Visualizing Social Sentiment: Designing an Interactive Dashboard for Informed Decision-Making

David Borukhson
Institute of Information Systems and Marketing, Karlsruhe Institute of Technology, Karlsruhe, Germany
borukhson@kit.edu

Louisa Glaum
Institute of Information Systems and Marketing, Karlsruhe Institute of Technology, Karlsruhe, Germany
louisa.glaum9@kit.edu

Christof Weinhardt
Institute of Information Systems and Marketing, Karlsruhe Institute of Technology, Karlsruhe, Germany
weinhardt@kit.edu

Jonas Fegert
FZI Research Center for Information Technology, Germany
fegert@fzi.de

Abstract

Amidst a polycrisis involving global health emergencies, climate change, and geopolitical conflicts, decision-makers face the challenge of discerning relevant and reliable social sentiment information from vast data streams. This study addresses the need for near real-time insights into public attitudes to support data-driven policy-making. Utilizing design science research, we present a qualitative study (n=19) for the development of meta-requirements for an interactive dashboard displaying social sentiment data. It is based on sentiments from over 26 million data points collected biweekly since November 2022 from representative panels in Germany and the US. Thereby, this research aims to create a Policy Advice Sentiment Dashboard (PASD) that informs decision-makers, emphasizing data quality and methodological rigor. We explore additional attributes required for impactful information and variations in informational preferences among different decision-making groups. Our findings guide the development of a prototypical PASD, addressing the critical need for effective data-driven decision-making in governmental contexts.

.

Keywords: Policy Advice Dashboard, Design Science Research, Qualitative Study, Digital Government, Digital Democracy

1. Introduction

Achievements in the development of information technology have made news from around the world readily available at all times. However, these same advancements have also led to the rapid proliferation of automated information manipulation, including disinformation, designed to generate attention or deceive audiences. Fueled by the increasing adoption of artificial intelligence, both reliable information from trusted sources and false content have resulted in unprecedented quantities of data.

Therefore, decision-makers seeking to understand social sentiments on important matters in their fields face a significant challenge: in a vast sea of data, they must identify relevant and reliable information. This unique challenge implies the necessity of accessing near real-time information on the attitudes of specific demographics and subgroups, with the required level of granularity.

Data literacy varies greatly, even among individuals in decision-making positions. This includes understanding data that captures public sentiments, expectations, and reactions, which could be crucial for effective policy making. Research suggests that decision-makers in high positions do not employ different cognitive mechanisms than regular individuals (Vis & Stolwijk, 2022). At the same time, the gap between those who can work effectively with data and those who cannot is growing in business and governmental realms alike (D'Ignazio, 2017). In contrast to the business sector, which is investing heavily into establishing analytics infrastructures for data-driven decision-making, our democracies and their governmental agencies lag significantly behind in this regard. In digital government, there seems to be a high demand for suitable technologies – among them platform solutions that assist decision-making in government and administration (Agbozo & Asamoah, 2019; Hossin et al., 2023; Nel et al., 2023). This reticence of democracy's adaptation to the digital age represents a threat of our democratic systems (Weinhardt et al., 2024).

At the same time, states and their governmental systems are grappling with multiple unexpected crises, stemming from global health emergencies, climate

URI: https://hdl.handle.net/10125/109020
978-0-9981331-8-8

change, geopolitical conflicts, and the rise of authoritarianism. This challenging context inspired the initiation of the project *Social Sentiment in Times of Crises (SOSEC)*. In an innovative study, we are collecting millions of data points on social sentiment during the polycrisis in Germany and the US. The study investigates how events, such as actions by politicians, media, and other actors, affect sentiments among different social subgroups. It is loosely based on the experience sampling method (Hektner et al., 2006) which originates from psychology research. Since November 2022, a representative panel has been conducted biweekly. Participants are presented with a 210-item questionnaire that examines their attitudes, opinions on politically relevant topics, demographic information, and their general emotional state at the time of survey participation. The research configuration allows investigating inference on how societal sentiments react to certain events. By June 2024, the dataset comprises responses from 1,500 participants each in Germany and the US, totaling over 200,000 completed questionnaires and more than 26 million data points. Given this enormous quantity of data, a significant challenge quickly arose: How do we effectively communicate the wealth of information derived from our study to decision-makers to enable them to make better-informed decisions?

To address the aforementioned issues, we adopt a design science research (DSR) approach as conceptualized by Peffers et al. (2007). This approach guides us through the various stages, from problem definition to the communication of our results. In developing an IT artifact to assist in this process, we focus on creating a Policy Advice Dashboard (PAD) with a focus on sentiment data (PASD). According to (Sedlmair et al., 2012), this is a problem-driven design science research setting, as we attempt to solve a real-world problem with real citizens.

Certain properties of the PASD, such as data quality and methodological rigor, are essential; research suggests that this must be guaranteed for sound data-based decision-making and may even pose a threat if not implemented with sufficient rigor (Cairney, 2016; Gluckman, 2017; Head, 2016). However, there are divergent views on additional requirements across different fields. Therefore, the following research questions emerge: *RQ0:* How should an IT artifact be designed to inform decision-makers appropriately about social sentiments? *RQ1*: What additional attributes are essential for information to effectively inform significant societal decisions? *RQ2*: Are there discernible variations in the informational preferences of distinct decision-making groups within society?

In this work-in-progress paper, we analyze the results of a qualitative study to gather requirements from potential stakeholders for the PAD. Hagen et al. (2023) recommend this approach of working in close contact with potential stakeholders. This allows us to present informed requirements for a prototypical PAD presented in the outlook of this paper.

Our paper follows the following structure: The first section reviews a selection of practical examples of PADs as well as theoretical design principles specific for PADs. Next, the research design and data collection methodology of the present survey is presented, followed by a section that sums up the study results and shows the resulting design meta-requirements. The findings are discussed and compared with existing literature. Finally, an outlook is provided on how these findings can be applied and the subsequent steps in designing a PASD suitable for informing decision-makers. This includes a prototype PASD artifact developed based on these meta-requirements.

2. Background

2.1. Sentiment Data in Surveys

Social sentiment data is informative on numerous dimensions, including marketing research as well as audience research motivated by political parties. Various companies, especially in business intelligence, analytics, and advertisement, provide data on social sentiment. *Talkwalker*, a social media analytics platform providing sentiment analysis of political conversation, offers real-time insights into public sentiment, trending topics, and key influencers in the political landscape (Talkwalker, 2024). *Meltwater* and *Brandwatch* are other social listening and analytics platforms, offering sentiment analysis for political discussion. They track mentions of political parties, leaders, and issues across social media channels and providing insights into public sentiment and media coverage for political campaigns and organizations (Brandwatch, 2024; Meltwater, 2024). Further, *YouGov* is company that conducts political polling and sentiment analysis. It offers insights into public opinion, voter preferences, and political trends through surveys and data analysis (YouGov, 2024). However, it is important to note that all of these entities operate with commercial interests as part of their business models and are not independent research institutions. This orientation may influence the scope of the data and insights they provide.

2.2. Policy Advice Dashboards

The success of data-based dashboards in business is well described by Bartlett and Tkacz (2017). They have been accepted as useful in business contexts – with 73% of organization already investing or planning to invest in big data by 2016 (Marr, 2015). The business intelligence visualization tool Microsoft Power BI had “more than 6 million users and 97% of Fortune 500 companies” in 2021 (Kenneth Leung, 2021) and the software Tableau had further 3 million user profiles in 2023 (Kate VanDerAa, 2023).

There already exist PADs directed to either civil society or political actors. Examples include the Pacific Disaster Center DisasterAWARE Dashboard (PDC, 2024), disaster related, Climate Data Explorer (Climate-ADAPT, 2021), climate crisis related, Dominican Republic Institutional Trustworthiness (SIGOB, 2022), and the institutional transparency, or UN Sustainable Development Goals Dashboards (United Nations, 2023). Further, during the Covid-19 pandemic, a rise in health-related public dashboards and PADs could be observed that aimed to visualize the spread of the virus and its effects on the public health systems. Here, some examples are Covid Dashboards, e. g. Covid WHO (World Health Organization, 2024), the Ebola Outbreak Response Dashboard (IOM, 2023), the Global Health Security Index Dashboard (Bell & Nuzzo, 2021). Despite the proliferation of PAD artifacts, there remains a notable gap in the inclusion of social data, particularly sentiment data, within these dashboards. However, as evidenced by the survey of companies utilizing sentiment data, this omission is not due to a lack of availability or demand (Adams-Cohen, 2020; Chen et al., 2021).There already exist PADs directed to either civil society or political actors. Examples include the Pacific Disaster Center DisasterAWARE Dashboard (PDC, 2024), disaster related, Climate Data Explorer (Climate-ADAPT, 2021), climate crisis related, Dominican Republic Institutional Trustworthiness (SIGOB, 2022), and the institutional transparency, or UN Sustainable Development Goals Dashboards (United Nations, 2023). Further, during the Covid-19 pandemic, a rise in health-related public dashboards and PADs could be observed that aimed to visualize the spread of the virus and its effects on the public health systems. Here, some examples are Covid Dashboards, e. g. Covid WHO (World Health Organization, 2024), the Ebola Outbreak Response Dashboard (IOM, 2023), the Global Health Security Index Dashboard (Bell & Nuzzo, 2021). Despite the proliferation of PAD artifacts, there remains a notable gap in the inclusion of social data, particularly sentiment data, within these dashboards. However, as evidenced by the survey of companies utilizing sentiment data, this omission is not due to a lack of availability or demand (Adams-Cohen, 2020; Chen et al., 2021).

Moreover, the social sentiment dataset that we want to visualize has several differences compared to these commercial products: First, we do not focus on live social media data, but rely on consensual data gathered via a representative online panel. Data is gathered willingly and monetarily incentivized, monitored on a biweekly basis, and is representative oriented to AGMA distributions. Furthermore, we do not focus on any specific political party or sentiments. Instead, we analyze a curated set of items selected by an interdisciplinary research team, aiming to provide a comprehensive and analyzable characterization of society. Lastly, given the potential risks associated with such an extensive dataset, we do not make this information publicly available. Controlling access to data used for policymaking is essential to prevent potential misuse, such as actors attempting to undermine social cohesion through targeted disinformation campaigns (Luthfi & Janssen, 2019). This precautionary measure ensures that the data is used responsibly and ethically, safeguarding against threats that could exploit the information for malicious purposes. The PAD is thus necessary to allow decision-makers to interpret the dataset without revealing the whole dataset and risk data leaks.

However, the main objective is broadly applicable to many target groups: to quickly understand relationships in data obtained through scientifically sound methods.

2.3. Theoretical Background

Societal actors require data for their policy making, when their policy related decisions concern complex situations that can be accurately described by measured values. Accurate descriptions of complex scenarios usually include large quantities of data. Therefore, attention must be paid to how visualization design supports data literacy and learnings from evidence-based research. A basis of design principles for designing effective PADs was put forth by Matheus et al. (2020). This work includes principles from other synthesis efforts (such as Maheshwari & Janssen, 2014) and offers the most exhaustive collection of requirements to PADs. We condense Matheus et al.’s principles 1.-7. by listing them combined with a brief explanation (Table 1). This allows to easily compare them to our experimental results und resulting meta-requirement in Section 4.

Table 1. Design Principles 1.-7. from Mattheus et. al. with explanations.

Data accuracy	PAD design should ensure the data presented is accurate and precise to prevent misinterpretation and support informed decision-making.
Customized views	PAD views should be customizable and tailor-made to address specific problems or organizational strategies, enabling decision-makers to gain insights relevant to their needs.
Support different views	PAD should provide multiple perspectives on the data to avoid bias and improve understanding, allowing users to create new views and update the dashboard as needed.
Clear presentation	The design of PAD should include visualization of data using charts, graphs, and other visual aids in an easy-to-understand manner, facilitating monitoring and analysis of performance.
Offer decision making support	PAD should establish relationships between performance metrics and organizational goals using predictive analytics to support decision-making and evaluate alternative scenarios.
Interaction support	They should enable user interaction to gain deeper insights, suggest recommendations, and provide feedback for improvement, especially through real-time information updates.
Provide overview and details	PAD should handle large volumes of data by presenting both an overview and detailed information, allowing users to zoom in on specific details as needed.

The three remaining principles by Mattheus et al., “Create public values” (8.), “Ensure real-time updates” (9.) and “Ensure institutional support” (10.), were excluded here. The first (8.), as in our case it is inherent to the choice of the target group that the artifact is used to create public value. The second (9.), as real-time updates are not applicable for biweekly sentiment data. The third (10.) is an organizational issue that should be taken care of in a later stage of our DSR cycle, as it requires a functional artifact.

With regard to specialized dashboards, guided design processes were previously applied to make sure that an artifact fits its use case. One notable work for example elaborates different performative uses of an educational learning analytics dashboard and what design requirements they imply (Sedrakyan et al., 2019). Apart from this well-established general PAD design principles, some design questions remain unanswered for our context of application: What visualization preferences do users have for a Policy Advice Sentiment Dashboard (PASD)? Do users from different backgrounds or with varying interests have distinct visualization preferences? Are there specific user needs that are unique to a social sentiment PASD?

3. Research Design and Data Collection

We opted for a DSR framework to develop an artifact closely aligned with the requirements of its potential users. This approach is particularly suited to a field with no foundational research. Additionally challenging, our target user group consists of highly heterogeneous actors, such as decision-makers in politics or civil society institutions, who are often not used to work with researchers and their respective methods. To tackle these challenges, we employed a two-step process within the DSR framework. First, we conducted a qualitative survey to gather requirements. At this stage, a medium to small sample size is sufficient, allowing us to include open-ended questions and gain a broad understanding of stakeholders’ preferences. Second, after developing a prototype PAD, we conducted a larger-scale quantitative evaluation to ensure that the artifact is both user-centered and rigorously tested.

According to Hevner et al. (2019), design science research "aims to add to knowledge of how things can and should be constructed or arranged (i.e., designed)" to provide "a solution to a real-world problem of interest practice" (Kuechler & Vaishnavi, 2008). Maedche et al. (2019) emphasize the importance of clearly defining the problem space in DSR. In this paper, we concentrate on the motivation phase of DSR projects, where the problem must be precisely defined to translate it into actionable suggestions. Our research employs the approach by Peffers et al. (2007) and opted for a DSR framework since we wanted to create an artifact which is closely linked to the requirements of its potential users. In this paper, the first steps of the DSR cycle will be presented to discuss and communicate, as foreseen in Peffers DSR framework, early on and iteratively findings to the greater research community and practitioners. In order to define our design goals, we decided to explore the requirements through conducting a qualitative survey with potential users of PASD. Axelsson et al. (2010) and Holgersson et al. (2018) demonstrated the importance of participatory approaches in digital government projects, and we want to respond to this call by bringing citizens insights into this information systems project. Specifically, Sæbø et al. (2010) and Axelsson

(2010) demonstrated how identifying stakeholders involved in a digital government project can help recognize their group-specific needs with regards to the artifact in question and, thereby, help enhance the artifact design according to the stakeholders needs. To understand the design requirements for a PAD, which we seek to develop, we conducted a qualitative study that explored the attitudes of previously identified stakeholder groups on the initiators' (researchers) and the participants' side (policy-makers, media, leading figures in civil society organisations) through qualitative questionnaires. Due to their explorative character, qualitative methods turn the traditional research in information systems the other way around: Interviewing designated stakeholders allows them to map out a set of preferences as pointed out by the interviewed themselves, and attempt generalization following the analysis. In our case, we look for the need for features specifically required in a PASD. Therefore, we designed a qualitative questionnaire in reference to the design principles listed in the above subsection and reached out to actors that shape politics and society – individuals from different civil society and governmental institutions, that could be potential users as well as those researchers who would like to use the dashboard for their interaction with those decision-makers. Thereby, we develop a dashboard design to visualize social sentiment panel data in an intelligible manner.

4. Preliminary Results and Meta-Requirements

4.1. Survey Results

In total, 19 participants answered our questionnaire. 13 of these answered the complete questionnaire, six skipped one or more questions. Twelve respondents come from the scientific field, two each are professionals in public service, and media and three from civil society like NGOs.

Ten participants indicated that they are "not familiar" or "slightly familiar" with using sentiment data in their work. Six participants reported being "moderately familiar" or "familiar." Among these six, five participants come from scientific fields. Additionally, the sole participant who described themselves as "very familiar" with sentiment data also works in science. This suggests that familiarity with sentiment data may be more prevalent among individuals in academia.

The query "Do you already use data on social sentiments in your current decision-making? In which contexts?" was answered by seven participants. The answers were all negative except for one participant who wrote: "Online-experiments on political online participation". Our findings thus indicate a lack of data-centric decision-making methodologies. To further explore potential applications for our dashboard, we subsequently asked: "What would you like to use this data for?" Here, some particularly specific answers were: "better insights into important target groups. Learning on how to communicate more effectively.", "Research on the correlation of sentiments and the spread of conspiracy theories", as well as "[…] comparing negative sentiment (hate) against male vs. not-male political actors […]".

The response distributions of most design-related questions turned out homogenous for different selected subgroups: For different institutions (academia vs. non-academia), there were no notable differences with respect to design and feature preferences such as customization of the visualization, decision-making support, interactivity, etc. Also, when investigating for topic specific preferences ("v*ery relevant*" to "m*oderately relevant*" responses to each topic in "*How interested are you in data about the following topics?*"), no pronounced group differences were observed. This points to a shared set of basic visualization requirements for actors in both scientific and non-scientific domains as well as dealing with different topics.

In the following, design preferences by the average response on the scale transformed into numeric values from -1 (*"Not important"*) to 1 (*"Highly important"*) are presented (Table 2). It is important to note that this survey is qualitative in nature, despite the display of numeric values.

Table 2. Ranking of design preferences.

Design Preference Query	Score
"The visualization is based on high-quality data."	0.88
"How relevant is it for you which methods or models have been used to analyze the visualized data?"	0.79
"How relevant is it for you how the visualized data has been collected or generated?"	0.79
"The visualization includes multiple analysis methods for the same data (such as types of clustering, regressions),"	0.69
"The visualization is customizable."	0.75
"The visualization is clear (immediately understandable)."	0.65
"The visualization gives both general overview and detailed views."	0.62

“How relevant is it for you to be shown these methods or models together with the visualized data?”	0.38
“The visualization is interactive.”	0.25
“The visualization offers decision making support,”	0.00
“The visualization includes predictions of future trends”	0.00
“The visualization includes gamification elements”	-0.62

Certain responses are quite straightforward, such as the importance placed on high data quality and the preference to exclude gamification elements in this specific context. However, it is remarkable that explicit decision-making support as well as interactivity is ranked low by average. Customizability and clarity, on the other hand, are seen as comparatively more important. Further, according to the participants’ responses, statistical methods underlying the visualizations should be accessible to the user.

One design question yielded strongly polarized responses: The item “The visualization includes predictions of future trends” in question group “How important are the following design principles for your work with the dashboard?” was responded to as follows (Figure 1).

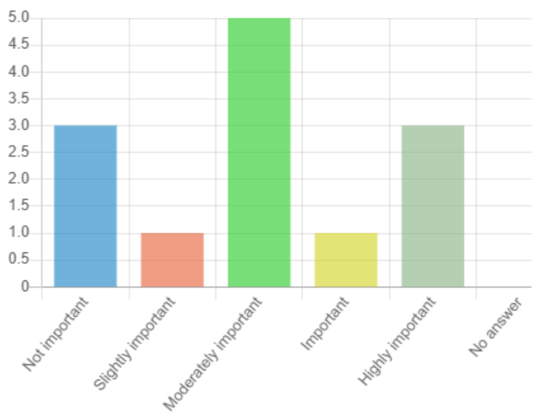

Figure 1. Importance of predictions in the PASD.

Again, there are no significant differences when distinguishing by professional groups or topics. However, when looking at other responses, a pattern becomes apparent: Participants who reported higher familiarity with sentiment data were more likely to rate predictions of future trends as "important" or "highly important." Conversely, those with less familiarity tended to consider these predictions "slightly important" or "not important“. Answers to other questions suggest that it is the prediction component that causes this polarized distribution: Design preferences referring to observing present trends show high importance, i. e. for intra-time comparisons and to match sentiment data with social media trends.

Responses to *“The visualization offers decision-making support”* were also polarized, however without a clear division boundary between groups of expertise or profession.

4.2. Meta-Requirements

Based on the results reported above, the meta-requirements for the PASD are formulated. These meta-requirements are detailed in Table 3, integrating findings from our qualitative study.

5. Discussion

The participants largely agree on the features implied by MR-1.1 to MR-1.4. Two notable observations can be made about the usability-design features from Matheus et al. (2020) design principles. Firstly, our survey identified these features as the most relevant among stakeholders for a PASD, surpassing aspects such as interactivity. Secondly, these features were consistently important across all groups of participants, regardless of their profession, level of expertise, or other factors.

Additionally, we observed a significant divide among participants regarding the desirability of explicit decision-making advice. This finding aligns with HCI studies, which suggest that algorithmic guidance can significantly influence decision-making processes in governmental contexts, potentially leading to substantial changes in policy-making (Green & Chen, 2021; Sayogo et al., 2023). This insight goes beyond reporting the mean importance of zero that participants assigned this feature (see Table 2). It provides valuable information and specifically motivates the inclusion of MR-2.1, and particularly MR-2.1.2. Similarly, responses to the question of including future trends in the PASD show significant variability. This variability highlights the differing needs of participants based on their levels of expertise. This is captured in MR-2.2.1, which provides a highly informative guideline for making group-specific design choices for two distinctly divergent groups (see Figure 1).

The interviews also revealed that the set of demographic groups stakeholders wish to compare in the PASD can be limited to a few key categories. These categories are summarized in MR-3.1, MR-3.2, and MR-3.3. They align well with the lists of commonly used demographic measures provided by social science research institutes. (Niehues & Stockhausen, 2024).

Additionally, MR-4.1 names societal subgroups that only participants of a particular area of work have named. These are, in contrast to the more wide-spread group definitions in MR-3, specific not only to the context of a social sentiment PAD, but also to user groups with particular professional interest.

Lastly, MR-4 emphasizes the importance of ensuring the PASD is suitable for users with varying levels of expertise. Literature on digital government methods extensively documents that many such technologies presuppose a specific set of competencies. Users lacking these competencies may struggle to effectively utilize the features of an artifact that requires them (Banerjee et al., 2015; Hunnius & Schuppan, 2013; Pantiru, 2019).

6. Outlook and Conclusion

Following our design science research cycle (Peffers et al., 2007), the next step is incorporating these meta-requirements into the design and development of a prototype. As pointed out by Sedlmair et al. (2012), rapid software prototyping is very helpful in design science cycles. The development of such a prototype has already begun, and we include the screenshot of a first version in this paper (Figure 2) to show the application of the developed meta-requirements. This prototype will subsequently undergo experimental testing with study participants in a later stage of our DSR cycle. Here, participants from various domains will be involved, enabling quantitative insights into their preferences and needs. Prototype testing could be conducted across different countries to account for regional and societal variations. This approach will allow for a quantitative assessment of the transferability of the meta-requirements outlined here – one of the key contributions of a DSR project (Sedlmair et al., 2012).

The first step of creating a prototype was transforming our panel data into a suitable format using a Python script in the backend. We then used Microsoft PowerBI as a frontend to display our data. The data we wish to display is multi-layered and extremely varied in topic. Therefore, we found that M-1.1 and M-2.1 were crucial for the basic framework of the artifact. We applied these meta-requirements by choosing a multiple page report as a format for our artifact. This format leads the user through various pages, reading explanations about the data and filtering by their interests before entering the main page (Figure 2). These filters can later be changed; however, they help prevent the user from becoming overwhelmed.

On each page, there is a control panel on the left and multiple data visuals on the right. In the control panel, the data can be filtered by “ethnicity”, “age”, “gender” and “income”, based on MR-3. The pre-selected topics of interest and the timeframe can be changed. This basic setup applies to all the following pages, adding to the understandability of the displays.

To implement MR-1 and MR-2, we decided to keep the display on the main page simple, without

Table 3. Meta-Requirements (MR).

MR	Details of MR	
MR-1: Cognitive involvement level	MR-1.1	The PAD should require little effort to be understood by the user.
	MR-1.2	The PAD should not include gamification elements.
	MR-1.3	The PAD should not include interactions if not crucial to use.
	MR-1.4	The PAD should include an option to view underlying methodology.
MR-2: Field and expertise appropriateness	MR-2.1	The PAD should be tailored to the user’s specific interest.
	MR-2.1.1	The PAD should only display data relevant to the user’s field.
	MR-2.1.2	The PAD should only provide explicit support if asked for.
	MR-2.2	The PAD should only provide advanced functionality to expert users.
	MR-2.2.1	The PAD should only provide future predictions to expert users.
MR-3: Differentiation group set	MR-3	The PAD should allow to compare different demographic groups.
	MR-3.1	Groups defined by age.
	MR-3.2	Groups defined by gender.
	MR-3.3	Groups defined by socioeconomic status.
MR-4: Field and experience specific customizability	MR-4.1	The PAD should provide an option to compare customized groups.
	MR-4.1.1	Groups defined by activism.
	MR-4.1.2	Groups defined by party preference.
	MR-4.1.3	Other groups relevant to the user’s field.
	MR-4.2	The PAD should support different views.
	MR-4.2.1	The PAD should support users with different levels of experience.

adding too many clashing components. We opted for a simple line chart, showing the mean of the selected data rows as well as a distribution chart. On the bottom right, we added an explanation panel, displaying the currently selected data and its scaling.

We considered MR-1.1 when choosing the colors for the distribution graph – red for disagreement, blue for agreement with a given statement.

We opted to create multiple “focus-pages” that zoom in on certain topics or demographic groups. For example, incorporating the requirement MR-3.1, we created a page dedicated to comparing survey responses from people with an immigration background and those without.

Ultimately, we want these “focus-pages” to be more customizable. While we already have implemented some “drill-down” options, more options for advanced users will be added according to MR-2.2 and MR-4. So far, only rather simple statistical methods are implemented, showing means, averages, and distributions of variables over time. More complex methods such as regression models or cluster analysis have not yet been implemented. To stay compliant with MR-1.4, they will need more detailed explanations than the current, simpler methods. Here methods and explanation guidelines from explainable artificial intelligence literature may be used for reference (Molnar, 2024).

Our study forms the foundation for a larger research project aimed at developing a PASD. The presented meta-requirements will guide the first iteration of the design cycle. This is the main contribution of the present paper: it lays the groundwork for creating a social sentiment PAD technology that is both effective and aligned with stakeholders' needs and interests.

We have reported only the initial steps of our DSR approach, as the artifact is currently not at a stage where testable evaluation results can be provided. However, the societal and scientific significance of our specific application, the sentiment PAD (PASD), is particularly high. To our knowledge, no design science publications have yet addressed the subject of dashboard design for non-corporate data. Presenting these initial findings, we hope to facilitate scholarly discussion and provide valuable insights for researchers and organizations developing similar PASD.

7. Acknowledgments

We would like to express our gratitude to the Alfred Landecker Foundation for their generous support in funding the SOSEC project.

8. References

Adams-Cohen, N. J. (2020). Policy Change and Public Opinion: Measuring Shifting Political Sentiment With Social Media Data. *American Politics Research*, *48*(5), 612–621. https://doi.org/10.1177/1532673X20920263

Agbozo, E., & Asamoah, B. K. (2019). Data-driven E-Government: Exploring the Socio-Economic

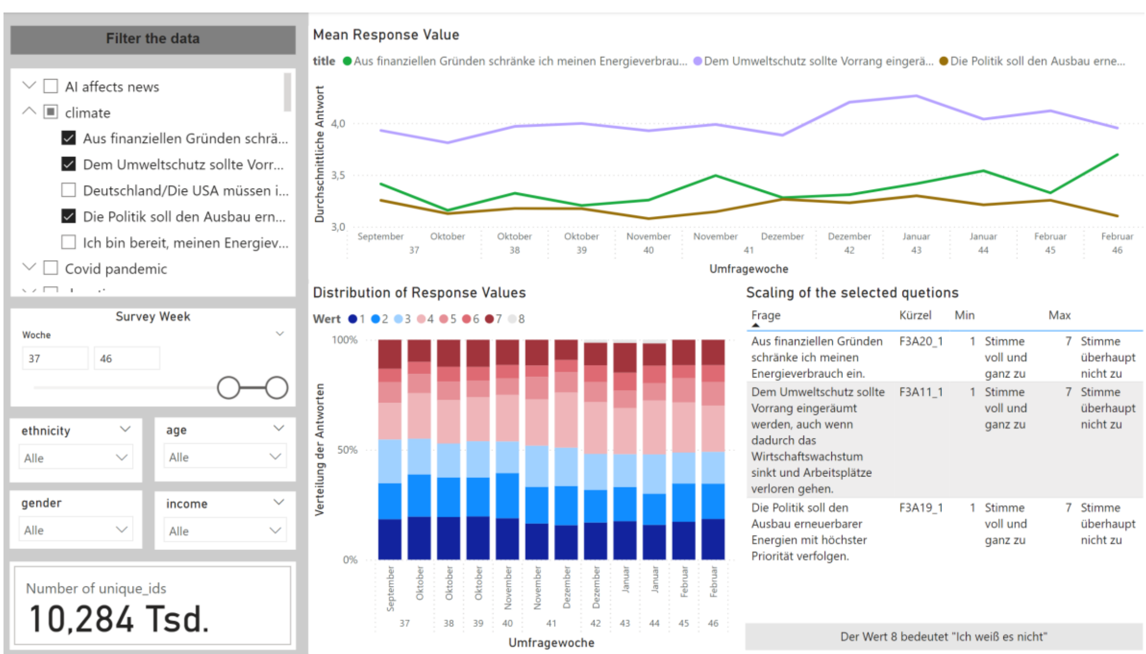

Figure 2: Main page of prototype artifact.

Ramifications. *JeDEM - eJournal of eDemocracy and Open Government*, *11*(1), Article 1. https://doi.org/10.29379/jedem.v11i1.510

Axelsson, K., Melin, U., & Lindgren, I. (2010). Exploring the importance of citizen participation and involvement in e-government projects: Practice, incentives, and organization. *Transforming Government: People, Process and Policy*, *4*(4), 299–321.

Banerjee, P., Ma, L., & Shroff, R. (2015). E-governance competence: A framework. *Electronic Government, an International Journal*, *11*, 171. https://doi.org/10.1504/EG.2015.070120

Bartlett, J., & Tkacz, N. (2017). *Governance by dashboard: A policy paper*. http://dera.ioe.ac.uk/28793/1/Demos-Governance-by-Dashboard.pdf

Bell, J. A., & Nuzzo, J. B. (2021). *Global Health Security Index: Advancing Collective Action and Accountability Amid Global Crisis*. GHS Index. https://ghsindex.org/

Brandwatch. (2024). *The social suite of the future*. Brandwatch. https://www.brandwatch.com/

Cairney, P. (2016). *The Politics of Evidence-Based Policy Making*. Palgrave Macmillan UK. https://doi.org/10.1057/978-1-137-51781-4

Chen, Y., Silva, E. A., & Reis, J. P. (2021). Measuring policy debate in a regrowing city by sentiment analysis using online media data: A case study of Leipzig 2030. *Regional Science Policy & Practice*, *13*(3), 675–693. https://doi.org/10.1111/rsp3.12292

Climate-ADAPT. (2021). *European Climate Data Explorer*. https://climate-adapt.eea.europa.eu/en/metadata/portals/european-climate-data-explorer-health-focus

D'Ignazio, C. (2017). Creative data literacy: Bridging the gap between the data-haves and data-have nots. *Information Design Journal*, *23*, 6–18. https://doi.org/10.1075/idj.23.1.03dig

Gluckman, P. D. (2017). *Enhancing evidence-informed policy making*. Office of the Prime Minister's Chief Science Advisor. https://www.dpmc.govt.nz/sites/default/files/2021-10/pmcsa-17-07-07-Enhancing-evidence-informed-policy-making.pdf

Green, B., & Chen, Y. (2021). Algorithmic Risk Assessments Can Alter Human Decision-Making Processes in High-Stakes Government Contexts. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW2), 1–33. https://doi.org/10.1145/3479562

Hagen, L., Patel, M., & Luna-Reyes, L. (2023). Human-supervised data science framework for city governments: A design science approach. *Journal of the Association for Information Science and Technology*, *74*(8), 923–936. https://doi.org/10.1002/asi.24764

Head, B. W. (2016). Toward More "Evidence-Informed" Policy Making? *Public Administration Review*, *76*(3), 472–484. https://doi.org/10.1111/puar.12475

Hektner, J., Schmidt, J., & Csikszentmihalyi, M. (2006). *Experience Sampling Method: Measuring the Quality of Everyday Life*.

Hevner, A., Brocke, J. vom, & Maedche, A. (2019). Roles of Digital Innovation in Design Science Research. *Business & Information Systems Engineering*, *61*(1), 3–8.

Holgersson, J., Melin, U., Lindgren, I., & Axelsson, K. (2018). Exploring User Participation Practice in Public E-Service Development–Why, How and in Whose Interest? *Electronic Journal of E-Government*, *16*(1), pp72-86.

Hossin, M. A., Du, J., Mu, L., & Asante, I. O. (2023). Big Data-Driven Public Policy Decisions: Transformation Toward Smart Governance. *Sage Open*, *13*(4), 21582440231215123. https://doi.org/10.1177/21582440231215123

Hunnius, S., & Schuppan, T. (2013, January 8). *Competency Requirements for Transformational E-Government*. Proceedings of the Annual Hawaii International Conference on System Sciences. https://doi.org/10.1109/HICSS.2013.139

IOM. (2023, June 5). *Uganda—Flow Monitoring Dashboard: Ebola Virus Disease Outbreak*. https://dtm.iom.int/reports/uganda-flow-monitoring-dashboard-ebola-virus-disease-outbreak-january-2023

Kate VanDerAa. (2023, March 21). *Celebrating the DataFam and 3 Million Tableau Public Profiles*. https://www.tableau.com/blog/celebrating-datafam-and-3-million-tableau-public-profiles

Kenneth Leung. (2021). *How Power BI Helps Your Organization Achieve Greater Data Insights*. https://www.datacamp.com/blog/how-power-bi-helps-your-organization-achieve-greater-data-insights

Kuechler, B., & Vaishnavi, V. (2008). On theory development in design science research: Anatomy of a research project. *European*

Journal of Information Systems, *17*(5), 489–504. https://doi.org/10.1057/ejis.2008.40

Luthfi, A., & Janssen, M. (2019). Open Data for Evidence-based Decision-making: Data-driven Government Resulting in Uncertainty and Polarization. *International Journal on Advanced Science, Engineering and Information Technology*, *9*(3), 1071–1078. https://doi.org/10.18517/ijaseit.9.3.8846

Maedche, A., Gregor, S., Morana, S., & Feine, J. (2019). *Conceptualization of the Problem Space in Design Science Research* (pp. 18–31). https://doi.org/10.1007/978-3-030-19504-5_2

Maheshwari, D., & Janssen, M. (2014). Dashboards for supporting organizational development: Principles for the design and development of public sector performance dashboards. *Proceedings of the 8th International Conference on Theory and Practice of Electronic Governance*, 178–185. https://doi.org/10.1145/2691195.2691224

Marr, B. (2015). *Big Data: 20 Mind-Boggling Facts Everyone Must Read*. Forbes. https://www.forbes.com/sites/bernardmarr/2015/09/30/big-data-20-mind-boggling-facts-everyone-must-read/

Meltwater. (2024). *Meltwater: Media, Social & Consumer Intelligence*. Meltwater. https://www.meltwater.com/en

Molnar, C. (2024, June 3). *Interpretable Machine Learning*. Christoph Molnar. https://christophmolnar.com/books/interpretable-machine-learning/

Nel, E., MacLachlan, A., Ballinger, O., Cole, H., & Cole, M. (2023). Data-Driven Decision Making in Response to the COVID-19 Pandemic: A City of Cape Town Case Study. *Sustainability*, *15*(3), Article 3. https://doi.org/10.3390/su15031853

Niehues, J., & Stockhausen, M. (2024). *Einkommensverteilung in Europa: Wo stehen wir?* (Vol. 32). Institut der Deutschen Wirtschaft (IW).

Pantiru, M. C. (2019). Competencies necessary for eGovernment. *National Agency of Civil Servants, Romania*.

PDC. (2024, April 22). DisasterAWARE - Pacific Disaster Center. *Pacific Disaster Center*. https://www.pdc.org/disasteraware/

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A Design Science Research Methodology for Information Systems Research. *Journal of Management Information Systems*, *24*(3), 45–77. https://doi.org/10.2753/MIS0742-1222240302

Sæbø, Ø., Rose, J., & Molka-Danielsen, J. (2010). eParticipation: Designing and Managing Political Discussion Forums. *Social Science Computer Review*, *28*(4), 403–426. https://doi.org/10.1177/0894439309341626

Sayogo, D. S., Yuli, S. B. C., & Amalia, F. A. (2023). Analyzing the perceived understanding of public managers of data quality for data-driven decision-making at local government in Indonesia. In *Environmental Issues and Social Inclusion in a Sustainable Era*. Routledge.

Sedlmair, M., Meyer, M., & Munzner, T. (2012). Design Study Methodology: Reflections from the Trenches and the Stacks. *IEEE Transactions on Visualization and Computer Graphics*, *18*(12), 2431–2440. IEEE Transactions on Visualization and Computer Graphics. https://doi.org/10.1109/TVCG.2012.213

Sedrakyan, G., Mannens, E., & Verbert, K. (2019). Guiding the choice of learning dashboard visualizations: Linking dashboard design and data visualization concepts. *Journal of Computer Languages*, *50*, 19–38. https://doi.org/10.1016/j.jvlc.2018.11.002

SIGOB. (2022). *Dashboard de Indicadores de Integridad y Gestión. SIGOB - América Latina y El Caribe*. https://documentacion.sigob.org/dashboard-de-indicadores-de-integridad-y-gestion-dig/

Talkwalker. (2024). *Talkwalker—Leading consumer intelligence platform*. https://www.talkwalker.com

United Nations. (2023). *Sustainable Development Report 2023*. https://dashboards.sdgindex.org/

Vis, B., & Stolwijk, S. (2022, March). *In "A League of Their Own?": Judgment and Decision Making By Politicians and Non-politicians* [Part of book]. Cambridge University Press. https://doi.org/10.1017/9781108774871.008

Weinhardt, C., Fegert, J., Hinz, O., & van der Aalst, W. M. P. (2024). Digital Democracy: A Wake-Up Call. *Business & Information Systems Engineering*, *66*(2), 127–134. https://doi.org/10.1007/s12599-024-00862-x

World Health Organization. (2024, April 30). *WHO COVID-19 dashboard*. Datadot. https://data.who.int/dashboards/covid19

YouGov. (2024). *YouGov Deutschland*. https://yougov.de/