Materials and methods

AutoEncoder and TFDeepSurv model

AutoEncoder is an unsupervised learning feature extraction model widely used to predict cancer prognosis from medical images. Its main architecture includes an encoder and a decoder. The loss function used was the difference between the original input feature and the reconstructed output feature, also known as the reconstruction error. The main task of the encoder is to reduce the dimensionality of the original input, which is a hidden space *h*. The decoder converts the minimum space representation obtained by the encoder into reconstructed output features and performs gradient inversion by minimizing the reconstruction error.

In this study, muscle features extracted from the CT images at the L3 level of 345 HCC patients (train set) were used to train the Autoencoder. The trained Autoencoder was then used to extract 100 deep learning features from the original radiomics features of the internal test set, external test set, and the LT test set. Dimensionality-reduced deep learning features and survival data were incorporated into the TFDeepSurv network to train the survival model in the train set. Based on the best model performance in the training set, the corresponding model parameters were selected as optimal model parameters in the training process. The construction of TFDeepSurv (Autoencoder and TFDeepSurv network) was based on Python 3.6.4 and was implemented using Pytorch.

Details of CT images

The three datasets are from two centers. The first dataset included the patients underwent hepatectomy (n = 492, divided into the training and internal test set), and the second dataset included the patients underwent transplantation (n = 173, an external LT test set). The first and second datasets are from the Institution I. The Institution I performed contrast-enhanced CT using two CT scanners: a 16-slice scanner (Aquilion; Toshiba Medical Systems, Tokyo, Japan) and a 256-slice scanner (Brilliance iCT; Philips Healthcare, Cleveland, OH, USA). The third dataset included the patients who had undergone hepatectomy in Institution II (external test set). Institution II performed contrast-enhanced CT using two CT scanners: a 320-slice scanner (Aquilion ONE; Toshiba Medical Systems, Otawara, Japan), and a 2×64-slice dual-source scanner (Discov-ery CT750 HD; GE Healthcare, Milwaukee, WI, USA). The CT parameters were tube

voltage of 100 or 120 kVp, tube current of 200-700 mAs, pixel spacing of 0.539-0.881mm, and slice thickness of 0.625-5.000 mm. Radiomics features are extracted under some constants due to diversity in voxel sizes. A resampling strategy of voxel size is used for medical images reconstructed at different voxel sizes. We used spline interpolation to resample all images to an identical pixel size of 1x1 mm. The voxel intensities within the ROI (region of interest) were discretized to a limited intensity range of 64 bins.

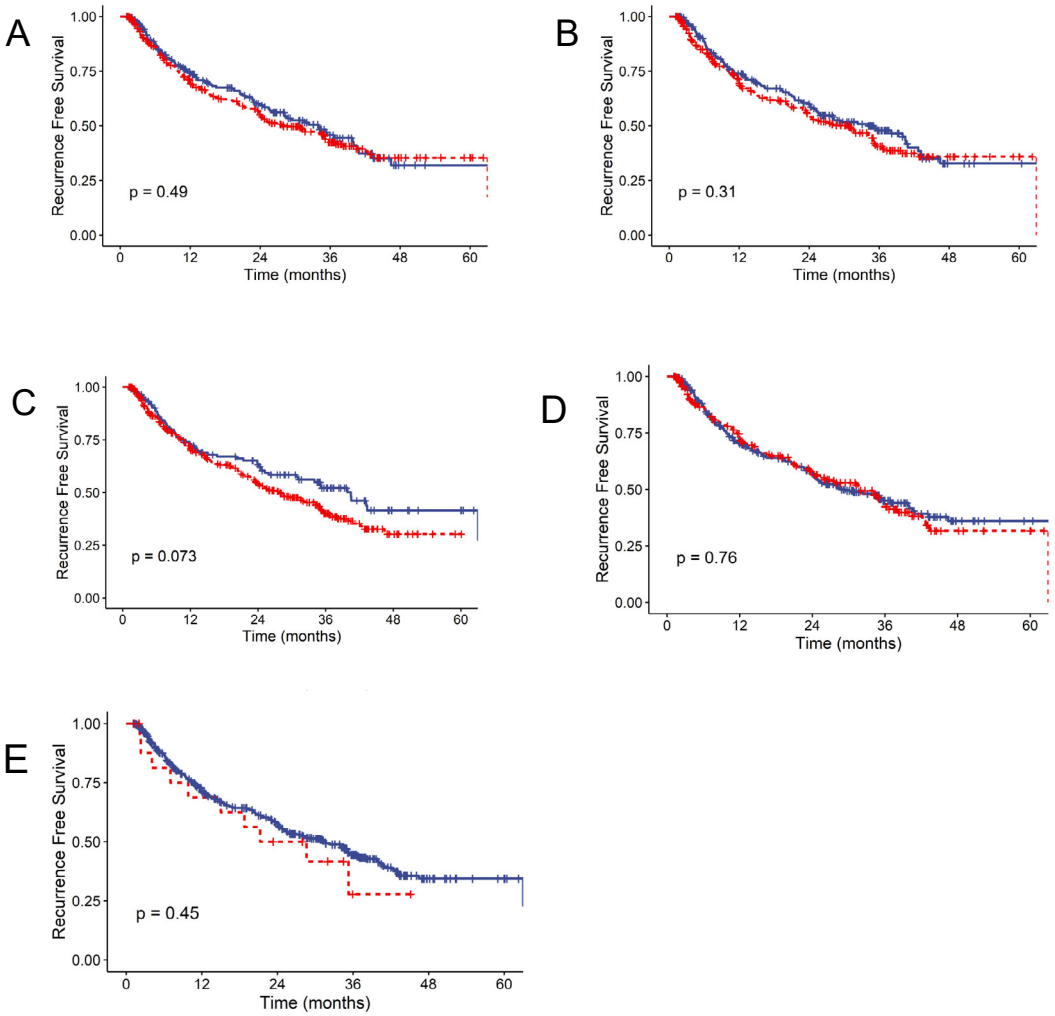

Fig. S1 Role of traditional definitions of sarcopenia on the prognosis of RFS after liver resection in patients with HCC. A, SMI; B, PMI; C, IMF; D, PMA; E, PD. Red=sarcopenia, blue=non-sarcopenia.

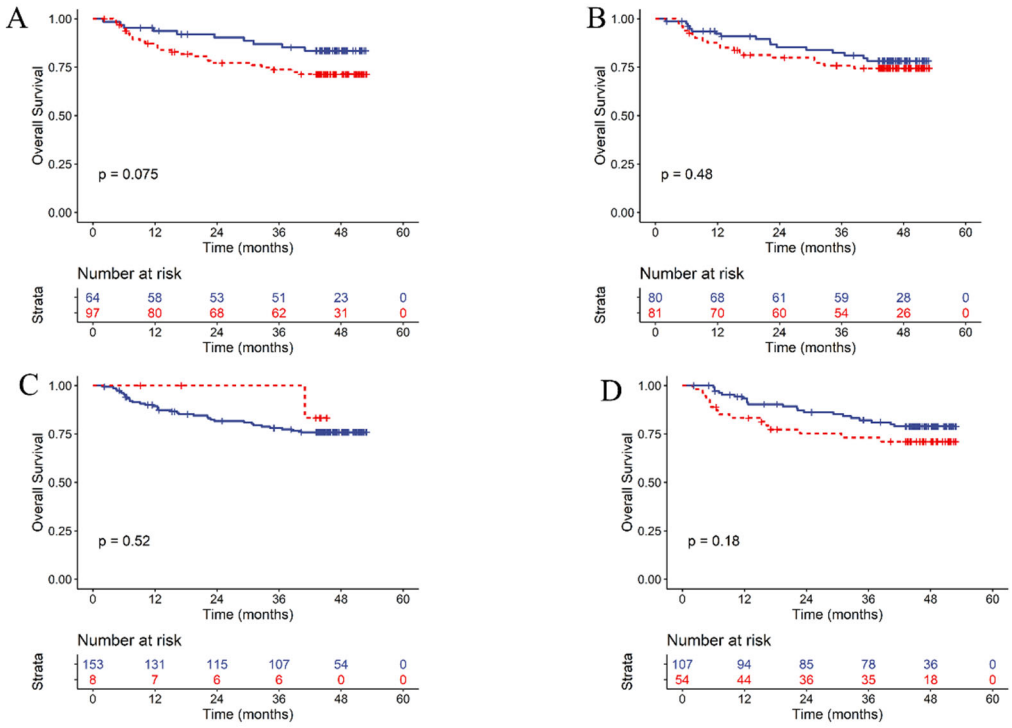

Fig. S2 Role of traditional sarcopenia definitions on the prognosis of OS in patients with HCC in the external test set. A, SMI; B, PMI; C, IMF; D, PMA. Red=sarcopenia, blue=non-sarcopenia.

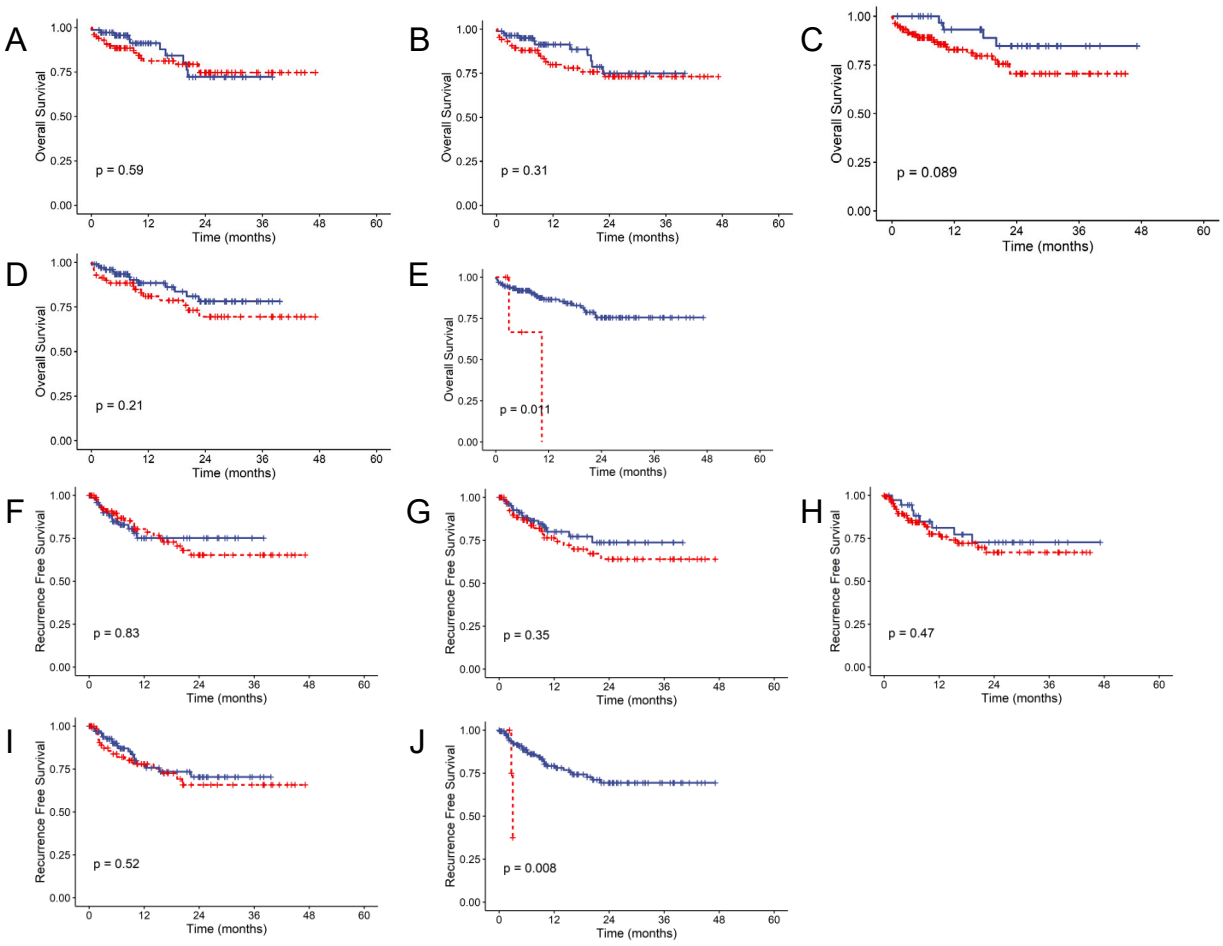

Fig. S3 Role of traditional sarcopenia definitions on the prognosis after LT in patients with HCC in the external LT test set. OS: A, SMI; B, PMI; C, IMF; D, PMA; E, PD. RFS: F, SMI; G, PMI; H, IMF; I, PMA; J, PD. Red=sarcopenia, blue=non-sarcopenia.