

Age-dependent health data visualizations: a research agenda

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Summary

While current data visualization research is profoundly driven by innovation and technical aspects, the project Tech4Age focusses on the evaluation of human factors in health-related data and information visualization. This workshop paper initially describes the background and motivation of ergonomic health-data visualization research. Subsequently we present planned studies as well as preliminary results from one general and one task-dependent study which we see as basis for generalizable results of ongoing ergonomic health-visualization evaluations. Finally, we present the research design of an evaluation study aiming at general recommendations for the age-differentiated design of health data visualizations.

1 Introduction

Health is a fundamental social value and is a valuable commodity. From an economical point of view, the benefit of healthcare is comprised of the prevented health-dependent failures and reduced disease spending. The healthcare industry in Germany is growing faster than the overall economy and has generated eleven percent of the German gross value.

Furthermore, demographic change constitutes a vital challenge for the healthcare sector. With progressive aging of western population, the number of those who need medical care as well as the morbidity of individuals increases. Age patterns, but also the quantitative ratio between men and women, the proportion of a countries residents, foreigners and naturalized citizens are the demographic parameters that are expected to change.

At the same time the medical domain evolves from a reactive to a predictive and preventive one, where an early intervention strives to prevent or at least detect illnesses early, as to start treatment earliest and as individualized as possible. Changing the medical approaches and processes from general to individual and stratified is expected to improve well-being during course of life and especially in old age. Side effects of individualized medicine include less

health expenditures and constant quality of care compensating the implications of demographic change.

The collection of large, heterogeneous personal data is referred to as one way to implement individualized and preventive medical processes. Data for personal medicine include clinical data, census data, epidemiological data and data from imaging methods, but on the other hand miniaturization of technology and sensors also foster collection of personal data in home settings. The applications of digital medical sensors in private usage scenarios range from sensor-equipped intelligent homes to active implants, to intelligent prostheses, to small wrist gauges activity tracking devices measuring steps and blood pressure to glucose meters smartphone extensions. Especially, data collected and displayed on smartphone and wearables-applications provide private users with an overview about their own nutrition and exercising behaviour but also about vital data like blood pressure or glucose.

Analysing those personal health-related data by data-mining and deep learning technologies generates new knowledge for pathogenesis, prevention and individualized diagnosis, mentoring and monitoring. Besides tailored medical treatment and efficient resource usage individual medicine also opens up new perspectives for individuals: a greater leeway in decision-making regarding a detection of personal health risks, selection of preventive measures and therapy methods. Health-related and vital decisions are thus increasingly being made on the basis of personal data and because the (elderly) patient as well as his family and care givers should remain an important contributor in their own care processes, ways must be found, to provide people who do not possess knowledge about abstract data concepts with an insight into their own health data.

2 Motivation

Attaching graphical features to data, -types,-characteristics and -transitions puts the highest bandwidth channel to mediate between data and human. The definition of visualization implies a “formation of mental visual images”¹ and “putting something into visual form”¹¹. We consider data visualization as statistical visualization which attaches graphical features to abstract data and statistical concepts (e.g. correlations) in order to support the analysis and understanding of data. Any definition considering visualization as graphical or photorealistic representation of physical or non-statistical objects will not be considered.

Since many years interactive visual representations of *abstract statistical data* have been successfully applied to amplify cognition of data analysis experts (Card & Shneiderman, 1999). Despite the fact that data becomes increasingly important for non-data experts and supports the understanding of data characteristics by a larger target group, lay people and especially older adults are less considered in data visualization research. Age-differentiated recommendations for the design of graphical user interfaces exist (Schlick et al., 2013); but

¹ <http://www.merriam-webster.com/dictionary/visualization>

they not completely apply for data visualizations. However, externalizing ones mental visualization creates cognitive tools whose virtue is not automatically given by the fact that it is visible. Instead different human aspects including perceptual, attentional and cognitive processes, user tasks, goals, needs and behaviour; but also contextual factors such as optics, lightning, display size and resolution, lightness, brightness, contrast, have to be considered. Such an ergonomic design of data visualizations is in our opinion essential for including people into data-driven processes. While some recommendations for the design of data visualizations exist (Ware, 2004) these rarely consider age-related aspects. We thus consider an age-dependent research on ergonomic data visualizations as important.

The importance of an ergonomic perspective on data and information visualization research for digital healthcare information systems becomes especially apparent in the light of age-related changes in society. Many visual functions deteriorate slightly with age. This age-related decrease of visual function has been interpreted as reduced processing efficiency or effectiveness. Data visualizations thus need to consider age-related changes in order to be usable for the elderly. Accordingly, our work focusses on an age-differentiated design of visual representations for abstract personal health data as one aspect of information visualization in health care settings.

3 Research agenda

In general, data visualizations are determined by the context, task and user of the information system they are built-in. Instead of investigating context, tasks and user requirements for one specific system our approach focusses on the analysis of context, task and user characteristics where the results will be as generalizable as possible to information systems where personal health data has to be visually represented for elderly patients.

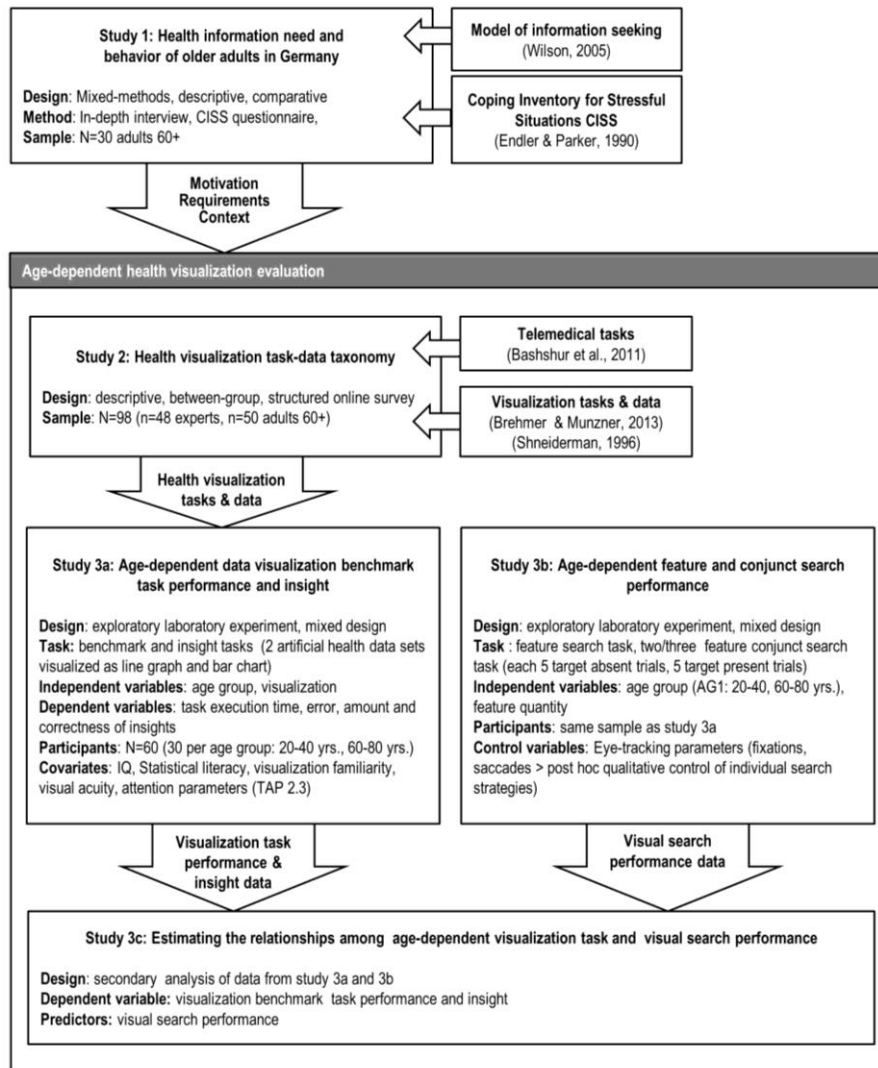


Figure 1: Research agenda on age-dependent evaluation of health data visualizations.

3.1 Study 1: health information need and behaviour 60+

Examination of the general information needs and behaviour of the elderly leads to a general description of user-centric requirement for information systems including data visualizations (study 1, figure 1). It characterizes user-requirements, recognizes acceptance hurdles in order to adopt measures to overcome those obstacles. Beyond that, new or less considered application areas for digital health systems including data visualizations can be discovered.

3.1.1 Research question

“Information Seeking Behaviour is the purposive seeking for information as a consequence of a need to satisfy some goal. In the course of seeking, the individual may interact with manual information systems (such as a newspaper or a library), or with computer-based systems (such as the World Wide Web)” (Wilson, 2000). Concerning information needs in health care Miller & Mangan (1983) showed that individual coping strategies have an impact on individual information needs. People avoiding to handle their illness are more aroused by a large quantity of illness related information, while they are less if provided information quantity fits their coping strategy. Wilson & Walsh’s (1996) model of information seeking behaviour illustrates the influence of personal and environmental factors. Besides, coping strategies as part of activation mechanisms, psychological, demographic, role, environmental and source characteristics have an impact on a person’s information need. Aim of this study was to investigate which health-related information need and behaviour do older adults in Germany have and how is this influenced by individual coping strategies and demographic variables. Research questions were: do older adults dispose of an information need / behavior motivating patient centered visualization evaluation? (How) Differs the information need of older adults depending on demographic characteristics and coping strategies?

3.1.2 Method

A mixed-method study was conducted—involving structured surveys and in-depth interviews—with people about their health information sharing routines and preferences for different information sources. Aim was to find out which information elderlies need to maintain their personal health and how they currently acquire that information and if information need and behaviour depends on individual coping strategies. Participants (n=30) older than 60 years took part in our study. At the beginning of each session, the participant first filled in a questionnaire about demographic parameters. Then the semi-structured interview investigating health related information needs and behaviour was completed. The interview were probing questions participants had about health, personal health and related concepts (medication, prevention, health and vital data, health insurance, hospitals or institutions) and questioned which activities, goals and tools they use to share, and access health information with. The interview was based on existing interview guidelines on information needs of urban residents (Warner et al., 1973). A standard questionnaire measuring coping strategies (Coping Inventory for Stressful Situations, Endler & Parker, 1990) was applied to post hoc divide the sample into groups in order to describe health related information need for groups with different coping strategies. Finally, auditory material recorded was transcribed and coded.

3.1.3 Preliminary results and prospect

Preliminary results for n=10 showed that the information the elderly require to stay healthy most frequently consists of a diagnostic assessment of an observed symptom along with cause estimations and treatment recommendations (n=9). Three participants reported that they were completely satisfied with the health information they get, while six participants reported that they were partly satisfied with the information available to them. Four participants described problems getting information about examination results and related procedures. Six other participants also reported having trouble contacting their physicians or ex-

change vital data from laboratories or monitoring activities. In addition, four participants described information-sharing between medical experts as cumbersome. One participant suggested “a solution that documents the content of each appointment, diagnosis and treatment as patient history that could be shared between physicians and viewed or even edited by patients.”

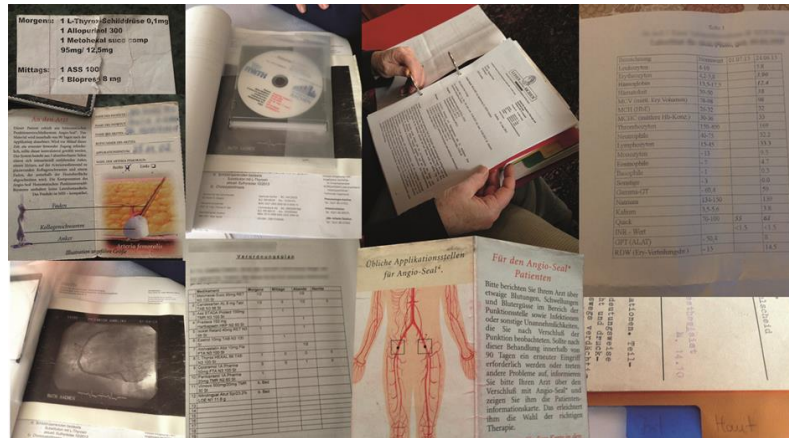


Figure 2: Private documentation of health information is common for older adults, but paper-based documentation of patient histories, vital data and medication information makes data exchange difficult.

Last but not least, four participants described information needs regarding health insurance services. Details about pricing and availability of chargeable health services were considered insufficient, especially if covered by private health insurance. Four participants desired greater transparency regarding billed services versus performed services. Sixty percent of the preliminary sample believed that an excessive preoccupation with health-related information could trigger a disease. As a result, they avoid devoting any more attention than necessary to health issues. In contrast to the 60% group that believes an excessive preoccupation with health-related information could trigger a disease and so they avoided engaging in health information-seeking behavior, we identified a second group of 40% that actively engages in health-related information behavior. They (1) put effort into quantifying and documenting personal health data in order to monitor their health, (2) strive to improve health-relevant behavior and (3) cooperatively use the data they gathered to communicate health-related information to stakeholders. Elderly patients perceive their physician as a competent professional authority to whom they outsource information processes and decisions so as to not burden themselves with information searches and decision-making in addition to dealing with their disease. Participants rated their family doctor or a specialist as their most important health information source (n= 9).

3.2 Study 2: health visualization task-data taxonomy

3.2.4 Research questions

Investigating ergonomic aspects of data and information visualizations requires a solid model of relevant tasks in order to use these them as experimental tasks during evaluation. Tasks per se differ in domain relevance and abstraction level. To our knowledge no information on user tasks relevant for visualizations in health information systems exist. Furthermore, the relevance of individual abstract visualization tasks, and corresponding data-types, for domain-specific health tasks remains unclear. Brehmer and Munzner's (2013) differentiated perspectives of visualization tasks based on the concept of cognitive task analysis (Vicente, 1999). Unfortunately, healthcare and telemedicine taxonomies predominantly try to differentiate ambiguous terms representing the concept of IT supported medical processes. Bashshur et al. (2011) provide a conceptual context of the terms e-health addressing tasks as functionality dimensions: consultation, diagnosis, monitoring and mentoring. His research remains vague when it comes to the origin of his classification. Therefore, we initially want to verify it from the user's perspective and extend it. Furthermore, it should be investigated which abstract visualization tasks and data types are relevant for each medical task (consultation, diagnosis, mentoring and monitoring). Research questions include: Which medical tasks perceive experts and elderly patients as relevant for digital health systems? Which visualizations tasks and data types are important for given medical tasks? To which extent support experts and adults 60+ existing classifications?

3.2.5 Method

In order to find an answer to the previously mentioned research question we set up an online questionnaire consisting of fifteen questions. Bashshur's et al. (2011) classification of telemedical functionality dimensions, Brehmer and Munzner (2013) multi-level model of abstract visualization tasks and Shneiderman (1996)'s task-by-data-type taxonomy for visualizations build the basis for the questionnaire (see table 1). n=48 experts in medical health care systems and n=50 non-medical experts older than 60 years completed the online questionnaire.

	Question	Answer option
1.	What medical tasks and activities can be supported by digital health systems?	Open-ended
2.	Which data play an important role for digital health systems?	Open-ended
3.	What data are required for medical consultation?	Open-ended
4.	What data are required for medical diagnosis?	Open-ended
5.	What data are required for medical mentoring?	Open-ended
6.	What data are required for medical monitoring?	Open-ended
7.	Specify what data is required for the following medical tasks. (horizontally: consultation, diagnoses, mentoring, monitoring; vertically: datatypes Shneiderman (1996))	Checkbox matrix
	Question	Answer option

8.	Indicate which abstract visualization tasks (vertically) are required for given medical tasks (horizontally). (horizontally: consultation, diagnoses, mentoring, monitoring, vertically: abstract tasks from Brehmer & Munzner (2013))	Checkbox matrix
9.	Assess the benefit of digital health systems for the following tasks. (Horizontally (tasks): consultation, diagnoses, mentoring, monitoring, vertically (benefit assessment): very high, high, moderate, low, very low)	Checkbox matrix
10.	What medical domains benefit from digital health systems?	Open-ended
11.	Which diseases can be treated better with digital health systems?	Open-ended
12.	For which places of care are digital health systems suitable?	Open-ended
13.	What treatment methods can be supported by digital health systems?	Open-ended
14.	How important do you think are the following application dimensions for digital health systems? (Horizontally: medical domain, symptoms, location of care, method of treatment, vertically: very important, important, neutral, unimportant, very unimportant)	Checkbox matrix
15.	Assess your knowledge in digital health systems.	Likert Scale

Table 1: Questionnaire items investigating abstract visualization and domain specific tasks.

3.2.6 Summary and prospect

Preliminary results based on a sample size of $n=10$ suggest that participants answers reflect parts of Bashshur's telemedicine tasks. Experts agreed that 1-dimensional data, group data, single values, tree structures and distributions are relevant for medical consultation tasks, while quantitative, time dependent, 2-dimensional data as well as data organized in a net structure, single values, outliers and nominal data are the most important ones over all tasks. Concerning relevant data types for data visualizations during mentoring, time dependent, ordinal, 3-dimensional data are together with anomalies tree data and distributions the most important ones. Quantitative, time dependent and ordinal data are instead together with group dependent and distributions the most important ones. The final analysis of the whole sample and all questions and especially differences and accordance between digital health system expert and the elderly is still ongoing. Final results remain to be published.

3.3 Study 3a-c: age-dependent health data visualizations

3.3.7 Research questions

Older adults often report difficulties when searching for items within cluttered visual scenes (Kline et al., 1992). Often feature search characteristics and pre-attentive visual features are expected to have an influence on visualization task performance (Healey et al., 1996; Treisman, 1986; Treisman & Gelade 1980). The first objective of this study is to investigate age-related performance of visualization tasks involving standard time based visualizations of health data (line graph, bar chart, study 3a, figure 1). A second objective will be to investigate age-dependent feature and conjunct search performance (study 3b, figure 1) and to which extend their feature search performance influences the performance in visualization benchmark and insight tasks (study 3c, figure 1). Additionally, the influence of attention and perception on visualization task performance will be investigated (control variables, study

3a). Study 3 will provide answers to the question (1) are there age-dependent performance differences in feature search and conjunct search tasks depending on feature count? Are there age-dependent differences in visualization benchmark and insight tasks and (3) to which extent is visual search performance associated to visualization benchmark task performance and insight?

3.3.8 Method

For the identification of age-related differences we will use a mixed design in which older (> 60 years) younger (20-40 years) participants will perform visualization benchmark and insight tasks with different visualization of health data (study 3a, see fig. 1). The visualization and the experimental task will be defined by the output of health visualization task-data taxonomy (see section 3.2, study 2, figure 1). Preliminary perceptual and cognitive tests include intensity and selectivity aspects of individual attention measured by means of the TAP 2.3 (Testbatterie zur Aufmerksamkeitsprüfung, Zimmermann & Fimm, 2009) as well as a standard IQ-test. Furthermore, statistical literacy and visualization familiarity, contrast sensitivity and individual visual acuity will be captured. During the analysis these control variables will be treated as covariates. After the visualization tasks the same participants will complete feature and conjunct search tasks. Within different trials participants will search for a target item within a group of distractors (study 3b). Target stimulus and distractors will vary on one, two and three graphical features (shape, shape + colour, shape + colour + orientation). Ten search displays will be used to assess feature, double and triple conjunction search (5 x target present and 5 x target absent trials). Reaction times and errors will be analysed depending on age group. To understand mental processes during feature search and during visualization tasks more objectively, the participant's eye movement will additionally be captured during the visualization tasks and the feature search trials. Last but not least, study 3c will consist of a secondary analysis of the performance data from study 3a and 3b in order to determine the relationship between feature search performance and visualization task performance. Relationships here will be tested by means of correlation and multiple regression analysis. As study 1 and 2 have already been conducted the presentation of our research agenda at the HFIDSS workshop aims at discussing feasibility of study 3a-3c. We therefore reserve the right to change details of study 3 including methodology, study design and analysis.

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