

Time-of-day-dependent variation of the human liver transcriptome and metabolome is disrupted in MASLD

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5 6	Time-of-day-dependent variation of the human liver transcriptome and metabolome is disrupted in MASLD
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44 Validation: MJ, JTH, JV, BD, VR, JE, BS, PL; Formal analysis: MJ, JTH, JV, JE, PL; Investigation:

45 MJ, JTH, JV, BD, MD, AB; Resources: AB, PF, FP, BS, PL; Data curation: MJ, JTH, JV, BD, MD, VR,

46 PL; Writing: MJ, JTH, JV, BS, PL; Visualization: MJ, JTH, JV, PL; Supervision: BS, PL; Project

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- 48

ABBREVIATIONS

ANOVA	Analysis of variance
cAMP	Cyclic adenosine monophosphate
CCGs	Core clock genes
CRN	Clinical research network
Dihome	Dihydroxy-9-octadecenoic acid
GO	Gene ontology
GPC	Glycerophosphocholine
HFD	High fat diet
HODE	Hydroxyoctadecadienoic acid
KEGG	Kyoto encyclopedia of genes and genomes
LPA	Lysophosphatidic acid
MASLD	Metabolic dysfunction-associated steatotic liver disease
MASH	Metabolic dysfunction-associated steatohepatitis
PA	Phosphatidic acid
PNPLA3	Patatin-like phospholipase domain-containing protein 3
PPARγ	Peroxisome proliferator-activated receptor gamma
PUFAs	Polyunsaturated fatty acids
TDG	Time-of-day-dependent genes
TDM	Time-of-day-dependent metabolites
TGFβ	Transforming growth factor beta
TLR	Toll-like receptor
τνγα	Tumor necrosis factor-alpha
TTFLs	Transcriptional-translational feedback loops

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ABSTRACT

Background and aims: Liver homeostasis is ensured in part by time-of-day-dependent processes, many of them being paced by the molecular circadian clock. Liver functions are compromised in metabolic dysfunction-associated steatotic liver (MASL) and metabolic dysfunction-associated steatotic liver (MASL) and metabolic to metabolic dysfunction-associated steatotic liver disease (MASLD) progression in rodent

66 models. We therefore investigated whether time-of-day-dependent transcriptome and 67 metabolome are significantly altered in human steatotic and MASH livers.

68 Methods: Liver biopsies, collected within an 8 hour-window from a carefully phenotyped 69 cohort of 290 patients and histologically diagnosed to be either normal, steatotic or MASH 70 hepatic tissues, were analyzed by RNA sequencing and unbiased metabolomic approaches. 71 Time-of-day-dependent gene expression patterns and metabolomes were identified and 72 compared between histologically normal, steatotic and MASH livers.

Results: We provide here a first-of-its-kind report of a daytime-resolved human liver transcriptome-metabolome and associated alterations in MASLD. Transcriptomic analysis showed a robustness of core molecular clock components in steatotic and MASH livers. It also revealed stage-specific, time-of-day-dependent alterations of hundreds of transcripts involved in cell-to-cell communication, intra-cellular signaling and metabolism. Similarly, rhythmic amino acid and lipid metabolomes were affected in pathological livers. Both TNF α and PPAR γ signaling were predicted as important contributors to altered rhythmicity.

80 **Conclusion:** MASLD progression to MASH perturbs time-of-day-dependent processes in 81 human livers, while the differential expression of core molecular clock components is 82 maintained.

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Impact and implications: This work characterizes the rhythmic patterns of the transcriptome and metabolome in human liver. Using a cohort of in-depth phenotyped patients (n=290) with known biopsy collection time-of-day, we show that time-of-day variations observed in histologically normal livers are gradually perturbed in liver steatosis and metabolically-associated steatohepatitis. Importantly, these observations, albeit obtained on a restricted time window, bring further support to preclinical studies evidencing alterations of rhythmic patterns in diseased livers. On a practical side, this study calls for considering time-of-the-day as a critical biological variable which may significantly affect data interpretation in animal and human studies of liver diseases.

Graphical abstract:





INTRODUCTION

Normal tissue homeostasis requires a precisely timed expression of genes and proteins 109 110 around the clock and its alignment with cycles of light/dark exposure, feeding periods and physical activity. The central clock, located in the suprachiasmatic nucleus, is light-entrained 111 112 and connects with peripheral tissues to synchronize clock oscillators in these tissues. However, peripheral tissue clocks can operate autonomously, *i.e.* independently of the central 113 hypothalamic clock. For example, the major Zeitgeber ("time giver") setting the liver clock is 114 115 food intake/nutrient availability rather than daylight [1, 2]. Studies in nocturnal rodents of 116 molecular mechanisms controlling these circadian regulations generated a global picture defining an universal molecular clock machinery [3]. This cell-autonomous circadian core clock 117 118 is made of 2 autoregulatory loops comprising 14 transcription factors, encoded by so-called core clock genes (CCGs). Heterodimeric BMAL1 (ARNTL) and CLOCK (or NPAS2) transcriptional 119 120 activators and PER and CRY transcriptional repressors, along with the nuclear receptors RORs, 121 REV-ERB α and β constitute interlocked transcriptional-translational feedback loops (TTFLs). These TTFLs define a cell-autonomous clock machinery which controls clock output genes [4], 122 123 in turn regulating multiple cellular functions [3].

124 Because most of primates (including humans) are diurnal, there are likely important differences from rodents in circadian regulation that have yet to be explored. A limited 125 number of human time-of-day-resolved transcriptomes is available, especially for internal 126 organs. Transcriptomes from whole blood [5, 6], peripheral blood mononuclear cells [7], skin 127 [8], subcutaneous white adipose tissue [9, 10], heart montaigne [11]or skeletal muscle [12-128 14]were analyzed for a relatively low number of subjects (n<30). A gene expression study in 129 130 subcutaneous white adipose tissue and skin from 625 healthy volunteers allowed the 131 identification of time-of-day-regulated genes strongly enriched in CCGs [15].

Circadian rhythm dyssynchrony is observed in, and likely causative of, various diseases such as obesity and its complications like metabolic dysfunction-associated steatotic liver disease (MASLD), formerly known as non-alcoholic fatty liver disease (NAFLD). MASLD is a spectrum of liver conditions characterized by hepatic steatosis which combines, upon time, with varying degrees of necroinflammation and excluding excessive alcohol consumption [16]. Its more severe, yet generally asymptomatic form, called metabolic dysfunction-associated steatohepatitis (MASH; formerly known as NASH, non-alcoholic steatohepatitis), may evolve

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139 towards liver fibrosis, cirrhosis and hepatocellular carcinoma Large-scale MASLD patient cohort studies reported differences in gene expression between disease stages without time-140 of-day information [17-20]. While hepatic metabolomes and transcriptomes are deregulated 141 in rodent models of MASH and fibrosis [21, 22], whether this occurs similarly in human MASLD 142 remains unknown. A 24 hour-circadian transcriptome atlas of 64 tissues from healthy 143 144 baboons identified only a small set of robustly cycling genes in liver, surprisingly not including CCGs [23]. Rhythmic gene expression patterns were inferred from the analysis of tissues 145 146 collected *post mortem* from 600 human donors. Relatively few genes (n=648), including only a few CCGs, exhibited predicted time-of-day-dependent expression [24]. Thus, both ethical 147 148 and technical hurdles hinder the thorough investigation of time-of-day-dependent processes in healthy human liver and the deregulation thereof in MASLD. Importantly, this conclusion 149 150 extends to the hepatic metabolome, which is clock-controlled and disturbed in various liver dysfunction models [22, 25-28]. Disturbances in the hepatic chronometabolome observed in 151 rodent MASLD models have not been reported for humans so far [29]. 152

Considering these knowledge gaps, we asked whether the hepatic time-of-day-153 154 dependent transcriptome and metabolome are affected during MASLD progression. We 155 leveraged a large cohort of morbidly obese patients undergoing bariatric surgery from whom liver biopsies were taken peri-operatively (HUL cohort, [18]). Hepatic transcriptomes and 156 metabolomes were obtained from a sub-cohort of 290 patients whose biopsies were 157 histologically identified as either normal, steatotic, or MASH livers and for which the exact 158 biopsy time-of-day was known (Figure 1A). In an original approach integrating multiple 159 statistical tests, we provide the first-ever robust analysis of time-of-day-dependent gene 160 161 expression and tissue metabolite abundance in human liver, as well as changes associated 162 with the different stages of MASLD.

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MATERIALS and METHODS

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166 Liver biopsies from the HUL cohort

167 The Hôpital Universitaire de Lille (HUL) cohort, also known as the Biological Atlas of Severe 168 Obesity (ABOS) cohort was established as from 2006 by the University Hospital of Lille, France 169 (ClinicialTrials.gov: NCT01129297) from severely and morbidly obese patients visiting the Obesity 170 Surgery Department. The study protocol conforms to the ethical guidelines of the 1975 Declaration of 171 Helsinki. All patients of the cohort fulfilled criteria for, and were willing to undergo, bariatric weight-172 loss surgery (for details, see [18]). Written informed consent was obtained from each patient included 173 in the study. The protocol required that patients were fasting from midnight to surgery time. During 174 the surgical procedure, wedge biopsies were taken from the liver to be immediately snap-frozen and 175 the exact time of the biopsy was noted. A total of > 1,500 patients are currently included in the HUL 176 cohort, amongst whom 319 were selected to build a sub-cohort with complete clinical, biometric 177 parameters and a robust histological MASLD classification of quality-controlled biopsies eliminating all 178 intermediary MASLD stages (see [18] and Figure 1B for more details). Both transcriptomes and 179 metabolomes were obtained for these 319 patients with biopsy mass >100mg. Out of these, 290 had 180 known biopsy time-of-day, ranging from 8am to 4pm, and were included in this study. Main clinical 181 and histological characteristics are indicated in Table 1. Patient clinical data shown in Table 1 were 182 analyzed using the package "gtsummary" (v1.5.0).

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184 Total RNA sequencing and data processing

- 185 A detailed procedure can be found in the Supplemental Information file.
- 186

187 Liver metabolomics by LC-MS

188 All tissue samples were flash frozen and maintained at -80°C until processing. Sample preparation was

189 carried out as described previously [30] at Metabolon, Inc. (Morrisville, NC, USA). A detailed procedure

190 can be found in the Supplemental Information file.

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192 Bioinformatic analysis

Bulk RNAseq: All analyses were carried out using RStudio (v1.4.1106) with R (v4.1.0). Data processing
for differential expression as a function of time-of-day can be found in the Supplemental Information
file.

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197 Single cell RNAseq: All analysis has been made under R (v 4.2.0). A detailed procedure for data
198 extraction and processing can be found in the Supplemental Information file.

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200 Enrichment analysis

Time-dependent gene lists were analyzed for enrichment of Kyoto Encyclopedia of Genes and Genomes (KEGG) pathways and gene ontology (GO) biological process terms using Metascape 3.5 [31] with default settings (<u>https://metascape.org/</u>). A detailed procedure for data processing can be found in the Supplemental Information file.

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206 Data visualization and illustrations

Graphs were generated as *.svg files using R packages mentioned above. Data were imported in CorelDraw2020 to assemble figures. Drawings in Figure 1A are from Renée Gordon, Victovoi, and Mikael Häggström, M.D. and were made available to the public domain via Wikimedia Commons with no restriction of use. Bubbleplots were generated in R studio using the ggplot2, plotly, reshape2, rcpp, and tidyverse packages as described in [32].

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RESULTS

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5 Time-of-day is a major factor affecting gene expression in human liver

216 Human liver biopsies were collected from patients with obesity and undergoing bariatric surgery, for which the exact daytime of the liver biopsy was recorded (Figure 1A). Key 217 218 clinical parameters of the 290 patients are summarized in Table 1. Based on histological 219 features of liver biopsies (steatosis, hepatocyte ballooning, lobular inflammation), patients 220 were grouped according to MASLD stages and labelled as histologically normal (HN), steatotic 221 or MASH liver following the decision tree shown in Figure 1B. The proportion of men in this 222 cohort increased with MASLD severity, rising from 16% (HN) to 38% (MASH) with an average 223 Clinical Research Network (CRN) NAS score rising from 0 to 5, respectively. Since sex is an important biological variable in this context [18], this was considered during further analysis 224 (see below). Patients in the steatosis and MASH groups were slightly older than those in the 225 226 HN group, and expectedly had also higher insulin resistance on average.

227 The source of variation in gene expression levels was estimated by a multivariate analysis of variance (ANOVA) (Figure 1C). The F-ratio (ratio of the between-group variance to 228 229 the within_group_variance) not only confirmed sex and group (*i.e.* MASLD stage) as the main sources of variation as previously reported [18], but very interestingly identified biopsy time 230 231 (AM vs. PM) as the third most significant source of variation (Figure 1C). Age had only a minor 232 contribution to signal variation. The distribution of biopsy times (Figure 1D) revealed a daytime window of about 8 hours. Biopsies were predominantly (>60%) taken in the morning 233 with a first peak around 9:30 AM and a second, lower peak around 2:30 PM, due to the 234 logistical schedule of surgical interventions. There was, however, no significant difference in 235 biopsy time distribution between histological groups (Table 1). Since exclusion of biopsies 236 237 collected between 11am and 1pm did not modify the outcomes of preliminary statistical analysis, the "AM" subgroup was defined as biopsies taken before noon (12:00), the "PM" 238 239 subgroup as biopsies taken after noon.

Gene expression profiles were thus compared between morning (AM) *vs.* afternoon (PM) samples. Differentially expressed genes were identified using DEseq2 independent of the MASLD status but correcting for sex. Transcript counts for 1,660 genes were significantly

243 different (Benjamini-Hochberg adjusted p-value < 0.05) between AM or PM biopsies (Figure 1E). Among the 100 top hits were most of the CCGs (PER3, ARNTL/BMAL1, NPAS2, NR1D1, 244 NR1D2, PER2, CRY1, PER1), clock-related genes (CIART, DBP, NFIL3) (Figure 1E) as well as 245 circadian-regulated genes involved in lipid metabolism (PPARD, LIPG, LPIN2...). Because 246 patients were fasting from midnight irrespective of surgery time, genes implicated in hepatic 247 gluconeogenesis (G6PC, PCK1, SGK2...) were, as expected, higher expressed in PM samples 248 (Figure 1E and Supp. Table 1). Opposite to nocturnal rodents, genes from the negative limb of 249 250 the clock displayed lower expression in the afternoon (PER3, NR1D1, NR1D2, CIART...), whereas genes from the positive clock limb were higher expressed in the afternoon 251 (ARNTL/BMAL1, NPAS2...)(Figure 1E). Globally, genes displaying AM vs. PM differential 252 expression were significantly enriched for the KEGG pathways "circadian rhythm", "PPAR 253 254 signaling pathway", carbohydrate and lipid metabolic pathways, as well as cellular architecture and communication, among others (Figure 1F). 255

Thus an 8-hour time frame allowed the detection of significant changes in time-of-daydependent liver gene expression, with a large proportion of transcripts functionally related to circadian rhythmicity.

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260 Time-dependent genes vary between MASLD stages

261 We next examined whether time-of-day-dependent distributions of gene expression would differ between the histological states "HN", "steatosis" and "MASH". In order to 262 achieve statistical power and obtain robust and exhaustive lists of time-dependent gene 263 expression over the available daytime window, we used 3 complementary statistical methods 264 analyzing different aspects of gene expression distribution (differential expression, partial 265 Spearman correlation, Kolmogorov-Smirnov test), the results of which were agglomerated by 266 267 a Fisher test to yield a combined p-value for each gene (Figure 2A-C and Supp. Figures 1 and 2). The 3 types of analyses are graphically exemplified for the core clock gene ARNTL/BMAL1 268 269 (Figure 2A-C) which served as positive control to validate our approach, as it is among the 270 most highly time-dependent genes regardless of the histological group. First DEseq2, which 271 relies on a negative binomial distribution of gene expression, was used to identify differential 272 gene expression between 2 conditions (AM vs. PM as in Figure 1) (Figure 2A). Second, partial

273 Spearman correlation was computed between ARNTL gene expression and daytime (Figure 2B). Both approaches integrated sex as a confounding factor. Third, the Kolmogorov-Smirnov 274 275 test was employed to determine whether AM and PM ARNTL expression distribution followed 276 a similar law and thus were similar in shape (Figure 2C). Finally, the Fisher combined probability test or "Fisher's method" was used as a meta-analysis method for p-value 277 278 combination: individual raw p-values resulting from each statistical test were agglomerated into a single p-value per group (Figure 2D). The detected expression profile of ARNTL, of other 279 280 CCGs (Supp. Figure 1) and of all other transcripts (Supp. Figure 2), clearly confirmed that the available time window was sufficient for robust time-of-day analysis of gene expression. A 281 total of 1,427 genes with an absolute fold change greater than 1.2 (AM vs. PM) (FDR < 0.01) 282 was identified (Figure 2E). The vast majority of these time-dependent genes (TDGs) were 283 284 strikingly distinct when comparing the 3 patient groups. Less than 10% (132 genes) were indeed common to all 3 groups ("common TDGs") (Figure 2E) and notably included most CCGs 285 286 (ARNTL, NR1D1/2, NPAS2, CRY1, PER1/2/3, DBP, CIART)(Supp. Table 1). TDG repartition 287 outside of this core set was strongly unequal between groups, with ≈50% (558) of non-shared 288 TDGs found in HN, ≈35% (392) in steatotic and less than 15% (177) in MASH livers. Along the same line, we found that AM to PM fold changes of common TDGs were, on average, 289 290 decreased in steatotic and even more in MASH livers when compared to HN livers (Figure 2F). These differences are illustrated for a selection of TDGs with AM-PM differences either 291 decreasing (PCAT18, ARMC4, SIK1B) or increasing in MASH (CYP4Z1, RHOBTB1, 292 293 PPIAP71)(Figure 3A,B).

Common TDGs were collectively enriched for KEGG terms like "circadian rhythms" as 294 295 expected from the content in transcripts coding for CCGs, and for metabolic regulatory 296 pathways like the PPAR and FoxO pathways (Figure 4, Supp. Figure 3), illustrated by genes 297 such as S1PR1, G6PC1, PCK1, SGK2, FASN, AQP7 and PPARD. TDGs unique to the HN group 298 were also enriched, albeit to a lesser extent, for pathways linked to circadian rhythm (notably 299 including CLOCK) as well as to fatty acid and amino acids metabolism. The most highly represented pathway was "gap junctions" (Figure 4A, Supp. Figure 3), characterized by genes 300 301 such as PDGFB, MAP2K1 and transcripts encoding for tubulins TUBA1C/8, TUBB, TUBB1/2B (Supp. Table 1), suggesting that epithelial barrier integrity/permeability homeostasis, which is 302 303 known to be disturbed in MASLD [33], requires an oscillating expression of these genes in

304 healthy conditions. Genes unique to the steatosis group (Supp. Table 1) were mostly linked to metabolism of lipids and fatty acids (DGKG, PLA2G4B/5, LPIN2/3, ETNK2, ETNPPL, PLPP4, 305 FADS1/2, CYP2C8, GDPD1, SCD) and also to metabolism of peptides and amino acids 306 (DNMT3B, GCLM, SDS, PSAT1, GNMT, ALDOC, GPT2, CSAD, UPB1)(Figure 4A, Supp. Figure 3). 307 Lastly, TDGs specific to the MASH group (Supp. Table 1) were highly enriched for signaling by 308 309 calcium, cAMP or neurotransmitters (ADRB2, DRD1, GRM1, NTRK1, NTSR1, P2RX7, RYR2, CACNA1H, SSTR5, TBXA2R, FFAR2, SUCNR1) as well as for lipolysis (ADRB2, IRS1, 310 311 PNPLA2) (Figure 4, Supp. Figure 3). The temporal pattern of gene expression in homeostatic conditions is thus strongly affected by the disease state and indicative of compromised cellular 312 communication and metabolic pathways. 313

Inferring upstream regulatory cues or altered biological processes may be achieved by 314 315 comparing differentially expressed gene lists to consensus gene expression patterns induced by a given perturbagen (Figure 4B-D). Speed2 (Signaling Pathway Enrichment using 316 317 Experimental Datasets [34]) analysis allows probing gene lists against ranked gene signatures for 16 signaling pathways, with the aim of identifying upstream signaling mediators. Ranked 318 319 signatures suggested that cues in homeostatic (HN) conditions could be TGFβ, TNFα, oxidative stress, TLR and estrogen (Figure 4B). In steatosis and MASH conditions, this pattern shifted 320 321 towards a more limited signaling pathway panel with similar statistical significance, which included either TLR and VEGF (steatosis) or TNF α and TLR (MASH)(Figure 4C and 4D 322 respectively). Although causative links cannot be proven, this data could reflect a loss of 323 324 physiological rhythmic function(s) in steatotic and MASH livers, which in turn gain rhythmic 325 functions associated to pathogenic immune and proliferative stimuli and responses.

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327 MASLD stages correlates with time-of-day changes in liver metabolites

Our results suggested that metabolic pathways are altered in a time-of-day-dependent manner as MASLD progresses, with an enrichment in amino acid- and lipid metabolismregulating genes (Supp. Figure 3). Therefore, an unbiased tissue metabolomic study by LC-MS was performed on the same 290 liver samples. Similar to the gene expression analysis, a global approach was initially employed to evaluate overall time-of-day dependence of tissue metabolite levels regardless of the MASLD status. This global analysis identified ≈220 metabolites whose amounts were significantly different in AM and PM biopsies (DEseq2

corrected for sex, FDR<0.1) (Figure 5A, Supp. Table 2). Visual inspection of the volcano plot
highlighted intermediates of lipid β-oxidation (carnitine derivatives), amino acids (kynurenate,
oxo-arginine...) as differentially detected in AM *vs.* PM livers (Figure 5A). It also confirmed the
more marked fasting status of "PM" patients exhibiting an increased hepatic content in 3hydroxybutyrate (BHBA). A biological term enrichment analysis confirmed that the majority of
the identified metabolites belonged to amino acid, lipid and fatty acid metabolic pathways
(Figure 5B).

342 To highlight a possible time-of-day differential representation of metabolites between 343 MASLD groups, we again combined the 3 statistical approaches as described for gene expression analysis (DEseq2, Spearman correlation, Kolmogorov-Smirnov test) followed by 344 345 Fisher's agglomeration for a robust identification of time-dependent metabolites (TDMs) (Figure 5C). A total of 251 TDMs were identified using this method (combined FDR<0.1), out 346 347 of which only 14 (6%) were common to all 3 MASLD groups (Figure 6A, 6B). These common TDMs included amino acids such as proline and threonine, several fatty acids and the ketone 348 body component β-hydroxybutyrate (Figure 6B and Supp. Figure 4A-F). KEGG metabolic 349 350 pathway enrichment analysis revealed that these common TDMs were most significantly 351 associated to metabolism of amino acids (arginine, proline, threonine)(Figure 6B and Supp. Figure 4A-C). In agreement with the identification of the PPAR pathway based on gene 352 353 expression patterns (Figure 4) and the detection of 3-hydroxybutyrate (Supp. Figure 4D), 354 synthesis of ketone bodies was also identified as a relevant term (Figure 6B),

Among the 197 stage-specific TDMs, 31% were specific to HN, 47% to steatosis and 20% to MASH (Figure 6A and Supp. Table 2). TDMs specific to HN livers, and thus lost at the steatosis and MASH stages, were mainly associated to metabolism of sphingolipids (Figure 6C and Supp. Table 2) such as CDP-choline and sphinganine (Supp. Figure 4G, H). Glycerophosphoethanolamines, glycerophosphocholines as well as derivatives of cholesterol, amino acids and pyrimidine were also identified as time-dependent in normal livers (Supp. Table 2 and Supp. Figure 4I-L).

A similar enrichment analysis identified amino acid metabolic pathways (branchedchain, sulfur-containing, arginine, taurine) (Figure 6D, Supp. Figure 5A, B and Supp. Table 2) as time-dependent in steatotic livers. Visual inspection of steatosis TDMs also identified a carnitine precursor (N6,N6,N6 trimethyl-lysine, Supp Figure 5C) and derivatives (Supp. Table

366 2 and Supp. Figure 5D, E) which could reflect an altered fatty acid oxidation activity. Finally, 367 MASH-specific TDMs were enriched mainly for vitamin, glycan and glycosylphosphatidylinositol (GPI) metabolic intermediates (Figure 6E, Supp. Figure 5 and 368 Supp. Table 2). 369

Taken together, these analyses highlight the disruption during MASLD progression of time-of-day-dependent bioactive phospholipid metabolism and of amino acid biotransformation pathways. Intriguingly, PPARy ligands of the linoleic acid class (9,10 DiHOME [35] and 9- and 13-HODE [36]) displayed a differential abundance in AM *vs.* PM steatotic and MASH livers, with estimated concentrations in the 10-100µM range which are sufficient to activate PPARy (Supp. Figure 5F, J).

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377 Integrative analysis of time-dependent genes and metabolites.

We next performed an integrative analysis of the transcriptomic and metabolomic data 378 379 at the pathway level using the KEGG database. This analysis combined TDGs and TDMs specific to either HN or MASH stages and common TDGs and TDMs, irrespective of their relative time-380 381 of-day direction of change, to identify associated transcriptomic and metabolomic conditions operating in normal and MASH livers (Figure 7A). TDGs and TDMs characterizing the HN stage 382 were enriched for metabolic pathways related to lipid and amino acid metabolism, while most 383 384 of them were not detected at the MASH stage, or with a decreased significance [arginine (Arg) 385 and proline (Pro) metabolism, glycerophospholipid metabolism]. Linoleic metabolism was associated to the MASH stage (Figure 7B, C). HN-or MASH-enriched pathways 386 (glycerophospholipid and linoleic pathways, respectively) were further detailed for daytime 387 variation of associated TDGs and TDMs. The glycerophospholipid pathway was characterized 388 by an increased abundance in AM livers of 3 out of 4 detected diacylglycerol (DAG) species 389 specifically at the HN stage. Glycerophosphocholine (GPC) intermediates (CDP-choline, GPC) 390 displayed stage-specific time-of-day variations that were not correlated to the occurrence of 391 392 glycerophospholipid species (X-GPC) (Figure 7D). Higher abundance of DAG species in the 393 morning did not correlate with HN TDG expression changes in transcripts encoding enzymes involved in this metabolic pathway, with the exception of the patatin-like phospholipase 394 395 domain–containing protein 3-encoding gene (PNPLA3). PNPLA3/adiponutrin has

acyltransferase activity, increasing the formation of phosphatidic acid (PA) from 396 lysophosphatidic acid (LPA), which may lead to more DAG synthesis. It might also reflect 397 PNPLA3 hydrolytic activity on triacylglycerol molecules, favoring DAG accumulation. Along the 398 399 same line, we compiled TDG and TDM data related to linoleic acid metabolism (Figure 7E). The increased abundance of the PPARy ligands 9- and 13-HODE in the afternoon at the MASH stage 400 401 was mirrored by the gene expression of ALOX15, a dioxygenase catalyzing the synthesis of 402 these 2 hydroxyoctadecadienoic acids which was higher in the morning. A similar lack of 403 correlation was observed between 9,10-DiHOME hepatic content and the expression of the linoleic acid-converting CYP2C8 at the steatosis stage. These results suggest that time-404 405 dependent metabolite variation in these pathways is delayed with respect to gene regulation, 406 and/or controlled by post-transcriptional processes.

407 Of note, mapping of human transcript expression to liver cell types using a reference 408 single cell RNAseq dataset [37] suggested that the identified enzymatic pathways may follow 409 a cell-specific expression pattern. They appear as mainly restricted, but not limited to, hepatocytes. As an example, ALOX15 is detected in dendritic cells, whereas ALOX5 is also 410 411 detected in monocytes, neutrophils and basophils (Supp. Figure 6). Therefore time-412 dependent metabolite variation may occur in either identical or distinct cell types, reflecting a functional compartmentalization. Yet these observations confirmed the presence of time-of 413 day variation in hepatic gene expression and metabolome, and identified several new 414 oscillating metabolites at the MASH stage (Figure 7 and Supp. Table 2). 415

DISCUSSION

Chronobiological studies require multiple replicates at 2h-intervals over a total period 418 419 of 24 or even 48 hours, within a controlled environment including timed exposure to light and food. These conditions are not achievable in human studies, precluding the analysis of cyclic 420 421 processes and particularly in internal organs [38]. While human circadian rhythms are appreciated by genome-wide association study studies and the phenotypic manifestation of 422 423 disturbed cyclic processes such as sleep, light exposure and eating patterns [39], their study 424 in healthy or pathological conditions is indeed hindered by ethical and technical constraints. 425 Despite controlled experimental setup with regard to sleep behavior and food intake in previous studies [5-14], a limited number of samples of mostly healthy individuals were 426 427 collected, thereby limiting data interpretation due to high inter-sample variability.

428 Here we reveal the first ever time-of-day-resolved human liver transcriptome with associated liver tissue metabolites using a 290-patient cohort. Although the available time 429 430 window of liver biopsies was only about 8 hours, this temporal window was sufficient to robustly identify TDGs and TDMs. Time-dependency of genes and metabolites was distinct 431 432 between histologically-defined MASLD groups. However, a small proportion of genes was 433 identified as time-dependent in all three patient groups and included CCGs, indicating that the molecular lock is rather robust in pathological conditions. In contrast, the alignment of 434 435 rhythmic biological processes such as intercellular communication (gap junctions) and 436 metabolic regulations is disrupted upon MASLD progression. Interestingly, none of the detected TDGs in MASH patients belonged to the human and mouse core set of 437 438 MASH/fibrosis-associated genes [20], underlining the need for considering time as an important biological variable. Interestingly, the number of stage-specific TDGs (Figure 2E) 439 440 decreases from the HN to the MASH stage, and concomitantly enriched pathways lessen 441 (Supp. Figure 3), hinting at a loss of functional adaptability/(metabolic) flexibility. In high fat 442 diet (HFD)-fed mice, transcripts gaining rhythmicity when compared to chow diet-fed mice are 443 strongly enriched for glycerophospholid metabolism [22], similarly to steatotic_patients (Supp. 444 Figure 3), indicating convergent mechanisms for liver adaptation to dietary imbalance as often occurring in MASLD. At the cellular level, Ca²⁺ fluxes are submitted to ultradian variations and 445 coupled to metabolic regulations [40], and mishandled intracellular Ca²⁺ stores in MASH can 446 447 significantly impact parenchymal and non-parenchymal liver cellular functions [41]. A number

of genes encoding for Ca²⁺ channel components or involved in intracellular Ca²⁺ signaling 448 (PKD1L1, TRPC1 P2RX7, FFAR2, ADRB2, CACNA1H, GRM1, NTRK1) exhibited differential AM vs. 449 PM expression specifically in MASH livers. Thus, in addition to the lipid-induced dysfunctional 450 ER Ca²⁺ transport [42], de novo oscillation of the calcium handling process accompanies 451 progression to MASH. CLOCK gene deletion affected metabolite oscillations in mouse liver 452 [25] and we detected a time-of-day differential expression of *CLOCK* exclusively in HN livers, 453 which display a more diverse metabolic activity than MASH livers (Figure 7B). While hinting 454 at a possible role of (the loss of) CLOCK, the examination of individual metabolites 455 456 nevertheless showed little overlap between mouse CLOCK-dependent metabolites and HNspecific metabolites. This lack of clear concordance can be explained by species-specific 457 mechanisms, distinct effects of gene deletion vs. loss of time-dependent expression and/or 458 459 technical bias.

460 While examining the coherence between MASLD state-specific liver transcriptomes and metabolomes, we observed little correlation between enzyme-encoding genes and 461 metabolite abundance. This disconnection is not unprecedented and was also observed in a 462 463 highly standardized mouse study which minimizes the variability typically observed in human 464 samples [22]. The narrow time window of our study may explain in part this lack of correlation as transcripts are likely to precede metabolite production, hence affecting our statistical 465 approach for the PM sub-cohort. It may also indicate significant time-of-day-dependent 466 translational control [43] as well as post-translational modifications regulating enzyme activity 467 which are not captured by our analysis. 468

469 Finally, another point of convergence between our and mouse studies is the 470 differential abundance of linoleic acid derivatives and PPARy ligands 9,10-_DiHOME, 9-HODE 471 and 13-HODE in steatotic and MASH livers, respectively. The PPARy-encoding gene 472 NR1C3/PPARG itself did not display significant oscillatory expression in human liver, contrasting with HFD mouse livers [22]. Whether estimated released concentrations of these 473 compounds are indeed sufficient to differentially activate human liver PPARy, which is mostly 474 475 expressed in endothelial cells, hepatocytes and macrophages (Supp. Figure 6) and have a causative role in hepatic transcriptional reprograming requires further in-depth investigation. 476

477 On the one hand, it is remarkable that many of the biological processes and pathways 478 shown to be affected by MASLD in other studies, identified on the basis of changes in gene

479 expression or metabolite abundance levels regardless of time, also display altered time-480 dependent expression profiles in our study. On the other hand, we identified many novel potential links between genes with deregulated timed expression and MASLD pathogenesis, 481 which were not previously considered by standard analyses. It is probably the combination of 482 483 both types of deregulations that underlies the deeply disturbed liver functions once MASH is declared. Conversely, some of the changes detected when time-of-day information is absent 484 or ignored may turn out to be artefacts, as time-of-day as a biological variable might not be 485 486 equilibrated between groups.

487 Considering that the time-of-day dependence of transcript/protein/metabolite 488 measurements was previously neglected or ignored in nearly all human MASLD studies, our findings here reveal a significant impact of time-of-day on many relevant pathogenic 489 490 processes. As such, differences found between sample groups in cohort studies might reflect 491 a previously under-appreciated bias in sampling time between groups. Further investigation is needed in this regard, particularly when studying human material. In any case, a new 492 generality should be that sampling daytimes (or Zeitgeber times) must be carefully recorded 493 494 and included in post-hoc analyses whenever possible.

495

496 Strengths and limitations of the study.

497 This study has both strengths and limitations. This first-of-its-kind study revealed time-498 of-day transcriptomic and metabolomic alterations in human livers as a function of the histologically-proven MASLD stage. It used a large cohort allowing both the selection of 499 biopsies to adequately encompass healthy control, steatosis and MASH cases and robust 500 501 statistical analysis. There is however a number of limitations, inherent to the observational nature of the study. The narrow time window for biopsies collection (8 hours) precludes the 502 503 assessment of a 24h diurnal rhythmicity, hence of the integrity of the molecular clock. The 504 unavoidable difference in fasting duration could also be a confounding factor.

505 Our bulk RNA sequencing approach allowed a full coverage of the transcriptome, but 506 precluded the identification of liver cell types expressing TDGs. We thus calculated a cell 507 specificity index of TDGs in human resident parenchymal (PC, hepatocytes) and non-508 parenchymal (NPC) CD45⁻ cells. The tau (τ) index, calculated by a robust and simple method

to assess cell-type specificity, was used as a metrics [44]. Using a reference single cell-RNA sequencing dataset for human livers collected at unknown times [37], τ could be calculated for 584 transcripts out of the 1,481 identified TDGs (Supp. Table 1). Using this metric, only 51 genes displayed a cell type-restricted expression pattern in CD45⁻ cells (τ >0.85), which was not limited to hepatocytes (Supp. Figure 7). The remaining 533 transcripts including CCGs could be mapped to 2 or more cell types. Of note, 15 out of the 51 cellrestricted transcripts were mostly expressed in dendritic or Kupffer cells (Supp. Figure 6).

Taken together, our bulk RNAseq approach detected a high number of TDGs than previous efforts, including many pathways never previously reported as being timedependent. This resource will serve as an important basis for further investigations considering also the cell-type specificity in time-of-day gene expression variation in human MASLD.

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538 Author names in bold designate shared co-first authorship.

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Figure legends

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649

Figure 1: Timed liver biopsies from a large cohort of humans with obesity. (A) Overall 650 experimental strategy. (B) Decision tree to stratify the HUL sub-cohort. "HN" (histologically 651 normal), "steatosis" (benign steatosis only) or "MASH" (steatosis+inflammation). (C) Inter-652 653 sample variation in gene expression. ANOVA was used to reveal the main sources of overall inter-sample variation. (D) Biopsy daytime distribution. (E) Gene expression analysis. A 654 volcano plot was generated by comparing gene expression using DEseq2 from samples 655 656 collected in the morning (AM) or in the afternoon (PM) regardless of the pathological state. X 657 axis: log_2 (fold change), Y axis: $-log_{10}$ (p-values). (F) KEGG pathway enrichment analysis. Biological term enrichment was carried out using the 1,660 genes whose expression was 658 659 significantly different as determined in (E) (FC>1.2, FDR <0.05). (E, F): font size was adjusted for clarity purpose. 660

661

Figure 2: A multi-test method identifies time-of-day-dependent genes. BMAL1/ARNTL 662 663 expression as a function of time and of the liver histological grade (A-C). (A) A violin plot is 664 shown to illustrate DEseq2 results to compare AM vs. PM expression and correcting for sex as 665 confounding factor. (B) A dot plot with linear tendency lines is shown to illustrate partial Spearman correlation analysis between gene expression and biopsy daytime. (C) A density 666 plot is shown to illustrate the output of the Kolmogorov-Smirnov test for comparison of AM 667 or PM gene expression distributions. (D) Fisher's agglomeration method. Frequency 668 669 histograms of uncorrected Fisher p-values are shown for each group and the first (colored) 670 bar of each group histogram indicates genes with p<0.05. (E) TDG distribution within 671 histological groups. A Venn diagram shows the unequal distribution of 1,427 TDGs (FC>1.2, FDR<0.01) amongst groups. Numbers indicate the numbers of identified transcripts. (F) Gene 672 expression variation of 132 "common TDGs". CCGs and other transcripts are indicated. * 673 indicates p<0.05 using ANOVA and Fisher's LSD post-hoc test. 674

Figure 3: Example distributions of time-dependent genes (TDGs) altered in MASH. (A) Violin plots showing AM vs PM gene expression variations for representative TDGs losing their timedependency in MASH. (B) Violin plots showing AM vs PM gene expression variations for representative TDGs gaining time-dependency in MASH. Statistical tests were Kruskal-Wallis tests followed by unpaired Wilcoxon post-hoc test for AM-PM comparisons in each group (*p<0.05, **p<0.01, ***p<0.005, ****, p<0.001). VST: variance-stabilizing transformation.

682

Figure 4: Term enrichment analysis of time-dependent genes (TDGs) and upstream 683 684 regulatory pathway prediction. (A) Biological term enrichment analysis. TDGs identified in 685 Figure 2 were enriched for gene ontology (GO) terms related to biological processes (BP) using Metascape. Significantly enriched GO-BP clusters were manually collapsed for visualization 686 687 purpose and top hits are indicated. (B-D): Pathway activity ranking. Speed2 TDGs enrichment for pathway signature genes. Each pathway is represented as a bar showing the mean rank of 688 the query list. The "bar code" plot shows the distribution of genes from the query list in the 689 690 ranked reference signatures.

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Figure 5: Identification of time-dependent liver metabolites measured by LC-MS. (A) Volcano 692 plot of metabolite time-of-day-dependent differential abundance in liver. Fold-changes 693 694 values and corresponding p-values obtained using DEseq2 considering sex as confounding 695 factor. (B) Enrichment of KEGG metabolic pathways. A biological term enrichment against the 696 KEGG database was run using the differentially detected metabolites (TDM) identified in (A) (DEseq2 adjusted p-value <0.1). (C) P-value agglomeration by Fisher's method. Similar as gene 697 expression analysis (see Figure 2), p-value agglomeration from three separate statistical tests 698 (DEseq2, partial Spearman correlation, Kolmogorov-Smirnov) was carried out using Fisher's 699 700 method and identified TDMs within each group. The resulting uncorrected Fisher p-values are shown as frequency histograms and the first (colored) bar of each group histogram indicates 701 702 metabolites with p<0.1.

703

Figure 6: Distribution and characterization of time-dependent liver metabolites (TDMs).
 After correction for multiple testing, 238 metabolites with a Fisher FDR<0.1 were considered

as robustly time-dependent. (A) Distribution of TDMs among liver histological groups. (B-E)
 KEGG metabolic pathway enrichment of common (central intersection) or group-specific
 TDMs using the online metabolomics analysis platform MetaboAnalyst.

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Figure 7: Integrative analysis of time-dependent genes (TDGs) and metabolites (TDMs). (A) 710 711 Analysis strategy outline. Common and HN- or MASH-specific TDGs and TDMs were analyzed associatively for enrichment of KEGG metabolic pathways using the online metabolomics 712 analysis platform MetaboAnalyst, revealing potential links between metabolic pathways as 713 714 defined by time-dependent gene expression patterns and metabolomic profiling (B, C). 715 Reconstitution (partial) of metabolic pathways displaying time of the day-dependency in the HN (D) or MASH (E) group. LPA: lysophosphatidic acid, PA: phosphatidic acid, DAG: 716 diacylglycerol, CDP-choline: cytidine-diphosphate-choline, PC: phosphatidylcholine, GPC 717 glycerophosphatidylcholine, X-GPC: acyl-conjugated GPC, 9-HpODE: 9-hydroperoxy 718 719 octadecadienoic acid, 13-HpODE: 9-hydroperoxy octadecadienoic acid, 9-HODE: 9-Hydroxyoctadecadienoic acid, 13-HODE: 13-Hydroxyoctadecadienoic acid, 12(13)-EpOME: 720 721 12(13)-epoxy-9Z-octadecenoic acid, 9,10-EpOME: 9(10)-epoxy-12Z-octadecenoic acid, 12,13-722 DiHOME: 12,13-dihydroxy-9-octadecenoic acid, 9,10-DiHOME: 9,10-dihydroxy-9-723 octadecenoic acid.

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Table 1: Biometric and biochemical parameters of the HUL sub cohort. The main biometric,
 biochemical and liver histological features of selected patients are indicated. F: women, M:
 men; BMI: body mass index; NAS: NAFLD/MASLD Activity Score; HOMA-IR: Homeostatic
 Model Assessment for Insulin Resistance; AM: ante meridiem, PM: post meridiem. Continuous
 values are expressed as mean ± SD. Inter-group comparisons were performed using the
 unpaired Wilcoxon test for continuous variables (age, BMI, HOMA-IR) and Fisher's exact test
 for the remaining categorical variables.



FIGURE 1_R2 - JOHANNS et al.



FIGURE 2_R2 - JOHANNS et al.



FIGURE 3_R2 - JOHANNS et al.







FIGURE 4_R2 - JOHANNS et al.





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FIGURE 5_R2 - JOHANNS et al.



FIGURE 6_R2 - JOHANNS et al.



FIGURE 7_R2 - JOHANNS et al

		MASLD Group		p-values			
Variable	Ν	HN , n = 89	St. , n = 122	MASH , n = 79	HO vs. St.	HO vs. MASH	St. vs. MASH
Sex	290				0.003	0.008	0.7
F		75/89 (84%)	80/122 (66%)	49/79 (62%)			
Μ		14/89 (16%)	42/122 (34%)	30/79 (38%)			
Age	290	34.6 ± 11.4	41.8 ± 10.9	46.4 ± 10.4	< 0.001	<0.001	0.050
BMI	290	45.4 ± 6.8	47.3 ± 7.9	46.2 ± 7.9	ns	ns	ns
Steatosis score	290				<0.001	<0.001	<0.001
0		89/89 (100%)	0/122 (0%)	0/79 (0%)			
1		0/89 (0%)	0/122 (0%)	18/79 (23%)			
2		0/89 (0%)	71/122 (58%)	29/79 (37%)			
3		0/89 (0%)	51/122 (42%)	32/79 (41%)			-
Inflammation score	290				<0.001	<0.001	<0.001
0		89/89 (100%)	70/122 (57%)	0/79 (0%)			
1		0/89 (0%)	44/122 (36%)	55/79 (70%)			
2		0/89 (0%)	8/122 (6.6%)	23/79 (29%)			
3		0/89 (0%)	0/122 (0%)	1/79 (1.3%)			
Ballooning score	290				ns	<0.001	<0.001
0		89/89 (100%)	115/122 (94%)	0/79 (0%)			
1		0/89 (0%)	7/122 (5.7%)	57/79 (72%)			
2		0/89 (0%)	0/122 (0%)	22/79 (28%)			
Fibrosis score (Kleiner)	282			:	0.009	<0.001	<0.001
0		79/89 (89%)	78/118 (66%)	12/75 (16%)		÷	
1		9/89 (10%)	28/118 (24%)	22/75 (29%)			-
2		0/89 (0%)	7/118 (5.9%)	13/75 (17%)			
3		1/89 (1.1%)	5/118 (4.2%)	25/75 (33%)			
4		0/89 (0%)	0/118 (0%)	3/75 (4.0%)			
NAS score	290				<0.001	<0.001	<0.001
0		89/89 (100%)	0/122 (0%)	0/79 (0%)			
2		0/89 (0%)	40/122 (33%)	0/79 (0%)			
3		0/89 (0%)	51/122 (42%)	11/79 (14%)			
4		0/89 (0%)	26/122 (21%)	19/79 (24%)			
5		0/89 (0%)	5/122 (4.1%)	29/79 (37%)			
6		0/89 (0%)	0/122 (0%)	17/79 (22%)		-	
7		0/89 (0%)	0/122 (0%)	2/79 (2.5%)			
8		0/89 (0%)	0/122 (0%)	1/79 (1.3%)			
HOMA-IR	279	3.8 ± 4.8 ¹	13.5 ± 58.8 ¹	24.2 ± 55.2 ¹	< 0.001	< 0.001	< 0.001
Biopsy time	290				ns	ns	ns
AM		62/89 (70%)	70/122 (57%)	46/79 (58%)			
PM		27/89 (30%)	52/122 (43%)	33/79 (42%)		-	

TABLE 1_R2 - JOHANNS et al.