An Age-Differentiated Perspective on Visualizations of Personal Health Data

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Abstract

The digitalization of medical human-machine system equips data with an essential role during processes supported by digital information systems. Here, data and information visualizations are able to reduce complexity only if influencing variables on human understanding, insight, and decision-making can be controlled, quantified and ergonomically designed. Present chapter provides an review on previous work in computer sciences, engineering, psychology and medicine in order to descriptively summarize human aspects which are relevant for the design of data and information visualizations in healthcare settings. The second part of this chapter builds upon the outcome of this review by working out current challenges of information and data visualization for consumer healthcare systems and introducing three studies which serves to tackle those challenges.

Keywords

Visualization • Data validation • Health care • Human factors • Research agenda • Literature study

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

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C.M. Schlick et al. (eds.), *Advances in Ergonomic Design of Systems, Products and Processes*, DOI 10.1007/978-3-662-53305-5_21

Germany is growing faster than the overall economy and has generated eleven percent of the German gross value in 2015. In this regard, demographic change constitutes 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 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 required 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 patients and elderlies homes range from smart-homes to active implants to intelligent prostheses to small wrist gauges activity tracking devices measuring steps and blood pressure to glucose meters smartphone extensions.

Analyzing personal health-related data by data-mining and deep learning technologies generates new knowledge for pathogenesis, prevention and individualized diagnosis, prevention, mentoring and monitoring. Besides tailored medical treatment and efficient resource usage, individual medicine also opens up new perspectives for individuals. Especially, data collected and displayed on smartphone and wearables-applications provide consumers with an overview about their own nutrition and exercising behavior or their mental capability. A greater leeway in decision-making reveals to individuals regarding a detection of health risks, selection of preventive measures and therapy method. But safe, efficient and effective transmission of data characteristics only accrues by understandable, easy-to use data representations. If data and information is represented by graphic features, data characteristics and relationships can be understood more easily by a larger target group. Attaching graphical features to data, -types,-characteristics and -transitions puts the highest bandwidth channel to mediate between data and human. The original definition of visualization implies a “formation of mental visual images”, a second definition refers to “putting something into visual form”. Though, by externalizing the mental visualization it becomes a cognitive tool whose virtue is not automatically given by the fact that it is a visible. Instead different factors have to be taken into account during the creation or selection of visualization. Contextual factors such as optics, lightning, display size and resolution, lightness, brightness, contrast, but also more important human aspects including perceptual, attentional and cognitive processes but also and equally important the users tasks, goals corresponding with individual information need and behavior.

2 Digital Consumer Health Products and Visualizations

In order to get a first impression of existing personal digital health products which come together with data or information visualizations, preceding subchapter describes personal health applications and individual perspectives on visualization. Here an emphasize is put on mobile monitoring of private health-related aspects and on medical test results and personal health records which make frequent use of *data visualization* and *information visualization*. In some cases the borders between these two areas already overlap. This could be interpreted as hint to future development of both application areas towards cooperative care systems where private and professional medical data is merged together in one database and individually shown to the user depending on his/her role and tasks.

In order to establish a narrative overview, several research papers and reviews dating from 1980 to 2015 were considered using APA PsycNET (psychology) and ACM Digital Library (computer science). For the search in all libraries we used the following search terms: ((((“visualization technique”) OR “information visualization”) OR “data visualization”) AND “health”).

2.1 Mobile Personal Health Monitoring

Medication adherence is one of the most important tasks for consumer or personal health with incremental amount of digital information systems support. Pillboxes and bottles which automatically connect and send data in form of messages to patients or caregivers phones (Theng et al. 2013). Other than this pure medication reminder another application includes visualizations of diabetes patient’s continuous and discrete data plotted for a mobile health feedback system with the purpose to monitor medication ingestion events and physiological measures simultaneously with sensors, adhesive patches and a smartphone (Browne et al. 2015). Visualizations of this app included medication ingestion and activity, heart rate, sleep, rest, and glucose data over varying time intervals and supported insights into individual longitudinal patterns of medication adherence and self-management in the natural setting. The visualizations were accessible to healthcare professionals as well as patient consumers by preserving accuracy of the data and being understandable at the same time. Time-dependent line graphs were able to augment communication (interviews) between patients and medical professionals. Frost and Smith (2002) developed a system which users could apply to keep track of parameters important for a treatment of their diabetes. Data formats included behavioural and sensor data. Besides medication adherence, wellness or fitness applications are a domain in which lay users and consumers are provided with behavioral, physiological or affective information which poses certain relevance for their personal health. The quantified-self (QS) movement (Swan 2012) uses on-body sensors which provide input for traditional bar-chart und line graph visualization primarily displayed on web applications and mobile phones. By nature, people have a vague sense of their activities and often find it difficult to keep track of their progress over time. Furthermore of comparing themselves to others, a social element that helps many people sustains motivation. Ali-Hasan et al. (2006) found for example that visualizations showing pedometer data of activity encouraged students to set personal goals, activity planning, analyzing. Furthermore the insight into own data lead to an increase of motivation through virtual competitions and teamwork. The same effect was observed for a mobile system using photos and manual entries instead of sensor data. Users could take photos of their food, attach a category to it and manually enter their exercise behaviour. Photos and entries were displayed on a horizontal timeline. The authors found that it raised the awareness of health concerns and motivated users to engage a healthier behavior (Brown et al. 2006). Additionally, Goodman and Foucault found within their literature review that visualizing weight loss and fitness activities creates structure, accountability and motivates the users (Goodman and Foucault 2006). Subramonyam (2015) implemented an innovative solution to display data on a mobile phone for quantified self-monitoring data. Here, the so called "MagicMirror" maintains conjunction between data and its context by visualizing health data with the body as reference frame. The systems detect gestures and projects heart-rate, calories, steps and sleep data onto a virtual image of the user. By touching ones heart e.g., the mirror shows a numerical representation of the current heart rate value. Instead Epstein et al. (2014) analyzed the specific tasks of individuals using self-tracking devices and which data visualizations they appreciate. In total 14 participants regularly wearing self-tracking devices were interviewed about their tasks and goals. Results suggest that participant's main goal is to get an overview on their physical activity and an insight into their workout behavior serving the long-term goal of maintaining or increasing the personal level of physical activity. Subjective interviews with all participants revealed that visualization preferences are closely related with individual goals. All participants preferred to view workout-patterns, eleven participants mentioned their work schedules influenced their activity. Sensor data are the basis for many wellness visualizations and air quality plays an important role for personal health and wellbeing (Jones 1999) a lot of wellness devices monitor and visualize corresponding parameters. Within the "inAir" application as within most wellness applications time-based line graphs where the vertical axis being air quality level and the horizontal axis being time. A line graph representing particle counts over four hours within the main part of the screen. There are two modes of data visualization: a single-user and sharing mode. In single-user mode, the graph displays only its own data, and in sharing mode a user can choose to display either a single line from the local sensor or multiple lines in different colors from all participants. Additionally, the display renders a grey area in sharing mode, which represents the range of data from all participants. The visualization of air quality helped to improve air quality by fostering the behavior and awareness of the users regarding the measured (Kim et al. 2013). The psychological needs of users with chronic pain during fitness had concerns regarding visual appearances of fit instructors within exercise videos and preferred an abstract or realistic representation of the instructor (Swann-Sternberg et al. 2012). An interesting approach to investigate visual preferences of users was conducted by Jang et al. (2013) who focused on investigating the visual communication of pain. Eight Individuals drew pen-and-paper diagrams to communicate about their pain. Four subjects used color to describing surface-level symptoms and they tried to match the color to the symptom. Symptoms below the surface were never described with colors. Marks like crosses, dots and lines were used to indicate the location of pain while shape outlines and shading were used to refer to an area. Users preferred the body diagram and drawing as easier, accurate and more specific than textual representations. The happiness counter is on example for a digital health application and encouraged users to be happy by monitoring time based smiling and visualized in with the help of a calendar having one smiling icon each day the user smiled (Tsujita and Rekimoto 2011) . An affective health system for coping with stress and stressful situations was built by Vaara et al. (2009) logging data about a person's arousal (galvanic skin response), pulse (heart rate), movement (accelerometer) and contextual data from the device itself like photos, text messages, but also surrounding devices Bluetooth signal. All data were visualized for the user to detect patterns. The iteratively built visualization contained geometrical shapes as representations for places. Positions and activities were ordered linearly according to time on a horizontal axis and with a circular representation of time. Besides a participatory design the authors reported no evaluation.

Preceding summary illustrates the increasing amount of application domains where digital consumer health applications communicate aggregate health-related data to people interested in factors influencing their health by means of visualizations. The major part of mentioned applications relates to a less private setting where data are interpreted without professional expertise or additional clinical data sources.

2.2 Medical Test Results and Personal Health Records

Personal also professional medical records become increasingly intervened with personal data and are more and more being made available to patients. Non-experts and consumers primarily employ computers and smart phones to access their *personal health records* while initially personal health records (PHRs) include professional medical information. Personal health records contain personal health data administered by an individual often referred to as patient. PHR support people in medical care, but they also encourage healthy individuals to maintain their health, improve their well-being and prevent illnesses (Tang et al. 2006). This implies a promotion of autonomous and impartial handling of individual's own health. Just as electronic health records (EHR), PHRs refer to digital instance of patient data. Patients are able to maintain, aggregate, and analyze their own data which then can support caregivers and health care providers. PHR differ among providers and allow patients to directly enter information on personal diagnoses, medications, laboratory tests, diagnostic studies, and immunizations into an information system. A review on PHR systems literature (n = 130) by Archer et al. (2011) stated that due to the accessibility of health information on the internet, individuals increasingly incorporate online information to make health-related decisions for themselves and others. As care givers and physicians play a pivotal role in people's personal health life the authors identify a certain overlap and expect PHRs and EHRs to be brought together at some point within the digitization of healthcare services. The kind of health-related information which needs to be included into PHRs remains contentious. Showing individual's data which a health-care provider keeps about them might be as reasonable and useful as providing data and information an individual's keeps for personal use to clinicians. Information collection, information exchange/sharing, and information self-management count among important PHR systems activities. Relevant data include demographic information, lists of health problems, health procedures, illnesses, allergies, home monitoring data, family (health) and social history, lifestyle/wellness data like data generated by fitness trackers, health recommendations, immunizations, examinations, medications, laboratory test results and appointments as well as physicians and personal notes. Mentioned data can be provided by the patient his/herself, the caregiver, physicians, clinical EHR systems or insurances. Functionalities include sending and receiving electronic messages to and from doctors' offices, making completing prescription renewal forms, appointments, and referral authorizations; viewing lists of current medications and allergies; and accessing health and practice information. Decision support can also assist patients in managing chronic illnesses, based on monitoring data.

PatientsLikeMe is one example for a PHR application. Within a web-platform, patients could view and understand their personal health data and exchange personal disease-specific information with each other based on data visualizations (Frost and Massagli 2008). Initially PHR pointed to an analogous medical file which was kept at home and regularly updated by the patient including various health information. At the beginning digital personal health records were limited (Kim and Johnson 2002) but nowadays the digital personal access to health information is becoming increasingly important (Archer et al. 2011; Tang et al. 2006; Frost and Massagli 2008).

While patients are experts regarding their personal behavior, environment or their perceived symptoms they are assumed to have less knowledge about medical tasks like diagnoses medication or laboratory test result interpretation as well as less numeracy. Therefore a user-oriented perspective on data visualizations has an even greater relevance. If confronted with medical data in patient portals patients perceived the information storage, the time-based view of lab results and reminder notifications as a major benefit. Concerns relate to privacy and a fear of reduced face-to-face interaction. Much older patients felt that it would be too costly learning how to use digital healthcare information systems though the authors hypothesizes that interest in technology correlates with age and low educational level. They summarized that a lack of ability, confidence and interest of older adults but also system complexity and a lack of usability, prevents elderly from using ICT supported systems. Elderlies said that looking at laboratory test results, schedule appointments, sending questions to the healthcare providers and functions to online renew their prescriptions are tasks they want to perform with online health platforms (Latulipe et al. 2015).

In order to provide patients with context information for the more autonomous interpretation and handling of their *medical records* Solomon et al. (2016) designed meaningful representations of test results within patient portals in a user-centered way. The authors found that color or text conveying contextual information can be effective, but may conflict with graphic related goals such as eliciting emotional responses or supporting clear communication between doctors and patients. The LifeLines system for example visualizes personal time-dependent data such as medical histories (Plaisant et al. 1996). Its evaluation included qualitative non-statistical approach to improve the software. Another system, InfoZoom, displays data sets as highly compressed as an interactive table. Both systems visualize raw data without temporal conclusion or domain knowledge. The KNAVE visualization platform instead visualizes time-oriented clinical data of a single patient. Clinicians can query, visualize and explore those data with the help of context-sensitive time data interpretations, as well as the dynamic visual exploration of the raw data (Goren-Bar et al. 2004). All three examples suggest, that time-oriented data plays an important role in health information visualization.

In comparison with the computer science domain, literature from psychological journals relevant for an age-dependent visualization design, do not focus on the visualization artifacts themselves but on perception and cognition related to it. Given our previous query results only (Breslow et al. 2009; Salthouse 2010, 2015) apply the term "visualization" explicitly and investigate data visualization relevant objectives. From the seven results of our initial search query only four appeared to be relevant for data and information visualizations. (Breslow et al. 2009) replicated the results from Merwin and Wickens (1993) showing a task x scale type interaction where the performance is higher-ranking using multicolored scales on identification task and superior using brightness scales on relative comparison task. Their results suggested that people use different search strategies during an identification task and a comparison task with color and brightness scales which are a parallel search strategy for comparison tasks and a serial search for identification tasks. The results of Breslow et al. (2009) implicate that a legend within a visualization increase execution time of visualization tasks. They furthermore emphasize the importance of color distances for the visual search in multicolored displays which require a color-difference standard to guide designers of color scales to produce easy to use color scales. While (Padilla et al. 2015) concentrate on non-expert decision making. Understanding how people interpret and use visually presented uncertainty data is an important yet seldom studied aspect of data visualization applications. The authors found that there was a difference in how decisions were made with spatial versus nonspatial glyphs, but no difference among the spatial glyphs themselves. Furthermore, the effect of different glyph types changed as a function of the variability of the distributions. Hesse et al. (2015) found through their review that life-sensitive, personal health record (PHR) can be used to support persistent conversations and situational awareness for teams involved into cancer care, while *mobile health apps* make it easier to support healthy behavior through self-regulatory feedback. Spence et al. (1999) found out that color codings for quantitative coding, which are close to perceptual linearity, were best for both simple and complex judgments in data visualization.

In summary we conclude, based on the literature we found, that visual representations of private health data and personal clinical data are an important field of research in computer sciences and in medical informatics. Research concentrates on the development of computational systems, data handling, system architecture and interaction methods. User-centered development and usability engineering methods are largely applied to build interactive health systems. Recent systems use mobile and wearable input and output devices. Data visualizations are used in the major part of all systems to provide healthy and ill subjects as well as physicians and clinical experts with health-related information. What appears is, that data visualizations are most of the time considered as just one part within the system and that age-differentiated recommendations regarding an ergonomic design merely exist.

3 Problem Statement

Human information processing is central for the perception and understanding of data visualizations. During the design and evaluation of data visualization human information processing has to be taken into account, especially as the fast aging of many western and eastern societies and their increasing reliance on information technology create a compelling need to reconsider older users' interactions with computers. Changes in perceptual and motor skill capabilities that often accompany the aging process bring important implications for the design of information and communication technologies.

The importance of an ergonomic perspective on data and information visualization research for digital healthcare information systems becomes apparent especially in the light of age-related changes. Many visual functions deteriorate slightly with age. This age-related slowing 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 who can be considered as one major target group. While general recommendations for age-related design of graphical user interfaces exist sparse can be found for data visualizations.

So far, the human factor has mainly been involved at an a posteriori stage of novel visualizations techniques or tools. As tasks strongly influence a certain evaluation their analysis needs to precede the visualization development and its further evaluation. The problem of such task-oriented research evolves from the different abstraction levels tasks have. Either they are domain dependent or domain independent. Domain-independent tasks which are used as basis for further evaluation studies might not be relevant for domain specific activities. Therefore, a detailed task analysis on the relation between various task abstraction levels and their interrelationship are necessary in order to generate generalizable results for all tasks relevant to the domain of digital healthcare information systems.

User-centred design for digital health-care systems prevalently starts after the main purpose or application area has been defined. Research and development activities are driven by a project idea or an initial hypothesis. Only few development activities consider the actual information needs of users as starting point for the development of a system.

4 Efforts Towards an Age-Differentiated Design of Data Visualizations

While the Tech4Age project (www.tech4age.de) focuses age-differentiated evaluation of digital health care systems in order to built a general pattern language summarizing design recommendations for system designers and engineers, given article presents the projects efforts on visualizations of personal health data. In total three studies will be described. Initially Sect. 4.1 describes results of a context analysis investigating health-related information need of people older than 60 years in Germany. Subsequently Sect. 4.2 describes efforts to formalize health-related tasks and abstract visualization tasks and according data types. This formalization will be the input for a study described in Sect. 4.3. This study will examine age-differences in performance and insight of data visualization in proportion to feature and conjunct search task performance. A conclusion and summary is provided in Sect. 5.

4.1 Elderlies Health Information Need and Behavior as Context of Visualizations of Personal Health Data

Deep understanding of user needs is crucial for building successful digital services and technology. At the beginning of research activities it is thus important to understand and specify the context of use, specify the user goals and activities in order to achieve quality in use. This is especially important for health-related systems with end users having exceptional requirements: elderlies, for example, are less familiar with modern information and communication technology (ICT) while visual acuity (Elliot et al. 1995), spatial vision starts declining (Sekuler et al. 1982) and visual sensitivity alters (Zhang and Sturr 1995). Also mental models of elderlies are characterized by enormous life experiences and thus strongly differ from users who are familiar with ICT systems. While we see information technology as a tool to which humans assess information, the analysis of user's *health information need* and *health information-seeking behavior* can motivate technology usage as it presides over engineering processes.

4.1.1 Research Questions and Background

Present context analysis aims at investigating which information has a meaning for elderly's personal health. Knowing what a patient needs to know about her/is health and which sources s/he applies to find those information, creates the basis for the design and the development of artifacts conveying health information to the elderly patient. This leads to the questions (1) how do elderly currently gain relevant health information, (2) what health-related information do elderly need (3) and how and why to they elderly approach certain information sources?

Information behaviour as human behaviour in relation to sources of information includes both active and passive information seeking, and information use. It includes direct communication between people, but also the passive information perception. Information seeking behaviour instead is an active and directed behaviour, where the user purposive seeks for information as a consequence of a need to satisfy some goal. In the course of seeking, the individual may interact with digital or non-digital information systems. Information behavior in general and especially within the healthcare context is determined by intrinsic and extrinsic factors which should also be captured during our investigation. Concerning information needs in healthcare Miller and Mangan (1983) showed that individual coping strategies have an impact on 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 and Walsh (1996)$_s$ 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 (Auerbach 2001). Activity-theory (Miettinen 2009; Nardi 1996) and Wilsons model (Wilson 2000, 2005) on information seeking behavior build the foundation for questions on health-related activities, required information and confounding aspects. Validated tools captured the confounding concepts of coping strategies (Endler and Parker 1999) and need for cognition (Cacioppo et al. 1984; Verplanken et al. 1992). The Need for Cognition Scale is an assessment instrument that quantitatively measures the tendency for an individual to engage in and enjoy thinking. Results indicate that need for cognition was related weakly and negatively to being close minded, unrelated to social desirability, and positively correlated with general intelligence.

4.1.2 Method

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. In order to investigate the context of health information systems, qualitative interviews provide rich and detailed information. Our aim was to generate insights and hypotheses rather than generalizable results. Respectively, we conducted a mixed-method study—involving structured surveys and in-depth interviews—with people about their health information sharing routines and preferences for different information sources. Participants (n = 20) older than 60 years were acquired via adult education institutions. At the beginning of each session, the participant first filled in a questionnaire about demographic and role-related parameters. Then the semi-structured interview investigating health-related information needs and behaviour was completed. All interviews were probing questions participants had about health, personal health and related concepts (medication, prevention, health and vital data, health insurance, hospitals or institutions) and regarding activities, goals and tools they use, share, and access health information with. The interview was based on existing interview guidelines on information needs of urban residents (Warner et al. 1973), information behaviour and needs related to information source/technology usage (internet, VT, print, smartphone, doctor, family and pharmacist). A standard questionnaire on coping strategies (Coping Inventory for stressful situations, CISS, Cosway et al. 2000) helped to post hoc divide the sample into groups. Finally, audio recordings were transcribed by means of the T4 transcription software (www.audiotranskription.de/english/f4.htm). Then two independent analysts iteratively developed an open and a theory-oriented coding theme with the Dedoose Software (www.dedoose.com).

4.1.3 Results

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 exchange 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*." 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 behaviour 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).

4.2 Formalizing Health Visualization Tasks and Data Types With Regard to Generalizable Evaluation Results

Investigating ergonomic aspects of data and information visualizations requires a solid model of relevant tasks in order to use these as experimental tasks during evaluation. Tasks per se differ in domain relevance and abstraction level. To our knowledge no information exists about user-centred general task analysis for the digital information systems domain. 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 different 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) provides 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 want to verify it from the user's perspective and extend it. Additionally we want to know which abstract visualization tasks are relevant for the tasks in digital healthcare systems (telemedical systems).

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).

We sent the link to the online questionnaire to N = 400 health-care systems experts and elderlies while getting N = 48 answers from experts and N = 50 from non-expert elderly (older than 60 years). Preliminary results based on a sample size of n = 10 experts suggest that their answers reflect parts of Bashshur's telemedicine tasks. Experts agreed that one-dimensional data, group data, single values, tree structures and distributions are relevant for medical consultation tasks, while quantitative, time dependent, two-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, three-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.

Table 1 Questions investigating general health tasks in relation to abstract visualization tasks and according data types

No.	Question	Answer option
1	What medical tasks and activities can be supported by digital health systems?	Text field
2	Which data play an important role for digital health systems?	Text field
3	What data are required for medical consultation?	Text field
4	What data are required for medical diagnosis?	Text field
5	What data are required for medical mentoring?	Text field
6	What data are required for medical monitoring?	Text field
7	Specify what data is required for the following medical tasks. [horizontally: consultation, diagnoses, mentoring, monitoring; vertically: datatypes (Shneiderman 1996)]	Text field
8	Indicate which abstract visualization tasks (vertically) are required for given medical tasks (horizontally) [horizontally: consultation, diagnoses, mentoring, monitoring, vertically: abstract tasks from Brehmer and Munzner (2013)]	Text field
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)	Text field
10	What medical domains benefit from digital health systems?	Text field
11	Which diseases can be treated better with digital health systems?	Text field
12	For which places of care are digital health systems suitable?	Text field
13	What treatment methods can be supported by digital health systems?	Text field
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

4.3 Investigating the Relation Between Age-Dependent Visual Search Task Performance and Visualization Task Performance and Insight

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 reported to have an influence on visualization task performance. The efficiency of an individuals search is known to vary with age which leads us to the assumption that visualization benchmark and insight tasks might vary as well. This subchapter will therefore describe background, problem and planned experiment to investigate age-dependent performance on feature and conjunct search in relation to visualization performance and insight tasks.

Visual information acquisition and processing can be described by the paradigm of *feature search* and *conjunct search*, where a target must be identified within a number of distractors. The process of search and the search time in visual search tasks depend on the characteristics of the target and distractor objects. Treisman and Gelade (1980) constituted in their feature integration theory (FIT) that certain fundamental features exist which are perceived in parallel (shape, color, texture). When an object is different from other objects in one of these characteristics, this object is pre-attentively perceived (feature search). This is done automatically and unconsciously within a few milliseconds (200 ms) and is independent of the number of other objects. The top-down-driven perception of objects with conjunct properties (conjunct search) instead corresponds to a sequential process that requires more time and depends on the number of distractors.

The model of *directed search* (Wolfe et al. 1989; Wolfe 1994) however, assumes that the pre-attentive search, is processed at a large part of the visual field. Wolfe and his colleagues assumed that information that has been detected in parallel during the pre-attentive phase are used to direct the sequential process of perception, which are then proceeded in a smaller area of the field of with more attention. This can also be observed by means of the symmetry factor during conjunct search tasks. Wolfe and Friedman-Hill (1992) have shown that the visual search can be facilitated by a vertically symmetrical arrangement of distractors. This suggests that the distractor symmetry is processed in parallel and facilitates to detect a target among an array of distractors. One question that arises regarding the sequential search is to which extent the working memory is involved and whether once detected distractors are stored as such in memory and are not considered in the further search again, or whether the visual search corresponds to a non-cognitive process. By means of empirical and inferential studies following the dual-task paradigm, visual search task were associated with a task of visual working memory, Woodman et al. (2001) showed that an occupation of the working memory (through remembering one, two or four colors as well as forms had to be kept in mind) does not affect the performance in visual search tasks. Oh and Kim (2004) conducted a similar study, but they differentiated between the availability of visual working memory and spatial working memory. With regard to the visual working memory this results are similar with those of Woodman et al. (2001). The simultaneous execution of a task of spatial working memory however interferes with visual search processes. Woodman and Chun (2006) came based on the literature to the conclusion that the spatial working memory for storing position properties is involved to visual search and that a once fixated item is supposed to be memorized there. The visual working memory for storing object properties, however, is not required for visual search. But additionally, the eccentricity of the target object has an effect on the visual search: the further a target is away from the place of fixation, the later it is detected (Carrasco et al 1995;. Wolfe 1998). Rayner and Fisher (1987) assume that there are two parts or areas within the search for a target letter: a central area by which all the information about the target object are available, and a preview area by which some information about the target can be detected, which is not in a recognizable range. The more the size of both areas increases, the more similar target and distractors are. Wolfe et al. (1998) were able to provide evidence that it is the eccentricity effects not a purely visual process, but that attentional process plays a role in here. Their studies show that attention is drawn more quickly to central/foveal items than on peripheral ones. In addition to the eccentricity effects of the target object the position of distractors has an additional impact on the visual search.

Already from the age of 30 on, longer reaction times are observed during (Hommel et al. 2004). Age-differences occur only slightly within the pre-attentive search tasks (feature search), while they are more prominent during attentive top-down-driven conjunct search tasks. However, the strong age-differences of conjunct search tasks add by the number stimuli (Hommel et al. 2004; Plude and Doussard-Roosevelt 1989) and by heterogeneity of the distractors (Madden et al. 1996). Nothing is known about age-dependent feature number thresholds from which on the performance in conjunct search tasks declines. Furthermore, an age-related shift of the speed-accuracy trade of was found in the visual search. Elderly require typically more time but make fewer mistakes than younger participants (Strayer and Kramer 1994; Rogers and Gilbert 1997). In this context, it could further be shown that older adults stronger tend to fixated a stimuli a second than younger participants (Veiel et al 2006; Mitzner et al. 2010) and elderly tend to fixate the target stimuli longer than younger participants (Veiel et al. 2006). The results of Maltz and Shinar (1999) also revealed that older people have significantly longer search times, more fixations and shorter saccades than younger people. Studies of Scialfa et al. (1994) and Ball et al. (1988) suggest that the area in which stimuli can be detected without fixation change during visual search tasks is smaller in elderly subjects than in younger subjects.

As pre-attentive and conjunct features have been cited to have an impact on humans handling and understanding of data visualizations, and as age-related differences have been reported there, our first objective of this study is to investigate age-related performance in visualization tasks involving standard time based visualizations of health data. A second objective will be to investigate the feature search performance of a large sample of participants across adulthood and to which extend their feature search performance influences the performance in visualization benchmark and insight tasks. Additionally, the influence of different attentional and perception parameters on visualization task performance will be tested.

For the identification of age-related factors we will use a mixed design in which participants in each age group (20-50, 50-90 years) will perform benchmark and insight-tasks by using different visualization of health data. The data type and kind of benchmark tasks will be defined by the output of the study on task-data-type-taxonomy. Only health-relevant tasks and data types will be considered. After the visualization tasks participants will complete 30 trials searching for a target item on each of 5 different visual search displays. Three search displays will be used to assess feature, double and triple conjunction search (target present trials only). Two search displays will be used to assess exhaustive searching versus stopping in feature and conjunction searches (target absent versus present trials). Preliminary perceptual and cognitive tests include intensity and selectivity aspects of individual attention, like general attention, vigilance and short-term, early and long-term attentional activation measured by means of the TAP 2.3 (Zimmermann und Fimm 2002). To understand mental processes during feature search and during visualization tasks more objectively, the participant's eye movement will additionally be captured. In addition, contrast sensitivity and individual visual acuity will be recorded with the Optovist vision test equipment. The planned study is used to determine the relationship between perception- and attention parameters and performance in dealing with data visualization quantitatively. Potential age-differences will finally be examined with analysis of variance; relationships between individual factors will be tested by means of correlation and regression analysis.

5 Summary and Conclusion

A review on existing computer science and psychology literature revealed the importance of visualizations for personal health information systems. It became clear that digitalization of health processes and services increasingly incorporate medical experts and elderlies into cooperative care processes where personal health data is exchanged between medical experts and private users. While a lot of health applications incorporate data visualizations their definition is ambiguously and ranges from graphical representation of abstract statistical data to graphical representations of realistic physical objects. Data visualizations are treated as a part a technical system and are seldomly evaluated and designed age-dependently. Consequently a lack of knowledge regarding an age-differentiated design of health data visualizations was identified. A description of three individual studies addresses this lack of knowledge was precedingly presented. Preliminary results from a qualitative user study on health information need and behavior of older adults in Germany substantiated findings from the initial literature review and identified the need for cooperative health care and data exchange between patients and medical experts. Furthermore, a task-dependent study which we see as basis for generalizable results of ongoing visualization studies was described. So far time-dependent data are the most important data types, while diagnosis and symptom evaluation are important medical tasks for experts as well as novices. Finally the research design of an evaluation study aiming at general recommendations for the age-differentiated evaluation of health data visualizations was presented. Here, the relation of age-dependent feature and conjunct search performance on visualization benchmark and insight tasks will provide general recommendations for the age-dependent design of health data visualizations.

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