Data Visualization in Real-World Studies to Aid Understanding and Interpretation

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Introduction

Real world observational studies provide valuable data on key clinical endpoints but are often very complex, particularly in oncology.

Collected data usually includes efficacy endpoints such as overall survival (OS) and progression-free survival (PFS) as well as information on treatment sequences and large volumes of adverse events (AEs) data.

Despite significant software advances to describe such data, very little progress has been observed/published in terms of graphical representation.

There is limited guidance on the use of data visualization tools during the review of data and results of real-world studies.

This project aims to explore various data visualisation outputs to enable easier interpretation and dissemination of results within the scientific community.

Method

Data from an observational retrospective study in metastatic colorectal cancer were used for the purpose of illustration in this poster.

Levels included conjunctions of main objectives, which were treatment sequence patterns, OS and PFS. In addition, adverse event visualization was a special focus.

Several plots were tested combining multiple dimensions.

Conclusion

This poster provides visual aids, based on the dataset's multiple dimensions, to aid the assimilation and interpretation of the data.

Such visualizations could be of outstanding help throughout the whole study, particularly during the data review process, to support decisions relative to missing data mechanisms.

Glossary

AE: Adverse Event

CT: Chimiotherapy

OS: Overall Survival

PFS: Progression Free Survival

SOC: System Organ Class

TAK: Time sequence Analysis through K-clustering

TT: Targeted therapy

Reference

1. Putter, H, M Fiocco, et R B Geskus. « Tutorial in Biostatistics: Competing Risks and Multi-State Models », 2006, 42.
2. C. Chouaïd et al., « Machine Learning–Based Analysis of Treatment Sequences Typology in Advanced Non–Small-Cell Lung Cancer Long-Term Survivors Treated With Nivolumab », JCO Clinical Cancer Informatics, févr. 2022, doi: 10.1200/CCI.21.00108.
3. Cornelius, V., Cro, S. & Phillips, R. Advantages of visualisations to evaluate and communicate adverse event information in randomised controlled trials. Trials 21, 1028 (2020). https://doi.org/10.1186/s13063-020-04903-0

Data sources

internal real-world data from Pierre Fabre were used.

Pierre Fabre

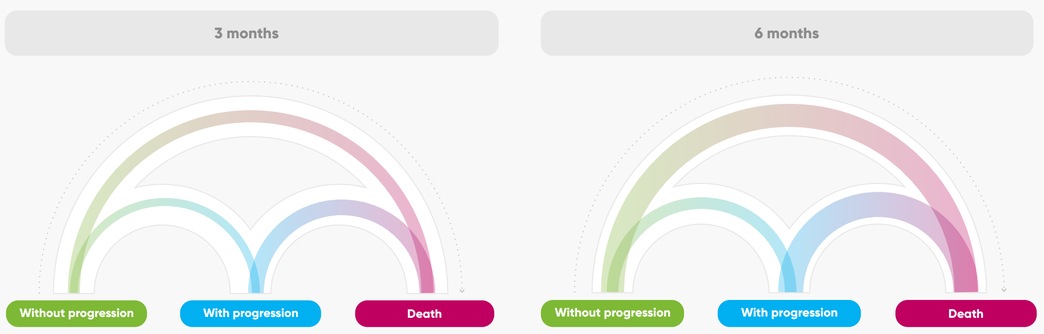
Designed by Heva

Results

Vizualization of efficacy endpoints (OS + PFS) with illness-Death model[1]

Analysis | Cost models

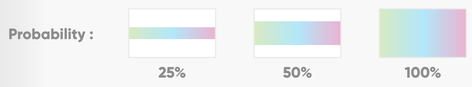
Fig.1: Probability of transition from one stage to another at specific timepoints



How to read fig.1?

The size of arrows indicates the strength of the transition between the stages, from 0% (no patient) to 100% (all patients).

The probability of death is very high in this study and the probability of transition to progression is minimal at 3 months and a bit higher at 6 months.



Goal

To present the probability of transition from one stage to another. In this example:

- from without progression to death
- from without progression to with progression
- from with progression to death

Strengths

- View of the general temporal trends between stage
- Possibility to represent the association between the transition and a chosen factor (treatment/patient characteristic)

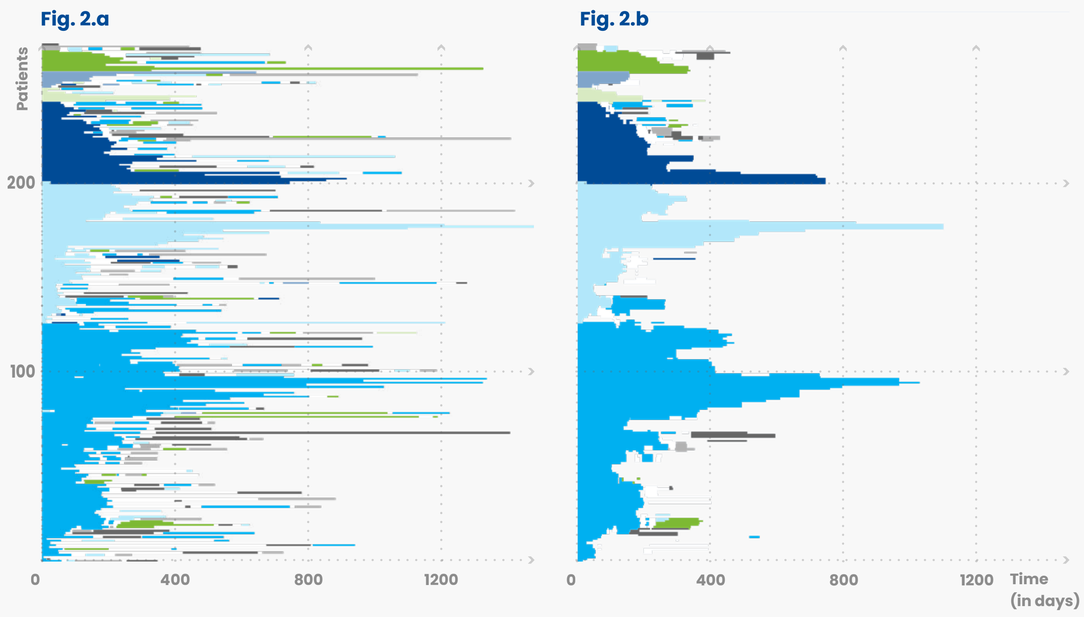
Possible alternatives to represent efficacy endpoints

- The illness-death model can also provide state probability view as time varying curve.
- Kaplan Meier curves remain the most commonly used visualization of OS and PFS.

Visualization of treatment sequences

TAK® | Data review | Analysis

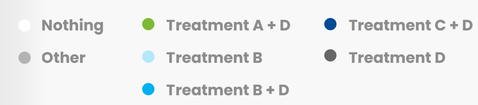
Fig. 2: Time sequence Analysis through K-clustering: TAK® by Heva[2]



How to read fig.2?

Each patient in the cohort is represented horizontally. The x-axis shows the temporality of the events. Similar patients are grouped together and highlight the main treatment patterns.

Treatment received



Several views can be provided depending on the goal of the representation

- the graph displayed on fig. 2.a provides a more detailed visualization
- Blurring events with a convolutional filter highlights global patterns and helps readability (fig. 2.b)

Goal

- Providing a full picture of drug history pathways
- An automatic segmentation in relevant groups, for subsequent analyses
- An explanation of patterns

Strengths

- Full overview
- Shows complex correlations
- Manages unusual patients well
- Automatically finds groups

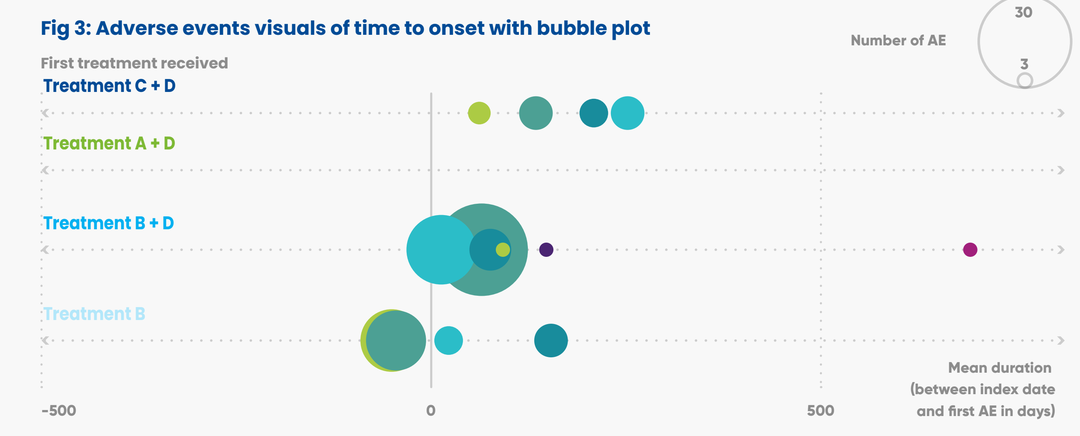
Possible alternatives for treatment sequence vizualization

Visualizations such as Sunburst plots or Sankey diagrams can also provide a clear view of treatment lines by omitting the temporal dimension.

Representation of adverse events

Analysis | Data review

Fig 3: Adverse events visuals of time to onset with bubble plot



How to read fig.3?

The bubble graph allows to investigate the mean delays and the frequency of AE in the same representation. For example, a small circle near of the inclusion date corresponds to an infrequent AE occuring shortly after the inclusion.

SOC labels of AE

- Blood and lymphatic system disorders
- Nervous system disorders
- Skin and subcutaneous tissue disorders
- Gastrointestinal disorders
- Renal and urinary disorders
- General disorders and administration site conditions
- Hepatobiliary disorders

Goal

- Present the number and time of onset of AE event
- X-axis: Mean duration between date of start of first AE of the category and index date in days
- Y-axis: First treatment received
- Size of bubble: Number of AE

Strengths

- Many adverse events can be presented at the same time
- Simple way to identify AE of interest such as frequent AE or short-term AE

Possible alternatives for AE representation

- Dot plot or cumulative incidence plot are commonly used to represent the adverse events
- In case of high number of AE to describe, volcano plots can identify severe imbalance between groups for some AE.[3]