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## Bayesian methods for mixed method synthesis

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Bayesian methods generate summative statements of the evidence through the meta-aggregation of data, and this can involve attributing a numerical value to all qualitative data, facilitating a final statistical analysis of individual syntheses (i.e. translating qualitative data into quantitative), or attributing a qualitative thematic description to all quantitative data, thereby permitting a final meta-aggregation of individual syntheses (i.e. translating quantitative data into qualitative) (Table 1) [1-4].

The Bayesian method of data analysis can be used to summarize uncertainties and make estimates and predictions using probabilistic statements conditioned by the observation of data in an assumed model. The Bayesian approach to statistical inference has the characteristic of considering the unknown parameters of the models as random quantities, and thus expresses the uncertainty about these parameters through a priori distributions of probabilities. Through the use of the Bayes' theorem, the updating of the uncertainty about the parameters can be done sequentially with the arrival of new information [1-4].

The Bayesian approach more comfortably accommodates metaanalysis techniques where uncertainty about the effect of a treatment and can be updated sequentially with the execution of another study on the subject, this allows more flexible models where individual

Table 1. Comparison of Bayesian methods for mixed method synthesis

Method of synthesis	Description
Bayesian conversion: Qualitative → Quantitative	A numerical value is attributed to all qualitative data in a format that is complementary to that of the quantitative data; Separate prior distributions (presumed probabilities) are applied individually to quantitative and qualitative data; Posterior distributions (evidence informed probabilities) are compared and, if 95% confidence intervals overlap, combined.
Strengths	Facilitates the statistical analysis of both quantitative and qualitative data; Attributes equal strength to quantitative and qualitative data instead of simply using qualitative data for the generation of themes in which to impute quantitative data
Weaknesses	Significant problems associated with conversion of verbal counts (e.g. "many", "few" etc) to numerical format; Non-overlapping 95% confidence intervals prohibit combined analysis of data.
Bayesian conversion: Quantitative → Qualitative	All quantitative data is thematically synthesized and codified according to strength of effect.
Strengths	Codification of quantitative data is less error prone than quantification of qualitative data; Existing data provides a more accurate basis for the development of prior distributions through which to base subsequent analyses.
Weaknesses	Whole study focus produces a reliance on reasonable number of studies for strength of conclusions; The weighting of individual studies needs to be adjusted based on the varying levels of evidence and methodological quality of these included studies.

characteristics of the studies can be easily incorporated. The Bayesian approach has as a principle to combine the external information to the studies, defining an a priori distribution for the meta-analytical measurement and for the variability between the studies and incorporate them to the analysis [1-4].

Bayesian inference is an alternative method to classical inference that allows incorporating a priori information about the parameters of the model. Bayesian methods consider the parameters of the models as random quantities assigning probability distributions to them (a priori and a posteriori distributions), that is, Bayesian methods incorporate information extraneous to the data of the experiment on the parameters through priories [1-4].

This information is combined with the information obtained from the analysis data of the experiments through Bayes' theorem and the inferences are based on the posterior distributions [1-5].

In conclusion, Bayesian methods can improve the accuracy and interpretation of study results.

## References

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