Given the ADCM method's focus on decomposing the PET image correction process into anatomy-independent textures and anatomy-dependent corrections, we expect that

This method's core innovation of estimating anatomy-dependent corrections while implicitly referencing its deep learning foundation and the specialized focus on anatomical nuances.

This is especially helpful if the data are private or sensitive and cannot be shared with a central server or other hospitals

The normalization of ADCM in this study represents a departure from conventional practices, driven by the imperative to uphold the interpretative power of SUVs in a clinical context. By selecting a unique normalization constant, we navigated the challenges presented by the heterogeneous scale of ADCM values—foregoing the typical min-max approach that would compromise quantitative depth for the sake of uniformity. The careful exclusion of extreme outliers underscored our commitment to model precision and robustness. This approach highlights the importance of customizing data preprocessing methods to the specific demands of the dataset and the analysis objectives, which, in this case, are governed by the exigencies of clinical applicability and diagnostic accuracy.

In our study, we applied the ADCM method to decompose PET image correction into anatomy-independent textures and anatomy-dependent corrections. Unlike the referenced method which utilized a resolution of 6.6 × 6.6 × 8 mm/voxel, our images were processed at a higher resolution of 4 × 4 × 3 mm/voxel (see Figure 5). This increase in resolution, although advantageous for capturing finer anatomical details, presented its own set of challenges, particularly in generating reliable anatomy-dependent textures in some instances.

Theoretically, higher resolution should enhance the ADCM's ability to delineate anatomy-dependent corrections. However, we observed that the ADCM occasionally failed to exhibit these textures distinctly, particularly in cases with lower radioisotope uptake or in regions where anatomical variations are subtle but critical. This limitation suggests that while our ADCM model benefits from higher resolution data, it does not consistently translate into improved delineation of anatomy-dependent features, which are crucial for accurate PET image correction.

This inconsistency might be attributed to several factors, including the inherent variability in radioisotope distribution and the complex interaction between image resolution and the deep learning model's ability to learn from such data. Given these observations, we cannot expect uniformly ideal results from the ADCM approach across all scenarios. The challenge remains to enhance the model's sensitivity to subtle anatomical details without compromising the overall accuracy, suggesting a potential area for future research to refine the approach and address these specific issues.

Our findings underscore the importance of tailoring the ADCM methodology to suit specific clinical scenarios and highlight the need for ongoing adjustments and validations to ensure its effectiveness across varying conditions. This underscores the need for further research incorporating a broader array of data conditions to better understand the limitations and optimize the technique for clinical application.

The approach to ADCM normalization adopted in this study was informed by the necessity to preserve the clinical significance of SUVs. This led to the selection of an empirical normalization constant, circumventing the use of standard min-max normalization, which could diminish the quantitative richness essential for clinical interpretation. The omission of extreme outliers further emphasizes the precision and robustness of our analytical model. The histograms in Figure X depict the effective normalization, capturing the essential data distribution while excluding the extremes, thereby underscoring the significance of tailoring preprocessing methods to the dataset's unique characteristics and the analysis goals—paramount among these being the exigencies of clinical utility and diagnostic precision.

Future work:  
Furthermore, we can measured clinical imaging parameters such as SUVmean, SUVmax, total lesion metabolism, Table 1 | Information on patients as well as the most relevant radiomics features within the sphere