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Reporting 2.0 – Interactive Visualizations and Dashboards for *Big Data*

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ABSTRACT

Numerous companies are currently challenged by a disruptive change as a result of digitalization. In reporting, *Big Data* in particular promises to turn long-cherished wishes into reality. In order to be able to generate benefits from the increasing data volumes, significant design and technology changes are necessary to replace traditional paper-based reports with interactive real-time reports. Several studies conducted by the authors show the need for the immediate processing of *Big Data* in user-centered interactive dashboards and reports. Experiments with eye-tracking tests pave the way for the generation of design guidelines by means of usability-analysis and finally assure perception-optimized dashboards and user-friendly interactive visualizations. Particularly for *Big Data*, multidimensional visualizations, such as Sankey diagrams or parallel coordinates plots, allow a more efficient recognition of correlations and trends than traditional diagrams. However, this also presupposes extensive knowledge in the areas of information design and interaction techniques. The integration of these multidimensional visualizations in interactive dashboards enables a user-friendly self-service-BI, supports management in complex decision-making situations and thus finally generates considerable added-value in *reporting*.

Classification JEL: MO, Z0

KEYWORDS

Digitalization, *Big Data* Visualization, Interactive *Reporting*, Eye-Tracking, Multidimensional Visualization, Information Design.

RESUMEN

Numerosas empresas se enfrentan actualmente a un cambio disruptivo como resultado de la digitalización. Al informar, *Big Data* en particular promete convertir los deseos anhelados en realidad. Para poder generar beneficios a partir de los crecientes volúmenes de datos, se necesitan cambios significativos de diseño y tecnología para reemplazar los informes tradicionales en papel por informes interactivos en tiempo real. Varios estudios realizados por los autores muestran la necesidad del procesamiento inmediato de *Big Data* en paneles e informes interactivos centrados en el usuario. Los experimentos con pruebas de seguimiento ocular allanan el camino para la generación de pautas de diseño mediante análisis de usabilidad y finalmente aseguran cuadros de mando optimizados para la percepción y visualizaciones interactivas fáciles de usar. Particularmente para *Big Data*, las visualizaciones multidimensionales, como los diagramas de Sankey o los diagramas de coordenadas paralelas, permiten un reconocimiento de correlaciones y tendencias más eficientes que los diagramas tradicionales. Sin embargo, esto también presupone un amplio conocimiento en las áreas de diseño de información y técnicas de interacción. La integración de estas visualizaciones multidimensionales en cuadros de mando interactivos permite una inteligencia de negocio de autoservicio fácil de usar, apoya la gestión en situaciones complejas de toma de decisiones y, por lo tanto, finalmente genera un valor añadido considerable en los informes.

Clasificación JEL: MO, Z0

PALABRAS CLAVE

Digitalización, Visualización de *Big Data*, Informes interactivos, Seguimiento ocular, Visualización multidimensional, Diseño de información.

1. Digitalization as a driver for a change in reporting

The increasing degree of digitalization and the decreasing costs of data storage and sensor technology enable the generation and storage of huge amounts of data, which can be retrieved and evaluated on demand to optimally support decision-making. By analyzing the data in a meaningful way, companies hope to gain more knowledge, e.g. about customer preferences or machine maintenance intervals, in order to deduce data-driven and informed actions (Perkhofer, Hofer, Walchshofer, Plank, & Jetter, 2019). As a result, companies tend to continually increase the data stored for future analyses, while currently only being able to effectively use a fraction of the stored data. This data-collecting trend is also visible in the constantly rising amount of annually generated data, which is currently estimated to reach 40 zettabytes in 2020 and is expected to rise to 175 zettabytes by 2025 (Tenzer, 2020).

The storage of data itself, however, does not automatically improve a company's performance. More precisely, a company must change their style of analysis and incorporate the use of statistics not only in strategic decision-making, but more importantly, into the daily routine and into their operative tasks. Working with large amounts of data therefore, increases the required skillset of controllers and accountants. Consequently, controllers must change their focus from *reporting* the past to near-time or real-time *reporting* and they must be able to effectively and efficiently present an increased amount of information from multiple data sources to their users. (Perkhofer, Hofer, Walchshofer, Plank, & Jetter, 2019).

This paper summarizes findings in the fields of "Reporting" and "Information Design" from over eight years of research and introduces promising new *Big Data* visualization options for the discipline of management accounting. It includes survey results on the current use of visual analytics tools and *Big Data* visualization techniques in German-speaking countries, as well as results from international experimental studies on the design and usability of novel and interactive visualizations, and results from laboratory studies on the topic of "Information and Dashboard Design" based on visual tracking and decision evaluation. The reader is thus provided with a comprehensive insight into current and future practices in the fields of "Interactive Reporting and Visualization for *Big Data*".

The remainder of this paper is structured as follows: First of all, there will be an overview on how to increase the efficiency of the decision-making process and decrease the user's mental effort by analyzing visualizations, dashboards and reports with eye-tracking tools. Subsequently, the next part of this paper will provide several empirically tested guidelines to improve the creation of reports and will introduce the reader to a continuous example about a fictitious wine trade to better illustrate the use of traditional business graphics and later on novel multidimensional visualizations. In the fourth and main chapter several *Big Data* visualizations such as the Sankey chart or the parallel coordinates plot will be explained and then illustrated in accordance with the example mentioned above, as well as analyzed in terms of utilization among German-speaking countries based on a survey conducted by the authors in 2017 (target group: managers and employees from finance and accounting, number of participants: 145). The last part of this paper will list and describe several interaction techniques and examine why interaction is crucial in order to be able to use novel *Big Data* visualizations to their fullest potential.

2. Eye-Tracking: A new approach to measure the quality of report designs

The design of reports and the appropriate use of dashboards and visualizations need to be custom-tailored to efficiently and effectively support the decision-making process. This is important as unnecessary decoration and bad design as well as the use of inappropriate visualizations without a specific message, tie cognitive resources without providing additional knowledge.

In this context, authors such as Edward Tufte, Stephen Few as well as Rolf Hichert and Partners (in German-speaking countries) have already developed widely recognized standards and guidelines for the use of business charts such as line, pie, column and bar charts (Eisl *et al.*, 2012; Few, 2017; Guterman & Tufte, 2009; Hichert & Faisst, 2019). Our research complements these recommendations by objectively testing their impact while at the same time tracking a decision-makers gaze behavior. This approach allows for a detailed analysis of various design principles as well as an evaluation of appropriate visualization use given specific topics that need to be visible within the dataset. The results in the following sections therefore summarize a variety of laboratory experiments supported by eye-tracking recordings, which allow not only for an evaluation of static business charts and paper-based dashboards but also for an evaluation of novel and interactive visualizations to present larger and more complex data sets.

Eye-tracking records the sequence in which people scan a report with their eyes. One record (also called scanpath) contains fixations, where the eye movement stops in order to process the presented data, and saccades, where the eye moves from one point of interest to the next without any information intake. Fixations are depicted by circles, whereby the larger the circle, the longer the view. Saccades are represented by lines. By looking at these recordings, the "black box" of visual perception can be made transparent and a distracting design or an inappropriate use of a visualization type becomes visible. Figure 2 illustrates such a scanpath indicating ample room for improvement (Losbichler & Michels-Kim, 2017).

The example in Figure 1 shows two pie charts, each representing revenues by regions –once for actual and once for budget values. The implicit task of such a display is always to track proportions over time and analyze variances. Based on the high number of saccades and fixations presented in Figure 2, it was possible to observe that the participant had considerable difficulties in comparing the two diagrams and thus in completing this inherent task. Therefore, the pie chart visualization may not be considered as perception-optimized. In comparison, the design shown in Figure 3 presents a much cleaner and shorter scanpath, thus indicating higher efficiency in information processing. By additionally recording answers to given tasks, effectiveness can be evaluated as well, which is also part of our experimental design.

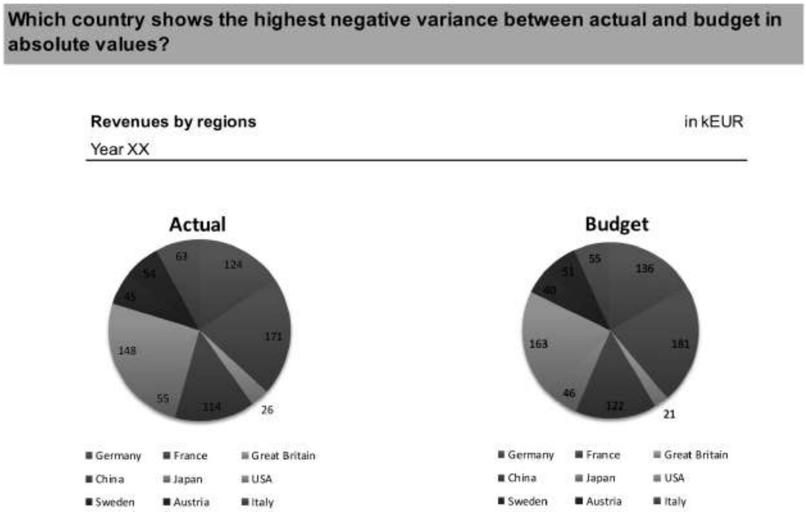


Figure 1. Example of eye-tracking test scenario with specific tasks.

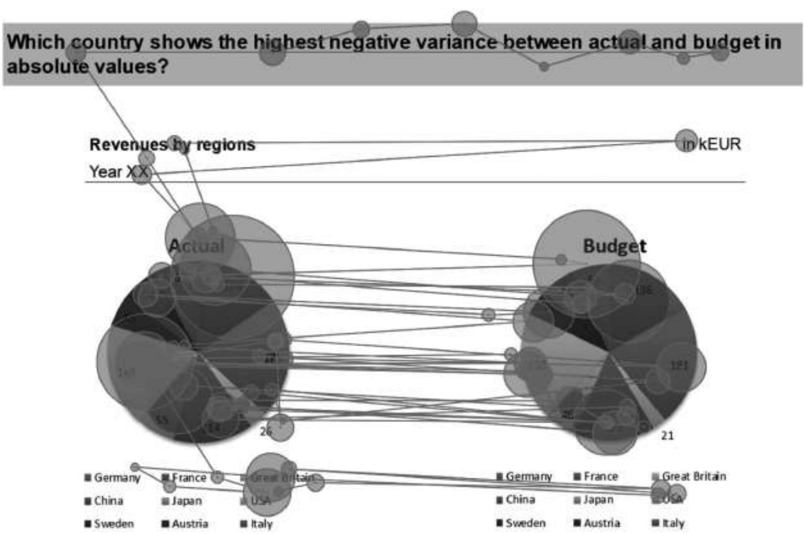


Figure 2. Scanpath indicating bad design and inappropriate visualization use.

The following Figure 3 continues the exemplary presentation of the scanpath shown in Figure 2. However, because the emphasis is on the comparison of the regions, the studies conducted by the authors have proven a bar chart to be perception-optimized. This visualization has both a higher degree of effectiveness (correct perception) as well as a higher efficiency (shorter perception time) than the two pie charts in Figure 2. The improved efficiency of the bar chart is also visible in detail in the lower number of fixations and saccades.

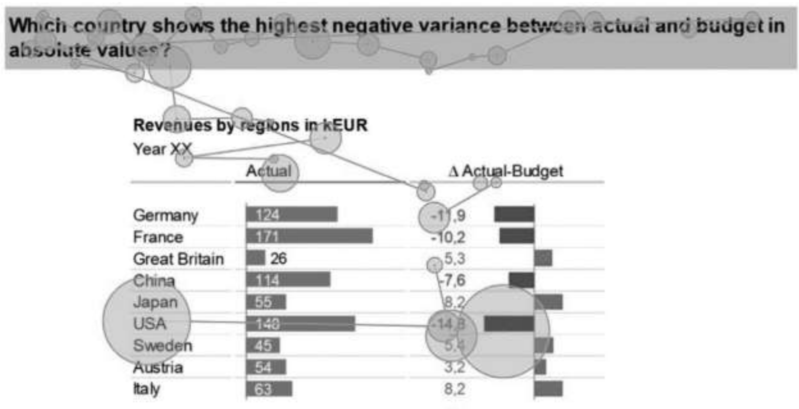


Figure 3. Scanpath indicating user-friendly design and perception-optimized visualization use.

3. Guidelines for optimized and user-centered dashboarding

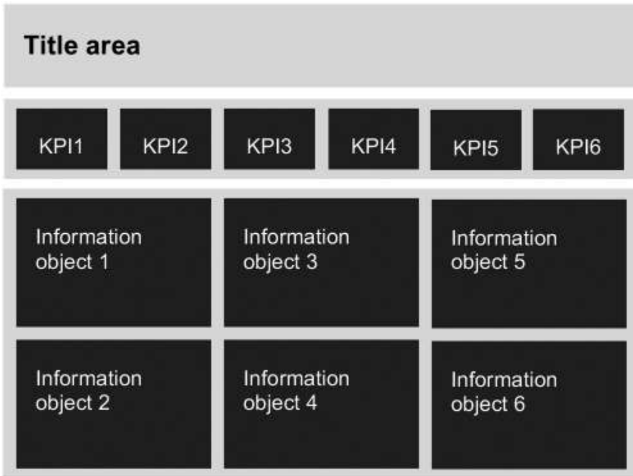
In this chapter, the reader will be introduced to empirically proven guidelines in order to be able to create perception-optimized visualizations and dashboards. In addition to classic *reporting* design guidelines for tables and charts, a further emphasis is on the optimal design of dashboards to increase their usability. With the support of software tools and interaction techniques the usability of visualizations and dashboards can be enhanced even more. Afterwards, in the section of traditional business graphics a continuous example will be used in order to better illustrate the differences between said graphics and novel *Big Data* visualizations.

The guidelines for optimized, user-centered and traditional *reporting* are as follows:

- **Reading direction:** When arranging elements or information objects, the most important content should be positioned in accordance with the usual reading direction from left to right and from top to bottom. Important key figures should therefore be placed at the top left (see Figure 4), as this area is given particular attention (Eisl *et al*., 2015).

Figure 4. Arrangement of the information objects in a dashboard according to the reading direction.

- **Local proximity**: Information in close proximity can be compared with a significantly higher effectiveness and efficiency and thus users are more likely to draw relevant conclusions. The example in Figure 5 shows that KPIs and associated information objects (e.g. with details of actuals or variances from the plan) should be placed in close proximity to each other in order to be able to identify correlations between the comparable KPIs.



- **Amount of information:** The author of a report also has to ensure that the user or decision-maker is not overloaded with too much information. The information processing capacity of humans is limited and a dashboard should therefore not be overloaded. A few but meaningful key figures and information objects are significantly more effective and efficient than a "data graveyard" without a defined structure (Falschlunger, Lehner, & Treiblmaier, 2016). As a rule of thumb, do not exceed six to eight information objects.

- **Interaction:** In order to counteract information overload, supplementary or additional information should only be visualized through interaction. After receiving an initial overview, the user can obtain further details by interacting with the dashboard (see Figure 6). Interaction can be triggered by click or touch, whereby the user either limits or changes the view to certain content (e.g. via filter settings or radio buttons in the title area), displays further information via a tool tip or uses the interaction to switch to another detailed report (further details on interaction are presented in Section 5).

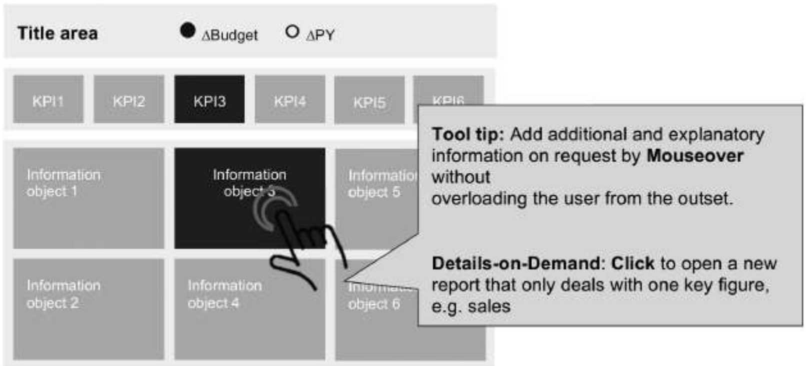


Figure 6. Interaction options in a dashboard.

- **Chart visualization**: In the information design of dashboards, diagrams in particular should be given a high priority. The more complex the data material and the decision-making situation, the more essential it is to use visual elements in order to gain a good overview during the initial analysis (Dilla & Raschke, 2015; Falschlunger, Lehner, & Treiblmaier, 2016). Evolution has led to visual perception becoming the most pronounced sense for human beings. A visual *reporting* system allows multiple processing operations to be carried out simultaneously, thereby increasing both the speed and the quality of decisions (Ware, 2012). To guarantee that a visualization serves its purpose optimally, the "right" type of visualization must be used depending on the task, the data type and the recipient (Perkhofer & Lehner, 2019).

- **Traditional business graphics in an interactive form:** Business graphics or charts include all forms of bar, column, line or pie charts. In connection with *Big Data*, business charts are mainly used in the form of interactive dashboards (Dilla *et al*., 2010). The disadvantage of these visualizations is that information is first summarized for the presentation of large amounts of data, which means that potentially relevant information such as outliers "disappear" (Elmqvist & Fekete, 2010). A major advantage is the high level of awareness of business charts and the knowledge that a majority of report recipients know how to interpret these forms of visualization (Falschlunger, Lehner, Treiblmaier, & Eisl, 2016). Furthermore, no additional software program is required for standard charts, good knowledge of Microsoft Excel is sufficient.

A frequently used visualization type for the presentation of dimensions and attributes is the bar chart. The use of such visualizations in a dashboard is explained by the following business case, which was part of an international experimental series conducted by the authors. The data set of the experiment is a fictitious wine trade consisting of 9,961 records, each record representing the order of a customer. It consists of 14 dimensions (Traders, Grape Variety, State, Continent, etc.) and 12 attributes (Gross Margin, Net Margin, Revenue, Discounts, Gross Profit, Shipping Costs, etc.).

Figure 7 shows a dashboard visualization consisting of four dimensions (Traders, Grape Variety, etc.) and four attributes (Revenue, Trade Margin, etc.). The resulting number of information objects in the dashboard has turned out to be a major disadvantage, thus causing potential information overload for users and impairing their ability to correctly capture and interpret the dashboard. Another disadvantage is that the dimensions cannot be combined with each other or only with difficulty. The question "How many bottles of red wine are sold by Trader "Schenki 1" worldwide?" cannot be answered without creating a new visualization. In addition, a large number of sub-dimensions renders a user-friendly representation virtually impossible. This can be observed in the dimension State, where the number of states is limited to the size of the dashboard element. Even though less information is visualized than in the following multidimensional graphics, the usability in this representation is significantly lower. Only with the interaction zoom is it possible to deduce the number of bottles sold by "Schenki 1" around the globe and the total amount of red wine bottles sold, but it is still not possible to combine these two dimensions in order to answer the above question.

Figure 7. Utilization of traditional business graphics for *Big Data* (A total of 4 dimensions and 4 attributes amount to 16 dashboard elements. Therefore, *Big Data* visualization is needed).

4. *Big Data* visualizations in the usability check

As already mentioned in the introduction, newly developed and interactive forms of visualization should also find their way into business practice in order to deal with the ever-increasing amounts of data. These interactive visualizations are created by visualization experts and data scientists for different purposes (e.g. identification of correlations and clusters, analysis according to one or more hierarchical levels) and can be used in several software tools (Bostock *et al*., 2011).

The pool of novel visualizations for the presentation of large amounts of data is extensive (Grammel *et al*., 2010a; Hofer *et al*., 2018; Perkhofer, Hofer, Walchshofer, Plank, & Jetter, 2019; van Wijk, 2005). For this reason, an extract of possible options for the visualization of *Big Data*, which are especially useful for accounting and controlling professions, is described and illustrated below. Figure 8 provides an overview of the different visualization types used to present *Big Data*.

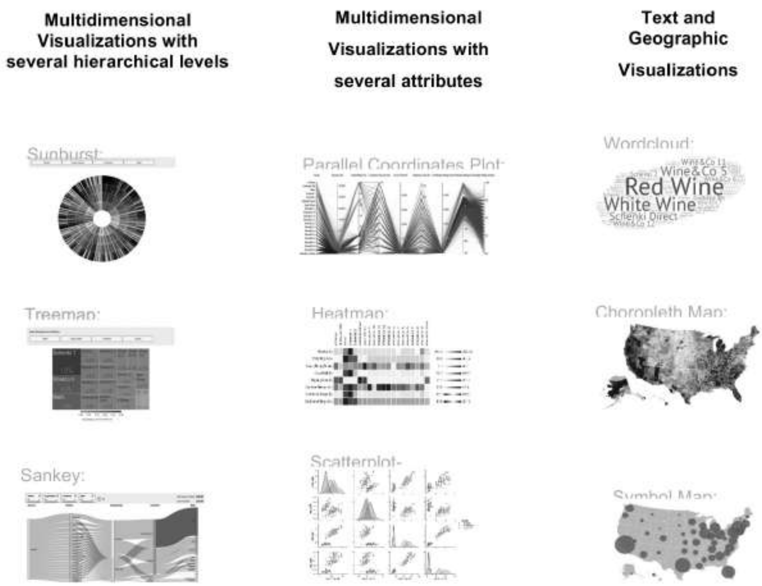


Figure 8. Infographics for the utilized visualization types for *Big Data*.

- **Multidimensional visualizations with several hierarchical levels:** In this category, several hierarchical levels are displayed and arranged according to the corresponding dimensions. This means that an attribute (e.g. sales) can be aggregated or disaggregated in various ways. With only 24,1% usage frequency, this result of the survey among German-speaking companies indicates that these types of *Big Data* visualizations are significantly less well known and less frequently used among participants. The most common forms of multidimensional visualizations with several hierarchical levels are sunburst, treemap and Sankey visualizations. All three were already introduced in Figure 8, whereas the latter is explained more thoroughly in the following example, again referring to the fictitious wine trade data set.

The emphasis of Sankey visualization is on sequences of data, which can either be time-related or dependent on a hierarchical structure (Hofer *et* *al*., 2018). It is often used in elections to present the flow of votes among candidates. This allows voters remaining loyal to the same party to be highlighted as well as those who changed their vote from one election to the other. Therefore, the purpose of the Sankey chart is to present data flows between multiple dimensions (e.g. processes). In terms of providing meaning and storytelling, interactions like arranging (changing the order of dimensions) and filtering (decreasing the amount of visible nodes to minimize visual turmoil) are crucial (Chou *et al.*, 2016). Furthermore, it is essential to use selectors to highlight information across nodes in order to ensure that a thorough analysis of data is possible.

The following Sankey visualization shows the same four dimensions as in the dashboard in Figure 7 as well as the first attribute (amount of sales). The arrangement of the dimensions can be changed at will (Traders can be placed before Grape Variety), thus shifting the focus of the analysis. Below you can see the adjustment of the chart after the arrangement and the selection of "Schenki 1" from dimension Traders and "Red Wine" from dimension Grape Variety. The highlighted connections display the continents and subsequently the states in which "Schenki 1" distributes red wine. In addition, a certain area can be selected and several dimensions can be evaluated in relation to each other. Another major advantage of the Sankey visualization compared to the business graphics dashboard in Figure 7 is the legible presentation of all four dimensions in one visualization. Moreover, the total number of bottles of wine (232.600) and the number of selected bottles are displayed in the upper right-hand corner. The mouseover interaction renders it possible to ascertain the worldwide red wine sales (144.400). In the end, the user can identify the share of globally sold red wine bottles by "Schenki 1" (19.100) and can answer the initially asked question.

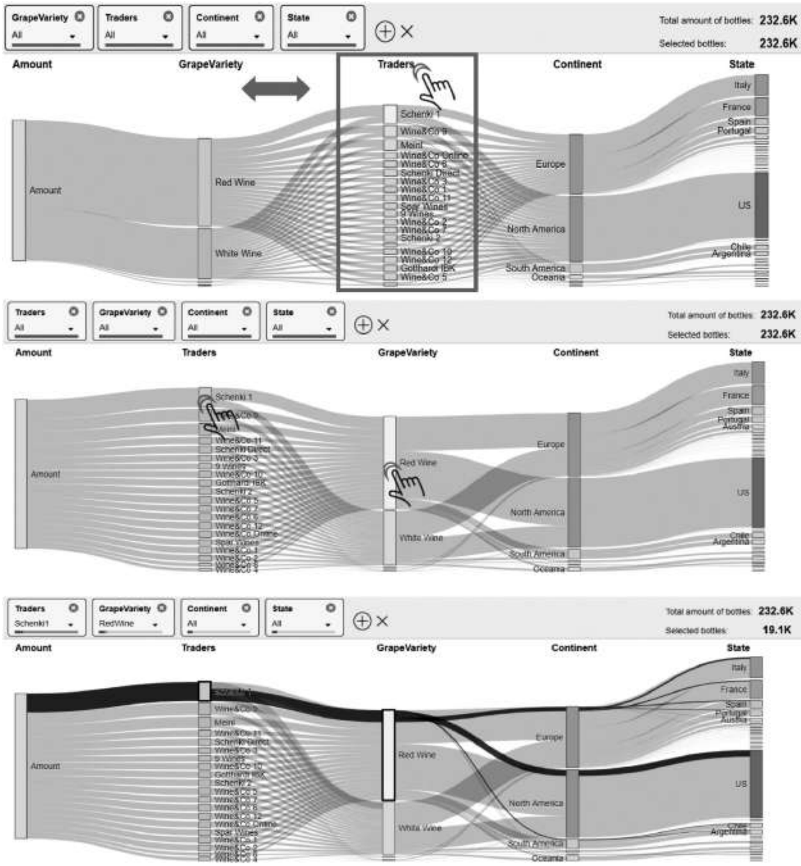


Figure 9. Sankey as representative for multidimensional visualizations with several dimensions (First, the dimensions are rearranged, afterwards the desired dimensions are selected and the connections are highlighted).

- **Multidimensional visualizations with several attributes:** Multidimensional visualizations for the representation of several attributes allow the visualization of large, transaction-based data sets as well as the recognition of further detailed information for the respective, originally presented aggregated data (Hofer *et al*., 2018; Perkhofer, Hofer, Walchshofer, Plank, & Jetter, 2019). This enables the user to recognize and analyze important facts per attribute efficiently and to compare the results of different key figures at a glance. While conventional visualizations allow the display of a maximum of three continuous attributes (e.g. bubble diagram -Y-axis, X-axis and bubble size), new forms can display significantly more of these attributes simultaneously. This is an essential characteristic for recognizing patterns and correlations of attributes (e.g. is a correlation present or not). The disadvantage of this type of visualization is the same low level of awareness as is the case for hierarchical charts (only 13.1% of the surveyed participants already use this type of visualization) and thus the same lack of user experience. In many cases, this leads to reduced effectivity and anomalies in the interpretation of the results (Falschlunger, Lehner, Treiblmaier, & Eisl, 2016). Examples for multidimensional visualizations with several attributes are parallel coordinates plots, heatmap visualizations and scatterplot matrices, which were already mentioned in Figure 8. The parallel coordinates plot is explained in more detail in the following example.

The parallel coordinates plot is one of the few visualizations capable of displaying one dimension in connection with multiple attributes in one chart (Hofer *et al*., 2018). Two or more vertical attribute axes are connected via polygonal lines at the height of the respective dimension value (Keim, D. A., 2002; Perkhofer, Walchshofer, & Hofer, 2019).

The following Figure 10 shows the visualization of key performance figures per Trader (n=20) on differently scaled and parallel placed axes. Each order is represented by a polygonal line to get a general overview of the individual key figures. It is possible to shift the axes and thus examine correlations between all attributes (correlations can be easily estimated with the naked eye using patterns that occur in neighboring axes). In addition, certain areas can be highlighted or filtered for more detailed analysis (multiple selection is also possible). With this possibility, details can be made visible and thus it can be analyzed that the traders in blue (all Traders "Wine&Co" in this example) show unfavorable margins and do not appear in a filtered display focusing on high margins.

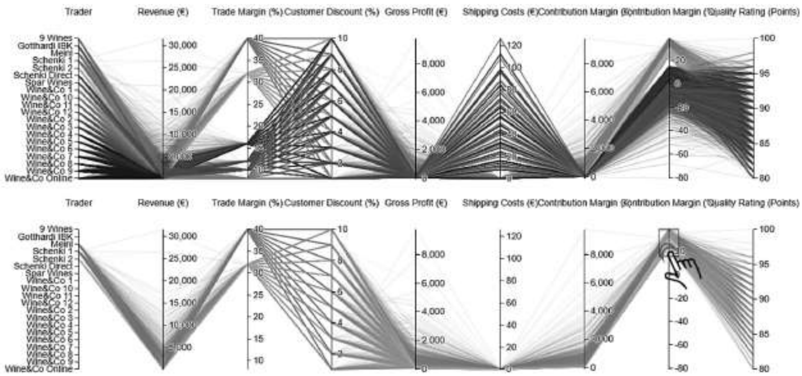


Figure 10. Parallel coordinates plot as representative for multidimensional visualizations with several attributes.

- **Text and geographic visualizations**: Geographical visualizations are the strongest representative of new interactive visualization forms in German-speaking companies. They allow information to be presented precisely in the form of maps. Either GPS data or postcodes can be used for the spatial representation of turnover, sales, or even customer origin areas (MacEachren & Kraak, 2001). Maps are often used as a starting point for the analysis of certain regions, which are characterized by either very high or very low values, to be able to analyze them more precisely compared to the utilization of conventional visualizations. Geographical visualizations are used by 34% of the participants in their own company, while text-based visualizations are used by about 19% to display information. Text visualizations represent the frequency of relevant terms via color and font size. Thus, for example, press releases can be examined for keywords and sentiment. Examples of these two forms of visualization were already mentioned in Figure 8.

Unfortunately, these newer and more powerful forms of visualization have not yet found their way into business practice (Grammel *et al.*, 2010b; Janvrin & Weidenmier Watson, 2017; Perkhofer, Hofer, Walchshofer, Plank, & Jetter, 2019). The study by Perkhofer *et al*. shows that almost 94% of the respondents use traditional business graphics of which over 40% rely exclusively on said graphics. A combination most often occurs with geographical visualizations. An overview of their use is shown in Figure 11. On average, 1.8 different visualization types are used for evaluation purposes. Thus, in addition to the business charts, only one further category is generally used.

Visualization Types	Number	Percentage	
Business Graphics	136	93,8%	93,8%
Text and Geographic Visualizations	77	53,1%	53,1%
Hierarchical Visualizations	35	24,1%	24,1%
Multidimensional Visualizations with several attributes	19	13,1%	13,1%

Figure 11. Application of *Big Data* visualizations (n=145, multiple answers allowed).

5. Interaction as the key to success

Dealing with *Big Data*, it is not only a matter of being able to answer the recipient's questions as quickly and precisely as possible, but also of gaining new, previously unknown insights during the analysis process. It is therefore essential to provide methods for supporting this discovery of correlations and new insights. This process is especially emphasized by the interactive work with *Big Data* and is resulting in the user's stronger analysis of the visualized data (Brehmer & Munzner, 2013; Dilla *et al*., 2010; Perkhofer, Hofer, Walchshofer, Plank, & Jetter, 2019). The user becomes deeply immersed into the data to explain certain striking anomalies or to grasp the full extent of certain events (Pike *et al*., 2009).

The order in which interaction techniques are used by the decision-maker and the way in which techniques are combined with each other is not predefined. This interaction technique constitute a fundamentally individual and user-dependent process (Brehmer & Munzner, 2013; Dilla *et al*., 2010; Liu *et al.*, 2017). For an interaction to be effective and efficient, the user should have the illusion of interacting directly with the visualization. This can only be accomplished through immediate visual feedback when the user clicks or touches the visualization. Furthermore, interaction must never be allowed to "end". There should always be the option to go back one step or to expand the data set after a reduction with the help of a filter or to choose a different focus (Elmqvist *et al*., 2011; Perkhofer, Hofer, Walchshofer, Plank, & Jetter, 2019).

The process of interaction is therefore naturally an individual one, which should optimally support the recipient's knowledge formation and consequently trigger a higher mental commitment and an improved decision-making capability (Pike *et al*., 2009; Shneiderman, 1996a). Interaction allows the user to filter the amount of data presented, to highlight (select) certain parts of the data, to present data in a different order or to alter the visual image (Dilla *et al*., 2010; Elmqvist *et al*., 2011).

The desired results, especially concerning new types of visualization, can only be achieved in an interactive form (the discovery of new, previously unknown connections and insights). After gaining an initial overview of the data, the user should be enabled to highlight and hide data or adapt the visual presentation to his own needs (see Shneiderman's mantra: "Overview first, zoom and filter, then details-on-demand" (Shneiderman, 1996b)). More details on the various interaction techniques are summarized in the table below. This table does not claim to be complete, but is intended to give the reader an overview.

Interaction technique	Description	Reference
Selecting	Selection allows data to be highlighted based on certain options presented to the user. The amount of visible data remains the same, but the highlighted data is moved to the spotlight (e.g. through increased color intensity). It is often possible to highlight or select several elements at the same time. However, the more selectors that are active, the higher the mental demand required on the part of the user. **Examples:** Linking and brushing, drop-down, checkboxes, radio-buttons, scrollable lists, sliders, directly clicking on elements in the visualization, etc.	(Liu *et al.*, 2017) (Johansson & Forsell, 2016) (Brehmer & Munzner, 2013) (Pike *et al.*, 2009)
Filtering	In contrast to selecting, filtering allows the excluded data areas to be hidden. Filtering therefore actively manipulates or limits the amount of visible data. Multiple active filters can be very helpful to identify details along multiple dimensions or facets, however, it is difficult maintaining overview (even more so if filters are not visible). **Examples:** Drop-down, checkboxes, radio buttons, scrollable lists, sliders, directly clicking on elements in the visualization, etc.	(Liu *et al.*, 2017) (Brehmer & Munzner, 2013) (Kehrer & Hauser, 2013) (Pike *et al.*, 2009) (Yi *et al.*, 2007)

Interaction technique	Description	Reference
Navigating	Navigating changes the user's perspective. This can be used, for example, for geographical maps, where it is possible to move the area of interest to user-defined locations (directly by mouse click). **Examples:** Zooming, panning, rotating.	(Johansson & Forsell, 2016) (Brehmer & Munzner, 2013) (Pike *et al.*, 2009) (Yi *et al.*, 2007)
Arranging	The spatial reorganization of elements of a visualization (data dimensions or attributes) is of great importance for representations where only neighboring data sets can be analyzed (e.g. changing axis within the parallel coordinates plot or Sankey visualization). **Examples:** Re-ordering axis, rearranging rows/columns, rearranging the spatial layout if multiple visualizations are involved.	(Liu *et al.*, 2017) (Chou *et al.*, 2016) (Brehmer & Munzner, 2013) (Pike *et al.*, 2009) (Brehmer & Munzner, 2013; Yi *et al.*, 2007)
Changing	Changing refers to altering the visual display itself. It is often referred to as a high-level interaction. However, following and understanding a complete change in the display can be cognitively difficult to process and should therefore be used sparingly. **Examples:** Reconfiguration of the view (change of visualization type, change of color schemes).	(Brehmer & Munzner, 2013) (Kehrer & Hauser, 2013) (Elmqvist *et al.*, 2011) (Pike *et al.*, 2009) (Yi *et al.*, 2007)
Aggregating	Using statistical measures to describe several data points with one measure can be very helpful to get a quick insight into the data Although statistical characterization is a very powerful approach, valuable information is often lost. **Examples:** Mean, median, variance, counts, summations.	(Liu *et al.*, 2017) (Chou *et al.*, 2016) (Brehmer & Munzner, 2013)

Table 1. Interaction techniques.

Interaction techniques support users significantly in exploratory data analysis by enabling them to effectively and efficiently identify patterns, trends or outliers. In the context of *Big Data*, the online survey conducted by the authors (Perkhofer, Hofer, Walchshofer, Plank, & Jetter, 2019) dealt especially with the regular application of interaction techniques, which are already used by companies with the support of their software tools. The results (Figure 12) of this survey show that the most commonly used interaction technique (86 of 145 companies = 59%) is the filtering of data. The second most important is the use of colors and symbols for selecting data (37%). In this case, data series are colored or provided with symbols to enable quick recognition. The average use of 1.7 interaction techniques per participant implies that interaction techniques have seldom been used so far.

Interaction Techniques	Number	Percentage
Filtering of data	86	59,3%
Assigning colour and symbols to data	54	37,2%
Assigning data to axis	48	33,1%
Multiple views of the same data	30	20,7%
Selection of data points for further analysis	27	18,6%

Figure 12. Application of interaction techniques (n=145, multiple answers allowed).

6. Conclusion

Numerous companies and their corporate management are currently challenged by a disruptive change as a result of digitalization. The megatrends of *Big Data* and self-service *reporting* offer new opportunities and lead to a sustainable transformation in the area of *reporting*. Traditional *reporting*, mainly based on obsolete data, visualized with traditional business graphics and supported by Microsoft Excel, is no longer "state-of-the-art" and must be adapted to current requirements. Efficient and agile *reporting* processes require forward-looking, interactive and user-centered information in order to provide management with a relevant basis for decision-making. In addition, our research has shown that efficient BI front-ends such as Microsoft PowerBI, QlikView or Tableau are becoming increasingly important, so-called "enablers" for a novel management *reporting*.

Due to the increasing volume of data from a wide variety of data sources, the authors of dashboards and reports should be careful not to overwhelm the decision-maker with a vast amount of information. The use of selected significant key figures, summarized in close proximity on one page, and the application of design guidelines have been tried and tested for eye-tracking, facilitate perceptually optimized visualizations and user-friendly dashboards. In particular, the means of user-centered interaction and visualization should be used to reduce mental effort and thus enable data-based decision-making. User-friendly data exploration, triggered by clicking on the visualization or touching the screen, allows information to be processed much faster and more analytically through graphical forms adapted to the needs of the user.

In *Big Data* environments, classic reports and dashboards consisting solely of tables, column, bar and pie charts should therefore be supplemented by multidimensional interactive visualization types such as Sankey visualizations or parallel coordinates plots in order to achieve optimal usability in a novel Reporting 2.0. The user gains a better understanding of the data through an initial overall view while trends and correlations between certain attributes can be explored in further analysis steps as required. An early, intensive examination of multidimensional visualizations in *reporting*, whether for the representation of several dimensions or several attributes, can thus provide a decisive advantage in tomorrow's data analysis compared to the competition. These multidimensional visualizations represent an integral component for real-time self-service *reporting* and support the holistic visualization of large data volumes in a *Big Data* environment.

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