An Approach for the Automated Generation of Engaging Dashboards

Ünal Aksu[1(✉)], Adela del-Río-Ortega[2], Manuel Resinas[2], and Hajo A. Reijers[1]

[1] Department of Information and Computing Sciences, Utrecht University, Utrecht, The Netherlands
{u.aksu,h.a.reijers}@uu.nl

[2] Dpto. de Lenguajes y Sistemas Informáticos, Universidad de Sevilla, Sevilla, Spain
{adeladelrio,resinas}@us.es

Abstract. Organizations use Key Performance Indicators (KPIs) to monitor whether they attain their goals. To support organizations at tracking the performance of their business, software vendors offer dashboards to these organizations. For the development of the dashboards that will engage organizations and enable them to make informed decisions, software vendors leverage dashboard design principles. However, the dashboard design principles available in the literature are expressed as natural language texts. Therefore, software vendors and organizations either do not use them or spend significant efforts to internalize and apply them literally in every *engaging dashboard* development process. We show that engaging dashboards for organizations can be automatically generated by means of automatically visualized KPIs. In this context, we present our novel approach for the automated generation of engaging dashboards for organizations. The approach employs the decision model for visualizing KPIs that is developed based on the dashboard design principles in the literature. We implemented our approach and evaluated its quality in a case study.

Keywords: Key Performance Indicators · Dashboard · Visualization

1 Introduction

To determine whether they attain their goals, organizations measure the performance of their business execution. To do so, they use Key Performance Indicators (KPIs). As a means to monitor KPIs, organizations use dashboards that are either developed by themselves or offered by software vendors. A typical dashboard aims to inform decision makers by displaying the information that they

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need to improve the business processes in their organization. In particular, such information is displayed mostly as a table or a graph. By doing so, it adds visual attractiveness to grab the attention of decision makers and enable them to make informed decisions at a glance.

However, most dashboards are poorly designed displays, although adequate technology is used while developing them. Therefore, most dashboards fail to communicate efficiently and effectively since they mainly focus on decoration rather than substance [7,9,12,21,25]. For example, the dashboard depicted in Fig. 1 is an incident management dashboard of an organization[1]. By analyzing this dashboard, one can see that the dashboard goes against the dashboard design principles in the literature. For example, pie charts have many slices that make them unreadable; also, their colors are distracting, which causes misleading associations. More importantly, this is a cluttered design that does not reflect the overall status of the related business processes in that organization. Since there is an overload of information displayed as a cluttered view, decision makers need to spend substantial effort to identify the messages that the dashboard designed to convey. As a result, the dashboard is "not engaging" decision makers to take relevant decisions for improving the performance of their organization.

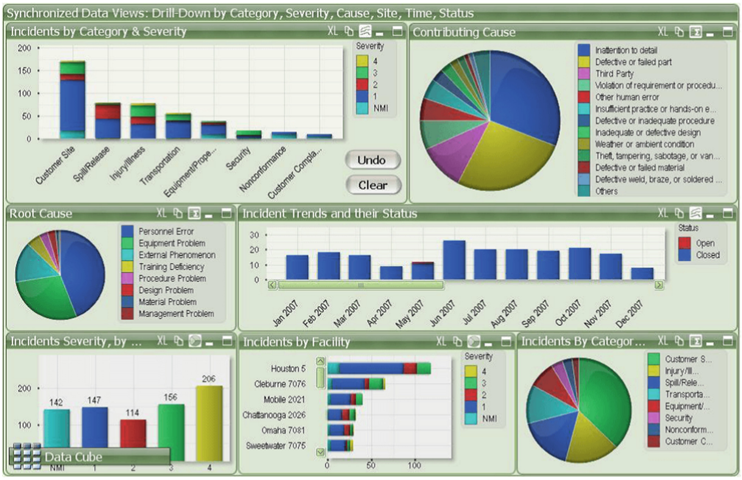

Fig. 1. An example of a non-engaging dashboard

Instead of providing only a fraction of the insight that is needed to monitor business, engaging dashboards communicate in a manner that enlightens decisions makers for informed decisions [4,9]. More specifically dashboards engage decision makers if the available dashboard design principles in the literature [7,11,12,17,19–21,23,25] are used when creating them. Moreover, engaging

[1] The example dashboard is taken from https://adniasolutions.com/dashboard-design-principles/introduction-to-dashboards/.

dashboards enable decision makers to sense and process the displayed information rapidly through the visualization elements, which can be quickly examined and understood without requiring any further interpretation. Not to distract decision makers with overloaded information, the right context for KPIs is visualized such a way that it inspires actions. Besides, "Are we on track?" and "How well is our organization performing its business?" are such questions in organizations to which complete answers can be obtained at a glance in engaging dashboards. Simply put, engaging dashboards do not require any investigation, analysis, or aggregation of the information, which is a must for informed decisions and is distributed inside an organization.

To overcome these issues in the field of dashboard development, several approaches are available in the literature. Within these approaches, mostly dashboards are either developed from scratch for each organization or a template is created and customized for organizations depending on their specific needs. This customization process is carried out by software vendors or by their client organizations. Although organizations may perform this customization process, it still requires a significant effort both from software vendors and organizations [7,9–12]. To deal with that, some approaches [5,13,14,22] focus on the automation of dashboard development. Creating a dashboard template and expressing the structure of a dashboard in terms of the elements of a descriptive dashboard design language are the two prominent ways in these approaches. However, these approaches either cover only a few of the state-of-the-art dashboard design principles [7,11,12,17,19–21,23,25] or require human intervention to incorporate each dashboard design principle consistently. Therefore, the KPIs that are visualized using these approaches still lead to misinterpretations.

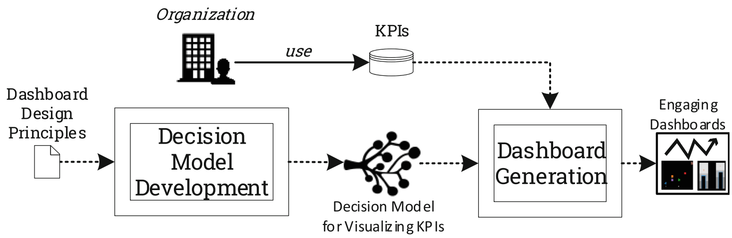

Fig. 2. Our Approach for the automated generation of engaging dashboards

With this paper, we propose a novel approach for the automated generation of *engaging* dashboards for organizations (See Fig. 2). The approach takes a set of KPIs with their attributes and values, as well as a decision model that is developed for visualizing those KPIs as inputs. As such decision models for visualizing KPIs are not readily available, we developed a decision model for visualizing KPIs, which is our second contribution in addition to the approach. The decision model that our approach uses is developed by analyzing the prominent dashboard design principles in the literature, and evaluated to show its common usability. Using the decision model, the approach determines which visualization element will be used to display each KPI on a dashboard. Depending on the attributes and the values of a KPI, a particular table or graph will be chosen as the visualization element. By means of the automatically determined visualization elements for each KPI, we automate the generation of engaging dashboards for organizations. Our approach sets itself apart from the state of the art in conveying relevant messages to decision makers via automatically generated engaging dashboards. Thus, decision makers can make informed decisions to improve the performance of their organizations.

In the evaluation of the approach, first, we check the common usability of the decision model developed for visualizing KPIs in two organizations with experts. Then, in one of the organizations, we execute the approach, and together with experts in that organization, we compare the newly created dashboard with an existing dashboard to see how our approach helps them at making informed decisions. The results that we obtained indicate that this new approach is able to fulfill the needs of organizations for improving their business.

We provide the background on dashboard design principles in Sect. 2. In Sect. 3, we present our approach for the automated generation of engaging dashboards. In Sect. 4, we evaluate the decision model for visualizing KPIs that our approach employs, and then present the results obtained while evaluating the dashboard generated using our approach in a case study. Section 5 is devoted to the discussion of the obtained results. In Sect. 6 an overview of the related work on developing dashboards for organizations is given. Finally, we present our conclusions and directions for future work in Sect. 7.

2 Theoretical Background

Dashboards are pervasive means to display important information at a glance, as needed to achieve objectives. Accordingly, much work has been conducted on developing the dashboards that are communicating important information and engaging. Notably, researchers developed guidelines [1,7,10–12,17–21,23,25,26]. Within these guidelines, they described principles for visualizing quantitative information in dashboards, i.e., dashboard design principles. Simply put, dashboard design principles describe what visual representations (e.g., various graphs) should be used and how they should be used. In this context, we list the dashboard design principles available in the literature.

2.1 Dashboard Design Principles

In the literature, numerous researchers provide various dashboard design principles [1,7,10–12,17–21,23,25,26] to develop dashboards that are communicating important information visually in the most informative way such that organizations can make informed decisions to improve their business. These dashboard design principles are mostly expressed as natural language texts in the form of rules and best practices. Some researchers [1,7,10–12,17–19,26] follow a more structured approach and provide mechanisms (e.g., a table consists of rules for selecting graphs or a diagram shows which graphs should be used in which condition) such that organizations can determine appropriate visualization elements while visualizing certain quantitative information in dashboards. In this context, we identify which of these dashboard design principles for visualizing quantitative information are more suitable to determine sense-making visual elements for displaying KPIs. Accordingly, we take the dashboard design principles that provide comprehensive guidance explained in [7,10–12,17,19–21,23,25] as the sources for developing a decision model for visualizing KPIs. In these sources, eight typical relationships that can be encoded in quantitative information are discussed. We explain each relationship by specifying the visualization elements, which are mostly recommended and used for visualizing that relationship.

Time Series: This relationship is about how a set of values change over time based on particular time units (intervals), e.g., by year, month, day, or hour. Line Graph is the graph that is well-know and mostly used for displaying this relationship. Bar Graphs and Area Graphs are also often used for displaying a time series relationship.

Ranking: How a set of values relate to each other in a particular order is described in ranking relationships. Since bars can be easily understood by any audience and best encode the values in a ranking relationship, Bar Graphs are mostly used to display a ranking relationship in dashboards.

Part-to-Whole: This relationship is about how much the parts of a whole contribute to the whole, i.e., expressing the proportions of a whole. As a common practice, Pie Graphs are used to display a part-to-whole relationship.

Deviation: In this relationship, the focus is on how one or more values in a set of values vary from a reference, e.g., forecast. This is achieved by comparing values with a reference and displaying the degree of that difference. The values that divert from a reference are represented as bars and displayed in Diverging Bar Graphs, i.e., Variance Graph in most of the time.

Distribution: This relationship expresses the way how a set of values are distributed across a particular range that is from lowest to highest. Histogram and Box-Plots are well-known graphs that are usually used for displaying a distribution relationship.

Correlation: How a set of values affect each other is expressed in a correlation relationship. Mostly, two-paired, i.e., categorized set of values are analyzed to see how they relate to each other: whether the values in one set increases or decreases based on the values in another set. Scatter Plot is the most used graph to display a correlation relationship.

Nominal Comparison: This relationship describes a set of values based on a categorical scale without an order. For instance, the revenue of each department in an organization. Bars best encode values on a categorical scale. Bars best encode values on a categorical scale and therefore Bar Graphs are the most common visualization elements used to display a nominal comparison in dashboards.

Geospatial: The values in a geospatial relationship are located based on their geographical location. Spatial Maps are always used for visualizing this relationship.

Although there are many types of graphs for visualizing quantitative information, most of them are not recommended and listed as the graph types to avoid [7,11,12,17,19–21,23,25], such as Pie, Donut, Radar, Funnel, Circle, Area Graphs, or 3D Graphs. The main reason for that is these graphs fail effectively communicating quantitative information and causing misinterpretations. Overlapping shapes, missing scales, hidden values, distracting decoration, and cluttered view are the problems these graphs commonly have.

Within the dashboard design principles available in the literature, researchers provide guidance on using colors, resizing visualization elements, and placing them in dashboards in addition to determining visualization elements. To decide how visualization elements should be placed in dashboards, layout patterns are devised. The most common layout pattern is the Z-diagram layout [3] where readers follow the shape of the letter z while scanning quantitative information. In this regard, we define our visualization element placement strategy in our approach. Moreover, to achieve the consistency in dashboards using colors and resizing visualization elements, there are guidelines in the literature [7,11,12,19,21,23]. Since these visual aspects of dashboard development are not our the main focus of our approach, we use an embedded mechanism, i.e, a fixed set of colors and size values.

3 Approach

This section elaborates our approach for the automated generation of engaging dashboards. The procedure to automatically generate engaging dashboards consists of two tasks, as introduced in Sect. 1: (1) developing the decision model for visualizing KPIs and (2) generating dashboards automatically using the decision model. The second task is automated and takes a set of KPIs with attributes and the values of these KPIs as inputs in addition to the decision model itself. KPIs with attributes and values are taken as input in a "machine-readable" format. For this, human involvement is required. To reduce that human involvement, KPIs with attributes and values are desired to be defined such a "machine-readable" format that enables their automated analysis and computation as proposed in [6].

Unlike the second task, the first task is not automated in our approach. The reason for that is the available dashboard design principles in the literature are in the form of natural language texts. Thus, human interpretation is required to develop a decision model for visualizing KPIs using those principles [7,10–12,17,19–21,23,25]. However, this task only needs to be performed once. The decision model created as its output, and presented in this paper, can be reused in any scenario for the automated generation of engaging dashboards. In particular, it is possible to prune or extend the decision model for a given set of

KPIs of a certain organization, which is part of the second step, the automated dashboard generation. In this sense, the amount of human involvement required will highly depend on the way KPIs are defined, i.e., the amount of information provided for them in their definition and its correspondence with the attributes required by our approach. In this context, we now explain how we developed the decision model for visualizing KPIs, and then give the details of the automated dashboard generation task.

3.1 Developing the Decision Model for Visualizing KPIs

As explained in Sect. 2, we identified the most prominent sources [7,10–12,17,19–21,23,25] for dashboard design principles. Using these sources, we construct a decision model for visualizing KPIs, which is shown in Fig. 3 and encoded as such in our approach. We explain how we construct the decision model by listing our considerations below.

A typical KPI may have a single value or a set of values as quantitative information. For example, the total revenue of an organization or the total revenue of each department within an organization. We take this attribute of KPIs as the top decision point of the decision model (see ① in Fig. 3). Then, we determine how a KPI with a single value and a KPI with a set of values should be visualized using the most common types of visualization elements, namely tables and graphs.

When a KPI has a single value, bar graphs better convey the message of that KPI [7,10–12,19,21,25]. Since a KPI must have a "*target*", that target needs to be displayed in a graph together with the value of the KPI. This can be achieved in the most informative way using a Bullet Graph [7,8,10,12,19,20] since it is a special, simplified bar graph and is designed for visualizing a value along with a comparative measure to enrich the meaning of the value.

If a KPI has a set a of values, then we need to determine the "*purpose*" of the KPI. That purpose can be taking the attention of a decision maker to "*look up*" the values or "*revealing the relationship*" between the values for the decision maker (see ② in Fig. 3). Tables are the visual elements that are designed to look up values [7,10–12,19,21,25]. While constructing a table, it is important to emphasize how individual values in a table relate to the target of the KPI, which is visualized. It is recommended to use a table where the values of the KPI represented are highlighted with colors according to the fulfillment of its target value, e.g. red if not fulfilled and green if fulfilled [7,10,12,19,21,25]. However, in addition to purpose, while looking up values, a KPI may require decision makers to focus on the "*changes of values*" rather than "*individual values*" (see ③ in Fig. 3). This can be achieved by using a Heat Map. In a Heat Map, values are represented by colors, and one can easily determine precise individual values using the color scheme if needed.

When the purpose of a KPI is to reveal the relationship between its values to decision makers, graphs are used. To determine what graphs are particularly useful for specific relationships (see ④ in Fig. 3), we take the relationships as the base that we listed in Sect. 2, and then describe how each relationship can be visualized such that decision makers will be engaged in.

Time Series: Although Line Graph is the commonly used graph for visualizing a time-series relationship [7, 10, 12, 17, 19–21, 23, 25], connecting the data points representing values as a line will cause a misleading communication when the values are not collected "*at a regular interval*". Dot Plot deals with that problem by displaying a time-series relationship in the form of points in which missing values are not displayed. Furthermore, a KPI may aim decision makers to "*focus on the history of changes in values*" over time instead of the values over time (see 5 in Fig. 3). To this end, there is a special graph, namely Sparkline [10–12], which provides a simple and quick view of the history of changes in values at a glance to determine whether there is anything unexpected. Although bar graphs and area graphs are commonly used for this relationship, they miserably fail to show changes over time [10–12], and they especially clutter the display when values are categorized or benchmarked against various comparative measures, e.g., target or forecast.

Ranking: Since a KPI must have a target, a Bullet Graph will perform better than classical Bar Graphs at displaying values along with a comparative measure [7, 8, 10, 12, 19, 20]. If "*changes in rankings over time*" are important, Slope Graph outperforms among other graphs [10–12, 23] since it focuses on the evaluation of rankings between two or more points in time (see 6 in Fig. 3).

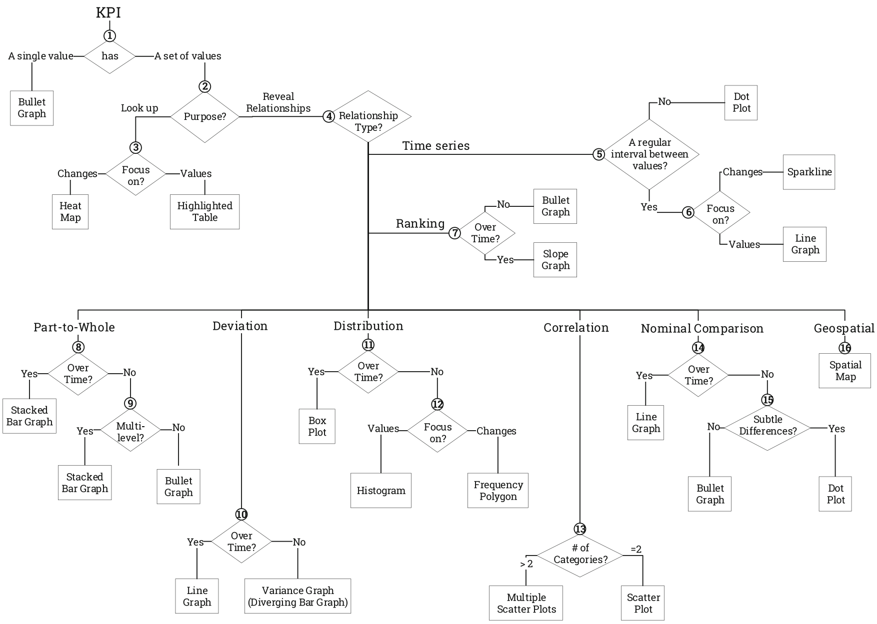

Fig. 3. The decision model used for visualizing KPIs within the approach

Part-to-Whole: Although Pie Graphs are quite often used for visualizing part-to-whole relationships, they are listed in the graphs to avoid [7,10–12,19–21,23,25] due to several reasons. One of the reasons for that is that view will be cluttered when there are many slices, and many of them have similar sizes. Another reason is the common practice of creating a slice named as "others," which mostly causes misleading interpretations [10–12,19,21]. In addition, as seen in many examples [7,10–12,19], the total of slices is not checked correctly, e.g., total does not add up to 100. To overcome these problems, bars are recommended to encode values [7,10–12,19–21,23,25]. While displaying a "*part-whole-relationship over time*" Stacked Bar Graphs outperform among other bar graphs since they will not require the duplication of each proportion for each time unit, which causes a cluttered view [10–12]. When a KPI is solely about a part-to-whole relationship with no time involvement, it is required to check whether a "*multi-level*" hierarchy exists between values (see ⑧ in Fig. 3). For example, the revenue of an organization may be the aggregation of the revenues of its branches, and even the revenue of each branch may be the total of the revenue of various departments. When there is a multi-level hierarchy in a part-to-whole relationship, we select Stacked Bar Graphs. Otherwise, Bullet Graph outperforms than classical Bar Graph displaying a KPI with its target. In Stacked Bar Graphs, the target of a KPI can be displayed using lines with a secondary axis.

Deviation: Since Diverging Bar Graphs perform well visualizing a deviation relationship [7,11,12,21,25] and there are no competing alternatives, we select them for visualizing the KPIs that reveal a deviation relationship. However, to see a "*deviation relationship from a time-perspective*", i.e., how deviations evolve, the Line Graph stands out as the best option [10–12,20,21,25] due to its power of showing things over time in a simple way (see ⑨ in Fig. 3).

Distribution: Although Box-Plots are common in visualizing distributions, interpreting Box-Plots requires specific statistic knowledge [10–12]. To take actions based on the displayed relationship, decision makers will prefer simple graphs that require less effort [7,10–12,19,23]. As the Histogram is a special type of bar graphs and bars are easy to understand by everyone, we select the Histogram (see ⑫ in Fig. 3) as the graph to visualize KPIs when the focus is on values across the range of distribution. If the "*changes of the shape*" of distribution are the main focus, Frequency Polygon (see ⑫ in Fig. 3) outperforms than Histogram [7,10–12,19–21,23,25]. Moreover, when a distribution relationship needs to be displayed "*over time*" (see ⑩ in Fig. 3) we select to use Box-Plots (see ⑩ in Fig. 3) since others will cause a cluttered view [7,10–12,19–21,23,25] due to the duplication of the range of the distribution.

Correlation: Although Scatter plots perform quite well visualizing a correlation relationship, an increase in the number of categories will make a Scatter Plot very complex. As the biggest negative effect of this increase, the readability and interoperability of a Scatter Plot will dramatically decrease since adding categories will hinder some values beyond others. Although circles are used to support the added categories in scatter plots [10,11,20,21,25], they overlap and decrease the understandability when values are closer to each other. Multiple Scatter Plots can be used. In this way, when a correlation between two categories is to be displayed, scatter plots are used. Otherwise, we propose multiple scatter plots to be used. A Multiple Scatter Plot consists of a number of scatter plots where each scatter plot displays the correlation in the values of two categories (see ⑬ in Fig. 3). In each scatter plot, the target of a KPI can be visualized using lines.

Nominal Comparison: As discussed in ranking relationship, instead of Bar Graphs, we select the Bullet Graph due to its simplified and beneficial view where bars best encode a particular relationship. However, if bars become similar in length, detecting the subtle differences between them can become difficult. To capture these subtle differences, a Dot Plot is the most effective alternative in which the scale has no longer need to start at zero, which is a must [7,10–12] for Bar Graphs (see ⑭ in Fig. 3). When the aim is to display a set of values on a categorical scale over time, bars fail since they cause a cluttered view [7,10–12,19–21,23,25] by duplicating each discrete value for each time point. For that reason, we select the Line Graph to show a nominal comparison relationship over time, where a separate line represents each discrete value (see ⑮ in Fig. 3).

Geospatial: The de-facto way of displaying a geospatial relationship is using a map called Spatial Map (see ⑯ in Fig. 3) and no criticism have been found in this regard [7,10–12,17,19–21,23,25].

To execute the developed decision model, it is required to provide the KPI attributes that map to the decision points of the decision model and identify which visualization element needs to be used. In this regard, first, we identified what attributes of KPIs are taken into account while visualizing KPIs within the described dashboard design principles in the literature. Then, we transformed the identified KPI attributes into a single set. Finally, we checked the completeness of the identified KPI attributes against the developed decision model. This check is conducted by controlling the existence of mapping both from each KPI attribute to the decision points in the decision model and vice versa. The identified KPI attributes are listed in Table 1.

3.2 Generating Dashboards Automatically

To generate dashboards automatically in our approach, a set of KPIs with attributes, their values, and the decision model for visualizing KPIs are needed as inputs. These attributes are common attributes described when defining KPIs [6]. The approach determines what kind of visualization element will be utilized for each KPI by applying the given KPIs with their attributes on the given decision model. In particular, a mapping from the decision points in the given decision model is searched for the given KPIs with attributes. The approach completes this search when a visualization element for each KPI is determined. Then, each determined visualization element is created and placed in dashboards, as shown in Fig. 4.

Table 1. KPI attributes required by the decision model

KPI attribute	Definition
Relationship type of values	Describes how the values of the KPI are related. For example, time series, correlation, ranking, part-to-whole, nominal comparison, or distribution
Purpose	Whether the KPI is about looking up its values or revealing the relationship between its values
Focus	Describes what is the focus of the KPI with respect to its purpose attribute. Example values: look up-changes, look up-values, relationship-changes in a time series, relationship-values in a distribution
Time interval	Whether the KPI needs to be displayed over time
KPI values	Describe the quantitative information of the KPI
Categories	The discrete groups in which one or more values exist. For example, the total revenue is a KPI that has a single category, which contains a single value. However, the revenue per department is a KPI that will have a category for each department
Sort direction	Describes how the categories or the values in a category will be ordered, e.g., ascending or descending. This is especially important in ranking and distribution relationships
Multi-level hierarchy	Whether there is a hierarchy or main-sub grouping in the categories attribute of the KPI. For example, main group: region and sub-group: county
Regular interval between values	This will be determined using the attribute time interval. If there is any missing value in the values of the KPI based its time interval, the branch "No" will be selected in the related decision point of the decision model
Subtle difference threshold for the values of the KPI	Describes the limit of the difference between the values of the KPI that should be clearly detectable at a nominal comparison

In addition to the KPI attributes, listed above as required by the decision model, the approach uses a set of KPI attributes while creating dashboards and displaying according to the values of KPIs. Those KPI attributes are listed in Table 2.

To determine how many dashboards need to be created, we defined a strategy so-called Dashboard Creation Strategy in the approach. The strategy is based on the relations between the KPIs of an organization. More specifically, the KPIs that are related to the business processes in a particular process area will be grouped and placed onto a particular dashboard. For example, the KPIs related to the sales process and the KPIs involved in the purchasing process of an organization are combined into the dashboard, Order Management. In addition,

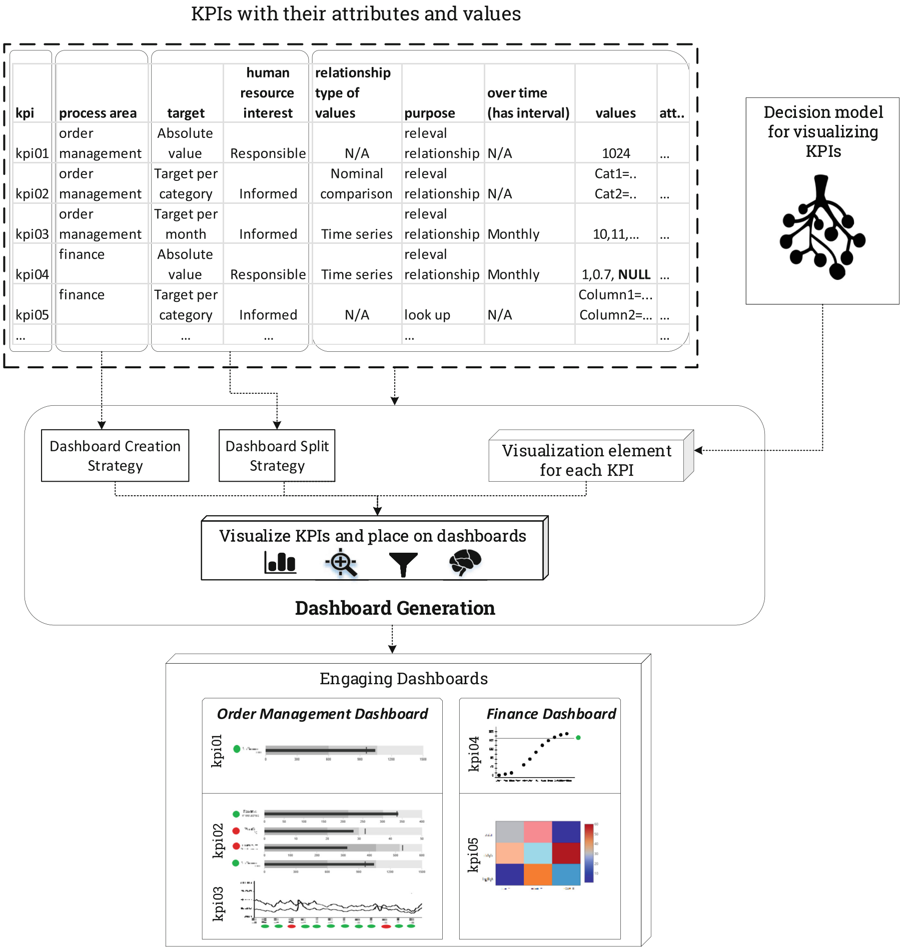

Fig. 4. Generating engaging dashboards for organizations

the KPIs about creditors and debtors are grouped into the dashboard, namely Finance dashboard.

The creation of each determined visualization element for a KPI consists of four tasks: (1) creating the visualization parts for the target thresholds of the KPI on the visualization element, (2) creating the visualization parts for the KPI values, (3) creating the visualization parts for the target of the KPI, and finally (4) combining all parts as a single visual element, e.g., graph or table. In the first task, the approach creates bars and arranges them with respect to the boundaries of target thresholds. Then, in the second task, the approach creates the visualization part in the form of bars, dots, or lines using the KPI values. These forms depend on the determined visualization element. Depending on the type of the target of the KPI (e.g., achievement, reduction, absolute, zero, or

Table 2. Additional KPI attributes required for visualizing dashboards

KPI attribute	Definition
Process area	The category of the business process that is related to the KPI. This attribute is used for determining the number of dashboards that will be created. Example values: order management, finance
Target	The value or value-range that needs to be achieved with respect to the related strategic goals of the organization. The target and its type may change over time for the KPI. Example target values: zero, at minimum €50K, a reduction of 10%, precisely 7 days, or within 1–3 days
Target Thresholds	The set of value-range that shows to what extent the target of the KPI is achieved. Each threshold has a lower and upper bound value. For example, good: [KPI target-10K, KPI target-30K], bad: [KPI target-30K, KPI target-50K]
Human resource interest	Represents the interest of the human resources in the KPI. It can have a value of Responsible or Informed. This attribute is used within the dashboard split strategy of the approach
Name	The textual description used to define the KPI
Unit	The quantity used as the standard for the measurement of the KPI's values. Although this is not important at determining visualization elements, it is essential to convey an informative message via KPIs

min-max), the visual signs that indicate the target are created as a visualization part in the third task. In addition, in the third task, noticeable alerts that indicate whether the KPI and its categories are on target or not (see the cross, check, and warning signs used as alerts in Fig. 5) are created. In the last task, the approach combines all these visualization parts as a single visualization element considering the embedded coloring[2], orientation, and resizing rules for visualization in it. How many categories should be visualized in graphs is determined using an implicit, configurable parameter in the approach. The reason for that is to determine the orientation (horizontal or vertical), which increases the readability. For example, a ranking relationship better reads when it is horizontal and has a maximum of 10 categories where the rest is grouped as "others."

Similarly, to determine how created visual elements will be placed on dashboards is determined using the strategy, Dashboard Split Strategy, that we defined in the approach. In this strategy, the approach creates a flow through a combination of visual weight and visual direction to take advantage of how people read through a design. The created flow splits a dashboard into two areas: top and bottom. By applying the most common layout pattern (the Z-diagram layout [3]), which is recommended for simple designs, the approach defines the route that the human eye travels on these areas: left to right and top to bottom. To determine the order of the KPIs that the human eye should read in this travel

[2] http://colorbrewer2.org is used as the source for color selection.

the approach uses the KPI attribute "human resource interest." The KPIs that have the value "Responsible" in their "human resource interest" attribute will be placed to the top area of dashboards. Then, the KPIs that have the value "Informed" in their "human resource interest" attribute will be placed to the bottom area of dashboards. The KPIs will be ordered in an ascending order based on their names in each area unless there is a particular ordering for displaying KPIs, such as the relevance of KPIs for decision makers.

In the next section, we give the details of the evaluation of both the approach[3] and the decision model for visualizing KPIs.

4 Evaluation

In this section, first, we explain how we evaluated the decision model for visualizing KPIs, which was described in Sect. 3. Then, we elaborate on the evaluation of the proposed approach in a case study.

4.1 Evaluation of the Decision Model

We evaluated the decision model within two organizations, A and B for confidentiality reasons. We did so by discussing our considerations and walking through each path in the decision model together with the experts in these organizations (for more details on their background, see Tables 3 and 4). The experts whom we worked together are actively involved in the dashboard development process in their organizations. We collected their opinions about the decision model using the three-points Likert-type scale (agree, somewhat agree, and disagree). While collecting experts' opinions in each organization, we had an open discussion meeting on the usefulness of the decision model to the needs of each organization at dashboard development. In particular, we gathered opinions related to two aspects of the decision model: (1) decision points, and 2 visualization elements. Then, an average value is calculated for each organization using the collected expert opinions. That average value shows to what extent the decision model is useful to the needs of an organization at visualizing KPIs.

Organization A: In order to automatically generate ERP software from a model, a Dutch ERP software vendor is developing a novel model-driven software generation approach. As part of that approach, a declarative modeling language is being developed that is aimed at modeling an organization's business in the form of an ontological enterprise model. In order to build dashboards automatically for its client organizations with the power of that declarative modeling language, this company is currently investigating how KPIs can be automatically visualized. Since this is highly related to the approach that we propose,

[3] The implementation of our approach for the automated generation of engaging dashboard is available at http://amuse-project.org/software/. In the implementation, two *Python* libraries are preferred: *Plotly* is for visualizing KPIs and *Dash* is for creating dashboards.

Table 3. Evaluation of the decision model in Organization A

Expert	Area of expertise	Years of expertise	Meeting duration (hours)	To what extent agree on the decision points in the decision model	To what extent agree on the visualization elements in the decision model
Software Architect-1	Dashboard development	>5	1	Agree: 13 Somewhat agree: 2 Not agree: 0	Agree: 20 Somewhat agree: 3 Not agree: 0
Software Architect-2	Product management and Information visualization	>20	1	Agree: 13 Somewhat agree: 2 Not agree: 0	Agree: 20 Somewhat agree: 3 Not agree: 0
Manager	Product management and Dashboard development	>15	1	Agree: 12 Somewhat agree: 3 Not agree: 0	Agree: 19 Somewhat agree: 4 Not agree: 0

in this company, we evaluated the decision model. The details of the evaluation of the decision model in this organization are listed in Table 3. As shown in the table, the experts on average *agree* on the decision points and also on the visualization elements in the decision model. Only for a minority of the decision points and the visualization elements in the decision elements they indicated their partial agreement, i.e., somewhat agree. In particular, the experts shared their partial agreement for the following decision points in the decision model: ⑥, ⑫, and ⑮. Similarly, for the visualization elements at these decision points, the experts shared their partial agreement. The experts did not mention any disagreement for the decision points or the visualization elements in the decision model.

Organization B: To monitor the usage of physical resources, the IT department of a Dutch bank uses a dashboard. This dashboard consists of a set of KPIs in which particular psychical resources are monitored with respect to their response rates. A performance management expert maintains that dashboard in accordance with the change requests coming from the performance monitoring chapter lead of the IT department. We followed the same procedure that we explained above as for the evaluation of the decision model in this organization. The details of the evaluation of the decision model in this organization are listed in Table 4. As depicted in the table, the experts agreed on average more than 70% of the decision points and also the visualization elements in the decision model. In addition, only for one visualization element in the decision model a disagreement is mentioned. This was for the Box Plot graph that is identified for visualizing a distribution relationship over time. As in the evaluation in Organization A, we received partial agreement feedback in Organization B for the decision points ⑥, ⑫, and ⑮ in the decision model.

Table 4. Evaluation of the decision model in Organization B

Expert	Area of expertise	Years of expertise	Meeting duration (hours)	To what extent agree on the decision points in the decision model	To what extent agree on the visualization elements in the decision model
Performance Management Expert	Dashboard development	>20	1.5	Agree: 12 Somewhat agree: 3 Not agree: 0	Agree: 18 Somewhat agree: 4 Not agree: 1
Performance Monitoring Chapter Lead	Dashboard design and monitoring	>15	1.5	Agree: 12 Somewhat agree: 3 Not agree: 0	Agree: 18 Somewhat agree: 4 Not agree: 1

In both organizations that we evaluated the decision model, the calculated average value of the usefulness of the decision model for the needs of the organizations is *agree*.

4.2 Evaluation of the Approach

The proposed approach was evaluated in the first organization, which we evaluated the decision model, namely Organization A. In that organization, the three aforementioned experts developed a finance dashboard template to create dashboards for the client organizations of the company. Together with the same three experts whom we worked in the evaluation of the decision model, we created a sample dashboard using that template. After that, the created sample dashboard was used as the *existing dashboard* in the evaluation of the approach. We executed our approach for the KPIs, in total 8, contained in the existing dashboard, and created a new dashboard. Then, together with the aforementioned three experts, we evaluated our approach by comparing the existing dashboard with the *newly generated dashboard*. The results that we obtained are explained below.

As shown in Fig. 5, the KPIs that have implicit target values on the existing dashboard, namely KPI-1, KPI-2, KPI-6, and KPI-7 are displayed differently in the newly generated dashboard than the existing dashboard. These KPIs are visualized as bullet graphs in the newly generated dashboard, since each of them has a single value. Moreover, the target values of these KPIs are also highlighted using a diamond shape; corresponding alerts are added next to each KPI based on those target values. Besides, the approach visualized KPI-4 as a dot plot as that KPI aims to display a nominal comparison relationship. To do so, whether the differences between values are subtle is checked with respect to the given subtle difference threshold by the experts.

Furthermore, the approach visualized 3 out of 8 KPIs, namely KPI-3, KPI-5, and KPI-8 slightly different than the existing dashboard. These KPIs are visualized in the newly generated dashboard in a way such that each KPI conveys its intended message clearly. More specifically, since KPI-3 is about a nominal

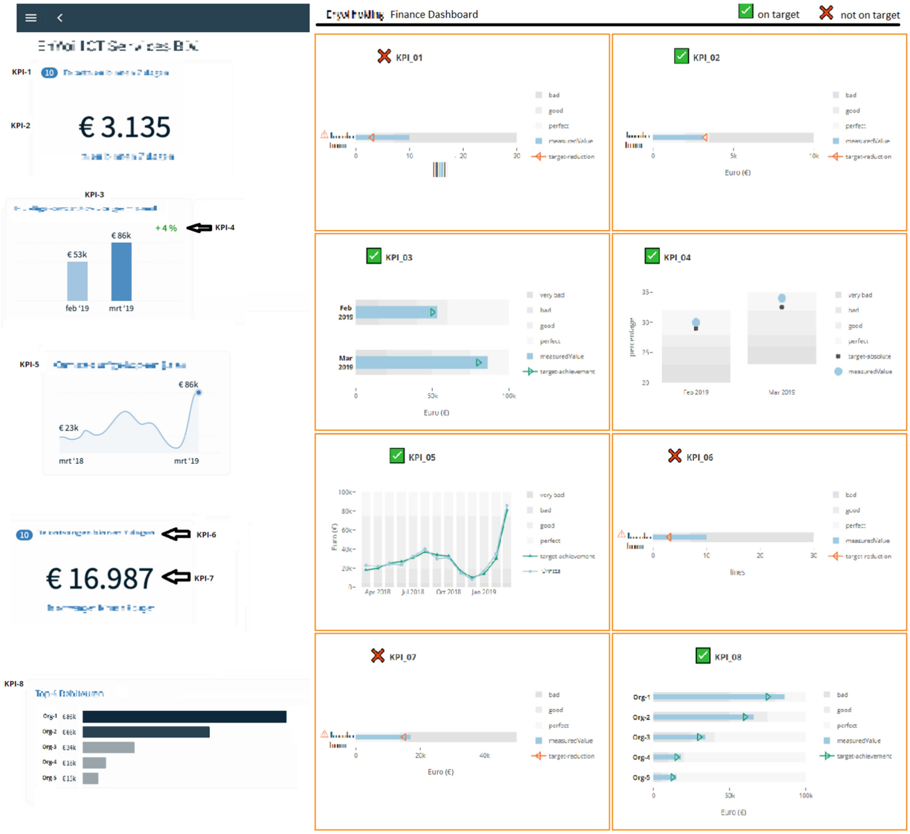

Fig. 5. The existing dashboard (left) in comparison to the newly generated dashboard (right)

comparison and has no subtle differences between its values, this KPI is visualized as a bullet graph. As KPI-5 presents values over time, the visualization element for that KPI has not changed. The only change is the addition of its target. KPI-8 reveals a ranking relationship, and it is visualized as bullet graphs accordingly. For each of these three KPIs, the approach added a noticeable alert next to each graph to indicate target achievement.

Since there were no defined values in the human resource interest attribute of the displayed 8 KPIs, the KPIs are displayed in the top area of the newly generated dashboard and placed in orange boxes, which is the assigned color for the value "responsible" of human resource interest attribute.

To determine the implications of the differences between the existing dashboard and the newly generated dashboard in the evaluation of the approach, we had an open discussion meeting with the experts who were involved in the evaluation of the approach. The experts confirmed that visualizing KPI-1, KPI-2, KPI-6, and KPI-7 as bullet graphs in the newly created dashboard helps them to observe a KPI along with its comparative measure, e.g., target. Similarly, the experts agreed on visualizing KPI-4 as a dot plot as the subtle difference become visible to make precise decisions. In addition, as KPI-1 and KPI-6 are visualized different in the newly generated dashboard than the existing dashboard and become noticeable, the experts decided to check the need for these KPIs. Besides, the experts agreed both on the usefulness of the displayed target thresholds (e.g., perfect, good) and the alerts (cross, check, and warning signs) that display whether the KPIs are on target and to what extent at a glance.

In the following section, we discuss the results that we obtained both in the evaluation of the decision model and also in the evaluation of the approach.

5 Discussion

Regarding the evaluation of the decision model we proposed, as listed in Tables 3 and 4, we obtained a partial agreement for the following decision points in the decision model: ⑥, ⑫, and ⑮. Similarly, for the visualization elements at these decision points, we obtained a partial agreement. The experts who are involved in the evaluation of the decision model expressed that the difference between the visualization elements at these decision points is not big since these decision points are rarely investigated in their organizations while developing dashboards. This shows that our decision model has a wide coverage of decision points, considering even the less common scenarios. Moreover, the experts mentioned that the visualization elements in those decision points, namely Slope Graph, Frequency Polygon, and Bullet Graph are very simple and useful. However, the experts noted that these graphs are not completely supported in most business intelligence software products although they are not very new. This means that our decision model helps organizations to determine simple and useful visualization elements for creating engaging dashboards.

Furthermore, there was no decision point that the experts neither in Organization A nor in Organization B disagree. However, only for one visualization element in the decision model, we received a disagreement in Organization B. This was about the Box Plot graph that is used for visualizing a distribution relationship over time. Since the Box Plot graph requires particular knowledge of statistics to interpret the message of it, especially for decision makers who are not familiar with the Box Plot graph grasping the conveyed message with it may not be easy. However, although there are alternatives, they have more drawbacks we think that required knowledge of statistics can be easily obtained.

As for the evaluation of the automated approach itself, since the newly generated dashboard enabled organizations to check and eliminate the KPIs that are not often a source for decision making in their organization, in that respect, the approach helps organizations to focus on the KPIs that are relevant to their business.

The results of the evaluation confirm that the approach proposed in this paper is of sufficient quality to show its practical usage. On the one hand, as we observed in the evaluation, the newly generated dashboard by the approach can help organizations to clearly observe KPIs along with their comparative measures. On the other hand, the approach enables organizations to focus on the message conveyed via KPIs with engaging visualizations, which is the main substance for wise decisions. Moreover, organizations can detect whether any KPI is not a good source for decision making and avoid misleading communications.

Software vendors that focus on automatically generating dashboards for their client organizations can apply our approach. To do so, these software vendors need to provide KPIs with attributes and the values of these KPIs to our approach in addition to the decision model, which is already encoded in the approach. For obtaining these required inputs, organizations may leverage formal notations for defining KPIs, such as PPINOT [6]. Using them, on the one hand, organizations can reduce their management efforts on KPIs since these formal KPI definitions enable their automated analysis and computation. On the other hand, formally defined KPIs can be integrated into our approach facilitating the automated generation of dashboards.

One of the limitations of the approach is the decision model development task since it is not automated. In addition, our approach is limited to visualizing KPIs as tables and graphs. However, in the literature, there are principles on how to combine multiple visual elements as a single visual element, e.g., multi-panes for visualizing a KPI. Additionally, the visual aspects of visual elements such as fonts, coloring, responsiveness are not covered so far.

6 Related Work

In this section, we list some of the works that relate to the approach we proposed for the automated generation of engaging dashboards.

A model-driven dashboard development approach is proposed in [5] to automatically create dashboards with the code necessary for their deployment. To create a dashboard automatically, the approach requires a dashboard user to model both the dashboard and the related KPIs. Then, an engine executes the model and creates the dashboard with its code. To handle the change management of dashboards, the approach is enriched with the observers [22] who manage the maintenance of dashboards. However, to derive dashboards automatically using this approach, organizations need to have the intensive knowledge required to visualize KPIs in an effective way and should model each dashboard using the notation in the approach. Since these tasks are manual, the approach will require a significant effort of every organization that wants to apply it.

To create customized dashboards automatically considering the requirements of different users, Vázquez-Ingelmo et al. have proposed an approach that uses domain engineering practices [24]. Based on the analysis of the similarities and differences between users' requirements and existing dashboards, a feature model is constructed. The constructed feature model specifies what visualization will be created within a dashboard. Since the approach uses existing dashboards as a base, for each existing dashboard users' requirements need to be obtained. Therefore, using this approach, each organization will need to spend a great effort in addition to the effort for internalizing dashboard design principles.

To visualize KPIs for production planning on a BPMN model in the manufacturing domain, Heidema et al. [13] present an approach. Based on the dashboard design principles defined in [11], the applicability of visualizations are determined in the context of BPMN. Then, a set of KPIs for the manufacturing domain, which are listed in ISO 22400 are automatically visualized on a BPMN model. However, the visualization elements that are supported by the approach are limited. For example, the values in a time series relationship cannot be seen since only sparklines are used, which do not contain values. Moreover, some relationship types are not covered, such as part-to-whole, distribution, correlation, and geospatial. Displaying the values over time in a various relationship is not addressed comprehensively within the approach. Since the approach is dependent on BPMN models, adding visualization elements on the relatively large BPMN models with numerous elements will clutter the view and distract decision makers.

To automatically build a monitoring infrastructure, Koetter and Kochanowski [16] have proposed a modeling language, called ProGoalML for KPIs. The language enables organizations to model their KPIs in their business process models, i.e., annotate the business process models using the language components proposed. Kintz [14] has proposed a dashboard design methodology that can transform the inputs created by ProGoalML to formal KPI definitions, which are required as inputs to derive dashboards automatically by the dashboard engine—a component of the proposed methodology. Kintz et al. have extended the proposed methodology by adding support to create the dashboards that are customized to users [15]. To determine how KPIs should be visualized, from data types to visualizations 4 mappings are employed within the aforementioned methodology. However, in these mappings, it is unclear what the data types imply, i.e., how the data type of a KPI can be determined is not explained. Furthermore, some important relationships in quantitative information, e.g., correlation, ranking, are not covered. Additionally, a data type is mapped to two visualizations in a mapping, which causes ambiguity.

As explained above, to develop the dashboards that are communicating important information and are engaging, each organization, first, has to internalize dashboard design principles, and then apply them. However, this is time-consuming and costly. To provide a solution to these problems, we proposed an approach for the automated generation of engaging dashboards.

7 Conclusion and Future Work

In this paper, we presented a novel approach aimed at the automated generating of engaging dashboards for organizations by means of automatically visualizing KPIs. A set of KPIs with their attributes and values and a decision model developed for visualizing those KPIs are the required inputs by the approach. The approach determines which visualization elements (a table or a graph) will be used to visualize each KPI using the given decision model. The approach creates the dashboards based on the dashboard creating strategy encoded in it, and then places the built visualization elements on dashboards using the dashboard split strategy, which is also encoded in it. Since the available dashboard design principles are not in the machine-readable form, we described how a decision model for visualizing KPIs can be devised.

To evaluate our approach, we conducted two tasks: an evaluation of the developed decision model and the evaluation of the created dashboards using our approach. The former was carried out in two organizations: an ERP software vendor and a bank. The latter was done with the ERP software vendor. In both tasks, we conducted the evaluation by informal interviews with the experts in the organizations who are actively involved in dashboard development. As a result, we showed that the approach enables organizations focusing on the messages conveyed via KPIs with engaging visualizations to make informed decisions for improving the performance of their organizations. In most recent approaches, visualizing KPIs is a manual endeavor and needs to be carried out in every single organization. Thus, we feel confident to that our approach lowers the efforts of software vendors for developing engaging dashboards for their client organizations and the efforts of these organizations doing this themselves.

In future work, we want to extend our approach by adding predictive technologies. In particular, we want to predict the values of KPIs such that decision makers can take preventive actions instead of corrective actions, which costs more to improve the business processes in their organizations. Moreover, to provide insights for organizations by means of the benchmarks that are developed using the relevant KPIs for them, we plan to integrate this approach with the approach we presented in [2]. In addition, we will add the support for automatically providing the consistency of visual aspects (e.g., colors, size, and spacing) in dashboards.

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