Additional file 2: A brief summary of each study included in the review

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Table 1: *A brief summary of the papers included in the citation-mining review*

	Reference	Summary
1	Achana et al., 2014	They extend network meta-analytic models to the multiple outcomes setting, allowing for strength to be borrowed across different outcomes. They also explain how the constant potency assumption, originally proposed by Dumouchel and Harris (1983), can be used to share information across interventions and outcomes simultaneously.
2	Achana et al., 2013	They extend methods that adjust for baseline-risk imbalances from the meta-analysis to the network meta-analytic framework. The models that they impose on the study-specific baselines, effectively share information across studies that enrol different populations (hence the baseline imbalances). They also describe models that can be imposed on the comparison-specific meta-regression slopes thus also sharing information across treatment comparisons.
3	Ades et al., 2010	They describe models that simultaneously analyse multiple mutually exclusive outcomes, specifically accounting for the negative, within-trial, correlations that are induced by this data structure.
4	Ades et al., 2008	This was one of the seminal papers included in the citation-mining review. The authors discuss multi-parameter evidence synthesis and the concept of borrowing strength describing models that have been suggested in the literature such the confidence profile method, hierachical models and multi-variate approaches.
5	Ades et al., 2006	This was one of the seminal papers included in the citation-mining review. The authors discuss the role of Bayesian methods that can accommodate borrowing of strength in cost-effectiveness analysis. They conceptually describe methods that can simultaneously analyse multiple outcomes, that share information across patient subgroups, that incorporate observational evidence and that can be used for bias-adjustment.
6	Ades and Sutton, 2006	They describe approaches for multi-parameter evidence synthesis including the confidence profile method, cross-design synthesis, hierarchical models and functions of parameters.
7	Bujkiewicz et al., 2016	They suggest multivariate models that simultaneously analyse surrogate and final outcomes. The models they suggest can impose structure to the covariance matrix to accommodate both cases where all outcomes are related to each other and cases where some outcomes are conditionally independent.

8	Bujkiewicz et al., 2014	They expand the evidence base by adding evidence on outcomes different than the target outcomes and simultaneously synthesise them using multivariate methods; thus, borrowing strength from related outcomes. In addition, they utilise a different dataset to derive informative prior distributions for the between study correlations.
9	Chaimani and Salanti, 2012	They describe models that estimate and adjust for small-studies bias, thus sharing information across studies of different designs. They also suggest models that can be imposed on the comparison-specific coefficients (i.e. the comparison-specific extend of the small-study effect modification), hence sharing information across treatment comparisons.
10	Cooper et al., 2009	They propose modelling approaches for the comparison-specific effect modification coefficients (i.e. slopes) in meta-regression models.
11	Copas et al., 2018	They explore the combination of primary and secondary outcomes using multivariate Random-Effects (RE) meta-analytic models. They further show that, usually, the extent of the information gain using multivariate approaches is only modest.
12	da Costa et al., 2017	They describe an application of network meta-analytic models in which they assume a linear (on the modelling scale - log relative dosage) dose-response curve; thus, sharing information across treatment comparisons. They also impose a random-walk across different the relative effects of different follow-ups hence sharing information across different outcomes.
13	Dakin et al., 2011	They describe models to relate outcomes that pertain to measurements taken at different parts during the day (This is here considered sharing information across different endpoints). They further model treatments within classes, allowing strength to be borrowed from interventions that function through similar mechanisms.
14	Daniels and Hughes, 1997	They propose multivariate meta-analytic models that evaluate the association between surrogate markers and final outcomes. Information is shared across the two outcomes by modelling their correlation structure.
15	Del Giovane et al., 2013	They describe network meta-analytic models that relate the relative effects of different dosages of the same treatment. Specifically, they explore lumping all dosages, imposing random-walks, constraints, dose-response curves and class-effects.

16	Dias et al., 2010	They describe meta-regression type models that simultaneously analyse studies in different levels of risk-of-bias (This is considered here as studies of different design). Their model can estimate and internally adjust for biases that are due to both active vs inactive treatment comparisons and active vs active treatment comparisons.
17	Dias et al., 2011a	They set out the basic model for Network Meta-Analysis (NMA) in which the between-trial heterogeneities are assumed to be comparison independent; Hence, information is then shared across different treatment comparisons both as part of the consistency equations of the model and as part of the common heterogeneity component.
18	Dias et al., 2011b	They describe models that explore and explain heterogeneity by accounting for specific effect modifiers. They also describe models that can be imposed on the comparison-specific effect modification coefficients to assist their identification.
19	Dias et al., 2011c	They describe models that can imposed across the study-specific baseline parameters such as a simple random-effect across all baselines. This is considered here as sharing information amongst different populations, because the baseline imbalances may be indicative of different types of populations enrolled in different trials.
20	Ding and Fu, 2013	They describe a longitudinal model that combines information from studies that report at multiple/different follow-ups periods without the need for data reconstruction, whilst allowing prediction of relative effects pertaining to follow-ups that have not been observed.
21	Dominici et al., 1999	They describe a meta-analytic model that allows the relative treatment effects of interventions that fall under the same 'class' to shrink towards their class-specific mean. Hence, this assumptions shares information across multiple treatment comparisons.
22	Duarte et al., 2017	Even though they seek to make a decision for a paediatric population, the authors extend the evidence base to include adult evidence and analyse the full evidence set assuming no differences across adult and paediatric patients.
23	Eddy et al., 1990	They describe the confidence profile method which adjusts for known sources of bias by directly modifying the likelihood function. This is categorised here as enabling information-sharing across studies pertaining to different designs.
24	Efthimiou et al., 2014	They describe two multivariate approaches to simultaneously model multiple outcomes in the NMA setting. The first models within- and between- trial correlations separately, and the second expands the alternative model suggested by Riley et al. (2008), which only models the overall correlation, from Meta-Analysis (MA) to NMA.

25	Efthimiou et al., 2017	They describe models to simultaneously synthesise evidence pertaining to several study-designs. The suggested models include hierarchical models, informative prior models and design-adjusted models.
26	Efthimiou et al., 2015	They describe multivariate approaches to simultaneously model multiple outcomes in the NMA.
27	Gamalo-Siebers et al., 2017	They describe prior-based and hierarchical methods (including power-priors) to combine paediatric and adult evidence; thus, sharing information amongst multiple populations.
28	Higgins and Whitehead, 1996	They describe the standard RE NMA model and in addition, suggest a method for using historical information to derive an informative prior for the between-studies heterogeneity. This can be particularly helpful when evidence is sparse and the heterogeneity cannot be appropriately estimated.
29	Hong et al., 2018a	They improve the alternative model suggested by Riley et al. (2008) by suggesting a robust variance estimator.
30	Hong et al., 2016	They describe contrast-based and arm-based parametrisations of a framework that allows simultaneous synthesis of multiple outcomes. This framework assumes that all studies can contain all treatment arms and hence considers missing arms as missing data and imputes for them.
31	Hong et al., 2018b	Described power and commensurate prior methods to combine aggregate-level and individual-patient level evidence in NMA.
32	Hwang and DeSantis, 2018	They demonstrate that, just as in the MA setting, the use of multivariate methods has the capacity to reduce outcome reporting bias under several outcome missingness scenarios in the NMA setting as well.
33	Jackson et al., 2011	They explained multivariate meta-analysis for multiple outcomes, including within- and between- studies level models and discussed potential benefits and areas of application as well as assumptions and disadvantages.
34	Jackson et al., 2013	They propose a method for multivariate RE meta-analysis that is also able to accommodate the inclusion of covariates through meta-regression.
35	Jackson et al., 2014	They propose a multivariate method to model studies that report survival outcomes at multiple/different follow-up points. Their method models the between-study covariance matrix across different time periods.

36	Jackson and Riley, 2014	They extend a refined method, previously developed by Hartung and Knapp (2001) in the univariate setting, to the multivariate setting where multiple outcomes are simultaneously modelled. This method is particularly useful when only few studies are included in the MA causing problems in the estimation of the between-studies covariance matrix.
37	Jackson et al., 2017	They describe multivariate NMA methods and further propose a method for calculating the extent of strength that is borrowed across outcomes. Their method is based on a comparison of the precision of the estimates under the univariate and the multivariate approach.
38	Jackson et al., 2018	They extend univariate NMA methods to the multivariate setting where multiple outcomes are simultaneously synthesised. Their model further allows for two types of variance components. One that is due to between-study heterogeneity and one that is due to inconsistency.
39	Kirkham et al., 2012	They show that multivariate meta-analytic methods have the capacity to reduce outcome reporting bias under several outcome missingness mechanisms.
40	Langford et al., 2018	They developed methods to meta-analyse studies reporting for different/multiple dosages of the same treatment; hence, sharing information across the relative effectiveness of different treatment comparisons. Their method utilises the Emax model that is commonly employed in pharmacology and has several advantages over other, unbounded, approaches such as linear dose-response models.
41	Liu et al., 2018	They develop a multivariate method for simultaneous synthesis of multiple outcomes where within- and between-trials correlations are accounted using copulas.
42	Lu et al., 2007	They extend NMA methods to accommodate cases where the available studies report for multiple/different fixed follow-up periods; hence, their methods borrows strength across different endpoints which is considered here as information-sharing across different outcomes.
43	Lu and Ades, 2009	They model between-trial variance structures that are compatible with consistency assumptions and allow one to incorporate prior information on correlations between treatment arms.
44	Lu et al., 2014	They suggest methods to model the treatment comparison-specific between-trials heterogeneities such as the use of triangle inequalities which stem from second order consistency.
45	Madan et al., 2014	They develop a method to simultaneously analyse multiple outcomes reported at different/several follow-ups of complex interventions. Their model shares information across outcomes and treatment comparisons simultaneously

46	Mak et al., 2009	They use observational evidence to derive an informative prior that is used for the analysis of the available randomised trials. This is a two-step process which results in information-sharing across studies of different designs.
47	Mavridis and Salanti, 2013	They provide a thorough introduction to multivariate meta-analytic methods and a tutorial on how to simultaneously analyse multiple outcomes.
48	Mavridis et al., 2013	They describe an extension of a selection model, previously suggested by Copas (1999) that can be used in MA to account for publication bias that at is due to studies' treatment effect size and precision. This is considered here as sharing information across studies that of different designs.
49	Mawdsley et al., 2016	They describe model-based NMA that simultaneously analyses trials that report for multiple dosages of a specific treatment. Their model enables information-sharing across multiple treatment comparisons using the Emax model which is commonly used in pharmacology/pharmacokinetics.
50	McCarron et al., 2010	They describe methods to combine randomised and non-randomised evidence adjusting for imbalances across study arms, within studies. Two approaches are used. One that extends the model previously suggested by Prevost et al. (2000) and is essentially a three-level hierarchical model, and another that initially meta-analyses the non-randomised evidence and subsequently uses the posterior conclusions as informative priors for the analysis of the randomised evidence.
51	McCarron et al., 2011	They describe a simulation study that compares the methods presented in McCarron et al., 2010. These include multi-level models and prior-based methods to combine randomised and non-randomised evidence, that share information across different designs, accounting for imbalances across study arms.
52	Melendez-Torres et al., 2015	They discuss emergent methods for modelling complex interventions by grouping them into 'clinically meaningful units' or, in other words, according to the components of interventions that they include.
53	Mills et al., 2012	They described methods that model complex interventions by assuming additivity of the relative effects of the various components on the modelling scale. This approach shares information across treatment comparisons and also enables the evaluation of treatment combinations that have not been used in practice.

54	Moreno et al., 2011	They propose a meta-regression method that accounts for publication bias and small-study effects by regressing the treatment effect on its associated variance. The model simultaneously analyses evidence pertaining to 12 interventions, all of which fall into the same 'class' of antidepressants. Their meta-regression model also assumes exchangeability across the treatment comparison-specific meta-regression slopes. Overall, it shares information across different study designs (small/large studies) and treatment comparisons (class of antidepressants)
55	Musekiwa et al., 2016	They describe a generalised linear mixed model that can simultaneously model studies reporting at multiple pre-determined timepoints (i.e. follow-ups) accounting for within- and between-studies correlations. This model is considered to share information across several outcomes.
56	Nam et al., 2003	They suggest multivariate models that can simultaneously model and share information across multiple outcomes. Two of their models, extend the traditional univariate approach and differ in the assumptions they make at the between-studies level; the third model is a mixed model approach. They compare their approaches using a simulation experiment.
57	Nixon et al., 2007	They suggest methods to model complex interventions. These include meta-regression approaches that assume additive effects among treatment components and also a bivariate approach. They also try a class-effects model where treatments are lumped within classes. All their models share information across parameters pertaining to different treatment comparisons.
58	Owen et al., 2015	They develop a multi-level approach that models interventions within classes of treatments allowing the relative effects of each treatment to shrink toward their class-specific mean. They also impose constraints on the dosages, forcing larger dosages to exhibit larger relative effects. Their models primarily share information across parameters that pertain to different treatment comparisons.
59	Prevost et al., 2000	They suggest a hierarchical, multi-level, approach to model studies pertaining to different study designs (e.g. randomised and non-randomised studies). This includes initially modelling studies within each design and subsequently modelling allowing all design-specific hyperparameters to shrink towards an overall design-independent hypermean. This approach also allow for separate heterogeneity components to be estimates within each design and across all designs. Their model shares information across studies of different designs.

60	Pullenayegum, 2011	They suggest the use of informative prior distributions for the between-study heterogeneneity when RE meta-analyses analyse sparse evidence. Their priors are derived based on previous meta-analyses and hence this is a meta-epidemiological approach.
61	Ren et al., 2018	They develop a method to elicit informative prior distributions that can be used for the between-trials heterogeneity in RE meta-analyses.
62	Rhodes et al., 2015	They use previous meta-analyses to obtain informative priors that can be used for the between-trials heterogeneity when the number of studies analysed with a random-effect is small and estimation of the between-studies heterogeneity becomes problematic.
63	Rietbergen, 2016	They describe the use of power-priors in many settings. In one of their applications they demonstrate how power-priors can be used to combine randomised and observational evidence by discounting the likelihood of the observational data. Their models share information across multiple study-designs.
64	Riley et al., 2007a	They describe how standard bivariate meta-analysis models can be used and compare them with the univariate approach under a set of scenarios where studies report either complete information on all outcomes or some outcomes are missing at random.
65	Riley et al., 2007b	They describe multivariate RE meta-analytic methods to model simultaneously multiple outcomes and further focus on issues that arise with the estimation of the between covariance matrix, particularly when only few studies are available and the within-study variance is large.
66	Riley et al., 2008	They describe an alternative bivariate random effect model to analyse multiple outcomes when within-trial correlations are unknown. This model does not distinguish between within-trials and between-trials correlations, and models it as a single correlation, so requires the same data as required for separate univariate meta-analyses. Hong et al. (2018a) showed that this model may not always appropriately estimate variance and suggested a robust variance estimate that improved on this model.
67	Rodgers et al., 2011	This is an HTA where the authors analysed studies that reported at different follow-up periods without accounting for this difference and effectively lumping across follow-ups. Even though they assumed that all studies reported the same outcome, since different length of follow-ups can be considered essentially different endpoints, here, it is considered that the authors lumped across multiple outcomes.

68	Roever et al., 2019	They demontrate how mixture priors can be used to combine adult and paediatric evidence where the adult evidence are part of the prior. They further show that this approach is robust to 'prior data conflict' (that is cases where direct and indirect evidence are in disagreement) and that therefore mixture priors facilitate adaptive borrowing of strength.
69	Salanti et al., 2010	They develop network meta-regression models to estimate and adjust for novelty bias in which the effectiveness of newer treatments is potentially exaggerated. This is considered here as sharing information across studies pertaining to different designs.
70	Salanti et al., 2009	They develop a network meta-regression model that estimates and adjusts for the effect modification caused by the year of publication. This is considered here a characteristic of the study-design and hence this model shares information across studies of different designs.
71	Schmitz et al., 2013	They suggest modelling approaches to combine randomised and non-randomised studies. These include a simple lumping approach where no differences are considered, using the non-randomised evidence as prior information and analysing both sources with a three-level model that initially models studies within each design and subsequently combines the design-specific hyperparameters.
72	Soares et al., 2014	They describe modelling approaches that can be used to overcome issues relating to evidence sparsity. Amongst the suggested models there are methods that lump across different population subgroups (patients of different disease severity) and methods that impose a 'class-effect' on intervention functioning through the same mechanism.
73	Spiegelhalter and Best, 2003	They describe a modelling approach that can be used in random-effect meta-analysis to adjust for internal and external biases and therefore combine studies that may pertain to several different study-designs.
74	Tan et al., 2018	They use a bivariate meta-analytic model to obtain estimates required for decision-making that have not been reported and would not be obtainable using standard methods.
75	Thorlund et al., 2013	They conduct a simulation experiment to compare different models, originally suggested by Lu and Ades (2009), that can be imposed on the treatment comparison-specific between-trial heterogeneities. These models share information across different treatment comparisons.

76	Trinquart et al., 2012	They describe meta-regression models, similar to those suggested by Chaimani and Salanti (2012) that can be used, to estimate and adjust for reporting bias. This is assumed to be linked with the study size and therefore their models share information across studies of different designs.
77	Turner et al., 2015	They utilise meta-epidemiological data from previous meta-analyses in order to obtain 'of-the-shelf' informative priors for the between-trials heterogeneity in RE meta-analyses. These informative priors are particularly useful when there are only few studies in the meta-analysis and the estimation of the between-studies heterogeneity becomes problematic.
78	Turner et al., 2009	They suggest bias-adjustment methods which allow synthesis of studies that differ in rigour (i.e. internal validity) and relevance (i.e. external validity). Their approaches allow for both additive and proportional biases on the modelling scale. These models share information across different study designs.
79	van Houwelingen et al., 2002	They describe extensions to the univariate approach (that can only model one outcome at a time). These include bivariate methods that simultaneously model two outcomes and allow information to be shared across outcomes at the within- and the between-studies level.
80	van Houwelingen et al., 1993	This is one of the seminal papers included in the citation-mining review. The authors set the initial ideas around the use of multivariate meta-analysis to simultaneously model multiple outcomes allowing strength to be borrowed across them through their correlation structure.
81	Warren et al., 2014	They describe how hierarchical, multi-level, methods can be used to model multiple dosages of the same interventions and multiple treatments that fall under the same 'class' (i.e. mechanism of action). Furthermore, they show how dosage constraints can be imposed assuming that larger dosages exhibit larger relative effects.
82	Wei and Higgins, 2013a	They suggest an approach that can be used for multivariate models to approximate within-study covariances when their estimation is problematic because the within-trial correlations are either unknown or cannot be estimated using Individual-patient data (IPD).
83	Wei and Higgins, 2013b	They set out to extend bivariate meta-analytic methods to cases where more than two outcomes are simultaneously modelled. They further suggest alternatives to the Wishart prior for the variance-covariance matrix and explore simplifying assumptions that can be imposed on the variances and the correlations when their number increases due to additional outcomes included in the analysis.

84	Welton et al., 2009b	They suggest NMA meta-regression approaches that can be used to model complex interventions with multiple treatment components. On top of simple additive -on the modelling scale- relative effects, they also show how synergistic or antagonistic effects can be incorporated in the model.
85	Welton et al., 2009a	They suggest hierarchical models that can be used to simultaneously model studies in high and low risk of bias using a bias-adjustment approach; hence, their models share information across multiple study-designs. They further show how external evidence can be used to derive informative priors for the bias component.
86	Welton et al., 2008	They suggest models that simultaneously synthesize two structurally related time-to-event outcomes. They use constraints to reflect that one outcomes needs to be reached before the other and they also model their between-studies covariance using multivariate methods.
87	Welton et al., 2010	They develop a multi-parameter evidence synthesis framework to model multiple time-to event outcomes. They reflect structural relationships among outcomes by forcing their relative treatment effects to differ by a fixed component term. They also reflect the between-study correlation structure amongst outcomes using multivariate methods.
88	Wolpert and Kerrie, 2004	They suggest models, similar to those developed by Eddy et al. (1990), to model multiple studies pertaining to several designs by directly modelling sources of bias using adjusted likelihoods.
89	Wu et al., 2018	They describe methods for model-based meta-analysis of biologic products using a linear dose-response relationship where the dosage is proportional to the relative effect -on the modelling scale- and also using the commonly employed in the pharmacokinetics field non-linear Emax model. Their models share information across treatment comparisons (i.e. the relative effects of different dosages of the same treatment).

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