Reviewer #1 asks a technical question regarding the existence of a regular conditional measure in Lemma 1. The reviewer is correct that we are implicitly assuming the conditional densities exist, which need not be the case in more complex spaces. However, we are only using Lemma 1 regarding elliptical processes (Thm 2). For elliptical processes the existence is not an issue, since the conditional distribution can be written explicitly based on Thm 1, which implies that the conditional distribution is a gaussian process. We will clarify in Lemma 1 that this condition is required, and explain why the conditional distributions exist for elliptical processes in the final manuscript.

While not necessary for the study of elliptical processes, with a few more assumptions on the space, we can ensure that an arbitrary probability measure has a regular conditional measure. Recall that conditional distributions exist as long as the measures are inner regular (Hoffman-Jorgensen, 1972). Since every probability measure over a complete separable metric space (equipped with the Borel sigma algebra) is Radon (e.g. THM A.3.11, Bogachev, 1998), and thus inner regular, restricting to such spaces removes this technical concern and still covers most applications of interest.

Reviewer #1 also asks how to determine whether two Gaussian measures are equivalent or orthogonal, a task that contributes to the proof of Theorem 2. We appreciate the reviewer raising this point. The claim follows from Theorem 2.4.5 of Bogachev (1998), which characterizes the equivalence/orthogonality of Gaussian measures with equal covariances. We will add this to the proof sketch and main proof in the manuscript and make it clear how the Theorem applies in our case. Briefly, (1) the covariance vC leads to the same Cameron-Martin space for any nonzero v since they induce equivalent norms (the v just scales each norm) (2) two Gaussian measures with the same covariance C are equivalent if the difference of their means lies in the Cameron-Martin space of C.

Reviewer #3 ask for more intuitive explanations throughout to better communicate our results to a reader with less measure theory background. We agree with this sentiment and will add more discussion and examples when technical concepts are introduced. Concepts that will be expounded upon include elliptical distributions (ln 30), function spaces (ln 37), equivalence of measures (ln 59), absolutely continuous (ln 104), Haussdorf (ln 122), Cameron-Martin theory (ln 140). We will also include discussion regarding the intuition and consequences of each of our technical results.

Both Reviewers #3 and #4 ask for concrete examples to motivate the use of elliptical distributions. We will include additional motivation to the introduction. Briefly, our motivation stemmed from the popularity of the Laplace mechanism over the Gaussian for achieving DP in $\mathbb{R}$, both of which are examples of elliptical distributions, as are certain instances of the K-norm mechanism. However, in dimensions greater than 1, neither the Gaussian nor Laplace provide ϵ-privacy. A recent technical report by Bun & Steinke: "Average-Case Averages: Private Algorithms for Smooth Sensitivity and Mean Estimation", they explore several univariate distributions such as Cauchy, Student's T, Laplace Log-Normal, Uniform Log-Normal, Arsinh-Normal. We hope that our paper may help motivate the study of elliptical versions of these distributions. In Bun & Steinke, they found that Laplace Log-Normal distribution and Student's T distribution had the lowest variance for their problem.

Reviewer #4 points out that we focus on the question of whether an elliptical distribution satisfies DP, and do not address the utility of the mechanisms. It has already been demonstrated that different elliptical distributions are useful for different applications (i.e. Awan & Slavković (2019), Bun & Steinke (above)). The focus of this paper is to better understand when different elliptical distributions can be applied and what level of privacy they achieve in general vector spaces.

Reviewer #3 requests more exposition in Section 4.2, to explain the relation between Thm 4 and Thm 5. The intuition is as follows: In Thm 4, we show that the mixing random variable V can be estimated arbitrarily well based on the output $\widetilde{T}(D)$. This implies that the result of this mechanism is essentially the same as adding a gaussian process to T, once the output is observed. Since gaussian processes do not satisfy ϵ-DP, neither can any elliptical process. However, gaussian processes do satisfy (ϵ, δ)-DP. Thm 5 explains what values of ϵ and δ a given elliptical process achieves, which is based on the same proof (Mirshani et al. 2017) used to prove that gaussian processes satisfy (ϵ, δ)-DP. We will include additional exposition in the final version to explain these points.

Related to the previous point, reviewer #4 notes out that the remark following Thm 4 is misleading. We meant to explain that once the sample is released, it is essentially a sample from a gaussian process. However, the covariance is scaled by the variable V, which is known after release.

Reviewer #3 remarks that the paper ends after Section 4.2, which is stylistically undesirable. As the final version allows an additional page, we will include a section with discussion/future directions.