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Jonas Gunklach
Karlsruhe Institute of Technology (KIT), jonas.gunklach@kit.edu

Katharina Jacob
Karlsruhe Institute of Technology (KIT), katharina.jacob@student.kit.edu

Sven Michalczyk
Robert Bosch GmbH, sven.michalczyk@de.bosch.com

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BEYOND DASHBOARDS? DESIGNING DATA STORIES FOR EFFECTIVE USE IN BUSINESS INTELLIGENCE AND ANALYTICS

Research Paper

Gunklach, Jonas, Human-Centered Systems Lab, Karlsruhe Institute of Technology, Karlsruhe, Germany, jonas.gunklach@kit.edu

Jacob, Katharina, Human-Centered Systems Lab, Karlsruhe Institute of Technology, Karlsruhe, Germany, katharina.jacob@student.kit.edu

Michalczyk, Sven, Robert Bosch GmbH, Stuttgart, Germany, Sven.Michalczyk@de.bosch.com

Abstract

With the proliferation of Business Intelligence and Analytics, data storytelling has gained increasing importance to improve communicating analytical insights to business users and support decision-making. While conceptual research on data storytelling suggests that these techniques can help improve decision-making, there is a lack of prescriptive knowledge on how to design data stories in Business Intelligence and Analytics. Moreover, it is not understood how data stories can facilitate effective use and support decision-making of business users. To address this challenge, we conduct a Design Science Research (DSR) project. Drawing on the theory of effective use and data storytelling techniques, we propose three design principles that we instantiate in a prototype. The results of two focus groups indicate that enhancing dashboards with data storytelling techniques increases transparent interaction and representational fidelity. Our DSR project contributes novel design knowledge for data stories that facilitate effective use.

Keywords: Data Storytelling, Business Intelligence and Analytics, Theory of Effective Use, Design Science Research

1 Introduction

In today's business environment, organizations rely on Business Intelligence & Analytics (BI&A) to make smarter and faster decisions (Trieu et al., 2022). In this regard, BI&A is defined as all "techniques, technologies, systems, practices, methods, and applications that analyze critical business and market and make timely business decisions" (Chen et al., 2012, p. 1166). To support decision-making, organizations specifically make use of dashboards to provide decision makers with a comprehensive overview of key performance indicators (Abbasi et al., 2016). Dashboards are "visual displays of the most important information needed to achieve one or more objectives; consolidated and organized on a single screen so the information can be monitored at a glance" (Few, 2006, p. 34). To create such dashboards, contemporary tools like Tableau are great aids to extract insights from data (Toasa et al., 2018). However, the visualization of data alone does not create value for users – the insights contained must be properly communicated to the right users in the right format (Watson, 2017). Recent research has highlighted several user-related challenges associated with dashboards, ranging from problems regarding the usage of dashboards to their interpretation to derive insights (Lennerholt et al., 2021). According to Lennerholt et al. (2018) users with limited analytical skills, often referred to as business users (Michalczyk et al., 2021), find it difficult to interpret and understand the content of dashboards. Dashboards must find a compromise in presenting data in a way it does not overwhelm the user, and presenting all information necessary (Ali et al., 2016). Toreini et al. (2022) also conclude that dashboard users face difficulties in managing their limited attentional resources when processing the presented information. Consequently, achieving effective use of dashboards for business users remains a challenge (Ruoff and Gnewuch, 2021).

"The benefits that organizations accrue from information systems depend on how effectively the systems are used" (Trieu et al., 2022, p. 645). According to Burton-Jones and Grange (2013), effective use of information systems (IS) involves three core elements: transparent interaction, representational fidelity, and informed action. Business users need to unimpededly interact with dashboards to obtain faithful representations (e.g., data visualizations), which ultimately enables them to take informed actions (e.g., make business decisions). Therefore, dashboards need to be designed to facilitate transparent interaction and representational fidelity.

To bridge this gap, data storytelling has attracted research interest as an approach to improve the quality of individual data interpretation and decision making (Boldosova and Luoto, 2019). The narrative structure of data stories facilitates knowledge acquisition because they positively influence the processing of information (Glaser et al., 2009). As a result, information conveyed through stories is easier to process and generates more attention and engagement in listeners than pure fact-based communication (Dahlstrom, 2014). The practice of storytelling dates back to the earliest forms of human communication and has always been used to pass knowledge from generation to generation (Joubert et al., 2019). But nowadays, storytelling has lost none of its importance. The advertising industry uses storytelling as an effective technique in the creation of brand images to inspire, entertain, and persuade customers by appealing to their emotions and attention (Casado-Aranda et al., 2021). In education, storytelling is successfully used as a communication technique to improve reading comprehension, teach math, and explain science (Rahiem, 2021). Further, data storytelling is also rapidly gaining prominence in digital journalism with significant adoption by small and large publishers (Ojo and Heravi, 2018).

Most research papers agree that data storytelling relies on data as well as visualizations and narrative elements to communicate the insights from the data appropriately for the target audience (Lee et al., 2015; Segel and Heer, 2010). Data storytelling can provide insights in a way that is easy to understand for audiences without analytical backgrounds, such as business users, by adding more information about the data and its context (Ojo and Heravi, 2018; Watson, 2017). According to Ojo and Heravi (2018), there is an ongoing discussion about which principles of data storytelling are effective. While conceptual research on data storytelling (Boldosova, 2020; Elias et al., 2013; Herschel and Clements, 2017) suggests that including data storytelling techniques can help improve decision-making, there is a lack of prescriptive knowledge on how to leverage data storytelling techniques in BI&A. Moreover, it is not well understood whether and how these techniques facilitate effective use and support decision-making of business users. Following Segel and Heer (2010), we apply data storytelling techniques to dashboards to create a data story. Hence, we articulate the following research question:

How should data stories be designed to facilitate effective use for business users?

To address this question, we conduct a Design Science Research (DSR) project (Kuechler and Vaishnavi, 2008). Drawing on the theory of effective use (Burton-Jones and Grange, 2013) and existing design knowledge for data storytelling, we synthesize design principles (DPs) for data stories in the context of BI&A. Afterwards, we design and implement a data story based on the identified DPs and evaluate the data story using two confirmatory focus groups with a global supplier for technology and services.

Our paper contributes to the body of design knowledge by demonstrating how data storytelling techniques can be applied in the context of BI&A to increase transparent interaction and representational fidelity in order to achieve effective use of data stories. The proposed DPs are based on existing guidelines for data storytelling and are grounded in the theory of effective use. In particular, we contribute with three DPs for data stories in the context of BI&A. Hereby, our work represents an improvement in the DSR knowledge contribution framework according to Gregor and Hevner (2013), as it represents a more efficient and effective solution for a known problem. For practitioners, we demonstrate how data storytelling techniques can be implemented in current dashboards to support business users in the implementation of data stories (Jones and Gregor, 2007).

2 Foundations

2.1 Business Intelligence & Analytics

BI&A refers to techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an organization understand its business better as well as to make timely business decisions (Chen et al., 2012). Following Chae and Olson (2013) and Chaudhuri et al. (2011), there are four essential technological elements of BI&A in organizations: (1) infrastructure, (2) data management, (3) analytical tools, and (4) reporting tools. To support decision-making, BI&A systems are generating insights by utilizing analytical techniques and then visualizing the insights in the form of dashboards (Rikhardsson and Yigitbasioglu, 2018). Dashboards hold a key role in the analysis of data and visualization of information (Lavalle et al., 2019) by supporting decision-making on operational, tactical, and strategic levels across all business domains of an organization (Sarikaya et al., 2019). A dashboard is an interactive information visualization tool that simplifies the process of exploring and extracting data insights from large amounts of data by presenting smaller and more understandable pieces of that information through different visual components (Kumar and Belwal, 2017; Watson, 2017). An essential factor in the successful implementation of BI&A solutions is whether the system is capable of supporting the skills of the targeted user (Michalczyk et al., 2020). While the specific contexts may differ, dashboards are usually designed for business users who are familiar with the application domain and use the dashboard regularly for their daily work (Ruoff and Gnewuch, 2021).

2.2 Data Storytelling

Data storytelling can be described as the process of preparing and presenting information appropriate to the target audience from the results of data analysis to motivate a decision (Neifer et al., 2020). Lee et al. (2015) characterized the data storytelling process as comprising three major phases – (1) exploring data, (2) making a story, and (3) telling a story. Exploring data involves activities centered around exploring and analyzing data - the result is a collection of chosen data excerpts (i.e. specific facts supported by data) (Lee et al., 2015). To make a story, the data excerpts gathered need to be assembled into a meaningful storyline that is interesting and compelling (Ramm et al., 2021). Finally, telling a story includes building, sharing, and evaluating the story (S. Chen et al., 2020). Therefore, creating data stories requires a combination of analytical, technical, and communication skills (Lee et al., 2015). Hereby, several data storytelling techniques such as narratives (structuring, highlighting, and transitions) as well as narrative structures (ordering, interactivity, and messages) are used (Segel and Heer, 2010). Segel and Heer (2010) closely links the goal of storytelling to that of visualization which includes communicating information in a psychologically efficient format. Therefore, data storytelling combines the benefits of narratives in terms of increased audience engagement and improved communication of insights with the benefits of data visualization (Kosara and Mackinlay, 2013).

2.3 Theory of Effective Use

The benefit that organizations obtain from an information system is determined by how effectively it is used by its intended users (Trieu et al., 2022). Effective use is defined as “using a system in a way that helps attain the goals for using the system” (Burton-Jones and Grange, 2013, p. 634). Their conceptualization of the theory of effective use is based on representation theory, which states that the purpose of an information system is to faithfully represent a real-world domain by relying on deep structure (specification of a domain offered by an information system), surface structure (interface that allows users to access and interact with the representations), and physical structure (devices supporting the other structures) (Burton-Jones and Straub, 2006). Effective use is formed as an aggregated construct formed by three dimensions, that influence each other: (1) transparent interaction, the extent to which a user can access the system's representation; (2) representational fidelity, the extent to which a user obtains a faithful representation of the domain; and (3) informed action (Burton-Jones and Grange, 2013). By enabling more transparent interaction, access to the system is improved and the obtained representation of the domain is more faithful. In turn, the higher representational fidelity improves the ability to take informed action by enhancing the user's knowledge and capabilities in the domain. Thus, the states of the user in each of the three dimensions jointly determine the level of effective use perceived from the system use (Burton-Jones and Grange, 2013). For example, users of a dashboard need to access accurate business information (transparent interaction), such as how the performance of products evolved over time (representational fidelity), to make timely business decisions (informed action). By designing data stories, we rely on adaption actions to positively influence effective use by improving (1) the system's representation of the domain of interest and (2) the user's access through the system's surface structure (Burton-Jones and Grange, 2013).

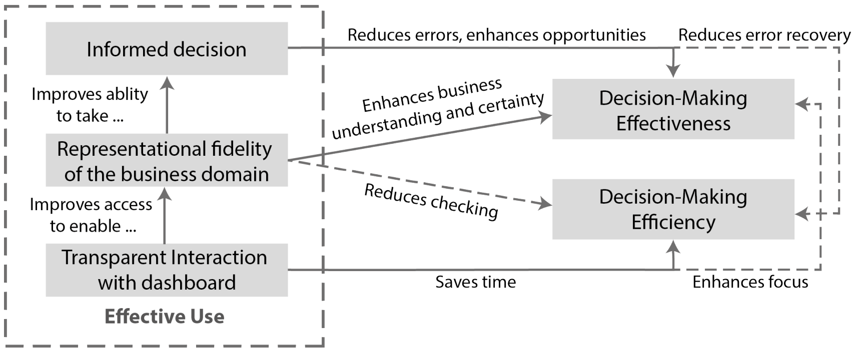

Figure 1. Theory of Effective Use (based on Burton-Jones and Grange (2013) and Trieu et al. (2022))

3 Method

3.1 Design Science Research

To design data stories that can be effectively used in the context of BI&A, we follow the design science research (DSR) approach as described by Kuechler and Vaishnavi, 2008. We argue that this research approach is suited to address our research question as it allows us to integrate existing design knowledge for data storytelling (Ojo and Heravi, 2018; Segel and Heer, 2010), descriptive knowledge from the theory of effective use (Burton-Jones and Grange, 2013), as well as empirical results from interviews to derive DPs for data stories in the context of BI&A.

Awareness of Problem: In order to better understand the problems business user face when they are relying on dashboards to inform business decisions, we started our research by conducting a literature review. Subsequently, to further sharpen the awareness of the problem and we relied on semi-structured interviews with 12 business users of a global supplier for technology and services. In qualitative research, semi-structured interviews are a flexible approach to explore and understand the perceptions, opinions, and experiences of respondents (Kallio et al., 2016). Our sample spans the business domains of product management, controlling, and purchasing. We relied on business users to explore their experiences when using dashboards for their daily tasks to explore data and derive decisions. We divided the semi-structured interviews in three parts: (1) general questions about the participant's role in the company and daily tasks, (2) questions about problems when using dashboards, and (3) an assessment of whether certain data storytelling techniques could be used to solve the problems. Concluding the awareness phase, we consolidated and integrated the results of the interviews with the issues identified in the literature using MAXQDA.

Suggestion: To investigate how data storytelling techniques can tackle the issues identified in the awareness phase, we conducted a literature review on data storytelling. Based on literature, the results of our interviews, and the effective use theory as a kernel theory, we derived six meta requirements (MR) and concluded three DPs for data stories in the context of BI&A.

Development: We instantiated the DPs in a data story implemented in Microsoft PowerBI.

Evaluation: We conducted two focus group evaluations. Focus groups reveal the collective view on a topic of interest of a group of selected participants and provide the usefulness of the data story in field use (Tremblay et al., 2010). Following Tory et al. (2022), we conducted two focus group evaluations to cover the two overarching goals encountered by dashboard users: (1) lightweight analysis activities to gather information, and (2) sensemaking and translating data for various audiences. In the first focus group, we invited business users from various departments, that work with the data less frequently for single tasks. The second focus group consisted of business users, that require a profound and collaborative analysis of the data monthly. Both focus groups consisted of six participants and followed the same procedure.

After a brief introduction of the goal and procedure of the confirmatory focus group, we presented the data story and underlying DPs to the participants. They have to actively interact and use the data story. Afterward, questions regarding the data story and DPs were discussed. Next, we explained the Strength-Weakness-Opportunity-Threat (SWOT) analysis method to the practitioners which we used to structure the evaluation of the DPs. Subsequently, we gave participants time to write down their perceived strengths, weaknesses, opportunities, and threats on index cards. Finally, the index cards were read out loud and explained by the respective practitioner, providing the researchers with the possibility to ask follow-up questions on recurring points. We recorded both sessions with the consent of the practitioners. We transcribed and analyzed the audio recordings using MAXQDA. Following Vitalari (1985), our coding scheme was based on the concepts of effective use (e.g., transparent interaction, representational fidelity, informed action) and the relationships between them. Second, we combined the cards of participants with similar meanings based on the results of the initial coding. Subsequently, we derived first-order concepts from these groups. For example, we merged "arrangement in sequence instead of in one view enhances focus" and "narratives present all information related to insight and reflect key messages" to the first-order concept "More self-explanatory: all information in one view" and mapped it to the corresponding DP.

3.2 Literature Review

To get a comprehensive overview of current data storytelling literature, we conducted a literature review following the guidelines of Arksey and O'Malley (2005) that consists of five stages: (1) identify the literature review research question, (2) identify relevant studies (3), select studies, (4+5) summarize and report the results. According to Schryen et al. (2021), scoping reviews aim to describe the scope and nature of the existing literature and therefore provide a sound basis for establishing DPs. Following Arksey and O'Malley (2005), our research question for the literature review was: *"What is known from existing literature about data storytelling for data visualizations"*.

The search string used for the database search was created in several steps. First, we conducted an initial exploratory search on Google scholar using the terms *"Data Storytelling"* OR *"Data Stories"* OR *"Data Story"*. In reviewing the results, we found the term "narrative visualization" to be a frequently used synonym for data storytelling, especially in older literature (e.g. Hullman and Diakopoulos, 2011; Hullman et al., 2013; Segel and Heer, 2010). We further added the term *"data journalism"* because much literature on data storytelling has appeared in this field (Jarke and Macgilchrist, 2021). To cover all literature on data storytelling, we divided our search string into two parts: The first part covers all papers using synonyms for data storytelling (e.g., "data stories", "narrative visualizations"). The second part covers articles investigating "storytelling" or "narratives" in (1) "data visualization", (2) "information

visualization", (3) "visual analytics", and (4) "business intelligence". Finally, we used Boolean-operators and wildcards to create the final search string:
"data storytelling" OR "data-driven storytelling" OR "data stories" OR "data story" OR "narrative visualization" OR "data comics" OR "data journalism" OR (("storytelling" OR "narrative") AND ("data visualization" OR "information visualization" OR "visual analytics" OR "business intelligence"))*
We selected IEEE Library, WebOfScience (WoS), and Scopus for our literature review as these databases are well-established and used by scholars as reliable sources for literature reviews (e.g. Bandara et al., 2015; Llave, 2017). To offer a holistic overview, we have not limited our literature review by year or publication outlet. Using this search string, we found 272 results at IEEE, 394 results at WebOfScience, and 1249 documents at Scopus in April 2022. After eliminating duplicate literature found in multiple databases, we were left with a total of 1507 papers. In the selection process, we manually excluded 1281 articles by carefully scanning the title-, abstract-, and keyword-section and by applying the following selection criteria: We included articles that investigated the implementation and evaluation of data stories. We also excluded articles that relied on data storytelling techniques in virtual or augmented reality, videos, or comics as these media formats are not frequently used in BI&A. Following the same criteria for a full-text review, 48 articles remained. Lastly, we performed a forward and backward search and included another 25 studies (in total, 71).
The identified articles can be classified into three categories (see Appendix): Articles investigating (1) the effects of data storytelling (#18), (2) data storytelling techniques (#46), and (3) data storytelling frameworks and processes (#7). To ensure inter-coder reliability, the studies were independently selected and assigned by two researchers, and any discrepancy between the two coders' findings was discussed and resolved by consulting a third researcher (O'Connor and Joffe, 2020). For example, we originally had one additional category *"data storytelling design principles"* but due to overlaps we merged it with *"data storytelling techniques"*.

4 Results

4.1 Awareness of the Problem

In the following, we present the results of the problem awareness along the two main dimensions of effective use: (1) transparent interaction and (2) representational fidelity. Based on the literature, we derived eight key issues (KI) business users face when using dashboards from the current literature. In the second step, we confirmed their relevance in practice through interviews with business users.
Transparent Interaction: To facilitate the effective use of dashboards, business users must have unimpeded access to the domain representation through the physical and surface structure of the dashboard (Burton-Jones and Grange, 2013). Tory et al. (2022) identified one issue in insufficient skills and knowledge of business users on how to operate the dashboard. Users do not receive sufficient guidance on how to properly use the dashboard features to interact with the dashboard transparently through its interface structure (**KI1**). Being able to actively explore the data yourself and make comparisons between data points of interest is a critical part of the decision-making process (Koesten et al., 2021). Therefore, dashboards do not support users sufficiently in exploring and comparing the data on their own (**KI2**). Ajani et al. (2022) concluded that cluttering the visual surface with too many visual elements such as color patterns, gridlines, and other highlighting elements, increases the cognitive load and can negatively influence guiding the viewers to a certain pattern in the data. Hence, it is unclear if the consolidated view in dashboards providing all relevant information at a glance is loaded with too many visual elements (**KI3**).
Representational Fidelity: To enable effective use, the representations the user obtains from the dashboard should faithfully reflect the business domain being represented (Burton-Jones and Grange, 2013). Based on literature, we identified the following key issues that threaten the ability of users to get a faithful representation from dashboards. In the studies from Vornhagen et al. (2021), some users acknowledge

that the dashboard they used does not accommodate their data needs and intention of use. Different users have different levels of domain knowledge and analytical skills, and thus different requirements regarding data aggregation and explanation (Dykes, 2019). If the dashboard does not accommodate the user's requirements in terms of the included data, aggregation level, and explanations, the dashboard does not provide unimpeded access to representations faithful for the user (**KI4**). Vornhagen et al. (2021) identified, that the identification of the data visualization purpose was a major challenge for some users in the sensemaking process of a dashboard. In studies conducted by Koesten et al. (2021), participants commonly reported the need to know and understand the original purpose of data analysis to successfully place the data into its real-world context. If the dashboard is not focused and does not communicate the intended purpose to the user, business users struggle to understand the received representations, which affects representational fidelity (**KI5**). Further, business users criticized that dashboards contained too little information about how the original data was filtered, transformed, or modeled to verify the insights they contained (Kandel et al., 2012). Without information about the data sources as well as the data preparation steps, business users do not understand and trust the results presented in the dashboard, limiting the faithfulness of the representations (**KI6**). In addition, Vornhagen et al. (2021) and Kandel et al. (2012) identified, that business users are not able to interpret the results if the dashboard does not supply them with sufficient data field definitions, labels, or tiles. Without further context and explanation (e.g., various KPIs), users have difficulties fully understanding the representations obtained from the data and drawing wrong conclusions (**KI7**).
In Table 1, we consolidated the issues identified in the literature with 12 interviews with business users to explore whether the employees were affected (X = affected, N = not affected, P = partially affected, (empty) = not mentioned).

	Key Issues	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
KI1	Users need guidance to use the dashboard	X	N		N	X	X	X			X	X	X
KI2	No sufficient self-selection and comparison of data		X	P	X	X	X		X				X
KI3	Cluttered visual surface		X	X	N		X						X
KI4	Dashboards do not accommodate different users		X	N	X	X	X	X	X		X	X	X
KI5	Purpose of the dashboard unclear	X		X			X			P	X		X
KI6	Background information about data & data preparation steps not sufficient				X			X	X	X	X		
KI7	Users need explanations for displayed information (e.g., KPIs, columns)	X		X	X	X			X	X	X	X	X

Table 1. Key issues from literature and interviews

4.2 Suggestion

To address the identified key issues of dashboards, we leverage data storytelling techniques proposed in literature and applied the theory of effective use to formulate six meta requirements (MR). Using MAXQDA, we qualitatively coded the identified studies of the literature review and integrated the results to derive the following MR and DP. Building on the theory of effective use, we argue that data stories that allow users to have unimpeded access to the system representation (transparent interaction) and obtain faithful representations (representational fidelity) can positively influence informed actions and thus facilitate effective use. Consequently, we formulate five MR based on the dimensions of effective use: To increase representational fidelity, data stories should contain a set of data-based story pieces, each of which is visualized and presented in a meaningful sequence (Lee et al., 2015). To apply this to the context of BI&A, the first DP suggests including a narrative structure that visually conveys the key insights by sequentially presenting them in a meaningful order (**MR1**). These individual visualizations should be linked together in a logical sequence that conveys the key insights in an understandable way (Hullman et al., 2013). To create a visual path that conveys the insights in a logical order and thus increases transparent interaction, Segel and Heer (2010) also suggest arranging data visualizations in a logical sequence and including appropriate transitions between the views. Further, presenting key insights sequentially in separate views rather than in a single view reduces the cognitive load on business users

MR	Description	KI	Supported by Literature
1 (TI + RF)	The data story should include narrative elements that present the insights in sequential order.	1, 3, 5	Dimara et al. (2021), Yau et al. (2019), Koesten et al. (2021), Lee et al. (2015)
2 (TI + RF)	The data story should allow interaction with the underlying data.	1, 2, 6	Elias et al. (2013), Yau et al. (2019), Boldosova and Luoto (2019) , Koesten et al. (2020)
3 (RF)	The data story should highlight and explain relevant insights.	6, 7	Tory et al. (2022), Sarikaya et al. (2019), Lee et al. (2015)
4 (RF)	The data story should only contain relevant information.	4, 6	Ajani et al. (2022), Lin et al. (2018), Kandel et al. (2012), Echeverria et al. (2017)
5 (RF)	The data story should accommodate different business users' data perspectives.	4, 7	Michalczyk et al. (2021), Ramm et al. (2021), Vornhagen et al. (2021), Knaflic (2015)

Table 2. Meta requirements (TI = transparent interaction, RF = representational fidelity)

(Segel and Heer, 2010). Through the sequential presentation of the data, the visual interface, and thus the surface structure of the data story maintains a clear focus to the relevant information. By reducing data visualizations to the essentials and highlighting relevant data (**MR3**), users can understand the key insights more efficiently and effectively (Ajani et al., 2022).

DP1: *To improve (1) transparent interaction and (2) representational fidelity, the data story should include a narrative structure that visually conveys the key insights by sequentially displaying simple, separated visualizations and highlights of relevant data values.*

To increase transparent interaction, Lee et al. (2015) suggest to add annotations and text-based explanations to the data story (**MR3**). Thus, **DP2** proposes to provide further guidance for business users. Guiding business users through the data interpretation process further increase their efficiency and effectiveness (Morana et al., 2017). Adding explanations to the data and visualizations to the narrative structure (proposed by DP1) also improves how business users understand data (Boldosova, 2020). Those explanations can also be used to explain important functionalities to business users. Stolper et al. (2016) further suggest adding context about the underlying data preparation process (**MR2**) through the purposeful use of annotations and other textual elements. Business users must be able to explore data for themselves in order to understand the presented insights (Alpar and Schulz, 2016) which increases the system's representation of the domain of interest (Burton-Jones and Grange, 2013).

DP2: *To (1) enhance transparent interaction and (2) increase the fidelity of the representation received from the system, the data story should provide guidance for the business user in the form of text-based explanations and annotations that include additional information about the visualization and underlying data.*

To increase the accuracy of the domain representations and structure of organizations, DP3 suggests adapting the data story to different user roles by including various user perspectives that the user can choose from (**MR5**). According to (Michalczyk et al., 2021), this is necessary as business users cover a wide range of business domain knowledge. Ramm et al. (2021) also acknowledge the fact that different user roles are targeted by data stories. Neifer et al. (2020) therefore suggest matching the data story to the individual requirements of the targeted user roles and presenting only the relevant data for that user (**MR4**). Potential data perspectives could relate to the business domain (e.g., marketing, supply chain management, finance) or specific user roles (e.g., logistics controller, HR manager).

DP3: *To improve the accuracy of the domain representations provided, the data story should be adapted to different user roles and requirements by including various data perspectives that the user can choose to quickly access relevant insights.*

4.3 Development

To instantiate our DP, we implemented a data story and relied on the data story creation process proposed by Lee et al. (2015) consisting of three main phases: explore data, make a story, and tell a story. The purpose of the data story is to help business users evaluate the monthly performance of various product groups by highlighting poorly and well-performing products to derive actions for improvement. We developed the data story in collaboration with a business user from the industry partner to ensure that the data story includes all relevant information.

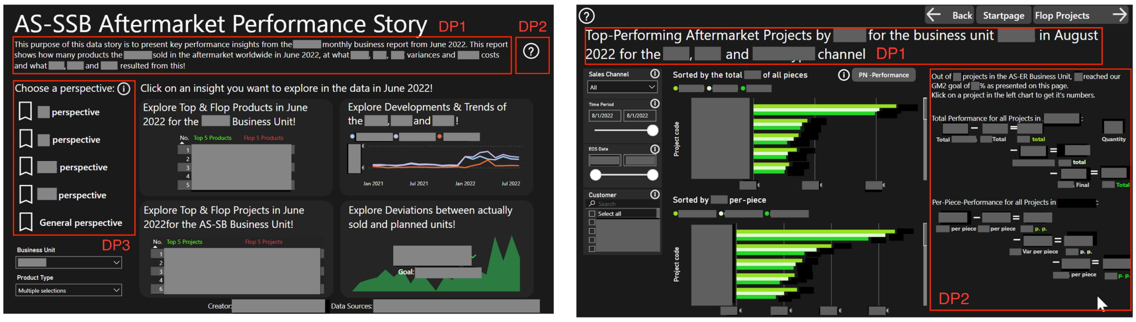

Figure 2. Overview page with introduction (left) and view with sub-story (right)

During the **explore data phase**, we analyzed the data and identified four different data excerpts relevant for the data story: performance of products, (2) performance of projects, (3) trends in performance, and (4) deviations of plan or target values. We further spoke to business users to confirm the relevance of the data excerpts. In the **make a story phase**, we implemented an overview page that introduces the purpose of the data story and explains the general narration. Specifically, we implemented the user-driven path through the overview page, from which the users can select the sub-stories they wish to explore and return to at any time. This way, business users can decide for themselves in which order and to what extent they perceive the story, since the interviews revealed that not every sub-story has the same relevance for all users and the sub-stories do not have a natural order. We assembled the data excerpts into a meaningful sequence by linking them in a logical sequence to convey the main purpose of our data story. In the **tell a story phase**, we created for each insight a sub-story relying on the assembled sequence (**DP1**). To build a narrative structure, the sub-stories are displayed in separate views through which the user can navigate using forward- and backward buttons (McKenna et al., 2017). In each sub-story, we followed an author-driven path to present the insights from the data excerpts (Stolper et al., 2016). Possible design features for DP1 relate to the arrangement of story excerpts in a meaningful storyline for business users. For that, we created various charts to visualize the insights. Using the "smart narrative" feature from Microsoft PowerBI we embedded text-based summaries of the insights presented in the data visualizations (**DP2**). "The smart narrative visualization helps you quickly summarize visuals and reports [...] as it provides relevant innovative insights that you can customize" (Microsoft, 2022). We customized the smart narratives by including calculations not visible in the visualizations to help business users better understand the data visualizations. The smart narratives also adapt to individual data points the user selected in the data visualization and provided details and explanations about the data. In addition to that, we provide on-demand explanations by including a help button in every view that redirects the user to the help page with more profound explanations of the data story and the interaction with the specific sub-story. Next, to increase data transparency, we visualized the transformations and calculations made in the data model. For instance, we visualized and explained the calculations of included KPIs (e.g., calculation of total performance for all projects). We also included an information button next to important data visualizations to provide the users with a short description of the components and functions to correctly interpret the visualizations and enable the users to interact more efficiently with them. Business users also can drill down to more detailed views and raw data. For further guidance, we used a traffic light color scheme in the data visualizations to highlight the performance insights and suggest their interpretation. For DP2, possible design features could be information buttons, visualizations of data transformations including calculations, and text-based summaries of insights. Finally, we take in different user perspectives (i.e., HR perspective, controller perspective) in the overview page to provide business users with the option to adapt the data story to their specific requirements (**DP3**). In particular, we implemented user perspectives using bookmarks in Microsoft PowerBI. With the bookmark, we defined user-specific data filter configurations to determine which visuals, and thus which sub-stories, are accessible to a specific user perspective. Using the user perspectives, sub-stories adapt to the required information for the specific user role.

4.4 Evaluation

To evaluate the data story, we conducted two confirmatory focus groups (Tremblay et al., 2010), each with six practitioners of our industry partner. Following Tory et al. (2022), focus group one consisted of business users that work with the data every month to derive insights for management, while focus group two consisted of business users that work with the data less frequently for simple tasks. Following Morana et al. (2014), we analyzed the focus groups using a SWOT analysis. Figure 3 represents the results of both focus groups combined.

In **focus group one**, participants stated that the narrative structure (**DP1**) helps them to use the data story more effectively. One participant stated: *"I am rather a friend of two-pagers or three-pagers because then you really tell the story"*. The business users reported that they liked the sequential presentation as the information is easier to process: *"If too much information is presented in one view, I often do not know where to look first and what information is really relevant"*. They concluded that the narrative structure helps to understand the purpose of the visualization and thus prevents misinterpretation of the data. A weakness of DP1 is that it makes *"comparing data a larger effort [...] which leads to users possibly having to switch back and forth between different views"* (W2). To improve that, one participant suggested an *"introduction or conclusion view with navigation progress like sections and breadcrumbs"* (O1). As a thread, participants feared that especially experienced business users may require more information at a single glance (T1). In general, the participants liked the fact that data stories provide guidance in form of annotations and text-based explanations that include additional information about the visualization and the data it contains (**DP2**). Participants mentioned that *"the explanations present all the information necessary for the analysis as well as the key messages in one view"* (S4). They conclude that *"especially novice users, or users who have not worked with the data for a longer time, are supported in understanding the insights"* (S7). The information buttons with business domain hints and also the explanation are found to be especially helpful (S5). However, too long explanations for optional insights and on the help page were mentioned as a weakness (W3). They suggested that *"detailed explanations on how to use the data story correctly should be displayed on separate help pages"* (O3). In addition, the natural language summaries of displayed charts provided no real benefit for the participants as they had no problems interpreting the shown charts (W4). Participants mentioned that a further opportunity for improvement could be to include information in the natural language representation by appending information that is not visible in the charts (O4). They mentioned that the natural language summaries could support people with visual impairments to interpret the data story which is currently not possible with a dashboard (O6). While guidance in data stories is especially helpful for novices and insight sharing with others, participants concluded that it is "less useful for people who know the data well and users will need fewer explanations over time" (T2). Moreover, participants considered **DP3** as particularly helpful. They stated that *"the user perspectives and adaptation of data slices to different requirements of the users are an intuitive and fast option to access the required data"*. The user perspectives *"enable users to quickly find their orientation and adapt the data to their needs"* (S7). The participants concluded that adapting the data story to specific user roles, tasks, and skills helps them to reach relevant insights faster (S8).

	Strengths	Weaknesses
DP1:	S1. Clearer, uncluttered display of one selected insight per view S2. Great for meetings S3. Great for novice users	W1. More effort to get to specific values W2. More effort to compare data
DP2:	S4. More self-explanatory: all information required to understand insight in one view S5. Optional hints improve understanding S6. Explanation of KPIs S7. Great for novice users	W3. Explanations use too much space, text too long W4. Summaries of charts in natural language provide no benefit W5. Can seem overwhelming
DP3:	S7. Quick access to desired data excerpts S8. Explanations are adapted to users	W6. Manual selection of user perspective
	Opportunities	**Threats**
DP1:	O1. Include the conclusion or navigation progress section O2. Increase usefulness for collaborative work	T1. For experienced users (1) too little different information at a glance (2) larger effort to use
DP2:	O3. Display detailed explanations in a separate view O4. Include information not visible in charts O5. Highlight important information O6. Summaries of charts in NL for people with visual impairment	T2. Guidance is less useful for users who know data well
DP3:	O7. Selection of user perspectives automatically	

Figure 3. Summary of the SWOT analysis

In **focus group two**, participants had mixed opinions about the narrative structure (**DP1**) implemented in the data story. For one-time usage of the data story, they liked the sequential presentation of insights. One participant stated: *"The data story feels like an automated presentation of data for management to present all insights and results in an understandable way"* (S1). They perceived that the narrative structure is suitable for presenting insights in regular meetings (S2). To improve the data story, they suggested adding collaborative features for meetings or presentations (O2). In addition, the participants also responded that *"novice users or users who rarely work with the data"* benefit the most from DP1 (S3). As a weakness, participants had problems finding the required information for their specific tasks: *"Getting an overview of the data and quickly comparing two values requires more time"* (W1). One participant even concluded that he likes "dashboards that provide the information at a single glance more than the narrative structure of data stories". As a thread, participants perceived that there is too less information presented at a glance for experienced users which makes operative analysis tasks slower (T1). Regarding **DP2**, participants reported that the additional guidance in form of explanations and additional data insights made the data story more self-explanatory. One participant reported: *"The arrangement between insights on the right and explanations on the left is clear, I could imagine relying less on other employees to understand the data story"* (S4). Further, the explanation and business calculation of KPIs were seen as one strength of DP2 as it *"helps to understand and interpret the shown data"* (S6). The use of tooltips, which are accessible through a button to provide explanations and additional information on demand was well received by participants, as it *"conserves space and keeps the interface simple"* (S5). As a weakness, participants named that the narratives take up to much visual space and the texts are too long: *"It makes it more difficult to distinguish important from unimportant information"* (W5). Similar to the findings of focus group one, the natural language summaries of the charts provided no benefit for the participants (W4). In particular, they concluded that the explanations are less useful for users who are familiar with the data and the data story (T2). Related to **DP3**, the participants stated that the user perspectives are *"intuitively understandable and allow to quickly select the appropriate user profile"*. Further, the separation of data was logical for them and the user perspectives provided a good overview of the information contained (S8). They liked the different user perspectives but perceived the manual selection as a weakness (W6). As an opportunity, they suggested switching from a manual selection to an automatic selection of user perspectives by using their organizational role including the business division (O7). To conclude, participants considered the user perspectives as particularly helpful.

5 Discussion

While conceptual research on data storytelling (Boldosova and Luoto, 2019; Elias et al., 2013; Herschel and Clements, 2017) generally suggests that including data storytelling techniques can help improve decision-making, there is a lack of prescriptive knowledge on how to design data stories in the context of BI&A. Moreover, it is not well understood whether and how the use of data storytelling techniques can facilitate effective use and support decision-making of business users. To address these problems, we conducted a DSR project to investigate the design of data stories in BI&A. Drawing on the theory of effective use, we examine how data storytelling techniques can facilitate the effective use of dashboards. In the first cycle of our DSR project, we proposed three DPs which we instantiated in a data story. We conducted two confirmatory focus group evaluations with our industry partner. The results suggest that applying data storytelling techniques to dashboards helps business users to understand and interpret business information. The results further indicate that using data storytelling techniques is particular helpful for novice users. Therefore, our DSR project provides valuable theoretical contributions and practical implications that we discuss in the following:

First, our research contributes to the body of design knowledge on data storytelling to inform business decisions. The results of our evaluation suggest that the narrative structure and sequential presentation of information can increase the transparent interaction of business users with data and thus help them to use the data story more efficiently (DP1). This DP is especially helpful for novices who have not seen the data before or for presentations in meetings. Furthermore, the additional guidance in form of explanations and data insights makes the data story self-explanatory, which in turn leads to improved transparent interaction (DP2). The explanations of business KPIs were most useful to novice users. Finally, the user perspectives allow business users to quickly find relevant data and customize it to their needs (DP3). Since a key factor in the successful implementation of BI&A solutions is whether the system can support the skills of the targeted users, adapting the system to users in the organization is critical to improving representational fidelity. Taken together, our research shows how the theory of effective use can be applied to improve the interaction of users with data stories and advances our understanding of how users interact with them.

The study's findings also have important implications for business users as well as organizations seeking to build or improve their data storytelling competencies. Based on our DPs, we offer a real-world implementation of a data story. Furthermore, within our study, we encourage business users to utilize the proposed DP and data story structure as a template while developing their own data stories. In this regard, business users can rely on the storytelling creation process by Lee et al. (2015). By applying data storytelling techniques to the context of BI&A, organizations will be able to make better decisions faster (Vora, 2019). Furthermore, we could imagine for future research to incorporate the identified DPs in data journalism articles and study their impact. Our evaluation suggested that organizations need to provide trainings to improve storytelling competencies. As discussed by Knaflic (2015), business users do not necessarily have formal training in data storytelling. Trainings in data storytelling will help business users to communicate and utilize information more effective (Daradkeh, 2021). To realize the value of storytelling, we advise business users to closely cooperate with the business domains to identify and create the story overview and sub-stories. Another promising attempt to support business users in the creation of data stories could be by including guidance in current data visualization tools (Ceneda et al., 2017). Data visualization tools could offer recommendations in form of data excerpts based on existing dashboards that analysts then can use to create their data story. Data visualization tools like Tableau started to implement data storytelling features that automatically generate narratives from visualizations (Avido, 2022). However, the creation of data stories is still a predominantly manual process (Shi et al., 2021).

Finally, there are some limitations of our work that should be considered. First, the data story is tailored to the issues of business users of one large company. We tried to address this by (1) incorporating issues from literature, (2) conducting a literature review on data storytelling to systematically derive DPs, and (3) interviewing business users from different business domains (i.e. product management, controlling, and purchasing). But due to a large number of products and the organization of the product portfolio, the interviewed business users may have different problems when using dashboards than in smaller organizations. Second, the data story was created in the controlling business domain. We focused on this business domain because controlling dashboards are also used in other business units. However, a data story in another business domain may require different data storytelling techniques. Finally, we used two confirmatory focus groups to evaluate the impact of the data story on the facilitation of effective use. Although we argue that this approach is appropriate due to the innovative nature of data storytelling, further research using a quantitative evaluation is needed and could provide additional insights on the effective use of data stories in the context of BI&A.

6 Conclusion

This paper reports the results of the first cycle of the DSR project investigating the design of data stories in BI&A. Our DSR project contributes with design knowledge that can be applied to facilitative effective use by offering three DPs that suggest including (1) narrative structure by presenting information sequentially, (2) guidance in form of text-based explanations and annotations, (3) data perspectives that the user can choose to quickly access the insights relevant for him. The DPs were derived based on the theory of effective use, current data storytelling literature, and empirical insights of business users. To cover current data storytelling literature, we conducted a literature review. We instantiated our DPs and developed a data story relying on performance data. Finally, our evaluation of the data story in the form of two confirmatory focus groups with an industry partner demonstrates the potential of our proposed artifact.

Appendix

Category	Articles
(1) Effects	Ajani et al. (2022), Bateman et al. (2010), Borkin et al. (2013), Bower and Clark (1969), Boy et al. (2015), Boy et al. (2017), Claes and Vande Moere (2017), Daradkeh (2021), Dykes (2019), Echeverria et al. (2017), Herschel and Clements (2017), Kim et al. (2012), Li and Moacdieh (2014), Liem et al. (2020), Lipford et al. (2010), Obie et al. (2019), Ramm et al. (2021), Zdanovic et al. (2022)
(2) Techniques	Behera and Swain (2019), Bertschi et al. (2011), Blount et al. (2020), Brath and Hagerman (2021), Bryan et al. (2017), Bryan et al. (2020), Choudhry et al. (2021), Dimara et al. (2021), Edmond and Bednarz (2021), Elias and Bezerianos (2012), Elias et al. (2013), Figueiras (2014a), Figueiras (2014b), Gershon and Page (2001), Ghidini et al. (2017), Harrison and Bukstein (2016), Hullman and Diakopoulos (2011), Hullman et al. (2013), Kandel et al. (2012), Knaflic (2015), Koesten et al. (2020), Koesten et al. (2021), Lan et al. (2021), Lan et al. (2022), Latif et al. (2021), Lin et al. (2018), McKenna et al. (2017), Michalczyk et al. (2021), Neifer et al. (2020), Ojo and Heravi (2018), Pandey et al. (2014), Rodríguez et al. (2015), Rodrigues et al. (2019), Sarikaya et al. (2019), Segel and Heer (2010), Sekar (2022), Stolper et al. (2016), Tong et al. (2018), Tory et al. (2022), Vornhagen et al. (2021), Waldner et al. (2014), Waldner et al. (2014), Watson (2017), Ya'acob et al. (2021), Yang et al. (2022), Yau et al. (2019), Zheng (2017)
(3) Frameworks and Processes	Boldosova and Luoto (2019), S. Chen et al. (2020), El Outa et al. (2020), Gutiérrez and Pérez (2016), Lee et al. (2015), Obie et al. (2019), Zhang and Lugmayr (2019)

Table 3. All articles of the literature review per category

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