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Marcel Ruoff
Karlsruhe Institute of Technology (KIT), marcel.ruoff@kit.edu

Ulrich Gnewuch
Karlsruhe Institute of Technology (KIT), ulrich.gnewuch@kit.edu

DESIGNING CONVERSATIONAL DASHBOARDS FOR EFFECTIVE USE IN CRISIS RESPONSE

Research in Progress

Marcel Ruoff, Karlsruhe Institute of Technology (KIT), Institute of Information Systems and Marketing (IISM), Karlsruhe, Germany, marcel.ruoff@kit.edu

Ulrich Gnewuch, Karlsruhe Institute of Technology (KIT), Institute of Information Systems and Marketing (IISM), Karlsruhe, Germany, ulrich.gnewuch@kit.edu

Abstract

Dashboards are increasingly used by governments and health organizations to provide important information to the general public during a crisis. However, in contrast to organizational settings, the majority of the general population has not or rarely used dashboards before and therefore often struggles to interact effectively with these dashboards. To address this challenge, we conduct a design science research (DSR) project to design a conversational dashboard that enables natural language-based interactions to facilitate its effective use. Drawing on the theory of effective use, our DSR project aims to provide theory-grounded design knowledge for conversational dashboards that help users to access and find information via natural language. Moreover, we seek to provide novel insights that support researchers and practitioners in understanding and designing more natural and effective interactions between users and dashboards.

Keywords: Conversational User Interface, Dashboard, Conversational Dashboard, Crisis Response, Design Science Research, Theory of Effective Use.

1 Introduction

Dashboards, visual displays of the most important information consolidated on a single screen (Few, 2006), are well established in organizations and provide relevant information to decision makers at a glance (Behrisch et al., 2018; Pauwels et al., 2009; Preece et al., 2015; Yigitbasioglu & Velcu, 2012). Increasingly, dashboards are also used by governments and health organizations to provide the general public with a comprehensive overview of relevant information during crises (Chan et al., 2004; Filonik et al., 2013; Horita et al., 2015). Among recent examples are dashboards for crisis response during or after earthquakes, wildfires, and pandemics such as the swine flu (Liu & Palen, 2010; Zook et al., 2010). This trend accelerated during the COVID-19 pandemic (Meijer & Webster, 2020) with more than 4.5 billion requests a day to the most popular COVID-19 dashboard provided by Johns Hopkins University (JHU) in cooperation with Esri (Milner, 2020). These dashboards visualize information about the spread of the virus around the entire globe (Dong et al., 2020) and therefore present an important and valuable source of information for many people. For example, based on information from these dashboards, users decide “whether they should go on holiday to a certain area, visit a friend or get their hair cut” (Flowers, 2020). Despite the popularity of dashboards in crisis response, several major challenges remain. Among them is that the majority of the general population has not or rarely used dashboards and, therefore, exhibits lower levels of data literacy (as opposed to users in organizational settings) (Matheus et al., 2020). Therefore, people who are new to dashboards often struggle to use them effectively in order to make informed decisions (Cay et al., 2020).

Research suggests that transparent interaction – the extent to which a user is accessing an information system (IS) unimpeded by its surface and physical structures (e.g., user interface) – is an important prerequisite for achieving effective use (Burton-Jones & Grange, 2013). If users are unable to interact with a dashboard in a transparent manner, it is unlikely that they can extract the information they need and act upon them. A main difficulty of users interacting with dashboards is expressing their goals and questions using the system functionalities (Kwon et al., 2011). For example, users with a lack of data literacy often consider even seemingly 'simple' interactive features, such as filtering for certain entities (e.g., positive cases in a specific area) as too complex (Sarikaya et al., 2019). A promising approach to address this problem is to enhance the current capabilities of dashboards with a more natural interaction through integrating a conversational user interface (CUI) (Quamar et al., 2020; Saktheeswaran et al., 2020; Zschech et al., 2020). CUIs enable users to interact with an IS using natural language, just like engaging in a conversation with another human being (McTear et al., 2016), and therefore may promise a more convenient and intuitive way of interacting with a dashboard than the traditional combination of mouse and keyboard (Murray & Häubl, 2011).

While some studies have investigated the design of *conversational dashboards*, they predominantly focus on technical challenges such as the recognition of the user's intent or managing ambiguity in natural language (Gao et al., 2015; Quamar et al., 2020; Srinivasan & Stasko, 2018). However, research suggests that effectively using a conversational dashboard and discovering how to interact properly with it remains a challenge that goes beyond improving its technical capabilities (Srinivasan et al., 2019). Therefore, merely equipping dashboards with CUIs might not be enough. As existing studies on conversational dashboards mainly adopt a technology-centric perspective (Turk, 2014) with limited attention paid to users and their requirements, we identify a lack of design knowledge on how to enable users to effectively use conversational dashboards. Therefore, we address the following research question:

How to design conversational dashboards that can be effectively used in crisis response?

To address this research question, we conduct a design science research (DSR) project (Kuechler & Vaishnavi, 2008). Drawing on the theory of effective use (Burton-Jones & Grange, 2013) as well as existing prescriptive knowledge for CUIs and dashboards, we designed and implemented a conversational COVID-19 dashboard that allows users to interact with it using natural language and mouse. For the evaluation of our artifact, we plan to conduct an online experiment in which users are asked to make decisions based on the dashboard in the context of vacation planning during a crisis. This online experiment is planned to be executed on Amazon Mechanical Turk. We expect to contribute to the body of design knowledge on conversational dashboards with a specific focus on effective use by average users. Practically, our research can inform governments and health organizations on how to design dashboards that can be effectively used by the general population.

2 Related Work and Theoretical Foundation

2.1 Dashboards

Dashboards are crucial for the orientation in complex data and the interpretation of this data as they provide a graphical visualization of the relevant data to the user (Igital et al., 2004). They are "expected to improve decision making by amplifying cognition and capitalizing on human perceptual capabilities" (Yigitbasioglu & Velcu, 2012, p. 41). In literature, dashboards have been mainly addressed as a management tool and, therefore, have been especially researched in the context of organizations (Yigitbasioglu & Velcu, 2012). However, even though this provides a variety of insights and design principles on how to design and develop dashboards with a data integration layer and access to data warehouses to facilitate data quality as well as system adoption (Igital et al., 2004; Sangupamba Mwilu et al., 2016) research on dashboards for societal issues and their requirements is scarce (Recker, 2021).

Casual users are interacting differently with dashboards and have different requirements as they do not interact with these systems on a regular basis. They especially have difficulties interacting properly with the dashboard due to missing experience and knowledge of the system and its data (Grammel et al., 2010; Kwon et al., 2011). In this paper, we will be mainly focusing a users' "failure to execute appropriate interactions" (Kwon et al., 2011, p. 7) as the unimpeded access to the dashboard is necessary for its effective use (Burton-Jones & Grange, 2013).

2.2 Conversational User Interfaces

Conversational user interfaces (CUI) enable users to interact with information systems such as dashboards and expert systems by using written or spoken natural language (McTear, 2002). The origins of CUIs can be traced back to the 1950s. However, the problems of accuracy and intent recognition of the user delayed its application. In the last decades, CUIs have experienced a large boost due to the advances in their foundational technology and due to more sophisticated algorithms supported by big data (McTear et al., 2016).

In its early foundations, CUIs were mainly used to enable a turn by turn conversation between system and user with the use of a simple vocabulary (McTear, 2002). These concepts have been enhanced to automate processes and to scale the interaction between companies and their customers (Diederich et al., 2019; Gnewuch et al., 2018; McTear et al., 2016). Furthermore, to better understand the possibilities beyond these applications, researchers have studied potential use cases apart from customer service (McTear et al., 2016).

A promising application of CUIs is their ability to "aid, assist and advise people in personal and organizational decision situations" (Power et al., 2019, p. 1). Therefore, CUIs are increasingly implemented in AI-enabled systems in general and dashboards in specific to assist the user in the interaction with these systems (Morana et al., 2020; Ruoff et al., 2020) and to enhance current systems for better decision making (Quamar et al., 2020; Rzepka & Berger, 2018). However, existing research has often focused on the technical challenges (Gao et al., 2015; Quamar et al., 2020), resulting in a lack of design knowledge for conversational dashboards.

2.3 Theory of Effective Use

Effective use is critical for achieving the benefits of an IS (Straub & del Giudice, 2012). According to Burton-Jones and Grange (2013), it can be defined as "using a system in a way that helps attain the goals for using the system" (p. 4). Based on their conceptualization, effective use is an aggregate construct formed by the following three dimensions: (1) transparent interaction, (2) representational fidelity, and (3) informed action (Burton-Jones and Grange 2013). As illustrated in Figure 1, the three dimensions of effective use form a hierarchy because "each lower-level dimension is necessary but not sufficient for the higher-level dimension" (Burton-Jones & Grange, 2013, p. 642). Initially, the unimpeded access to the system's representations (transparent interaction) enables one to obtain representations that faithfully reflect the domain (representational fidelity). The representational fidelity in turn improves the ability to take informed actions. Therefore, a user's overall level of effective use is determined by her/his aggregated levels of the three dimensions (Burton-Jones & Grange, 2013). For example, users of a dashboard during crises need to access accurate information of the current situation (transparent interaction), such as which region has currently an increase in positive cases during a pandemic (representational fidelity), to be able to decide whether to carry out certain activities (informed action).

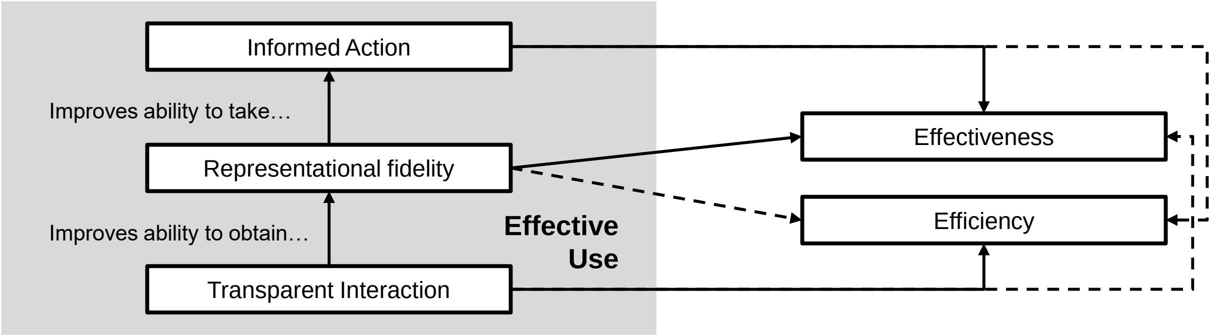

Figure 1. Theory of Effective Use (adapted from Burton-Jones & Grange (2013))

In order to positively influence effective use during the interaction between users and systems, Burton-Jones and Grange (2013) identified two major drivers: (1) adaptation actions and (2) learning actions. In our paper, we will not only draw on the concept of adaptation actions, which are defined as any action a user takes to improve (1) a system's representation of the domain of interest; or (2) his or her access to them, through a system's surface or physical structure. We will also use the concept of learning actions, which are defined as any action a user takes to learn the system as well as the domain the system represents. Therefore, researchers in the context of dashboards for societal issues need to expand their focus from organizational aspects and data quality (Surbakti et al., 2020) to include also how to enable users to make adaptations to dashboards as well as possible learning actions.

3 Design Science Research Project

To design a conversational dashboard that can be effectively used in crisis response, we follow the DSR approach as described by Kuechler and Vaishnavi (2008). We argue that this research approach is particularly suited to address our research question because it allows us to integrate existing design knowledge in the context of CUI and dashboards (Igital et al., 2004; McTear et al., 2016) with theoretical insights from the theory of effective use (Burton-Jones & Grange, 2013). These foundations provide a rigorous grounding and allow us to contribute to the existing knowledge base.

In our first design cycle, we focus on the transparent interaction of users with conversational dashboards in crisis response and the impact of the design on their effective use by following the subsequent procedure:

Awareness of Problem: To better understand potential issues in the design of dashboards in crisis response, we started our research by conducting a literature review. We especially focused on learning actions and adaptation actions by users who are not familiar with dashboards. This literature review, therefore, provided us with the opportunity to extract issues associated with this kind of dashboards and approaches on how to tackle these issues by combining insights from various disciplines, such as emergency management information systems, dashboards, and information visualization.

Additionally, we conducted elicitation interviews following the approach by Hogan, Hinrichs, & Hornecker (2016) in order to further inform the results of our literature review with comprehensive information about people's lived experience while interacting with dashboards in crisis response. This methodology is non-inductive and, therefore, the bias induced by the researcher performing the elicitation interview is minimized. Enabling us to receive an unbiased view on current dashboards in crisis response and their advantages and problems. Overall, three female and three male participants took part in the elicitation interviews, with an average age of 53.2 years (SD = 23.2). We aimed to include multiple backgrounds into our elicitation interview since information during a crisis is relevant to all ages and cultural backgrounds. Therefore, our participants had varying backgrounds, such as retirees, students, artists, and employees.

Suggestion: To address the issues identified in the problem awareness phase, we proposed two design principles for conversational dashboards. These design principles were derived based on our literature review, the results of our elicitation interviews, and the theory of effective use as our kernel theory.

Development: To demonstrate how these design principles can be implemented, we instantiated these design principles in a software artifact using state-of-the-art technologies for natural language interaction.

Evaluation: In the evaluation phase, we opted for an online experiment as this enables us to evaluate the impact of our design principles on the effective use of the conversational dashboard. Similar to field experiments, this type of study comes with the downside of decreased internal validity. However, we argue that this type of study is most appropriate in our case because to evaluate the artifact and to answer the research question a wide set of demographic characteristics and a realistic context is required (Birnbaum, 2004; Karahanna et al., 2018). The evaluation model and the procedure for our evaluation will be described in more detail in the subsequent section, as it is derived based on our design principles and the guiding theory of effective use.

4 Designing a Conversational COVID-19 Dashboard

4.1 Awareness of the Problem

In the last decade, the increasing availability of publicly available data has accelerated the usage of dashboards for crisis response (Watson et al., 2017). Currently, researchers striving to improve the benefit of these dashboards for users mainly aim to provide representations that faithfully reflect the domain, also known as representational fidelity (Burton-Jones & Grange, 2013). For example, Wissel et al. (2020) designed a COVID-19 dashboard while focusing on the aggregation of the data to provide a faithful representation of the current magnitude adjusted for the population (representation fidelity). Therefore, data quality and data management are key research avenues for dashboards in crisis response (Haworth & Bruce, 2015; Mansourian et al., 2006; Zook et al., 2010) as well as the technological infrastructure of these information systems (Karnatak et al., 2012).

However, even though representational fidelity is a core dimension of effective use (Burton-Jones & Grange, 2013), users cannot leverage their representational fidelity to take informed actions if they are not able to interact transparently with the dashboards to access the information they need. This is further informed by our interviews. For example, one participant stated that she first needed to "search the dashboard extensively before even knowing how to get the needed information". Furthermore, the appropriate usage of the functionality is challenging for users of dashboards in crisis response as well (Watson et al., 2017). Several participants struggled to interact effectively with the dashboard (e.g., filtering for relevant criteria or understanding the impact of their actions on the dashboard and its data) and one older participant wondered "why he could not just ask the dashboard and talk to it". Furthermore, even though the dashboard provided all the information needed, some participants were not able to complete all tasks due to their problems with the dashboard's functionality. For example, multiple participants were not able to determine the county with the highest number of positive cases per 100,000 inhabitants since the function they associated with filtering had a different functionality.

4.2 Suggestion

Guided by this initial problem awareness, we additionally reviewed existing dashboard literature in IS and related fields in order to derive two meta-requirements (MR) for conversational dashboards based on the theory of effective use (Burton-Jones & Grange, 2013): First, a conversational dashboard needs to enable users to adapt its surface structure according to their preferred way of interacting with it (i.e., beyond the current mouse and keyboard interaction) (MR1). Second, a conversational dashboard needs to support users in learning how to interact with it effectively (MR2). To address these meta-requirements, we propose two design principles based on the theory of effective use (Burton-Jones & Grange, 2013) as our kernel theory and existing prescriptive knowledge for dashboards and CUIs as additional justificatory knowledge to provide a direction for the design solution of our artifact (Kuechler & Vaishnavi, 2008). We formulated our design principles following established guidelines (Gregor et al., 2020).

The issues identified in our problem awareness phase and, therefore, our meta-requirements are closely related to the unimpeded access to the dashboards in crisis response (transparent interaction). As established in Section 2.3, there are two major drivers of transparent interaction: (1) adaptation actions and (2) learning actions. First, transparent interaction can be improved by enabling users to take actions to improve their access to the dashboard's representations. Lee et al. (2012) proposed extending current ways of interacting with dashboards, such as mouse, through more intuitive ways of interacting. Especially, since a key critique of current dashboard interaction is that they drown users in functionality (Lee et al., 2012), which is confirmed by our problem awareness. Because of its complementary nature to mouse interaction, researchers increasingly enable natural interaction through CUIs (McTear, 2017; Srinivasan et al., 2020; Zschech et al., 2020). This allows users to select the way of interaction they prefer for a certain task. For example, users could perform spatial interactions on dashboards (e.g., selecting) through mouse and more complex interactions (e.g., filtering) could be performed using the CUI. Therefore, we articulated the first design principle:

***DP1:** To improve users' unimpeded access to dashboards in crisis response, facilitate natural interaction through a conversational user interface extending current ways to interact with dashboards (i.e., mouse).*

Second, transparent interaction can be improved by enabling users to learn the system's surface structure, such as the functionality and the different ways of interacting with dashboards. Learning to use the different ways of interacting with dashboards is crucial for both existing ways of interaction, such as mouse (Lee et al., 2012), and for new ways of interaction, such as CUI (Srinivasan et al., 2019). However, it is especially important for CUI since the invisible nature of CUI leads to challenges for users in discovering possible commands or supported functionality (Furqan et al., 2017). Furthermore, in contrast to mouse interaction, where a single interaction is associated with a single integral functionality of the dashboard, a command in a CUI can results in multiple adaptations to the dashboard. Therefore, learning how to effectively interact with CUI is crucial (Corbett & Weber, 2016; Furqan et al., 2017; Zhong et al., 2014). Interactive instructions could emphasize the link between natural language commands as well as mouse interactions and the functionality of the dashboards. With this, users can learn in an initial instruction the possible functionality linked with exemplary natural language commands and mouse interaction. Therefore, we articulated the second design principle:

***DP2:** To improve users' unimpeded access to dashboards in crisis response, provide interactive instructions that support users in learning to use the different ways to interact with dashboards (i.e., mouse and CUI).*

4.3 Development

We instantiated our design principles in a conversational COVID-19 dashboard that allows users to interact with it using mouse as well as text and speech. Our software artifact was developed using state-of-the-art technology for dashboards and CUIs and integrates existing COVID-19 data sources. We implemented the dashboard using Microsoft Power BI, a platform for self-service and business intelligence and integrated the COVID-19 Data Repository by the JHU (Dong et al., 2020). In order to integrate a CUI and to provide conversational capabilities to our dashboard, we used Microsoft's Cognitive Services. Dashboard users are able to formulate their questions in natural language and the dashboard automatically adapts its visualizations to answer them. Additionally, the dashboard provides feedback to its users to inform them about incomplete or incorrect natural language requests (DP1). For example, users can ask "Filter for counties in California with more than 50 confirmed cases per population" and receive the respective information. Moreover, we implemented interactive instructions in the form of a guided tour that introduces users to the essential functionalities and how to use them effectively using the different interaction modalities (DP2). The screenshot in Figure 2 shows our artifact and illustrates how the design principles were instantiated.

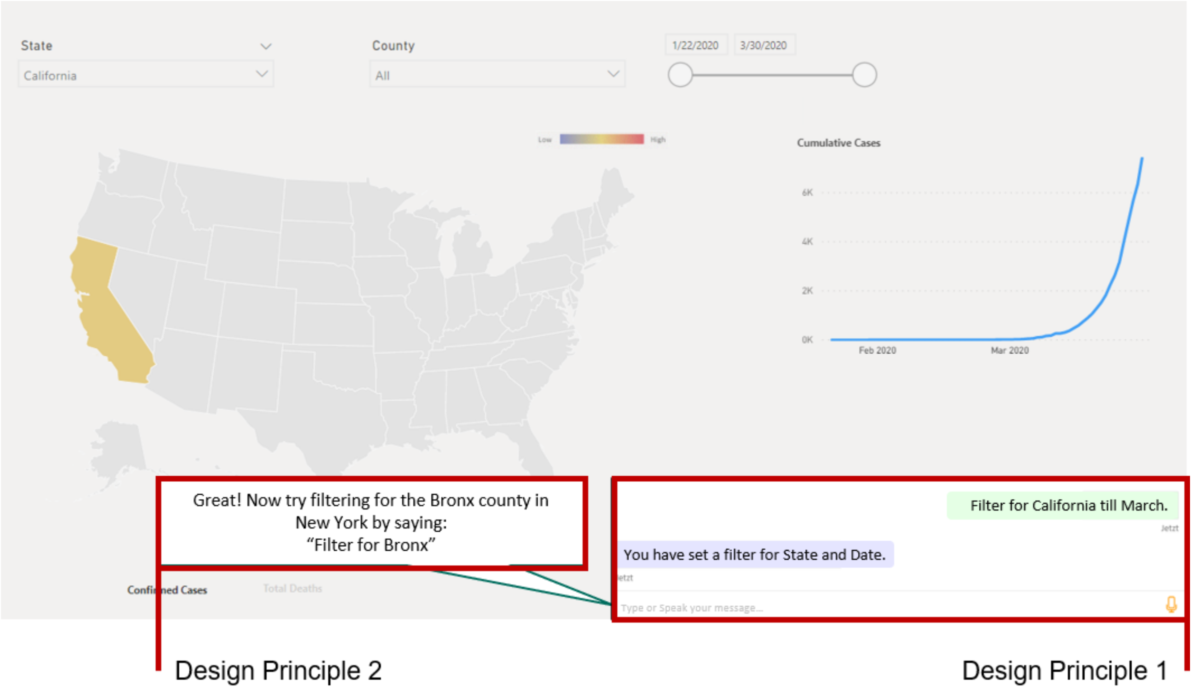

Figure 2. The Design Principles implemented in the Conversational Dashboard

4.4 Evaluation

To evaluate our design principles for conversational dashboards in crisis response, we plan to conduct an online experiment, in which participants interact with our artifact providing data regarding the current COVID-19 pandemic on a global level. In the experiment, the participants are provided with a hypothetical scenario of using the dashboard to decide different aspects of selecting a vacation destination. For example, participants are asked: "What are the 3 counties in California with the highest number of confirmed cases in September?". We employ a 3 (Design Principle 1: mouse vs. CUI vs. mouse and CUI) x 2 (Design Principle 2: absent vs. present) full factorial design with between-subject treatments to evaluate the impact of the design configurations. The evaluation model is depicted in Figure 3. Participants will be recruited via Amazon Mechanical Turk, an online crowdsourcing platform for business services and individuals, to reach a broad and diverse sample of potential users (Schneider et al., 2019). Furthermore, to provide the participants an incentive to interact efficiently and effectively, we will provide a fixed payment, which will encourage the participants to work faster in order to receive a higher hourly payment (efficiency), as well as bonus payments for correctly answered tasks (effectiveness).

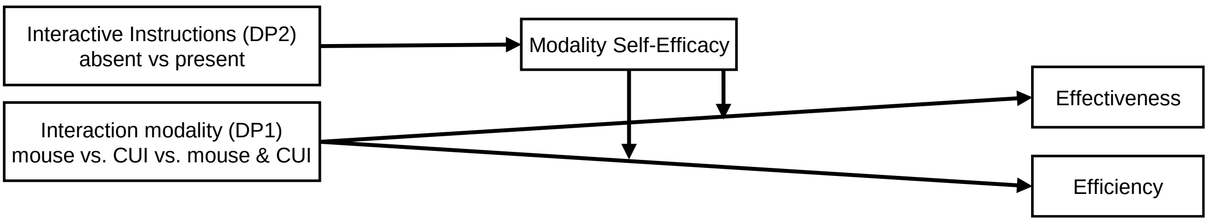

Figure 3. Evaluation Model

The experiment consists of the following five stages (Figure 4): (1) Introduction, (2) Onboarding, (3) Pre-Questionnaire, (4) Task, and (5) Post-Questionnaire. In the first stage, the participants are given a short introduction into the hypothetic scenario as well as the payment structure of the experiment and are asked to provide their informed consent. In the second stage, the participants are randomly assigned to one of the six experimental conditions. In conditions with interactive instructions (present), participants will use the artifact that includes the second design principle and will receive an interactive instruction. In conditions without interactive instructions (absent), participants will use the artifact without the implementation of the second design principle. In the third stage, participants will fill out a pre-questionnaire before starting the experiment task. The pre-questionnaire includes questions on demographics, experience with dashboards as well as questions regarding the self-efficacy of the participant with mouse and CUI (modality self-efficacy), which are adopted from Cassidy & Eachus (2002). After completing the questionnaire, the participants will use the artifact to perform three tasks that are relevant for planning a vacation during a pandemic. According to their experimental condition, participants will be able to interact with the dashboard to answer these questions either with mouse (disabled CUI input), with a CUI (disabled mouse input), or using both input modalities. After finishing the experiment task, in the last stage, the participant will be asked to fill out a post-questionnaire including self-evaluation questions, such as recently developed effective use scales (Eden et al., 2020), and have the opportunity to provide qualitative feedback.

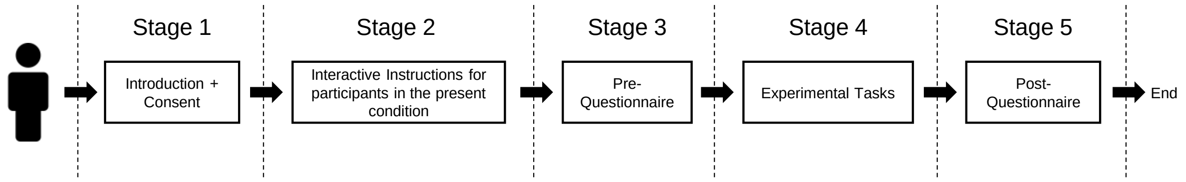

Figure 4. Experimental Procedure

To measure the dependent variables, we will use the percentage of the correctly answered questions for effectiveness and the time needed to measure efficiency.

5 Conclusion and Next Steps

We aim to contribute to research on the design of dashboards as one important class of information systems for crisis response. Our DSR project provides theory-grounded design knowledge for conversational dashboards that can facilitate their effective use among the general population. Moreover, we provide novel insights on how and when users employ different interaction modalities (natural language vs. mouse) to make decisions based on complex data. Furthermore, we show how users can be supported during the onboarding process through interactive instructions before using a dashboard. More broadly, we expect our results to empower users to make better decisions based on facts during global pandemics. Practically, our research can inform governments and health organizations on how to design dashboards that can be effectively used by the general population.

References

Behrisch, M., Streeb, D., Stoffel, F., Seebacher, D., Matejek, B., Weber, S. H., Mittelstaedt, S., Pfister, H., & Keim, D. (2018). Commercial Visual Analytics Systems-Advances in the Big Data Analytics Field. *IEEE Transactions on Visualization and Computer Graphics*, *25*(10), 3011–3031.

Birnbaum, M. H. (2004). Human research and data collection via the internet. *Annual Review of Psychology*, *55*, 803–832.

Burton-Jones, A., & Grange, C. (2013). From Use to Effective Use: A Representation Theory Perspective. *Information Systems Research*, *24*(3), 632–658.

Cassidy, S., & Eachus, P. (2002). Developing the computer user self-efficacy (CUSE) scale: Investigating the relationship between computer self-efficacy, gender and experience with computers. *Journal of Educational Computing Research*, *26*(2), 133–153.

Cay, D., Nagel, T., & Yantac, A. E. (2020). Understanding User Experience of COVID-19 Maps through Remote Elicitation Interviews. *2020 IEEE Workshop on Evaluation and Beyond - Methodological Approaches to Visualization (BELIV)*, 65–73.

Chan, T. C., Killeen, J., Griswold, W., & Lenert, L. (2004). Information technology and emergency medical care during disasters. *Academic Emergency Medicine*, *11*(11), 1229–1236.

Corbett, E., & Weber, A. (2016). What can i say? Addressing user experience challenges of a mobile voice user interface for accessibility. *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services, MobileHCI 2016*, 72–82.

Diederich, S., Brendel, A., & Kolbe, L. (2019). On Conversational Agents in Information Systems Research: Analyzing the Past to Guide Future Work. *Wirtschaftsinformatik 2019 Proceedings*.

Dong, E., Du, H., & Gardner, L. (2020). An interactive web-based dashboard to track COVID-19 in real time. *The Lancet Infectious Diseases*, *20*(5), 533–534.

Eden, R., Fielt, E., & Murphy, G. (2020). Advancing the Theory of Effective Use through Operationalization. *Proceedings of the Twenty-Eighth European Conference on Information Systems (ECIS2020)*.

Few, S. (2006). Information Dashboard Design The Effective Visual Communication of Data. In *Information Dashboard Design The Effective Visual Communication of Data*.

Filonik, D., Medland, R., Foth, M., & Rittenbruch, M. (2013). A customisable dashboard display for environmental performance visualisations. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *7822 LNCS*, 51–62.

Flowers, J. (2020). *The COVID-19 dashboard: bringing together data and statistics in one place - Public health matters*. https://publichealthmatters.blog.gov.uk/2020/09/04/the-covid-19-dashboard-bringing-together-data-and-statistics-in-one-place/

Furqan, A., Myers, C., & Zhu, J. (2017). Learnability through Adaptive Discovery Tools in Voice User Interfaces. *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems*, *Part F1276*, 1617–1623.

Gao, T., Dontcheva, M., Adar, E., Liu, Z., & Karahalios, K. G. (2015). DataTone. *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology - UIST '15*, 489–500.

Gnewuch, U., Morana, S., & Maedche, A. (2018). Towards Designing Cooperative and Social Conversational Agents for Customer Service. *Proceedings of the 38th International Conference on Information Systems (ICIS2017), Seoul, South Korea.*, *December*, 0–11.

Grammel, L., Tory, M., & Storey, M. (2010). How Information Visualization Novices Construct Visualizations. *IEEE Transactions on Visualization and Computer Graphics*, *16*(6), 943–952.

Gregor, S., Chandra Kruse, L., & Seidel, S. (2020). Research Perspectives: The Anatomy of a Design Principle. *Journal of the Association for Information Systems*, *21*(6).

Haworth, B., & Bruce, E. (2015). A Review of Volunteered Geographic Information for Disaster Management. *Geography Compass*, *9*(5), 237–250.

Hogan, T., Hinrichs, U., & Hornecker, E. (2016). The Elicitation Interview Technique: Capturing People's Experiences of Data Representations. *IEEE Transactions on Visualization and Computer Graphics*, *22*(12), 2579–2593.

Horita, F. E. A., Albuquerque, J. P. de, Degrossi, L. C., Mendiondo, E. M., & Ueyama, J. (2015). Development of a spatial decision support system for flood risk management in Brazil that combines volunteered geographic information with wireless sensor networks. *Computers and Geosciences*, *80*, 84–94.

Igital, D., Sawy, O. A. El, Gray, P., & Donegan, C. (2004). Vigilant Information Systems For Managing Enterprises In Dynamic Supply Chains: Real-Time Dashboards At Western Digital. *MIS Quarterly*, *3*(1), 19–35.

Karahanna, E., Benbasat, I., Bapna, R., & Rai, A. (2018). Editor's Comments: Opportunities and Challenges for Different Types of Online Experiments. *MIS Quarterly*, *42*(4), iii.

Karnatak, H. C., Shukla, R., Sharma, V. K., Murthy, Y. V. S., & Bhanumurthy, V. (2012). Spatial mashup technology and real time data integration in geo-web application using open source GIS – a case study for disaster management. *Geocarto International*, *27*(6), 499–514.

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.

Kwon, B. C., Fisher, B., & Yi, J. S. (2011). Visual analytic roadblocks for novice investigators. *VAST 2011 - IEEE Conference on Visual Analytics Science and Technology 2011, Proceedings*, 3–11.

Lee, B., Isenberg, P., Riche, N. H., & Carpendale, S. (2012). Beyond Mouse and Keyboard: Expanding Design Considerations for Information Visualization Interactions. *IEEE Transactions on Visualization and Computer Graphics*, *18*(12), 2689–2698.

Liu, S. B., & Palen, L. (2010). The new cartographers: Crisis map mashups and the emergence of neogeographic practice. *Cartography and Geographic Information Science*, *37*(1), 69–90.

Mansourian, A., Rajabifard, A., Valadan Zoej, M. J., & Williamson, I. (2006). Using SDI and web-based system to facilitate disaster management. *Computers and Geosciences*, *32*(3), 303–315.

Matheus, R., Janssen, M., & Maheshwari, D. (2020). Data science empowering the public: Data-driven dashboards for transparent and accountable decision-making in smart cities. *Government Information Quarterly*, *37*(3), 101284.

McTear, M. (2002). Spoken Dialogue Technology: Enabling the Conversational User Interface. *ACM Computing Surveys*, *34*(1), 90–169.

McTear, M. (2017). The Rise of the Conversational Interface: A New Kid on the Block? In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 10341 LNAI* (pp. 38–49). Springer Verlag.

McTear, M., Callejas, Z., & Griol, D. (2016). The Conversational Interface. In *The Conversational Interface: Talking to Smart Devices*. Springer International Publishing.

Meijer, A., & Webster, C. W. R. (2020). The COVID-19-crisis and the information polity: An overview of responses and discussions in twenty-one countries from six continents. *Information Polity*, *25*(3), 243–274.

Milner, G. (2020). *Creating the Dashboard for the Pandemic*. https://www.esri.com/about/newsroom/arcuser/johns-hopkins-covid-19-dashboard/

Morana, S., Pfeiffer, J., & Adam, M. T. P. (2020). User Assistance for Intelligent Systems. *Business and Information Systems Engineering*, *62*(3), 189–192.

Murray, & Häubl. (2011). Freedom of Choice, Ease of Use, and the Formation of Interface Preferences. *MIS Quarterly*, *35*(4), 955.

Pauwels, K., Ambler, T., Clark, B. H., LaPointe, P., Reibstein, D., Skiera, B., Wierenga, B., & Wiesel, T. (2009). Dashboards as a Service. *Journal of Service Research*, *12*(2), 175–189.

Power, D., Kaparthi, S., & Mann, A. (2019). Building Decision Adviser Bots. *MWAIS 2019 Proceedings*.

Preece, J., Sharp, H., & Rogers, Y. (2015). *Interaction Design: Beyond Human-Computer Interaction* (4th ed.). John Wiley & Sons.

Quamar, A., Özcan, F., Miller, D., Moore, R. J., Niehus, R., & Kreulen, J. (2020). Conversational BI. *Proceedings of the VLDB Endowment*, *13*(12), 3369–3381.

Recker, J. (2021). Improving the State-Tracking Ability of Corona Dashboards. *European Journal of Information Systems*, *March*.

Ruoff, M., Gnewuch, U., & Maedche, A. (2020). Designing Multimodal BI&A Systems for Face-to-Face Team Interactions. *SIGHCI 2020 Proceedings*.

Rzepka, C., & Berger, B. (2018). User Interaction with AI-enabled Systems: A Systematic Review of IS Research. *ICIS Proceedings*, *December*, 1–17.

Saktheeswaran, A., Srinivasan, A., & Stasko, J. (2020). Touch? Speech? or Touch and Speech? Investigating Multimodal Interaction for Visual Network Exploration and Analysis. *IEEE Transactions on Visualization and Computer Graphics*, *26*(6), 2168–2179.

Sangupamba Mwilu, O., Comyn-Wattiau, I., & Prat, N. (2016). Design science research contribution to business intelligence in the cloud — A systematic literature review. *Future Generation Computer Systems*, *63*, 108–122.

Sarikaya, A., Correll, M., Bartram, L., Tory, M., & Fisher, D. (2019). What do we talk about when we talk about dashboards? *IEEE Transactions on Visualization and Computer Graphics*, *25*(1), 682–692.

Schneider, D., Klumpe, J., Adam, M., & Benlian, A. (2019). Nudging users into digital service solutions. *Electronic Markets, 1*.

Srinivasan, A., Dontcheva, M., Adar, E., & Walker, S. (2019). Discovering natural language commands in multimodal interfaces. *Proceedings of the 24th International Conference on Intelligent User Interfaces*, 661–672.

Srinivasan, A., Lee, B., Henry Riche, N., Drucker, S. M., & Hinckley, K. (2020). InChorus: Designing Consistent Multimodal Interactions for Data Visualization on Tablet Devices. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–13.

Srinivasan, A., & Stasko, J. (2018). Orko: Facilitating Multimodal Interaction for Visual Exploration and Analysis of Networks. *IEEE Transactions on Visualization and Computer Graphics*, *24*(1), 511–521.

Straub, & del Giudice. (2012). Editor’s Comments: Use. *MIS Quarterly*, *36*(4), iii.

Surbakti, F. P. S., Wang, W., Indulska, M., & Sadiq, S. (2020). Factors influencing effective use of big data: A research framework. *Information and Management*, *57*(1), 103146.

Turk, M. (2014). Multimodal interaction: A review. *Pattern Recognition Letters*, *36*, 189–195.

Watson, H., Finn, R. L., & Wadhwa, K. (2017). Organizational and Societal Impacts of Big Data in Crisis Management. *Journal of Contingencies and Crisis Management*, *25*(1), 15–22.

Wissel, B. D., Van Camp, P. J., Kouril, M., Weis, C., Glauser, T. A., White, P. S., Kohane, I. S., & Dexheimer, J. W. (2020). An interactive online dashboard for tracking COVID-19 in U.S. counties, cities, and states in real time. *Journal of the American Medical Informatics Association*, *27*(7), 1121–1125.

Yigitbasioglu, O. M., & Velcu, O. (2012). A review of dashboards in performance management: Implications for design and research. *International Journal of Accounting Information Systems*, *13*(1), 41–59.

Zhong, Y., Raman, T. V., Burkhardt, C., Biadsy, F., & Bigham, J. P. (2014). JustSpeak: Enabling universal voice control on android. *W4A 2014 - 11th Web for All Conference*.

Zook, M., Graham, M., Shelton, T., & Gorman, S. (2010). Volunteered Geographic Information and Crowdsourcing Disaster Relief: A Case Study of the Haitian Earthquake. *World Medical & Health Policy*, *2*(2), 6–32.

Zschech, P., Horn, R., Höschele, D., Janiesch, C., & Heinrich, K. (2020). Intelligent User Assistance for Automated Data Mining Method Selection. *Business and Information Systems Engineering*, *62*(3), 227–247.