (VIP) values. Subsequently, 37 differential proteins were selected by using
299	the following three selection criteria: VIP > 1, $p < 0.05$ and FC > 2 (or FC < 0.5,
300	Figure 3a). We further used the LASSO regression to screen for important differential
301	proteins and found 15 urinary key proteins (Figure 3b and 3c). The clustering of
302	these 15 key proteins is shown in Supplementary Figure 3a, and their inter-
303	correlations are reported in Supplementary Figure 4a. By enrichment analysis, we
304	found that these key proteins are associated with ferroptosis, oxidoreductase activity,
305	and coenzyme A biosynthesis (Supplementary Figure 3b). Then, using ROC curve
306	analyses, we found that the top four urinary proteins among these 15 proteins were
307	EPHA10, CILP2, TMEM25, and MPST, respectively (Figure 4a). The correlation
308	analyses of these four key proteins showed that EPHA10 correlated with CILP2,
309	TMEM25 and MPST (Supplementary Figure 4b; Supplementary Table 2), but
310	none of these proteins showed evidence of collinearity (VIF $<$ 5). Further, we found
311	by stepwise regression analysis that the combined diagnostic model (UP <sub>NAFLD</sub> model)
312	of the three urinary key proteins (CILP2, TMEM25, and MPST) had an AUROC of

313	0.983 (95% CI: 0.961-1.000) in the training set and 0.968 (95% CI: 0.932-1.000) in
314	the testing set from derivation cohort, with excellent diagnostic efficacy (Figure 4b).
315	We also found that the $UP_{NAFLD}$ model had an AUROC of 0.961 (95% CI: 0.915-
316	1.000) in males and 0.993 (0.979-1.000) in females.
317	
318	Proteomic biomarkers for non-invasive identification of fibrosis stage $\ge$ F1 in the
319	derivation cohort
320	The R software package limma was used to obtain urinary differential proteins
321	between patients with liver fibrosis $\geq$ F1 and those without fibrosis. A total of 56
322	differential urinary proteins were subsequently selected by using the criteria of p $<$
323	0.05 and FC > 1.5 (or FC < 0.7, <b>Figure 3d</b> ). In addition, 22 key proteins were
324	identified using the LASSO regression (Figures 3e and 3f). The clustering results of
325	these 22 key proteins are shown in Supplementary Figure 3c, and the correlations
326	among them are shown in Supplementary Figure 4c. Our enrichment analysis
327	revealed that these key proteins were associated with the renin-angiotensin system,
328	cornified envelope, humoral immune response, and regulation of inflammatory
329	response (Supplementary Figure 3d). After analyzing these 22 key proteins using
330	ROC curves, we found that OGFOD3, ACE2, ENPP7, and P2RX4 were the top four
331	key proteins (Figure 4c). Correlation analysis of these four key proteins revealed that
332	ACE2 correlated with OGFOD3, ENPP7, and P2RX4 (Supplementary Figure 4d;
333	Supplementary Table 3), but none of these variables showed evidence of collinearity
334	(VIF $<$ 5). Moreover, we discovered that the combined diagnostic model (UP <sub>fibrosis</sub>

335	model) of the 3 key proteins (OGFOD3, ENPP7, and P2RX4) had an AUROC of
336	0.863 (95% CI: 0.725-1.000) in the training set and 0.858 (95% CI: 0.712-1.000) in
337	the testing set using stepwise regression analysis (Figure 4d). We also discovered that
338	UPfibrosis model had an AUROC of 0.877 (95% CI: 0.765-0.989) in males and 0.857
339	(95% CI: 0.669-1.000) in females.
340	
341	Proteomic biomarkers for non-invasive identification of fibrosis stage $\ge$ F2 in the
342	derivation cohort
343	By limma analysis, we identified 44 differential urinary proteins with the selection
344	criteria of p $< 0.05$ and FC $> 1.5$ (or FC $< 0.7$ , <b>Figure 3g</b> ). We also identified 12 key
345	proteins using LASSO regression (Figure 3h and 3i). Supplementary Figure 3e
346	shows the clustering results of these 12 key proteins, and the correlations among them
347	are reported in Supplementary Figure 4e. Using enrichment analysis, we identified
348	these key proteins as being associated with dense platelet granule lumens and
349	collagen-containing extracellular matrix (Supplementary Figure 3f). Using the
350	AUROC analyses, we found PECAM1, TMEM256, MSRA, and ICAM1 to be the top
351	four key proteins (Figure 4e). TMEM256 had the highest AUROC of 0.772 (95% CI:
352	0.658-0.886), with a sensitivity of 0.750 and specificity of 0.786 for significant
353	fibrosis in NAFLD. PECAM1 was correlated with TMEM256, MSRA, and ICAM1
354	(Supplementary Figure 4f; Supplementary Table 4), but none of these four key
355	proteins showed evidence of collinearity (VIF $<$ 5). Furthermore, using a stepwise
356	regression analysis, we found that in the combined diagnostic model ( $UP_{significant fibrosis}$

$357 \mod 1000$ model) two key proteins (TMEM256 and ICAM1) had an AUROC of $0.837$	(95% CI:
---	----------

0.711-0.963) in the training set and 0.916 (95% CI: 0.825-1.000) in the testing set,

respectively (Figure 4f). We also found UP<sub>significant fibrosis</sub> model had an AUROC of

- 360 0.829 (95% CI: 0.698-0.960) in men and 0.833 (95% CI: 0.690-0.977) in women.
- 361

# 362 Validation by ELISA analyses

ELISA analyses were performed to validate the combined diagnostic models of the 363 key proteins in above urine samples. In the independent validation cohort, we 364 365 included 45 healthy controls and 100 patients with biopsy-confirmed NAFLD. The baseline characteristics of this validation cohort are presented in **Supplementary** 366 **Table 5.** Of these 100 patients with NAFLD, 57 had fibrosis stage  $\geq$ F1 and 13 had 367 368 significant fibrosis (stage  $\geq$ F2). Baseline characteristics of NAFLD patients with different fibrosis stages belonging to the validation cohort are presented in 369 Supplementary Table 6 and Supplementary Table 7. It was found that the model 370 consisting of three urinary proteins, CILP2, TMEM25 and MPST, achieved an 371 AUROC of 0.850 (95% CI: 0.784-0.915) for differentiating NAFLD patients from 372 healthy controls (Supplementary Figure 5a). The combined model consisting of 373 three urinary proteins, OGFOD3, ENPP7 and P2RX4, showed an AUROC of 0.804 374 (95% CI: 0.718-0.889) for differentiating patients with fibrosis (stage F  $\geq$ 1) from 375 those without fibrosis (Supplementary Figure 5b). The combined model comprised 376 of two urinary proteins, TMEM256 and ICAM-1, was found to have an AUROC of 377 0.807 (95% CI: 0.715-0.899) for differentiating between patients with significant 378

fibrosis (stage F  $\geq$ 2) and those without significant fibrosis (F0 + F1 stages)

- 380 (Supplementary Figure 5c).
- 381

```
382 Discussion
```

383	Our urine proteomics profiling showed for the first time that there is a pattern of
384	urinary proteins in patients with biopsy-proven NAFLD and liver fibrosis in a Han
385	Chinese population. We discovered for the first time that TMEM256 had an AUROC
386	of 0.772 (95% CI: 0.658-0.886), with a sensitivity of 0.750 and specificity of 0.786
387	for significant fibrosis in NAFLD. The diagnostic model consisting of CILP2,
388	TMEM25, and MPST was useful to distinguish NAFLD patients from healthy
389	controls. The diagnostic models composed of OGFOD3, ENPP7, and P2RX4 for
390	NAFLD with fibrosis, and composed of TMEM256 and ICAM-1 for NAFLD with
391	significant fibrosis provide promising results for future clinical investigation in other
392	ethnic groups. Although Liu et al. identified some potential urinary biomarkers for
393	NAFLD diagnosis, these authors did not use liver biopsy (i.e., the gold standard) for
394	verifying each of the stages of liver disease in NAFLD. <sup>38</sup> In addition, the sample size
395	of the Liu study was small in both the discovery and validation cohorts (neither
396	exceeded 30 cases). <sup>38</sup>

397

398 The utilization of urinary protein panels in personalized medicine for the management

- of NAFLD and metabolic disorders has the potential to greatly impact current
- 400 approaches to patient care. Urinary protein panels can help identify individuals who

401	are at risk of developing NAFLD, NAFLD with fibrosis, or NAFLD with significant
402	fibrosis, even before the onset of symptoms. This early detection can aid in the
403	prompt initiation of lifestyle changes and therapeutic interventions that can prevent or
404	slow the progression of the disease. Urinary protein panels can also help monitor the
405	effectiveness of therapeutic interventions and track the progression of the disease over
406	time by changes in model scores. Meanwhile, NAFLD is closely associated with
407	metabolic disorders and may exacerbate the conditions of metabolic disorders. <sup>39</sup>
408	Therefore, utilizing these models to manage NAFLD can help patients improve their
409	metabolic status and reduce the risk of metabolic disorder-related diseases such as
410	cardiovascular disease, stroke, and kidney disease, on the basis of effectively
411	managing NAFLD.

We found that the model composed of MPST, CILP2 and TMEM25 was a reliable 413 non-invasive diagnostic tool for identifying NAFLD. Li et al. suggested that free fatty 414 acids increased hepatic MPST expression and inhibited the CSE/H<sub>2</sub>S pathway, thus 415 leading to NAFLD.<sup>40</sup> MPST might be a potential therapeutic target for NAFLD. 416 Genome-wide association studies have reported multiple loci associated with NAFLD, 417 including CILP2.<sup>41</sup> Meanwhile, we discovered that the diagnostic model composed of 418 OGFOD3, ENPP7 and P2RX4 was useful for identifying NAFLD with fibrosis. Xie 419 et al. showed that disrupting HIF- $2\alpha$  in the intestine specifically reduced liver steatosis, 420 along with diminished HIF-2 $\alpha$  signaling in the small intestine, several mRNAs 421 encoded by ceramide-synthesis-related genes, were significantly downregulated, 422

423 including ENPP7.<sup>42</sup>

425	We also found that TMEM256 and ICAM-1 could be used as reliable diagnostic
426	biomarkers for significant fibrosis (stage F $\geq$ 2) in NAFLD in the future. TMEM256,
427	which localized within the mitochondrial membrane, belongs to mitochondrial
428	proteins and is involved in oxidative phosphorylation. <sup>43</sup> More than 40% of the
429	mitochondrial proteome is associated with human diseases, including NAFLD.44
430	Mitochondrial dysfunction and endoplasmic reticulum stress are strongly implicated
431	in the development and progression of NAFLD. As an important member of the
432	immunoglobulin superfamily, the increased expression of ICAM-1 on the cell surface
433	is associated with development of several diseases, and can be used as a predictor of
434	liver fibrosis. <sup>45</sup> The results of animal experiments showed that in liver fibrosis tissues
435	ICAM1 is expressed in hepatocytes, mostly in the portal zone, inflammatory zone,
436	and focal necrotic zone, and the intensity of its expression increases progressively
437	with the severity of liver inflammation and fibrosis. <sup>46</sup>
438	



445	NAFLD. <sup>50</sup> A typical feature of NAFLD is development of oxidative stress and redox
446	imbalance. <sup>51</sup> In recent years, an increasing number of studies have found that
447	coenzyme A is closely related to NAFLD from different perspectives. Zhou et al.
448	revealed that inhibition of stearoyl-coenzyme A desaturases-1 ameliorated hepatic
449	steatosis. <sup>52</sup> Huang et al. suggested that enoyl coenzyme A hydratase-1 protected
450	against high-fat-diet-induced hepatic steatosis and insulin resistance. <sup>53</sup> In our study,
451	urine proteins in NAFLD with fibrosis were associated with the renin-angiotensin
452	system, cornified envelope, humoral immune system, and regulation of inflammatory
453	response. A prior report has suggested that ACE2/Ang-(1-7)/Mas may also contribute
454	to NAFLD development. <sup>54</sup> NAFLD is characterized by a dysregulated immune
455	response. <sup>55</sup> It is believed that inflammation and upregulation of inflammatory
456	mediators play a secondary role in the pathogenesis of NAFLD. <sup>56</sup> In our study, urine
457	proteins in NAFLD with significant fibrosis were associated with dense platelet
458	granule lumens and collagen-conjugate lumens. Yang et al. discovered that counting
459	platelets may help to determine the severity of liver injury and liver fibrosis. <sup>57</sup> The
460	above enrichment analysis suggests that urine proteomic data may reflect NAFLD
461	disease characteristics.

In the field of proteomics research, UPLC-MS/MS based techniques for the detection
and relative quantification of thousands of proteins in biological samples have been
widely used, and two mainstream methods have been developed for labeled
quantification and unlabeled quantification (label-free), both of which are based on

467	data-dependent acquisition. <sup>48</sup> These methods are based on the data-dependent
468	acquisition (DDA) model to acquire protein spectral data. The label-free proteomic
469	quantification was used in this study. Label-free proteomic quantification is a new
470	protein quantification technique that does not rely on isotope labeling and analyzes
471	enzymatic peptides by liquid-liquid mass spectrometry.58 This technique simply
472	analyzes the mass spectrometry data generated during the large-scale identification of
473	proteins and compares the signal intensities of the corresponding peptides in different
474	samples for the relative quantification of the corresponding proteins. It facilitates the
475	pursuit of more precise qualitative and quantitative results and avoids experimental
476	errors introduced by labeling and liquid-phase grouping. <sup>59</sup> In this study, a series of
477	frontier technologies such as protein extraction, enzymatic digestion, liquid
478	chromatography-mass spectrometry tandem analysis, and bioinformatics analysis
479	were combined to finally achieve quantitative proteomic data from the samples.
480	
481	There were some important limitations in the present study that should be mentioned.
482	First, the number of patients with NAFLD included in our study was relatively small.
483	Second, this study only explored the diagnostic biomarkers of NAFLD and associated
484	fibrosis from the perspective of high-throughput omics, but the underlying
485	mechanisms between these biomarkers and the disease were not addressed in depth.
486	
487	In conclusion, the diagnostic model consisting of CILP2, TMEM25, and MPST was

488 useful for distinguishing NAFLD patients from healthy controls. The diagnostic

489	models	comprising OGFOD3, ENPP7 and P2RX4 (for NAFLD with fibrosis), and
490	compri	sing TMEM256 and ICAM-1 (for NAFLD with significant fibrosis) now need
491	to be fi	urther tested in other ethnic groups. Urine-based biomarkers are more
492	accessi	ble and less invasive than blood tests; and may circumvent the need to invasive
493	liver bi	opsy to refine the staging of liver disease severity in people with NAFLD.
494	Refere	nces
495	1.	Fernando DH, Forbes JM, Angus PW, Herath CB. Development and Progression of Non-
496		Alcoholic Fatty Liver Disease: The Role of Advanced Glycation End Products. Int J Mol Sci.
497		2019;20(20).
498	2.	Han MAT, Yu Q, Tafesh Z, Pyrsopoulos N. Diversity in NAFLD: A Review of Manifestations of
499		Nonalcoholic Fatty Liver Disease in Different Ethnicities Globally. Journal of clinical and
500		translational hepatology. 2021;9(1):71-80.
501	3.	Rios RS, Zheng KI, Zheng MH. Non-alcoholic steatohepatitis and risk of hepatocellular
502		carcinoma. Chinese medical journal. 2021;134(24):2911-2921.
503	4.	Gadiparthi C, Spatz M, Greenberg S, et al. NAFLD Epidemiology, Emerging Pharmacotherapy,
504		Liver Transplantation Implications and the Trends in the United States. Journal of clinical and
505		translational hepatology. 2020;8(2):215-221.
506	5.	Kumar R, Priyadarshi RN, Anand U. Non-alcoholic Fatty Liver Disease: Growing Burden,
507		Adverse Outcomes and Associations. Journal of clinical and translational hepatology.
508		2020;8(1):76-86.
509	6.	Vilar-Gomez E, Calzadilla-Bertot L, Wai-Sun Wong V, et al. Fibrosis Severity as a Determinant
510		of Cause-Specific Mortality in Patients With Advanced Nonalcoholic Fatty Liver Disease: A
511		Multi-National Cohort Study. Gastroenterology. 2018;155(2):443-457.e417.
512	7.	Hagström H, Nasr P, Ekstedt M, et al. Fibrosis stage but not NASH predicts mortality and time
513		to development of severe liver disease in biopsy-proven NAFLD. Journal of hepatology.
514		2017;67(6):1265-1273.
515	8.	Angulo P, Kleiner DE, Dam-Larsen S, et al. Liver Fibrosis, but No Other Histologic Features, Is
516		Associated With Long-term Outcomes of Patients With Nonalcoholic Fatty Liver Disease.
517		Gastroenterology. 2015;149(2):389-397 e310.
518	9.	Marcher AB, Bendixen SM, Terkelsen MK, et al. Transcriptional regulation of Hepatic Stellate
519		Cell activation in NASH. Sci Rep. 2019;9(1):2324.
520	10.	Ekstedt M, Hagström H, Nasr P, et al. Fibrosis stage is the strongest predictor for disease-
521		specific mortality in NAFLD after up to 33 years of follow-up. Hepatology. 2015;61(5):1547-
522		1554.
523	11.	Dulai PS, Singh S, Patel J, et al. Increased risk of mortality by fibrosis stage in nonalcoholic
524		fatty liver disease: Systematic review and meta-analysis. <i>Hepatology</i> . 2017;65(5):1557-1565.
525	12.	Ballestri S, Mantovani A, Di Girolamo M, Baldelli E, Capitelli M, Lonardo A. Liver fibrosis in
526		nonalcoholic fatty liver disease patients: noninvasive evaluation and correlation with

527		cardiovascular disease and mortality. Metabolism and Target Organ Damage. 2023;3(1):1.
528	13.	Feng G, Zheng KI, Li YY, et al. Machine learning algorithm outperforms fibrosis markers in
529		predicting significant fibrosis in biopsy-confirmed NAFLD. Journal of hepato-biliary-pancreatic
530		sciences. 2021;28(7):593-603.
531	14.	Zhou YJ, Ye FZ, Li YY, et al. Individualized risk prediction of significant fibrosis in non-alcoholic
532		fatty liver disease using a novel nomogram. United European gastroenterology journal.
533		2019;7(8):1124-1134.
534	15.	Feng G, He N, Zhou YF, et al. A simpler diagnostic formula for screening nonalcoholic fatty
535		liver disease. Clinical biochemistry. 2019;64:18-23.
536	16.	Pappachan JM, Babu S, Krishnan B, Ravindran NC. Non-alcoholic Fatty Liver Disease: A Clinical
537		Update. Journal of clinical and translational hepatology. 2017;5(4):384-393.
538	17.	Zhou YJ, Wong VW, Zheng MH. Consensus scoring systems for nonalcoholic fatty liver disease:
539		an unmet clinical need. Hepatobiliary surgery and nutrition. 2021;10(3):388-390.
540	18.	Cheah MC, McCullough AJ, Goh GB. Current Modalities of Fibrosis Assessment in Non-
541		alcoholic Fatty Liver Disease. Journal of clinical and translational hepatology. 2017;5(3):261-
542		271.
543	19.	Leng W, Ni X, Sun C, et al. Proof-of-Concept Workflow for Establishing Reference Intervals of
544		Human Urine Proteome for Monitoring Physiological and Pathological Changes.
545		EBioMedicine. 2017;18:300-310.
546	20.	Li Y, Wang Y, Liu H, et al. Urine proteome of COVID-19 patients. Urine (Amsterdam,
547		Netherlands). 2020;2:1-8.
548	21.	Younossi ZM, Baranova A, Ziegler K, et al. A genomic and proteomic study of the spectrum of
549		nonalcoholic fatty liver disease. <i>Hepatology.</i> 2005;42(3):665-674.
550	22.	Hu S, Li P, Zhang R, Liu X, Wei S. Integrated metabolomics and proteomics analysis reveals
551		energy metabolism disorders in the livers of sleep-deprived mice. J Proteomics.
552		2021;245:104290.
553	23.	Nicholas SB. Use of urinary proteomics in diagnosis and monitoring of diabetic kidney
554		disease. The lancet Diabetes & endocrinology. 2020;8(4):261-262.
555	24.	Limonte CP, Valo E, Drel V, et al. Urinary Proteomics Identifies Cathepsin D as a Biomarker of
556		Rapid eGFR Decline in Type 1 Diabetes. <i>Diabetes care.</i> 2022;45(6):1416-1427.
557	25.	Sun Y, Wang F, Zhou Z, et al. Urinary Proteomics Identifying Novel Biomarkers for the
558		Diagnosis of Adult-Onset Still's Disease. Front Immunol. 2020;11:2112.
559	26.	Kleiner DE, Brunt EM, Van Natta M, et al. Design and validation of a histological scoring
560		system for nonalcoholic fatty liver disease. <i>Hepatology.</i> 2005;41(6):1313-1321.
561	27.	Bedossa P, Patel K. Biopsy and Noninvasive Methods to Assess Progression of Nonalcoholic
562		Fatty Liver Disease. Gastroenterology. 2016;150(8):1811-1822.e1814.
563	28.	Fabre B, Combier JP, Plaza S. Recent advances in mass spectrometry-based peptidomics
564		workflows to identify short-open-reading-frame-encoded peptides and explore their
565		functions. Current opinion in chemical biology. 2021;60:122-130.
566	29.	Tyanova S, Temu T, Cox J. The MaxQuant computational platform for mass spectrometry-
567		based shotgun proteomics. Nature protocols. 2016;11(12):2301-2319.
568	30.	Boccard J, Rutledge DN. A consensus orthogonal partial least squares discriminant analysis
569		(OPLS-DA) strategy for multiblock Omics data fusion. Anal Chim Acta. 2013;769:30-39.
570	31.	Zhou B, Zhou Z, Chen Y, et al. Plasma proteomics-based identification of novel biomarkers in

571		early gastric cancer. Clinical biochemistry. 2020;76:5-10.
572	32.	van Ooijen MP, Jong VL, Eijkemans MJC, et al. Identification of differentially expressed
573		peptides in high-throughput proteomics data. Briefings in bioinformatics. 2018;19(5):971-
574		981.
575	33.	Garay-Baquero DJ, White CH, Walker NF, et al. Comprehensive plasma proteomic profiling
576		reveals biomarkers for active tuberculosis. JCl Insight. 2020;5(18).
577	34.	Erdem C, Nagle AM, Casa AJ, et al. Proteomic Screening and Lasso Regression Reveal
578		Differential Signaling in Insulin and Insulin-like Growth Factor I (IGF1) Pathways. Mol Cell
579		Proteomics. 2016;15(9):3045-3057.
580	35.	Wu S, Zheng J, Li Y, et al. A Radiomics Nomogram for the Preoperative Prediction of Lymph
581		Node Metastasis in Bladder Cancer. Clin Cancer Res. 2017;23(22):6904-6911.
582	36.	Huang YQ, Liang CH, He L, et al. Development and Validation of a Radiomics Nomogram for
583		Preoperative Prediction of Lymph Node Metastasis in Colorectal Cancer. Journal of clinical
584		oncology : official journal of the American Society of Clinical Oncology. 2016;34(18):2157-
585		2164.
586	37.	Akinwande MO, Dikko HG, Samson A. Variance Inflation Factor: As a Condition for the
587		Inclusion of Suppressor Variable(s) in Regression Analysis. Open Journal of Statistics.
588		2015;Vol.05No.07:14.
589	38.	Liu CH, Zheng S, Wang S, et al. Urine Proteome in Distinguishing Hepatic Steatosis in Patients
590		with Metabolic-Associated Fatty Liver Disease. Diagnostics (Basel, Switzerland). 2022;12(6).
591	39.	Zarghamravanbakhsh P, Frenkel M, Poretsky L. Metabolic causes and consequences of
592		nonalcoholic fatty liver disease (NAFLD). Metabolism open. 2021;12:100149.
593	40.	Li M, Xu C, Shi J, et al. Fatty acids promote fatty liver disease via the dysregulation of 3-
594		mercaptopyruvate sulfurtransferase/hydrogen sulfide pathway. Gut. 2018;67(12):2169-2180.
595	41.	Speliotes E, Yerges-Armstrong L, Wu J, et al. Genome-wide association analysis identifies
596		variants associated with nonalcoholic fatty liver disease that have distinct effects on
597		metabolic traits. 2011.
598	42.	Xie C, Yagai T, Luo Y, et al. Activation of intestinal hypoxia-inducible factor $2\alpha$ during obesity
599		contributes to hepatic steatosis. Nature medicine. 2017;23(11):1298-1308.
600	43.	Kustatscher G, Grabowski P, Schrader TA, Passmore JB, Schrader M, Rappsilber J. Co-
601		regulation map of the human proteome enables identification of protein functions. Nat
602		Biotechnol. 2019;37(11):1361-1371.
603	44.	Morgenstern M, Peikert CD, Lübbert P, et al. Quantitative high-confidence human
604		mitochondrial proteome and its dynamics in cellular context. Cell metabolism.
605		2021;33(12):2464-2483.e2418.
606	45.	Rizk NM, Derbala MF. Genetic polymorphisms of ICAM 1 and IL28 as predictors of liver
607		fibrosis severity and viral clearance in hepatitis C genotype 4. Clin Res Hepatol Gastroenterol.
608		2013;37(3):262-268.
609	46.	Lv P, Paul SC, Xiao Y, Liu S, Luo H. Effects of thalidomide on the expression of adhesion
610		molecules in rat liver cirrhosis. Mediators of inflammation. 2006;2006(4):93253.
611	47.	Virreira Winter S, Karayel O, Strauss MT, et al. Urinary proteome profiling for stratifying
612		patients with familial Parkinson's disease. EMBO molecular medicine. 2021;13(3):e13257.
613	48.	Megger DA, Bracht T, Meyer HE, Sitek B. Label-free quantification in clinical proteomics.
614		Biochimica et biophysica acta. 2013;1834(8):1581-1590.

615	49.	Willebrords J, Pereira IV, Maes M, et al. Strategies, models and biomarkers in experimental
616		non-alcoholic fatty liver disease research. Progress in lipid research. 2015;59:106-125.
617	50.	Feng G, Byrne CD, Targher G, Wang F, Zheng MH. Ferroptosis and metabolic dysfunction-
618		associated fatty liver disease: Is there a link? Liver international : official journal of the
619		International Association for the Study of the Liver. 2022;42(7):1496-1502.
620	51.	Park M, Yoo JH, Lee YS, Lee HJ. Lonicera caerulea Extract Attenuates Non-Alcoholic Fatty Liver
621		Disease in Free Fatty Acid-Induced HepG2 Hepatocytes and in High Fat Diet-Fed Mice.
622		Nutrients. 2019;11(3).
623	52.	Zhou Y, Zhong L, Yu S, Shen W, Cai C, Yu H. Inhibition of stearoyl-coenzyme A desaturase 1
624		ameliorates hepatic steatosis by inducing AMPK-mediated lipophagy. Aging (Albany NY).
625		2020;12(8):7350-7362.
626	53.	Huang D, Liu B, Huang K, Huang K. Enoyl coenzyme A hydratase 1 protects against high-fat-
627		diet-induced hepatic steatosis and insulin resistance. Biochemical and biophysical research
628		communications. 2018;499(3):403-409.
629	54.	Stachowicz A, Wiśniewska A, Kuś K, et al. Diminazene Aceturate Stabilizes Atherosclerotic
630		Plaque and Attenuates Hepatic Steatosis in apoE-Knockout Mice by Influencing Macrophages
631		Polarization and Taurine Biosynthesis. Int J Mol Sci. 2021;22(11).
632	55.	Oates JR, McKell MC, Moreno-Fernandez ME, et al. Macrophage Function in the Pathogenesis
633		of Non-alcoholic Fatty Liver Disease: The Mac Attack. Front Immunol. 2019;10:2893.
634	56.	Wang Z, Li S, Wang R, et al. The protective effects of the $\beta 3$ adrenergic receptor agonist
635		BRL37344 against liver steatosis and inflammation in a rat model of high-fat diet-induced
636		nonalcoholic fatty liver disease (NAFLD). Molecular medicine (Cambridge, Mass).
637		2020;26(1):54.
638	57.	Yang YT, Wang LL, Yan LT, et al. Platelet count is closely associated with the severity of liver
639		injury in patients with chronic hepatitis B virus infection: A cross-sectional study.
640		Experimental and therapeutic medicine. 2020;20(1):243-250.
641	58.	Kang S, Kong F, Liang X, et al. Label-Free Quantitative Proteomics Reveals the Multitargeted
642		Antibacterial Mechanisms of Lactobionic Acid against Methicillin-Resistant Staphylococcus
643		aureus (MRSA) using SWATH-MS Technology. J Agric Food Chem. 2019;67(44):12322-12332.
644	59.	Battisti I, Ebinezer LB, Lomolino G, Masi A, Arrigoni G. Protein profile of commercial soybean
645		milks analyzed by label-free quantitative proteomics. Food chemistry. 2021;352:129299.
646		

### 648 Table legend

- **Table 1.** Baseline characteristics of patients with biopsy-proven NAFLD in the
- derivation cohort grouped by the severity of fibrosis (fibrosis stages < 1 vs. fibrosis

651 stages  $\geq 1$ ).

652

# 653 Figure legends

- **Figure 1.** Flow-chart of the study design, including the derivation cohort
- 655 (subsequently divided into the training set and testing set) and the validation cohort.
- 656 *Note:* Diagnostic models were developed for detecting NAFLD (UP<sub>NAFLD</sub> model),
- NAFLD with fibrosis stage F $\geq$ 1 (UP<sub>fibrosis</sub> model), or NAFLD with significant fibrosis
- $figure{1}{558}$  stage F $\geq 2$  (UP<sub>significant fibrosis</sub> model), respectively.
- 659 (a) Derivation cohort. (b) Validation cohort.
- 660
- **Figure 2.** The diagram illustration of discovering biomarkers of NAFLD and related
- 662 fibrosis from the perspective of urine proteomics.
- (a) Grouping of patients with liver biopsy-proven NAFLD in the derivation cohort. (b)
- 664 Label-free quantitative proteomics technology data analysis process. (c) Proteomics
- 665 identification results. The x-axis represents the identified substances and the y-axis
- represents the number of substances. (d) Molecular weight of the identified proteins.
- 667 The X-axis represents the size of the molecular weight and the Y-axis represents the
- number of molecular weights in this range. (e) OPLS-DA plots of urine proteomics
- from NAFLD and healthy individuals (R2Y, 0.956; Q2, 0.775).

671	Figure 3. Volcano plots and LASSO regression of differential proteins.
672	(a) Volcano map of differential proteins between NAFLD patients and healthy
673	controls. (b, c) LASSO regression screening for important differential key proteins
674	between NAFLD patients and healthy controls. (d) Volcano map of differential key
675	proteins between NAFLD patients with fibrosis stage $F \ge 1$ and those without fibrosis.
676	(e, f) LASSO regression screening for important differential proteins between
677	NAFLD with fibrosis and NAFLD without fibrosis. (g) Volcano plot of differential
678	key proteins between NAFLD patients with significant fibrosis stage F $\geq$ 2 and those
679	without significant fibrosis. (h, i) LASSO regression screening for important
680	differential proteins between NAFLD patients with significant fibrosis and those
681	without significant fibrosis.
682	
683	Figure 4. ROC curve analyses of key proteins and combined models in the derivation
684	cohort.
685	(a) ROC curves of EPHA10, CILP2, TMEM25, and MPST. (b) The combined
686	diagnostic model (UP <sub>NAFLD</sub> model) of three key proteins (CILP2, TMEM25, and
687	MPST) for NAFLD patients. (c) ROC curves of ACE2, OGFOD3, ENPP7, and
688	P2RX4. (d) The combined diagnostic model ( $UP_{fibrosis}$ model) of three key proteins
689	(OGFOD3, ENPP7, and P2RX4) for NAFLD patients with fibrosis. (e) ROC curves
690	of PECAM1, TMEM256, MSRA, and ICAM1. (f) The combined diagnostic model
691	(UPsignificant fibrosis) of the two key proteins (TMEM256, and ICAM1) for NAFLD

- 692 patients with significant fibrosis.
- 693 D set, training set; V set: testing set.

696	ONLINE-ONLY SUPPLEMENTARY MATERIAL
697	Supplementary Table 1. Baseline characteristics of patients with biopsy-proven
698	NAFLD in the derivation cohort grouped by stages of fibrosis (fibrosis stage F $< 2$
699	and fibrosis stage $F \ge 2$ ).
700	Supplementary Table 2. Correlation analyses of four key proteins (MPST, EPHA10,
701	TMEM25 and CILP2) between NAFLD patients and healthy controls.
702	Supplementary Table 3. Correlation analyses of four key proteins (OGFOD3,
703	ENPP7, ACE2 and P2RX4) between NAFLD patients with fibrosis and those without
704	fibrosis.
705	Supplementary Table 4. Correlation analyses of four key proteins (PECAM1,
706	TMEM256, MSRA and ICAM1) between NAFLD patients with significant fibrosis
707	and those without significant fibrosis.
708	Supplementary Table 5. Baseline characteristics of healthy controls and NAFLD
709	patients in the validation cohort.
710	Supplementary Table 6. Baseline characteristics of patients with biopsy-proven
711	NAFLD in the validation cohort grouped by stages of fibrosis (fibrosis stage F $< 1$

and fibrosis stage  $F \ge 1$ )

- 713 Supplementary Table 7. Baseline characteristics of patients with biopsy-proven
- NAFLD in the validation cohort grouped by stages of fibrosis (fibrosis stage F < 2
- and fibrosis stage  $F \ge 2$ )
- 716 **Supplementary Figure 1.** Plots of PCA (a) and PLS-DA (b).
- 717 Supplementary Figure 2. Permutation test of OPLS-DA.

718	(a) The	parameters of R2Y, and	Q2 in the	permutation test	of OPLS-DA.	(b)	)
-----	---------	------------------------	-----------	------------------	-------------	-----	---

719 Permutation analysis to verify whether the model has overfitting.

720	Supplementary	Figure 3.	Heatmaps and	enrichment analysis	5.
-----	---------------	-----------	--------------	---------------------	----

- 721 (a) Heatmap of hierarchical cluster analysis of differential key proteins in the NAFLD
- patient group (A) and in the healthy control group (B). (b) GO and KEGG enrichment
- analysis of 15 key proteins in NAFLD patients. (c) Heatmap of hierarchical cluster

analysis of differential key proteins in NAFLD patients with fibrosis stage F $\geq 1$  (C)

- and in those without fibrosis (D). (d) Enrichment analysis of 22 key proteins in
- NAFLD patients with fibrosis. (e) Heatmap of hierarchical cluster analysis of
- differential key proteins in NAFLD patients with significant fibrosis stage F $\geq$ 2 (E)
- and those without significant fibrosis (F) groups. (f) Enrichment analysis of 12 key
- 729 proteins in NAFLD patients with significant fibrosis.
- 730 Supplementary Figure 4. Correlation analyses between urinary key proteins.
- 731 (a) Correlation analyses among 15 differential proteins selected to distinguish
- 732 NAFLD patients from healthy controls. (b) Correlation analyses of four key proteins

733 (EPHA10, CILP2, TMEM25, and MPST). (c) Correlation analyses among 22

differential proteins selected to distinguish NAFLD patients with fibrosis from those

- without fibrosis. (d) Correlation analyses of four key proteins (OGFOD3, ACE2,
- ENPP7, and P2RX4). (e) Correlation analyses among 12 differential proteins selected
- to distinguish NAFLD patients with significant fibrosis from those without significant
- fibrosis. (f) Correlation analyses of four key proteins (PECAM1, TMEM256, MSRA,
- and ICAM1).

740	Supplementary Figure 5. ROC curves of combined models in the independent
741	validation cohort.
742	(a) The model consisting of three indicators, CILP2, TMEM25, and MPST, for
743	differentiating NAFLD patients from healthy controls (UP <sub>NAFLD</sub> model). (b) The
744	combined model consisting of three indicators, OGFOD3, ENPP7, and P2RX4, for
745	differentiating NAFLD patients with fibrosis from those without fibrosis (UP <sub>fibrosis</sub>
746	model). (c) The combined model comprised of two indicators, TMEM256 and ICAM-
747	1, for differentiating NAFLD patients with significant fibrosis from those without
748	significant fibrosis (UP <sub>significant fibrosis</sub> model).
749	
750	
751	
752	