Response-A

- We can categorize/summarize the false positives/negatives encountered during evaluation to discuss the real-world applicability/limitation of mmDefender.

Response-B

- Since the radar monitors humans in motion within an otherwise static and empty, constrained space, the setup is not highly sensitive to its surroundings (unlike home monitoring). Our tests show the system is unaffected by variations in human body size or shape, with cross-validation data available if needed. Unlike metal detectors, mmDefender performs on-body localization.
- Dataset imbalance is addressed in Section:5.1 using weighted loss function and ablation study (Fig:20) is provided. We also studied Conv, Conv+LSTM, ConvNeXt with different kernel sizes crucial for range/azimuth convolution and proposed the empirically best model.
- We use an NIJ-standard-0601.01 test object, along with an additional larger object.
- An additional rear-facing radar could solve the issue of localizing weapons in the back (while still keeping mmDefender more affordable than commercial products).
- We incorrectly described [20]. It detects open-carry (unconcealed) scenarios.

Response-C

- We originally aimed to convey that mmDefender is the first work in a specific condition. We should revise the claim to accurately reflect our contribution: on-body localization of concealed metallic objects on moving individuals (an inverse SAR problem). In contrast, Squigglemilli performs SAR imaging of static objects at closer distances with longer scanning times. mmDefender screens rapidly moving humans at longer distances with faster localization times.
- Considering the security scenario, mmDefender aims to localize any concealed metallic objects. Inferring object shape is possible using RCS values, spatial frequency, Doppler, and micro-Doppler patterns via a secondary classifier, but this is beyond the scope of this paper.
- We appreciate the reviewer pointing out these papers and acknowledge that we should have included quantitative comparisons. Here is a summary of how these works differ fundamentally from ours: **(a)** Squigglemilli uses SAR imaging, which requires a moving radar and static subjects, focusing on closer-distance scanning to reconstruct full object shapes for classification. In contrast, mmDefender is inverse SAR-like, suitable for fixed radar and moving subjects at longer distances, and addresses combined RCS scenarios,

such as concealed objects on the human body, which Squigglemilli does not. **(b)** mmWave-YOLO uses specialized mmWave hardware with 2D X-Y-Depth images as inputs to a YOLO detector but cannot handle combined RCS or concealed object scenarios. **(c)** Millieye employs image/radar fusion that is unsuitable for concealed objects, using radar data only for box proposals rather than classification. **(d)** the paper on small object detection over water involves image/radar fusion with lower AP for radar-only detections and degraded performance with RGB images, while our focus is on detecting concealed objects where visual detectors are ineffective.

Response-D

- We could use a lower-resolution radar (TI~xWR1843) to stream data in real-time to trade off accuracy for speedup.
- Due to the uniqueness of our setup/problem, please refer to Response(114C), we found no existing work directly applicable. If asked for, we can compare modified baselines (same model, tested in our setup).
- Synthetic mmWave generative AI (https://dl.acm.org/doi/10.1145/3625687.3625798) can be used for data augmentation to make mmDefender more robust.