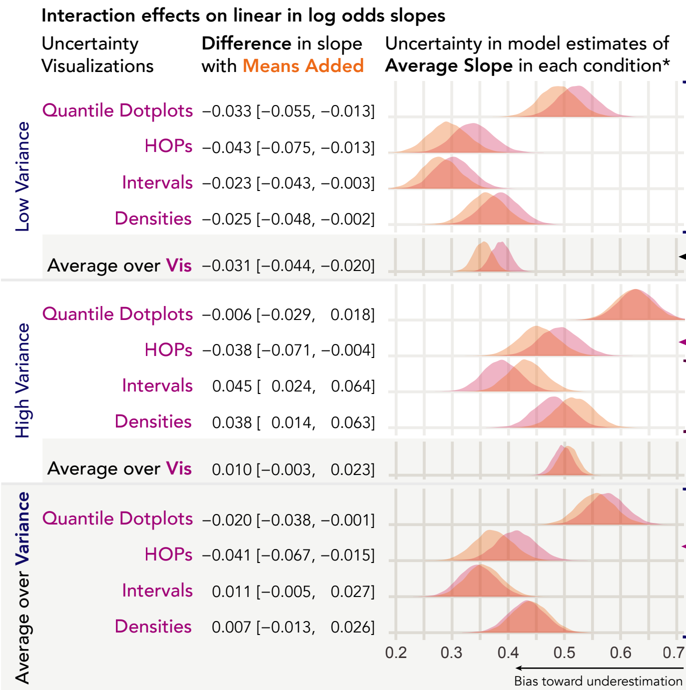

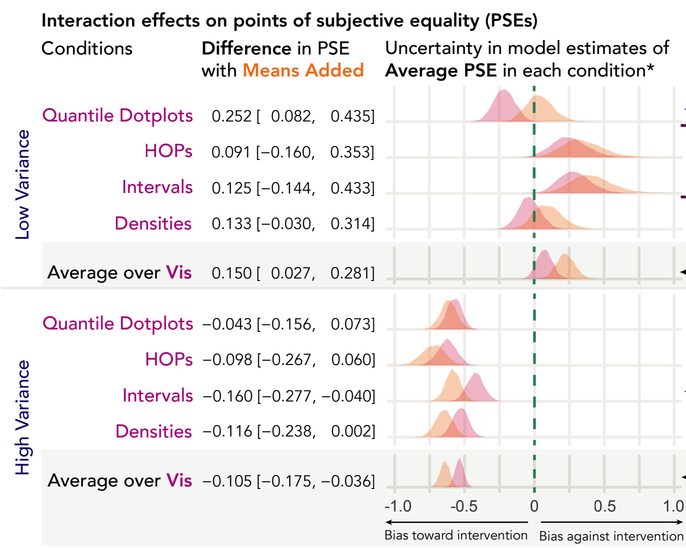

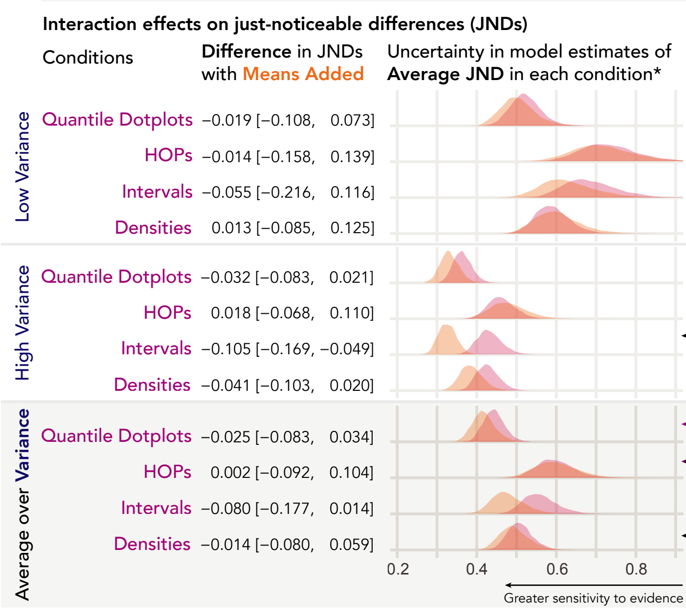

4 Results

4.1 Probability of Superiority Judgments

For each uncertainty visualization, **adding means** at **low variance** decreases LLO slopes. Recall that a slope of one corresponds to no bias, and a slope less than one indicates underestimation. When we **average over uncertainty visualizations**, **adding means** at **low variance** reduces LLO slopes for the average user, indicating a very small 0.8 percentage points increase in probability estimation error.

At **high variance**, the effect of **adding means** changes directions for different uncertainty visualizations. **Adding means** decreases LLO slopes for **HOPs**, whereas **adding means** increases LLO slopes for **intervals and densities**. Because differences in LLO slopes represent changes in the exponent of a power law relationship, these slope differences of similar magnitude indicate a very small increase in probability of superiority estimation error of 0.3 percentage points for HOPs and small reductions in error of about 1.5 and 1.0 percentage points for intervals and densities, repsectively.

Users in all uncertainty visualizations underestimate effect size. When we **average over variance**, users show an average error of 8.6, 14.0, 14.8, and 12.4 percentage points in probability of superiority units for quantile dotplots, HOPs, intervals, and densities respectively, each **without means**. In this marginalization, **adding means** only has a reliable impact on LLO slopes for **HOPs**, but the difference is practically negligable.

4.2 Intervention Decisions

4.2.1 Points of Subjective Equality

For each uncertainty visualization, **adding means** at **low variance** increases PSEs. This results in different effects depending on whether the visualization with **no means** has a PSE below or above utility-optimal. Recall that a PSE of zero is utility-optimal, a negative PSE indicates intervening too often, and a positive PSE indicates not intervening often enough. Users of **quantile dotplots** with **no means** have negative PSEs which become unbiased when we **add means**. Users of **HOPs and intervals** with **no means** have positive PSEs, biases which increase when we **add means**. Users of **densities** with **no means** have PSEs near zero and become more biased when we **add means**. Only the effect for quantile dotplots is reliable. When we **average over uncertainty visualizations**, at **low variance** the average user may have a PSE 0.6 percentage points above utility-optimal with **no means**, and **adding means** increases this mild bias by about 1.7 percentage points in terms of the probability of winning.

At **high variance**, **adding means** decreases PSEs. Since PSEs for all uncertainty visualziations with **no means** are below optimal, **adding means** increases biases in all conditions, however, the effect is only reliable for **intervals**. When we **average over uncertainty visualizations**, at **high variance** the average user has a negative PSE 9.5 percentage points below utility-optimal with **no means**, and **adding means** increases this bias by about 2.1 percentage points.

4.2.2 Just-Noticeable Differences

At **low and high variance**, the effects of **adding means** on JNDs are mostly unreliable. Recall that smaller JNDs indicate that a user is sensitive to smaller differences in effect size for the purpose of decision-making. **Adding means** only has a reliable effect on JNDs for **intervals** at **high variance**, where it reduces JNDs by 1.2 percentage points in terms of the probability of winning.

When we **average over variance**, **quantile dotplots with means** lead to the smallest JNDs, and users of **HOPs with** or **without means** have the largest JNDs, a difference of about 1 percentage point in terms of the probability of winning. Quantile dotplots **with** or **without means** have reliably smaller JNDs than other conditions, with the exception of unreliable differences between quantile dotplots with **no means** and **densities with** or **without means**.

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*Probability densities of model estimates show posterior distributions of means conditional on the average participant.