MSR31

Evidence Synthesis for Decision-Making: Is Meta-Analysis Always Required?

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BACKGROUND

- Evidence synthesis involves a critical analysis of collected research to identify patterns or trends in the data from which conclusions or inferences can be drawn
- Visual analytics (or data visualizations) construct visual representations of data to identify patterns, leading to discoveries that could otherwise go missed[1]
- When data are visualized, important insights such as correlations, patterns, groups, outliers, and trends can stand out
- Data visualization is often considered to be a necessary step before a quantitative meta-analysis
- However, data visualization on its own can be — and often is — a sufficient means to identify insights
- This work presents real-world examples where data visualization is appropriate and/or necessary to answer a research objective

DISCUSSION

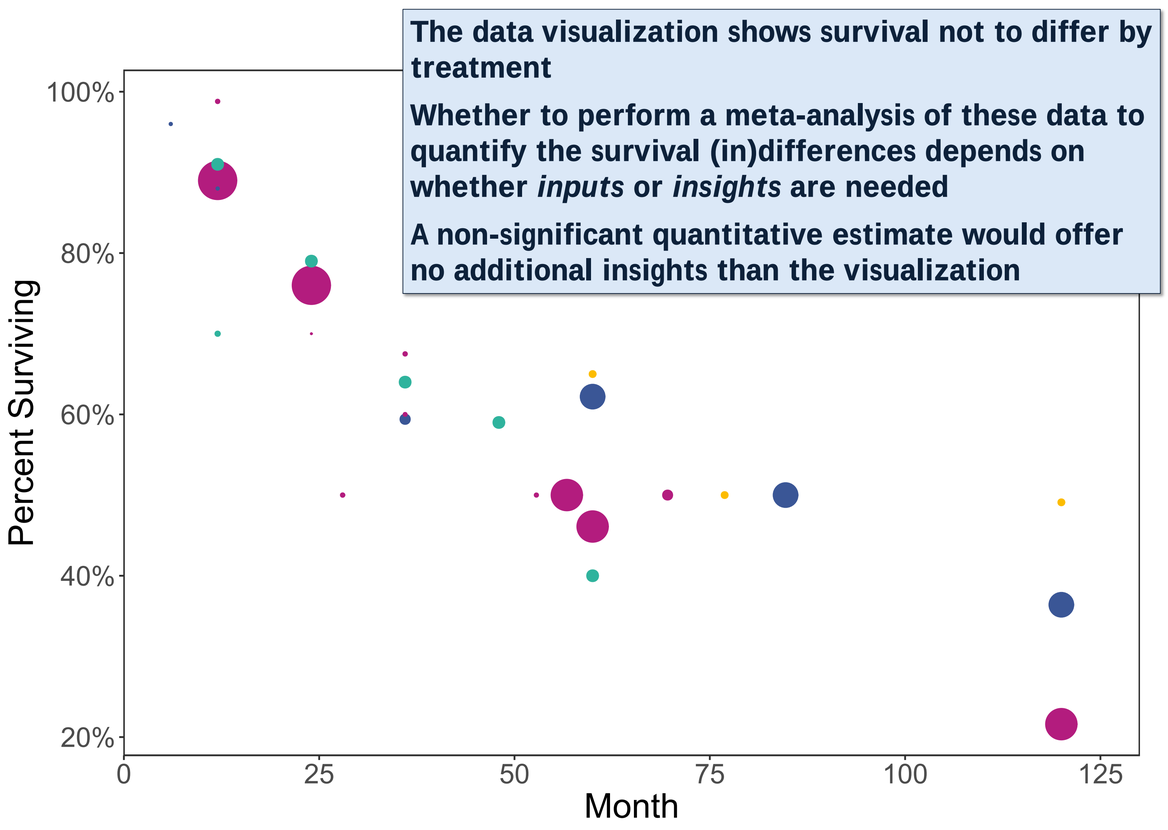
- Applications such as comparative effectiveness analyses for HTA submissions require meta-analyses, particularly when data inputs are needed for economic models
- When the objective is to make a claim comparing one group with another, quantitative meta-analyses are also helpful
- Caution should be taken, however, that quantitative analyses not be considered "better" or "more convincing"
- If the quality of the data is low, this strategy is prone to the "*P*-value fallacy" in which effects are classified as either "noise" or "real" based on the associated *P*-value[2]
- This dichotomous classification can erroneously lead one to view the evidence provided with more confidence than it should be

CONCLUSION

Data visualization/visual analytics is an often undervalued but powerful tool to help find insights, draw conclusions, and support decisions made from data

CASE STUDY 1: DOES A QUANTITATIVE ESTIMATE ADD VALUE?

- A common objective for evidence synthesis is to assess the available data to understand "What is?"
- Meaning, "What is the collection of data and what can we take away from them?"
- These assessments are "signal generating" and data visualization is often sufficient to understand their insights
- **Example: Study objective is to evaluate the collection of reported survival estimates**
- **Survival proportions were organized by time and treatment (color)**

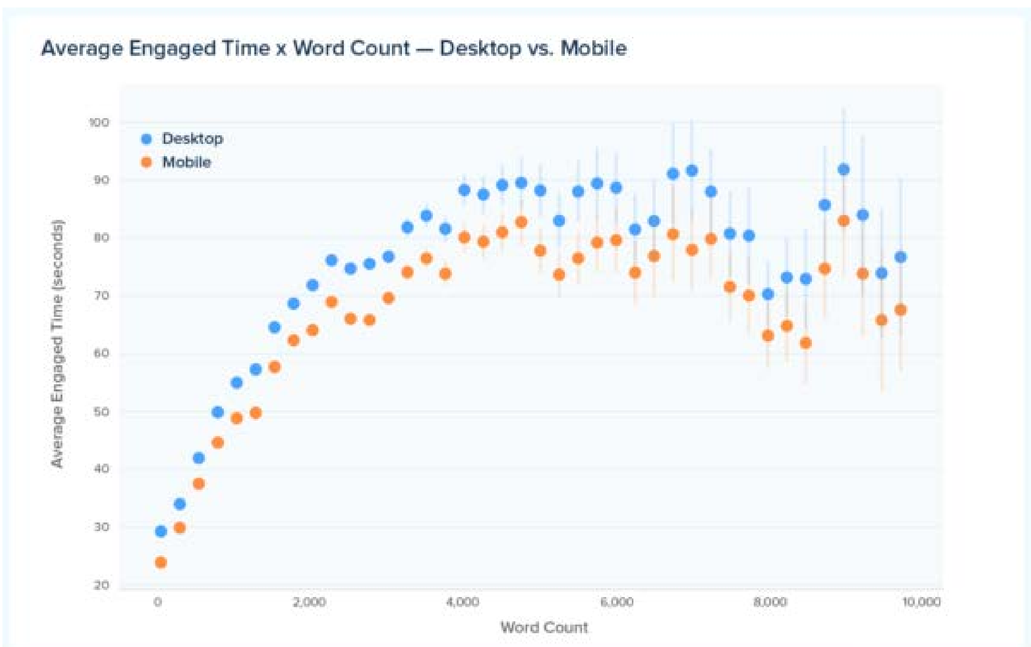


The data visualization shows survival not to differ by treatment

Whether to perform a meta-analysis of these data to quantify the survival (in)differences depends on whether *inputs* or *insights* are needed

A non-significant quantitative estimate would offer no additional insights than the visualization

- **Example: Study objective is to assess the relationship between word count and engagement with online content**
- **A quantitative estimate of this relationship would have little value to online publishers**



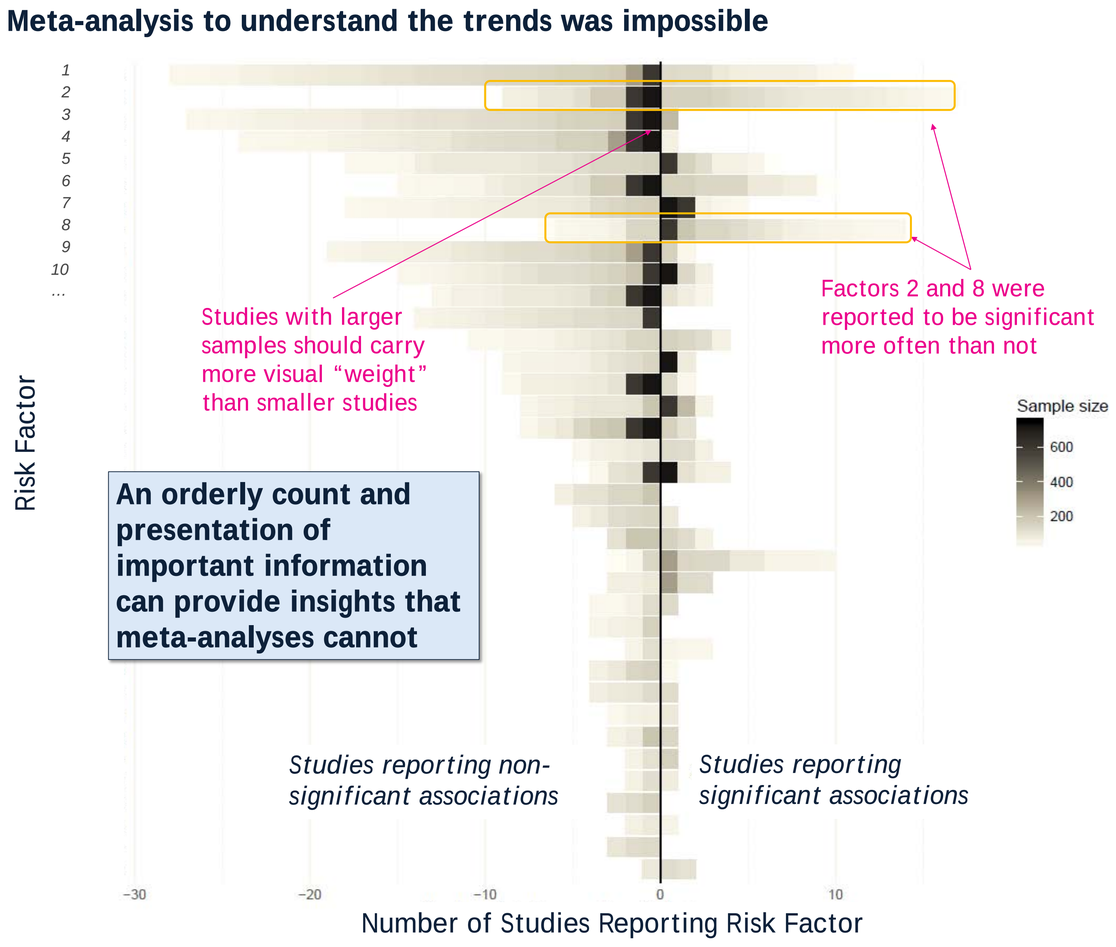
Source: https://blog.chartbeat.com/2022/07/07/optimal-article-length-for-engagement Chartbeat

This data visualization provides several insights

1. **Engagement increases with word count, up to a limit**
2. **Engagement is more variable on pages with word count >4000 compared to those <4000, due to either fewer examples or other variations in content (signal for future research!)**
3. **Mobile engagement is consistently lower than desktop**

CASE STUDY 2: ARE THE RELEVANT DATA QUANTIFIABLE?

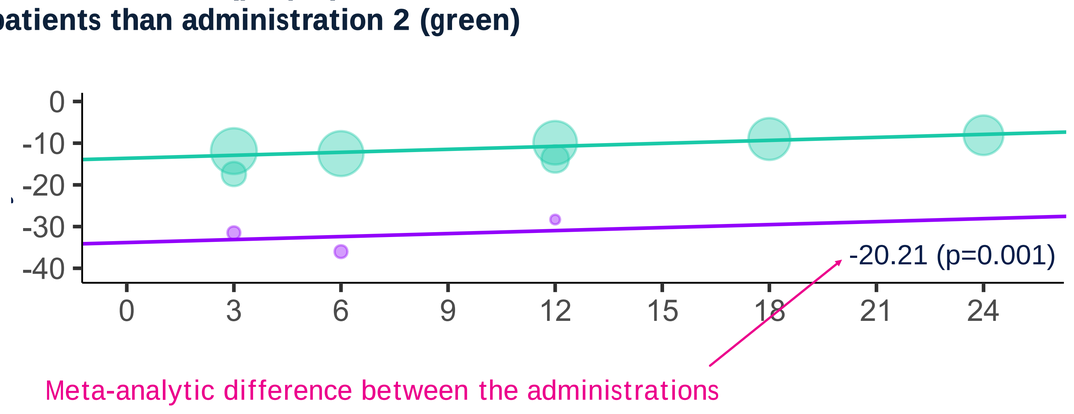
- When the study objective is to understand trends or more general associations, the data to inform that objective may exist in multiple forms
- **Example: Study objective to understand what risk factors are associated with survival**
- **Those data could be odds ratios, hazard ratios, non-significant associations, etc.**
- **Meta-analysis to understand the trends was impossible**



An orderly count and presentation of important information can provide insights that meta-analyses cannot

CASE STUDY 3: IS A QUANTITATIVE ESTIMATE RELIABLE?

- Many study objectives are to evaluate associations between 2 or more groups
- Data visualization is a good method to understand these associations
- **Example: Study objective is to evaluate the published outcomes between two administrations of a treatment for Parkinson's disease[3]**
- **Administration 1 (purple) has fewer available data and was studied in fewer patients than administration 2 (green)**



It is clear from the scatter plot that the purple data are consistently lower than the green

The meta-analytic difference is based on few data points of small sample sizes for the purple data

The low *P*-value of the analysis could lead the audience to conclude that this result is more accurate than would be assumed from the data points themselves

REFERENCES

1. Decker J. (2018). *Visual Analytics For Dummies®, Qlik Special Edition*. John Wiley & Sons, Inc. 2. Dixon P. The p-value fallacy and how to avoid it. Can J Exp Psychol. 2003 Sep;57(3):189-202. 3. Kovacs N, et al. Reported clinical and quality-of-life outcomes with 24-hour levodopa-carbidopa intestinal gel administration compared with 16-hour administration. International Congress of Parkinson's Disease and Movement Disorders, September 15–18, 2022, Virtual

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