Supplementary data

Search strategies

Total references retrieved = 5877

Total following de-duplication = 3916

Supplementary Table 1: Example of the search strategy used for Ovid MEDLINE(R) and Epub Ahead of Print, In-Process & Other Non-Indexed Citations and Daily 1946 to June 04, 2019, search date: 4th June 2019

PRISMA flowchart

Methodological quality assessment

Domain 1: Patient selection

Domain 2: Index test

Domain 3: Reference standard

Domain 4: Flow and timing

Additional items for assessing methodological quality in index test domain (McCleery et al,

2015).

Meta-analyses methods

Quantitative results of this systematic review were subject of meta-analysis in which outcomes from all primary studies were synthesized (Borenstein, Hedges, Higgins, & Rothstein, 2009; Schwarzer, Carpenter, & Rücker, 2015).

Logit transformation of proportions

All outcome measures included in this meta-analysis were reported as proportions in primary studies. To perform the analyses they had to be transformed to logit units (Wang, 2018). Logit transformation of proportions was required to satisfy the assumption of normal distribution, which is the key assumption on which statistical models and tests of significance used in this study are relying. Logit transformation of proportions is often used when dealing with proportional data, although other options like double arc-sine transformation or conducting analyses on untransformed data are also used (Wang, 2018). For this meta-analysis all available options were considered carefully. The option of no transformation was ruled out first as it requires a symmetrical distribution of proportions and all effect sizes to have values between the limits of 0.2 and 0.8. Otherwise it may potentially lead to biased estimates and misleading results of statistical inference testing. The other alternative considered, was the arc-sine option. This option performs best when the sample sizes are small and there are outliers in the data than needs to be handled (Viechtbauer, 2010; Wang, 2018). The latter was not the case in the current study and it was decided to undertake the simplest option of logit transformation. For a more detailed discussion on the above options please see (Wang, 2018).

Once all the analyses have been finished, for reporting purposes, all the estimates in logits and their associated confidence intervals were converted back to original proportions to simplify the interpretation of the results and make them more meaningful to readers. Summaries of study effects for each reported meta-analysis outcome was illustrated with forest plots.

Random effects model

There are two main options for calculating the meta-analyses effect sizes either the fixed or the random effects model. The fixed effect model provides the framework for studies based on the assumption that all studies share a common effect, and all observed differences are attributed to a random error. In other words, it is assumed that the true effect sizes are identical across all studies and vary only due to sampling differences. In the fixed effect model, all studies are weighted by the inverse of their sampling variances which is a function of proportions and sample sizes of studies included in the analysis (Borenstein et al., 2009; Wang, 2018).

In the case of a random effects model studies are allowed to differ on their effect sizes and additionally the sampling error within studies is taken into account. The model assumes that the total observed variance of effect sizes can be attributed to two parameters: the between-study variance, which is the part representing 'true' variability responsible for the real or systematic differences among studies, and the within-study variance being the effect of sampling variability of studies. In meta-analysis the between study variance is regarded as one of the key indicators of study effects heterogeneity. It is denoted by τ^2 and various methods exist to estimate its value. The most populars are the maximum likelihood (Hardy & Thompson, 1996), restricted maximum likelihood estimation (Raudenbush & Bryk, 1985, 2002) and DerSimonian Laird method based on moments (DerSimonian & Laird, 1986; Wang, 2018). All of them have their merits and perils but their results are usually rather similar and rarely lead to different conclusions.

Weights of the studies in this approach are based on the inverse of variance of studies. It is worth noting, however, that in the random effects model this variance is the sum of the above mentioned components: the within- and between-study variances.

In the current analyses it was decided to use a random effects model as it allows more realistic assumptions of the possible true heterogeneity of effects across studies (Borenstein et al., 2009). The between study variance was estimated with DerSimonian and Laird methods as recommended by Wang (2018). Summary effect sizes were estimated as weighted means of observed effect sizes of individual studies.

Outlying and influential studies detection

The influence of individual studies on the results was tested using 'leave one out' sensitivity analysis. This method allows to iteratively exclude each study from the analysis and to recalculate the size of the effect using only the remaining studies. Another approach was based on the analysis of residuals (z-values).

Heterogeneity quantified

Several indices to measure heterogeneity in meta-analyses exist. First measure of heterogeneity used here was the level of between study variance represented by τ^2 . This statistic has already been introduced above. Since τ^2 is the measure of absolute units its interpretation is rather difficult without additional tests. One of such tests is Q statistic. It is a formal test of the null hypothesis stating that $\tau^2 = 0$ which amounts to the testing the hypothesis whether there is significant level of heterogeneity of effect sizes. The p-values for this test are reported on forest plots. Finally, in the current analyses heterogeneity was also measured using I². It represents the ratio of between study variance to total variance of studies (Borenstein et al., 2009)**.** It was assumed that high heterogeneity is defined by values of I^2 greater than 50% (Higgins & Thompson, 2002). The above indices, their 95% confidence intervals (τ^2 , I^2) and p values (Q statistics) were reviewed and their summary information was used to interpreter the level of heterogeneity in the reported summary effects.

Moderator analysis (or searching for factors explaining heterogeneity)

For the domains with confirmed substantial level of heterogeneity further procedures were employed aiming at searching for possible explanation of observed differences in effect sizes between studies. A subgroup analysis and meta-regression analyses were used for this purpose.

Subgroup analyses

For the subgroup analyses, we used categorical variables from study level characteristics, usually with no more than two categories. When the original variable was continuous it was categorized according to the median. The summary effect sizes for each category were estimated using the random effects model as well. The between study variances of effects from given subgroups were pooled using estimations of overall summary effects. All summaries of study effects for each domain and given subgroup were illustrated with forest plots.

Meta-regression models

Meta-regression was another approach in the process of exploration of possible factors underlying observed level of heterogeneity of study effect sizes. Unfortunately due to the limited number of studies it was not possible to construct multivariable models with more than one predictor. We followed the known rule thumb that there should be at least 10 studies per predictor in metaregression analysis and performed separate univariate meta-regression models instead. Their effects were reported as beta coefficients and $R²$ indexes. Relations between outcomes and all tested

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moderator variables were graphically illustrated with scatter plots. All models were estimated under random effects model (Borenstein et al., 2009).

Publication bias

The final point of statistical analyses was the issue of publication bias. Although it is still under discussion in the literature whether it makes sense to include this part of meta-analysis for proportions as primary outcomes in which most them are reported from observational studies we decided to include the relevant output for this issue. In the current study, we present results of this type of analysis in a graphical form of the funnel plots followed by the formal test of the hypothesis that funnel plot is symmetrical (Wang, 2018).

Software information

All the analyses were performed in R programme (v 3.6.1). Two dedicated packages were used in for analyses and graphics which were *metaphor* (Viechtbauer, 2010) and *meta* (Schwarzer, 2010).

Methodological quality assessment

Study outcome data for meta-analysis.

Agreement between DaTscan and clinical assessment (only studies that reported results are shown).

Supplementary Table 5

Relationship between time since onset of symptoms and change in management (in blue) and change in diagnosis (orange).

Subgroup analyses forest plots

Region: North America vs. Europe

Study design: Retrospective, single-arm vs. other

Mean age of patients: < 64 years vs. ≥ 64 years

Supplementary Figure 5

Time since onset of first symptoms: >3.84years vs. equal or ≥3,84years

Female to male ratio: <1 vs. \geq 1

Supplementary Figure 7

Follow-up time: <16 months vs. ≥ 16 months

PD vs ET

PD vs DIP

PD vs vascular

PD vs Early

Leave-one-out sensitivity analyses

Change in management Summary proprotion leaving out each study

Supplementary Figure 17: Summary of leave-one-out sensitivity analysis for change in management.

Change in diagnosis Summary proprotion leaving out each study

Supplementary Figure 18: Summary of leave-one-out sensitivity analysis for change in diagnosis.

Univariable meta-regression results

Change in management

Female to male ratio

Supplementary Figure 19

Supplementary Table 6: Meta-regression with random effects model – coefficients. Outcome variable logit transformed proportions

Change in diagnosis

Mean age of patients

Supplementary Table 7: Meta-regression with random effects model – coefficients. Outcome variable logit transformed proportions

Female to male ratio

Supplementary Table 8: Meta-regression with random effects model – coefficients. Outcome variable logit transformed proportions

Supplementary Figure 22

Supplementary Table 10: Regression Test for Funnel Plot Asymmetry

References

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