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Comparison between Fully Bayesian Hierarchical Meta-analysis and Classical Meta-analysis: A Monte Carlo Study Based on Correlation Coefficient

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Abstract
Take the Pearson's correlation coefficient as an example, the difference between fully Bayesian hierarchical meta-analysis and classical meta-analysis was compared. Through the experimental design of following four factors

5 (research quantum) *3(effect size) *4(variance of heterogeneity) *2(two types of meta-analysis), simulation comparison was conducted. The results show that: when these two types of meta-analysis are analyzed with fixed effect, there was almost no difference between the point estimation and confidence interval; while when they are analyzed with random effect, regardless of the prior distribution of random effects, uniform or conjugate distribution, with the increase in research quantum, results of them tend to be consistent; the credible interval of fully Bayesian hierarchical meta-analysis is slightly wider than that of classical meta-analysis. Therefore, if the true effect is determined to be fixed effect, both two types of meta-analysis can be used. But when random effect is adopted, if the research quantum is less than 20, the fully Bayesian hierarchical meta-analysis should be the choice, and the selection of prior distribution should be determined according to practical situations; while if the research quantum is more than 20, both two types of meta-analysis can be used.
Keywords: FULLY BAYESIAN HIERARCHICAL META-ANALYSIS, PRIOR DISTRIBUTION, MARKOV CHAIN MONTE CARLO(MCMC), GIBBS SAMPLING

1. Introduction

1.1. Introduction

In psychology, classical meta-analysis refers to the statistical inference based on Frequency theory, the selection of the combined model of effect size (Fixed Effect Model, FEM; Random Effects Model, REM) depends on the statistical significance of Q statistic[1-3]. While the hypothesis of correct Q statistics include: Firstly, it should be in the study of meta-analysis, the number of the initial sample should be large enough to ensure the asymptotic normality of the effect size. Secondly, the data should not have real hierarchical or clustered structures, so that the ecological or aggressive fallacy will not happen[4, 5]. Thirdly, and effect sizes should be independent, but psychological traits (such as personality, intelligence and so on) are multi-dimensional, they are always highly correlated but do not meet this hypothesis, so it is necessary to rectify their standard errors, which they are always ignored in reality[6]. Due to great differences in research designs, measurement tools, sample size and other factors, there are differences between different researches, which is more obvious in social science researches, therefore, the application of FEM should be avoided [7]. Although the moment estimation of variances between researches (the variation of the heterogeneity, namely τ^2) can be obtained with REM based on Q statistics, but its uncertainty is difficult to obtain (that is, 95% confidence interval), and there is no evidence to support the hypothesis that τ^2 is subject to normal distribution, it appears to be too strong [8-10]. Its estimation methods (moment estimation and likelihood estimation) have not been unified so far [3, 11]. If there are extreme values in the researches included, it is difficult to find the exact finite sample distribution for statistics, and it is difficult to identify random effect with traditional methods, so it is necessary to find other better statistical methods[12, 13].

Fortunately, with the emergence of the method of Markov Chain Monte Carlo method, problems in high dimensional integral calculation are solved, which bring a great development and application to Bayesian statistics, especially, Gibbs sampling and free software (such as WinBUGS and OpenBUGS, R, etc.), which can calculated easily, have brought large amount of application researches relating to Bayesian statistics[14]. Bayesian statistics based on posteriori distribution is very intuitive and easy to understand, which does not depend on the asymptotic theory of large samples and gives a full consideration to the uncertainty of the model, especially for small samples, the correction of prior distribution reflects it unique advantages. In particular, after it is integrated with meta-analysis, fully Bayesian hierarchical meta-analysis has been widely used in the fields of sociology, medicine, ecology and epidemiology. However, these studies are based on the mean, risk ratio and other similar effect sizes, which are seldom used in the field of psychology, especially basic theories and application researches with correlation coefficient as the effect size are rare[15-17].

1.2. Fully Bayesian hierarchical analysis

Fully Bayesian hierarchical meta-analysis (Bayesian meta-analysis for short) is based on Bayesian statistics, which is a statistical school different from traditional statistics, based on the idea that the unknown parameters in the whole distribution are considered as random variables, it can describe the correct unknown state with the probability statement relating to prior information before sampling (i.e. prior distribution). By integrating the sample information and prior information, the posterior distribution of parameters is obtained as statistical inference[18]. Bayesian statistics is based on Bayesian Formula and Theorem, based on Regularization Factors and Likelihood Principle, the function of Bayesian statistical inference can be obtained, that is:

$$\text{Post} \propto \text{Prior} \times \text{Likelihood} \quad (1)$$

That is to say, the posterior distribution is proportional to the product of prior distribution and Likelihood Function. Compared with traditional statistics, it not only integrates the sample information (Likelihood Function), but also takes the prior information into account. The Bayesian meta-analysis is a Bayesian modeling method which determine the prior distribution with hierarchical prior distribution, and then do the statistical inference[6]. At present, there is still no uniform method for the selection of prior distribution so far, but, in view of practicability, there are two methods: (1) without prior information. That is, there is no or few prior information relating to the event, which can be regarded as no prior information, the uncertainty reaches the maximum, it is common to use uniform distribution as prior distribution [19]. (2) conjugate prior. That is, the prior and posteriori distribution of some parameter belong to the same distribution family[18], such as the mean or variance of the normal distribution.

The basic concept of Bayesian meta-analysis is the exchangeability, that is, the synthesis of researches is based on the idea that all researching effect sizes can be exchanged. That is to say, problems concerned in all researches (it is usually represented with effect sizes) are basically similar, but not the same[20, 21]. In the traditional statistical model, the REM of Bayesian meta-analysis is similar to that of classical meta-analysis, but there is a fundamental difference between the idea that REM is exchangeable and the hypothesis. According to Bayesian statistics, the random variation of real effect sizes is caused because researchers do not understand the producing process of random effects; while REM defines it into the vast of sampling studies[10]. Each parameter in Bayesian meta-analysis has its own distribution, which can be directly described with the probability or its uncertainty can be estimated with data, all relevant information of parameters can be combined as well[22].

Assuming k is for the research quantum included in the meta-analysis, $\grave{e}_i$ is the observation effect size of the ith research, μ_θ is the random variation of the real effect size in the ith research, and ε_i is the sampling error of the ith research. The model of Bayesian meta-analysis is as follows:

$$\grave{e}_i = \mu_i + \varepsilon_i \quad (2)$$

$$\mu_i = \mu_\theta + \zeta_i \quad (3)$$

$$\zeta_i \sim N\left(0, \tau^2\right) \quad (4)$$

$$\varepsilon_i \sim N\left(0, \sigma_{\varepsilon_i}^2\right) \quad (5)$$

$$\theta_i \sim N\left(\mu_\theta, \sigma_{\varepsilon_i}^2 + \tau^2\right) \quad (6)$$

$$\mu_\theta \sim (\cdots, \cdots);\ \tau^2 \sim (\cdots, \cdots) \quad (7)$$

Where, $i=1\cdots k$. If, $i \neq j$, then $\mathrm{Cov}\left(\varepsilon_i, \varepsilon_j\right) = 0$. It can be known from the above that, all unknown parameters (formula 5) of the model have their own probability distribution (i.e. prior distribution), which is different from classical meta-analysis[9]. When $\tau^2 = 0$, it is FEM, or it is REM[23]. Because of the mean μ_θ can be expressed as the form of normal distribution no matter what is it, fixed effect or random effect, the prior distribution is normal distribution, that is, $\mu_\theta \sim N(0,100^2)$ [18]. And the prior distribution of τ^2 often have two forms: (1) the uniform prior without prior information, that is $\tau^2 \sim U(0,1000)$; (2) the inverse Gamma distribution of conjugate prior, that is, $\frac{1}{\tau^2} \sim Gamma(0.001, 0.001)$ [21, 24].

Because Bayesian meta-analysis involves complex integral operations, MCMC method is needed. Different MCMC methods have different transition kernel constructions, in which Gibbs Sampling is particularly famous [18, 25]. It is an iterative sampling method based on the full conditional distribution, and has become the standard algorithm of WinBUGS software, it is most concerned by scholars [14, 26, 27]. The full conditional distributions of parameters in Bayesian meta-analysis are as follows:

$$\mu_i \mid \theta_i \cdots \theta_k, \mu_{i\neq j}, \mu_\theta, \tau^2 \sim N\left(\theta_i\left(\frac{\tau^2}{\sigma_{\varepsilon_i}^2 + \tau^2}\right) + \mu_\theta\left(\frac{\sigma_{\varepsilon_i}^2}{\sigma_{\varepsilon_i}^2 + \tau^2}\right), \frac{\sigma_{\varepsilon_i}^2 \tau^2}{\sigma_{\varepsilon_i}^2 + \tau^2}\right) \quad (8)$$

$$\mu_\theta \mid \theta_i \cdots \theta_k, \mu_1, \cdots, \mu_k, \tau^2 \sim N\left(\sum_{i=1}^{k} \mu_i \frac{kb}{kb + \tau^2} + a\left(\frac{kb}{kb + \tau^2}\right), \left(\frac{\tau^2 b}{kb + \tau^2}\right)\right) \quad (9)$$

$$\tau^2 \mid \theta_i \cdots \theta_k, \mu_1, \cdots, \mu_k, \mu_\theta \sim IG\left(\frac{k}{2} + c, \frac{1}{2}\sum_{i=1}^{k}(\mu_i - \mu)^2 + d\right) \quad (10)$$

In the practical application, the initial values of these three parameters above can be given firstly under selecting conditions of prior distribution, then, Gibbs sampling value is generated from the full con-

ditional distributions of various parameters according to the formula order. After these values are obtained for n times, the first m time is used for burn-in , and values obtained in the latter $n-m$ times are used to calculate the marginal posterior density of each parameter. This can be easily achieved in WinBUGS.

In this paper, the Pearson's correlation coefficient (r) is the effect size, simulation study is conducted through the experimental design of four factors: 5 (research quantum) *3(effect size) *4(variance of heterogeneity) *2(two types of meta-analysis), the former three ones are between-subjects design, while the forth one is within-subjects design, and the differences between Bayesian hierarchical meta-analysis and classical meta-analysis have been compared.

2. Methodology

2.1. Research design

Pearson's Correlation coefficient was taken as the effect size, and the specific experimental factors were as follows: (1) the variance of heterogeneity, namely, the values of τ^2 , 0, 0.08, 0.16 and 0.32 were taken[28, 29]; (2) the effect size, according to the correlation coefficient standard of Cohen (1988), three values: low, medium and high were taken, they were 0.1, 0.3 and 0.5[30]; (3) the research quantum, 5, 10, 20, 40 and 80 were taken[31, 32]; (4) two kinds of meta-analysis, classical met-analysis and Bayesian meta-analysis. In addition, the sample sizes were 200, 300, 500 and 1000, which were randomly assigned to each study, the objective was that their weights should not be congruent. the first three ones were between-subjects design, while the forth one was within-subjects design.

2.2 Data generation

In RStudio, taking $\theta_i \sim N\left(\mu_\theta, \sigma_{\varepsilon_i}^2 + \tau^2\right)$ as the model and the simulation data is generated (R version is 3.2.0).

2.3 Statistical analysis

When selecting Hedges-Olkin meta-analysis paradigm, it was necessary to transform correlation coefficients into Fisher z value and then analyzed. A batch of normal data was generated for each combination, and the p-value in the Shaprio's normal test should be at least 0.10, and then a sample was randomly selected for analysis. There, classical meta-analysis in RStudio used "metafor" package[33]; Bayesian meta-analysis was conducted in WinBUGS, only non-information prior and conjugate prior were considered in the prior distribution, and iterations were 10000[14]. Gelman and Rubin variance ratio methods were adopted in the convergence diagnosis of MCMC[34]. The prior distribution of the mean μ_θ of real effects was conjugate prior $N\left(0,100^2\right)$, τ^2 should be uniform and conjugate prior. By comparing the width of point estimates and confidence intervals, rules and differences in the results with changes in experimental factors shall be found.

3. Results

3.1 The comparison of FEM

In FEM, because there is no prior distribution of random variations, we only need to take the conjugate prior of means into consideration. The results show (Figure 1): in general, there is little difference in the results of these two types of meta-analysis, regardless of the point estimate and interval estimation. But it can be found after anatomizing that when the effect

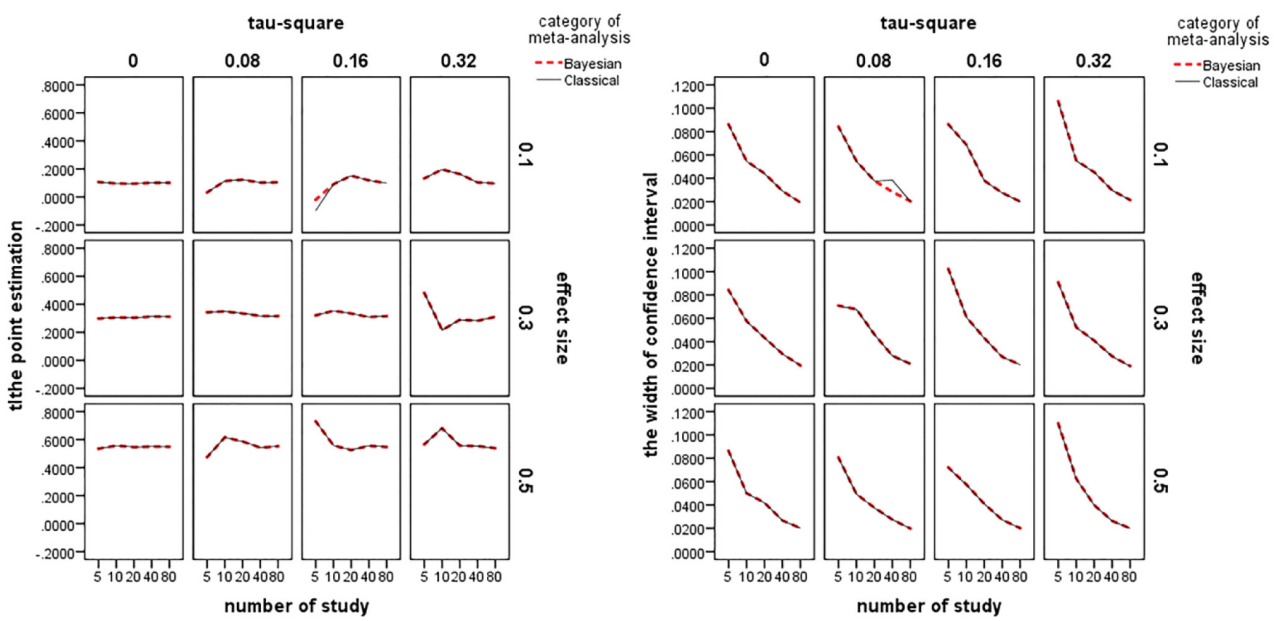

Figure 1. Change of point estimate and CI width under FEM

size is small, the confidence interval width of classical meat-analysis shows a significant bulge with the increase in research quantum, while its point estimate is lower than that of Bayesian meta-analysis.

3.2. The comparison of random effects models

Since the prior distribution of the heterogeneity variation is divided into uniform and conjugate prior, it can be divided into the following three situations.

(1) the comparison between Bayesian meta-analysis and classical meta-analysis under uniform prior. The results show (Figure 2): for the point estimate, there is little difference between them. But there are obvious differences in the interval estimation, especially when the research quantum is less than 20, the width of classical meta-analysis is significantly lower than that of Bayesian meta-analysis, which is not in conformity with the actual situation. In real time, when the sample size is small, the estimation error is great, then the corresponding confidence interval should be wider. Therefore, it can be seen that when the sample size is small, the theory and the practice show that classical meta-analysis has some inherent defects. In addition, with the increase of research quantum, differences between them become smaller gradually (>20); when the research quantum increases to 40 or more, the results of these two types of meta-analysis are basically the same, which shows that both them hold the features of big samples.

(2) The comparison between Bayesian meta-analysis and classical meta-analysis under conjugate prior. The results show (Figure 3): for the point estimate, there is little difference between them. But there are obvious differences in the interval estimation, especially when the research quantum is less than 20, the width of classical meta-analysis is significantly lower than that of Bayesian meta-analysis, which is similar to the analysis of Bayesian meta-analysis under uniform prior, however, the difference is much smaller. with the increase of research quantum, differences between them become smaller gradually (>20); when the research quantum increases to 40 or more, the results of these two types of meta-analysis are basically the same

(3) The comparison of Bayesian meta-analysis under different prior conditions. The results show (Figure 4): there is little difference in the point estimates of Bayesian meta-analysis under different prior distributions, but their precisions (interval estimations) are inconsistent. When the research quantum is less than 20, there are significant differences. But with the increase of research quantum, the differences become smaller and smaller.

4. Discussion

In the face of extreme values or small samples (that is, the research quantum is small), it is difficult to identify the random effect for classical meta-analysis, and it cann't guarantee the estimation accuracy of the results, the correctness of its conclusions will be questioned, so it is necessary to find a better way. With the development of computer and MCMC methods, Bayesian statistics is integrated with meta-analysis, and fully Bayesian hierarchical meta-analysis can avoid these defects, and it is a new method which is worthy of further exploration.

In this study, differences between Bayesian meta-analysis and classical meta-analysis are compared

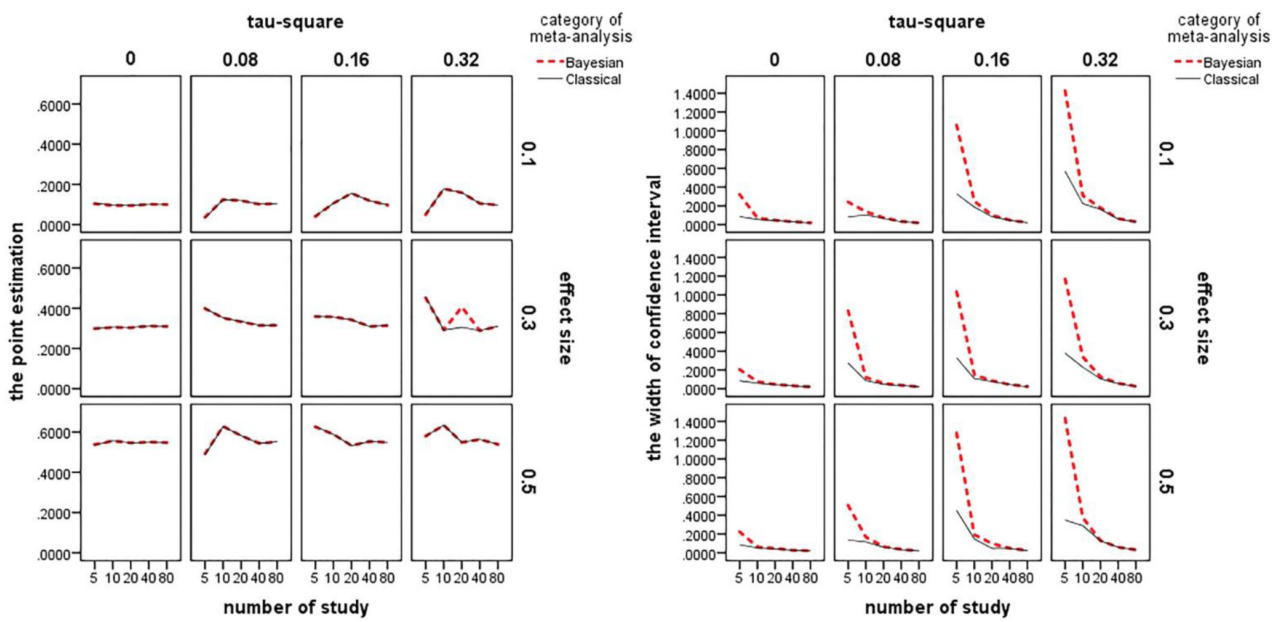

Figure 2. Comparison between Bayesian meta-analysis using uniform prior and Classical meta-analysis

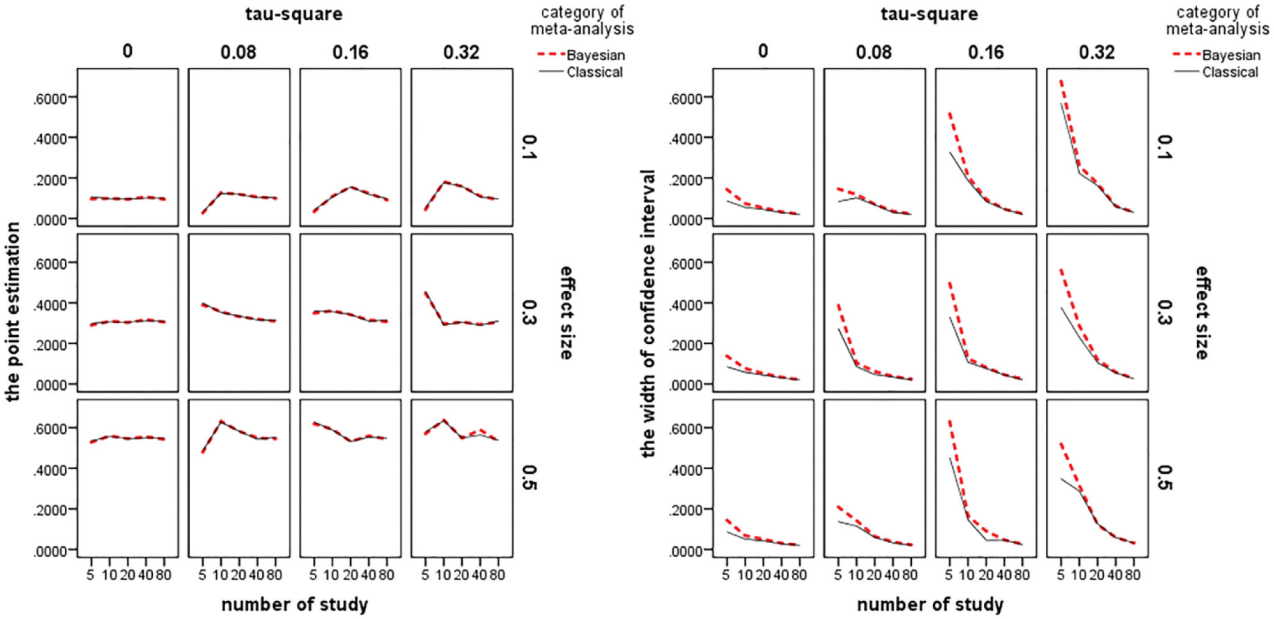

Figure 3. Comparison between Bayesian meta-analysis using conjugate prior and Classical meta-analysis

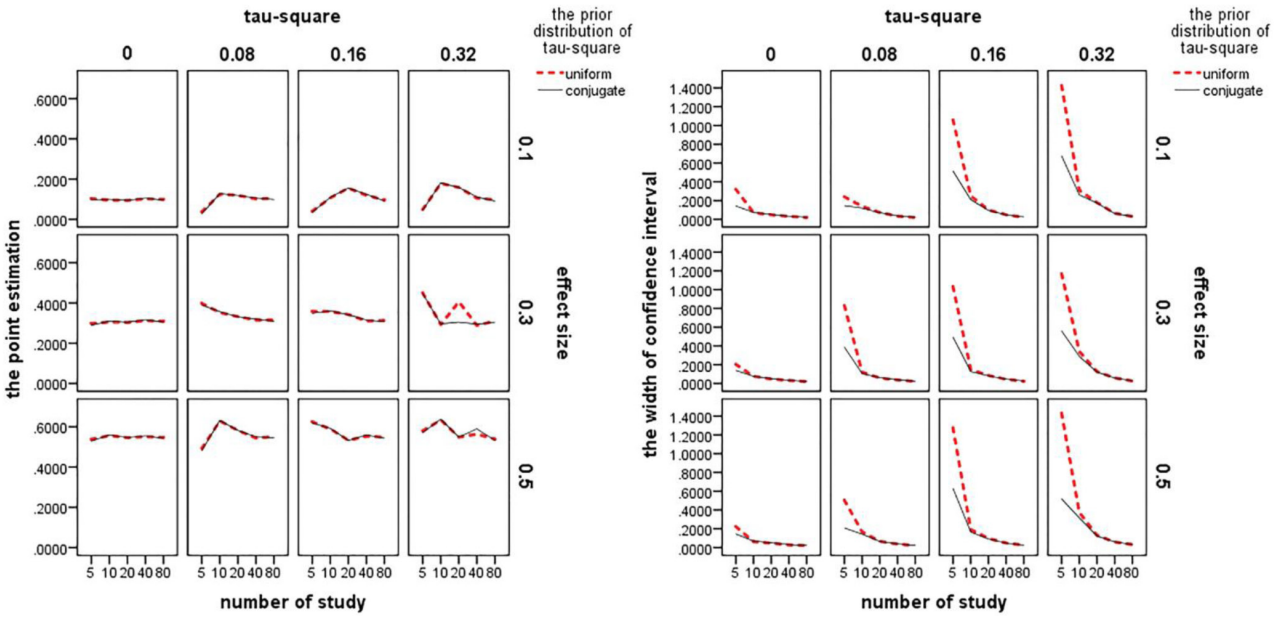

Figure 4. Comparison of Bayesian meta-analysis under different prior distributions

through simulation study. The results show that: as far as analysis on the fixed effect concerned, there is nearly no difference in the results of these two types of meta-analysis. This consistent with theories of them. In the absence of random effects, the main variation comes from the mean of real effects, it is assumed that classical meta-analysis is subject to normal distribution, and the conjugate distribution of this mean in Bayesian meta-analysis is also subject to normal distribution, so there is no difference. Therefore, if we choose fixed effect analysis, both of them can be used. But there are obvious differences in random effects. When the research quantum is small (<20), there are great differences in the interval estimations of Bayesian and classical meta-analysis with different prior distributions; however, with the increase in the research quantum, when it reaches to 20 or more, the differences between them are obviously reduced or there is almost no difference between them. This shows that, with the increase in the research quantum, results of these two types of meta-analysis are consistent with each other, which means they hold properties of large samples. At the same time, it also indicates that with the increase in the sample size, the effect of the prior information is getting smaller in Bayesian meta-analysis. The results of Bayesian

meta-analysis with different prior distributions show that the prior distribution of the random effect has a significant effect on the results. But the difference is mainly reflected when the research quantum is small (<20), and with the increase in the research quantum, the difference is reduced gradually. It indicates that, in Bayesian meta-analysis, no matter how the prior distribution is determined, as long al the sample size increase, the results will tend to reflect the sample information, and the prior information is gradually neglected. Of course, just as critique on Bayesian statistics from traditional statistics, the determination of the prior distribution is a difficult problem, but from the opposite perspective, it is also because of this feature of prior distribution that makes scholars can carry out researches more flexibly, which is the very charm that attracts many scholars. Finally, the conjugate prior is inferred according to the hypothesis that the random effect is subject to normal distribution in traditional model, however, the results are very different from this hypothesis. On the one hand, the evidence for this hypothesis is not insufficient so far, which is consistent with the study results of Raudenbush (2009); on the other hand, the accuracy of the deduction which made based on the analysis results of random effects in classical meta-analysis needs further investigations.

Bayesian meta-analysis has the theoretical advantages of Bayesian statistics, through integrating sample information and prior information, it updates knowledge constantly, compared to classical meta-analysis, its theory is more concise and results are easier to interpret, it is unique and eclectic. Firstly, compared with the traditional random effect model, although there is no difference in their models, their hypotheses about unknown parameters are distinct qualitatively, the former is a random variable with prior distribution, but no longer a fixed value. Secondly, as far as the parameters estimation, in Bayesian meta-analysis based on MCMC methods, it can find a convergent stable distribution all the time, this convergent estimation can make some abnormal or extreme researches do not deviate from real effects, so as to ensure the accuracy of the results; while the most common method in classical meta-analysis is D-L method, (also called moment estimation), which always overestimates the real effect and ignores the sampling variation. Just because of this, one of its creators has also suggested scholars not use this method. Moreover, all the variations in the model have been taken into consideration in Bayesian meta-analysis, and it can provide a credibility interval for each parameter, and can handle some complex data flexibly, such as missing data, hierarchical structures and so on. Finally, Bayesian meta- analysis only has a unified model, fixed effects and random effects in the model can be separated completely, it does not need those complicated premises and hypotheses in classical meta-analysis, it is easier to find and analyze those covariates affecting real effects (that is, characteristics of the study, subjects, types of journals, geographical features, etc.).

Although there are many advantages in Bayesian meta-analysis, it still exists some problems in the practical application, for example: there are still disputes on the selection of the prior distributions of real effect and random effect variations; the criteria for the stability of the model is not clear yet; the convergent diagnosis of MCMC needs a deeper basis in mathematical statistics. These are difficulties for scholars in the field of social science, and have limited the application and promotion of Bayesian meta-analysis. Along with the development of Bayesian statistical theory, especially the determination of prior distribution, such as the probability matching prior without prior information, Reference prior and Jeffreys prior based on Fisher information matrix, make up the limitation that uniform prior can not meet invariance of changing. In the future researches, these methods will be integrated into Bayesian meta-analysis, this is the main study direction in the future.

5. Conclusion

In summary, if the real effect can be determined to be fixed effect, both two types of meta-analysis can be adopted. However, if the random effect is chosen, Bayesian meta- analysis is suggested when the research quantum is less than 20. However, the selection of prior distribution needs to be determined according to the information hold by researchers. If there is less or no prior information about the random effect variation, uniform prior can be considered; if it is considered to be subject to normal distribution, the conjugate prior shall be selected. When the research quantum is 40 or more, both two types of meta-analysis can be used, the selection of the prior distribution do not need to be fixed, because the influence of the prior information is very small at this moment.

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Research on the Identity-related Services and Key Technology Application in Internet of Things

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Abstract
In this paper, the author researches on the identity-related services and key technology application in Internet of Things (IoT). The paper summed up the characteristics of the Internet of Things (IOT) applications and current application situation from the perspectives of IOT application. IOT protocols and research work of organization are analyzed from the technical level which provides help for IOT architecture. This paper also focuses on several key technologies for the IOT applications, which includes the IOT service framework based on semantic, semantic annotation method for web service discovery, the context model and reasoning model based on ontology, the composition service of IOT and QoS, the design and implementation of smart middleware.
Keywords: IDENTITY-RELATED SERVICES, KEY RECHNOLOGY, APPLICATION, INTERNET OF THINGS

1. Introduction

Under the impetus of the economic globalization and low carbon economy, the Internet of things is a new hope to the world economy. The financial crisis at the beginning of the21st century is the breakthrough point of the Internet of things appeared in human his-