Interactive Data Exploration Supporting Elderly Care Planning

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***Abstract*—Over the past decades, improvements in healthcare resulted in longer life expectancies and growing demand for specialized long-term care services for the elderly. Detailed up-to-date indicators describing the demographic status quo in order to enable adequate planning to meet the requirements of this population are missing. Today, these data are either scattered across different sources or only available in highly aggregated form. In the given paper, we share details about our interactive data exploration tool, which incorporates routine data from a large German health insurance to derive specific elderly care indicators, while ensuring scalability, data actuality and separation of data and visualization. Thus, governmental experts can access up-to-date data for elderly care planning in a structured and harmonized way.**

***Keywords*–Elderly care planning; key indicators; data exploration; on-line analytical processing.**

I. INTRODUCTION

Life expectancy has been increasing steadily in recent decades, particularly in high-income countries [1]. Coupled with declining birth rates, industrialized nations are faced with an ever-older population [2]. Competent authorities need to plan accordingly in order to meet changing societal needs, e.g., in terms of employment, pension funds, and health care provision. Although this is a widespread phenomenon in the developed world, Germany's position is particularly unfavorable: it ranks as the country with the oldest population in Europe and the second oldest worldwide [3].

While data on demographical developments in the form of census are usually available, data concerning elderly care, for instance the number of dementia patients in a given municipality, are scarce and/or insufficient, often lacking in quality and spread across different sources. This fact substantially hampers governmental planning efforts to this extent. Nevertheless, access to such data is crucial in devising adequate public policies that meet the needs of the elderly. In particular, a growing trend can be ascertained to support 'aging in place', that is, close to one's home and/or community, which is widely considered a more desirable alternative when compared to institutional care [4].

Healthcare data, e.g., in insurance companies can help bridge these data gaps, providing the basis for informed decision making. Figure 1 depicts the individual components of our tool modeled as a Fundamental Modeling Concepts (FMC) block diagram [5]. It builds on a combination of de-identified routine data from a large German health insurance together

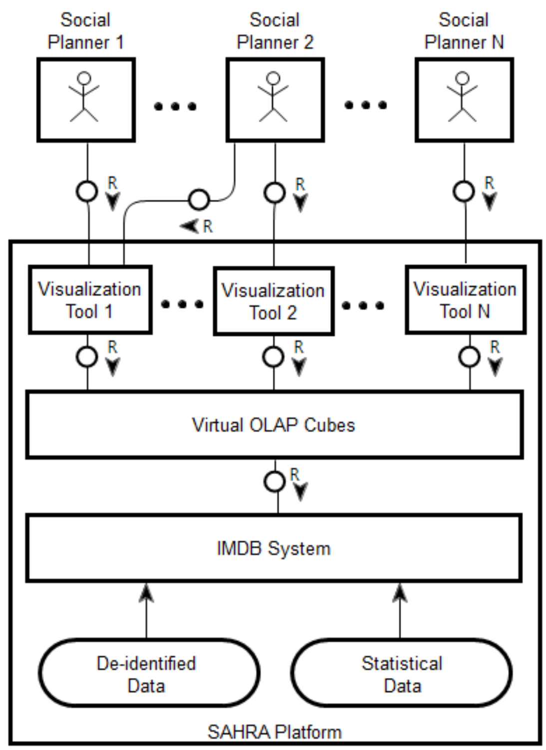

Figure 1. Software system architecture of the elderly care data exploration tool depicted as a FMC block diagram.

with statistical data provided by governmental bodies, both of which can be interactively explored by expert users. Data is integrated and harmonized in an In-Memory Database (IMDB), which provides On-line Analytical Processing (OLAP) cubes for a number of visualization tools. Governmental users, i.e., social planners, then can use such tools to explore the available data. Our tool is part of the project Smart Analysis Health Research Access (SAHRA) [6]. The consortium consists of industry and academia partners who aim to explore the opportunities inherent to data generated by healthcare actors to address research questions relevant for policymaking and health care provision.

The remainder of this work is structured as follows: Section II introduces our motivation, and objectives of our tool. In Section III, we set our work in the context of existing initiatives concerning elderly care planning, whilst our software architecture, incorporated data sources and data visualization tools are

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outlined in Section IV. Software requirements are detailed in Section V. Our contributions are shared in Section VI and their impact is discussed in Section VII. Our work concludes with an outlook in Section VIII.

II. Motivation

In the following, we present the motivation and the objectives pursued within the development of the elderly care data exploration tool.

In Germany, municipalities are often aggregated into districts for administrative purposes. Districts serve therefore as an intermediate governmental entity between the German states and the municipal governments themselves [7]. However, information on elderly and nursing care needs from the census and other sources is often provided not at the municipality level, where facilities and personnel are needed, but rather at an aggregated level (district or state) - if available at all. This information gap hinders planning efforts carried out by districts, which must rely on incomplete, partial information or commission expensive data collection from private entities. Furthermore, the data collection process and subsequent generation of reports is often resource-intensive and time-consuming, since it takes place manually and data sources are scattered in different providers.

Health and nursing care insurance companies possess a wealth of detailed routine information on their insured patients, e.g., where they live, what services they have used, relevant diagnoses, demographics, how long they have been cared for, if they are in an inpatient or outpatient facility, and so forth. The opportunity to bridge the existing data gap by the secondary use of routine data was the starting point for the elderly care data exploration tool within the SAHRA consortium.

The overall objective of our proposed solution is to support the planning and decision-making process concerning elderly and nursing care needs within German districts and municipalities. To this end, relevant elderly care indicators, such as number of inhabitants with nursing needs, percentage of individuals in an in-patient facility, among others, needs to be identified. For the pilot project, two administrative districts in Northeastern Germany have been selected. They provided the requirements for the solution and subject-matter experts were available for feedback. The names of the respective districts will not be disclosed for data protection reasons. Finally, it was necessary to ensure that data extraction and analysis are carried out in an automated and privacy-compliant fashion. As such, the specific objectives of the solution presented in this paper are 1) define a set of relevant care indicators, 2) extract and anonymize pertaining routine insurance data and 3) develop a web platform for interactive exploration of the defined indicators with automatic data flows and compliance with privacy regulations. In Section IV, we provide specific details on how these objectives have been achieved.

III. Related Work

Research on Information and Communication Technology (ICT) tools used for elderly care is often focused on supporting care delivery processes, for example via collaboration tools and data exchange. Since a patient will be treated by a number of different professionals across the care continuum, it is vital that they cooperate effectively [8]. Technologies for Ambient Assisted Living (AAL) and Building Automation (BA) represent another line of active research [9].

In contrast, our tool is targeted at providing high-quality data to support policy and decision making. For effective policies to be devised, a prerequisite is access to high-quality, up-to-date, precise information. Initiatives to this extent include information portals put together by governmental statistics services, for instance, the German Statistical Office's elderly care indicators [10] or the Healthy Aging Data Portal by the Center for Disease Control [11]. Likewise, the National Board of Health and Welfare in Sweden provides information on the state of its elderly population [12]. Moreover, a solution developed by a Portuguese software company provides operational management for nursing care homes on the cloud [13]. While it could potentially provide detailed aggregated information on elderly patients, it lacks the coverage necessary since nursing homes are only one of the actors in the care continuum [14].

Such initiatives have a number of weaknesses compared to our presented approach. Firstly, the content they provide is largely static and does not enable user-driven exploration. Exception to this rule is CDC's portal [11] and the PORDATA Contemporary Portugal Database on the elderly [15]. In both tools the user can interactively select indicators of interest and generate visualizations, albeit limited to few options.

Secondly, the scope of the indicators available on those platforms is rather limited, e.g., PORDATA offers four indicators while the CDC has nine. We have gathered more than 30 indicators of interest, which are extensible with ease. Third, the level of granularity of the current solutions is restricted either to the national or state-level, being therefore of reduced use for social planners in a district or municipality, for whom only fine-grained information is relevant. Forth, unlike existing solutions, the platform presented offers different stratification dimensions, e.g., according to legal criteria such as care level. Finally, automated data processing and compliance with privacy regulations ensure that up-to-date information is presented to the user once it was made available through the data provider.

IV. Methods

In the following, we share details about the incorporated research methodology. Section IV-A outlines the approach utilized for requirements engineering, while Section IV-B expounds upon the tool's technical infrastructure.

A. Requirements Engineering

We followed the design thinking methodology to create a user-centered prototype via interviews with subject-matter experts for elderly care planning [16]. In subsequent workshops, the team distilled the interview results into personas and user stories. Personas are a generic entity that represents a typical user of the solution. In particular, two personas have been identified. The first is the head of the district's social department, in charge of interfacing with numerous political entities and providing, among other tasks, guidance on elderly care issues. The second is a specialized officer or social planner, responsible to carry out data analyses and elaborate the elderly care plan, i.e., a comprehensive document containing an appraisal of the status quo on elderly care and a number of recommendations. User stories establish the aims pursed by the personas and often take the form of 'as persona

X, I want feature *Y* to achieve purpose *Z*'. This generated a catalog of user stories that has guided the implementation of the tool. They laid out the foundation for a set of functional and non-functional requirements as per the ISO/IEC/IEEE 24765:2017 [17], which are dealt with in detail in Section V.

B. IMDB Technology

One of the centerpieces of our tool is the incorporated In-Memory Database (IMDB) technology, which enables real-time data processing and analysis of the stored data [18]. We refer to IMDB technology as a toolbox of Information Technology (IT) artifacts to enable processing of data in real-time in the main memory of server systems [19]. Our incorporated IMDB backend has been proven to be an adequate tool providing real-time analysis features for big medical data [20]. In the following, we introduce selected building blocks of the IMDB technology incorporated in our SAHRA platform to enable real-time analysis of data relevant for interactive elderly care planning by governmental users.

1) Column-Oriented Data Layout: Most modern relational database systems fall into the category of transactional databases and store their data in a row-oriented format, i.e. all attributes of a record are stored in adjacent blocks [21]. This is advantageous when all data attributes of a single row have to be processed at once. In contrast, analytical database systems store and process data column-wise, i.e., all entries per column are stored in adjacent blocks, which is beneficial when only selected attributes of a data set are accessed [22]. The incorporated IMDB system supports both database layouts on a per table basis. Since user queries access only a subset of available attributes, in our tool tables are stored in columnar format. Thus, only a fraction of data needs to be processed.

2) Lightweight Compression: Lightweight compression refers to a data storage representation that consumes less disk space than its original pendant [19]. Storing data column-wise facilitates lightweight compression techniques, such as run-length encoding, dictionary encoding, and difference encoding [23]. Thus, the overall main memory footprint is reduced and the processing of data accelerated as existing CPU caches are used more efficiently. Since the elderly care exploration tool shall cover millions of inhabitants of a given region over many time periods, data size can quickly become an issue. For example, lightweight compression applied to our dataset results in an average compression of 5:1.

3) Partitioning: Our incorporated IMDB system provides vertical and horizontal partitioning [24]. The former addresses large database tables by splitting them up into multiple column-wise subsets that can be distributed across individual servers [25]. The latter handles large data sets by dividing them into smaller chunks of data row-wise, which supports parallel search operations and improves scalability [19]. Taking advantage of this approach, data belonging to different districts can be distributed and accessed across different server nodes on demand.

4) Multi-Core and Parallelization: Modern computer system architectures are designed to provide multiple CPUs with each of them having multiple individual CPU cores. For this capacity to be fully exploited, application execution must be parallelized, thereby resulting in maximum processing speed. Our IMDB system supports parallelization on various levels, e.g., parallelization both on inter and intra-operation level [19]. For instance, user queries spanning across multiple municipalities can be processed across different computing nodes, leading to faster response times.

C. On-line Analytical Processing Cubes

An OLAP cube is a multidimensional dataset containing different measures that can be aggregated/summarized across multiple dimensions [26]. In spite of their widespread adoption in Business Intelligence (BI) applications and data warehouse solutions, traditional OLAP cubes are often materialized, meaning they must be re-created every time new data is available [27]. In the IMDB cubes are virtual, allowing set operations, such as join, union, projections, etc., without the use of persistent, fixed aggregates [28].

V. Software Requirements

The software requirements were derived from interviews with subject-matter experts as outlined in Section IV-A. Following ISO 24765:2017, we were able to identify a set of functional and non-functional requirements, which will be related in detail in the following sections [17].

A. Functional Requirements

Functional requirements establish the set of functions that a system must deliver to the user in terms of inputs, processing and outputs, commonly expressed as "the system shall *do*" [29]. The functional requirements the elderly care tool must fulfill are:

- **F1: Data Privacy**. Since the tool is based on sensitive health data, appropriate measures shall be taken to ensure patients cannot be re-identified.
- **F2: Pre-defined Elderly Care Indicators:** A standardized list of elderly care indicators must be available in the tool covering the most relevant aspects for care planning.
- **F3: Fine-grained Exploration:** The proposed solution shall provide fine-grained, as well aggregated information using different aggregation dimensions, such as gender, care level and municipality.
- **F4: Access to Latest Data**. The tool shall employ automatic data flows from the provisioner to the analysis tool to ensure access to latest data at all times.
- **F5: User-defined Visualizations:** The tool shall enable the user to flexibly create his own reports using available elderly care indicators.
- **F6: Visualization Sharing:** The tool shall enable the user to share a given visualization with another user in digital form.
- **F7: Geographical Data Exploration:** The tool shall provide the user with the ability to generate cartographic visualizations based on the relevant administrative units.
- **F8: Long-term Forecasts:** The tool shall provide forecasts on all available elderly care indicators in 5 year time spans (e.g., for 5, 10, 15 and 20 years ahead). The forecasts must take into account demographic trends, as well as socioeconomic variables of interest.

B. Non-functional Requirements

Non-functional requirements are concerned with the overall properties of a system, as opposed to its functions, often written as ”the system shall be” [30]. In the following, non-functional requirements of our tool are listed:

- **NF1: Ease of Use**. The user interface shall be made of modern, self-explainable interaction components, which are familiar to the user, ensuring ease of use.
- **NF2: Fast Response Time**. The tool shall be designed so that even querying large amounts of sets does not result in a response time higher than an empirical threshold of two seconds to ensure interactive user experience [31].
- **NF3: Device Independence**.The tool shall be accessible from different device classes, e.g. from desktop computers and mobile devices.
- **NF4: Ease of Extensibility of Indicators**. Given that user needs are constantly evolving, the set of elderly care indicators shall be easily extensible, without the need to shut-down the tool for updates.

VI. Contributions

In the following, we share details about our software system architecture, incorporated data sources and set-up of data exploration tools, while pointing out how the requirements defined previously are met.

A. Software Architecture

The software system architecture of our tool is depicted in Figure 1. It is hosted within the SAHRA platform, which complies with pertinent data privacy regulations (F1) [6]. Governmental users responsible for elderly care planning in the districts, i.e., social planners have different data visualization tools at their disposal. A social planner can access one or more visualizations tools and created content can be shared with other users and user groups (F6).

1) Data Visualization Tools: Based on the infrastructure presented, different data visualization tools can be employed as long as they can consume IMDB OLAP cubes. We used a proprietary business intelligence suite for this purpose [32]. The suite makes extensive use of HTML5 and modern Javascript libraries, ensuring ease of use (NF1). Furthermore, it provides a web-based interface that is also accessible from mobile devices, being therefore device-independent (NF3).

2) Virtual OLAP Cubes: The use of virtual OLAP cubes ensures that as new data is available, analytical applications, such visualization tools, are updated in real time (F4). Another advantage provided by the use of virtual OLAP cubes is extensibility: new measures and dimensions can be added from new data sources or from calculations performed on existing measures (NF4). The analytical cubes were built upon relational database tables that were harmonized and integrated within the IMDB system.

3) IMDB System: The incorporated data sources, which cover de-identified routine data from the insurance company along with statistical data are integrated and harmonized within the IMDB. The building blocks discussed in Section IV-B namely column-based storage, lightweight compression, partitioning and parallelization ensure a fast response time for the tool even with a large data foundation (NF2).

TABLE I. Excerpt of elderly care indicators

Category	Indicator
Nursing care (NC)	Patients with NC needs Patients in a NC home Patients in home NC Patients receiving a NC allowance Patients using a nursing service
Respite care (RC)	Patients entitled to RC Patients who used RC Days with RC per patient
Day care (DC)	Patients entitled to DC Patients who used DC Days with DC per patient
Short-term care (SC)	Patients entitled to SC Patients who used SC Days with SC per patient
Dementia-related	Patients with dementia diagnosis Patients in nursing homes Patients in nursing services Patients cared for by relatives

B. Incorporated Data Sources

Based on routine data collected from insured patients from a given district, the health insurance partner extracted and consolidated a dataset of different data columns into a relational database table, each corresponding to a specific elderly care indicator, according to patient, reference year and a number of other attributes. This formed the standard list of elderly care indicators (F2). The resulting dataset is a sparse table indicating whether a given indicator applies for a specific patient or not. Furthermore, demographical statistics and prognostics compiled for the federal states to which the pilot districts belong were incorporated. They contain demographics by age segment (0-100) and gender for each of the municipalities in a district [33]. Routine data and statistical data can thereby be joined on year, municipality, age segment and gender.

C. Exploration Measures and Dimensions

Interactive exploration is enabled by a combination of measures and dimensions. Measures correspond to the elderly care indicators themselves. They cover, amongst others, number of people with nursing care needs, percentages of home, in-patient or out-patient care and aggregation by age group, gender and care complexity, offering fine-grained exploration options (F3). A partial list of the indicators identified is provided in Table I for illustration purposes.

The complete set of defined measures contains more than 30 indicators.The consolidated dataset also covers regional information, e.g., municipality of residence, that can be used to enable geographical exploration (F7). Dimensions encompass grouping attributes that can be arbitrarily combined to generate visualizations. Table II provides an overview of the exploration dimensions available on the platform.

D. Separation of Visualization from Data

To illustrate this characteristic of the tool, consider that a social planner in a district is interested to analyze age group distribution for dementia patients stratified according to different care levels (German: *Pflegestufen*). They are used

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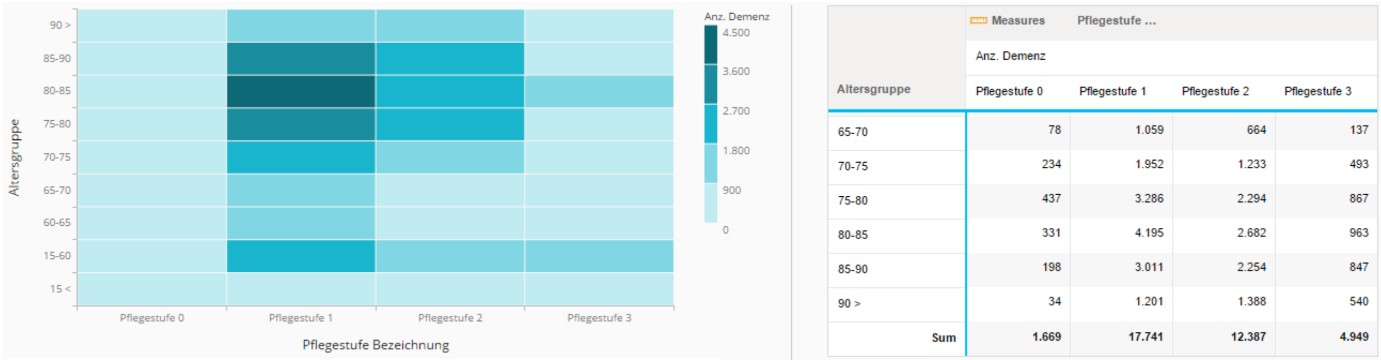

Altersgruppe	Pflegestufe 0	Pflegestufe 1	Pflegestufe 2	Pflegestufe 3
65-70	78	1.059	664	137
70-75	234	1.952	1.233	493
75-80	437	3.286	2.294	867
80-85	331	4.195	2.682	963
85-90	198	3.011	2.254	847
90 >	34	1.201	1.388	540
Sum	1.669	17.741	12.387	4.949

Figure 2. Different alternative representation modes are available to the user. Image depicts age group distribution of dementia patients according to care levels: heat map (left) vs. tabular (right). With the platform, more time can be spent on interpreting data rather than manually building the required visualization.

TABLE II. Exploration dimensions

Category	Dimension
Patient-related	Age group Patient gender Dementia diagnosis Nursing dependent Patient dead
Regional	Federal state Municipal association Municipality District Municipality type Social region
Nursing care-related	Reference year Has nursing care needs Level of nursing care Grade of nursing care Type of nursing care

by insurance companies, among other purposes, to establish reimbursement guidelines [34]. By selecting the appropriate measure and dimensions on the platform via drag and drop, the heatmap depicted in Figure 2 (left) can be generated. It can be readily ascertained that dementia patients are more often assigned care level 1 (German: *Pflegestufe 1*), particularly after 70 years of age. If another mode of presentation is desired, the same information can be displayed in tabular form (right).

VII. Evaluation and Discussion

The tool developed meets the requirements put forth in Section V as follows. From a functional perspective, it provides a privacy-compliant framework (F1) and covers more than 30 pre-defined indicators (F2) and fine-grained aggregation criteria (F3). The data foundation is updated automatically, without a manual extraction, transform and load step, that is, as soon as new data are available (FR4). Furthermore, it allows users to create their own visualizations without any IT-knowledge (F5) and share them with other users (F6). In addition, the database was augmented with geographic coordinates to generate map-based visualizations (F7), not displayed here for the sake of brevity. Forecasting is provided by means of a linear regression of past indicators (F8).

Considering non-functional requirements, ease of use (NF1) is ensured by extensive use of HTML5 and modern Javascript libraries [35]. Besides, the use of the IMDB platform enables a fast response time even with a large underlying database (NF2), since data resides in the main memory [19]. Furthermore, the elderly care tool can be accessed from desktop and mobile devices alike (NF3). To support extensibility (NF4), the necessary calculations are performed using the IMDB's calculation views. They allow complex set operations, such as join, union, projections, etc., without the use of persistent, fixed aggregates, which must be re-created whenever requirements change [28].

Our tool is currently being evaluated in two administrative districts in Germany for user feedback. The tool has a number of advantages over existing portals offering statistics on elderly care, particularly in terms of its exploratory capabilities with different stratification dimensions, scope of the indicators available, level of information granularity (down to the municipality level), as well as automatic data flows within a privacy-compliant environment. As new districts are added to the tool, we expect a steep increase in data and user workload, which might impact system performance and response time, specially considering analytic queries. The building blocks of the IMDB technology discussed in Section IV-B such as lightweight compression, partitioning and multicore parallelization make it possible not only to use available resources more effectively, but also to add more computing power to the system without disrupting current operations, ensuring scalability.

However, from a technological standpoint, since the platform is based on proprietary technologies, it might pose a challenge for other institutions aiming to establish a similar solution. The principles and strategy which have guided the development of this tool can notwithstanding be utilized in a landscape based on open-source software tools, for example SpagoBI [36] or Pentaho with MySQL [37].

VIII. Conclusion and Future Work

We shared details of our software approach, the user requirements and the technical infrastructure that was developed. The data foundation is comprised routine healthcare data generated by the partner insurance company. The platform presents the user with a number of pre-defined measures and dimensions that allow for interactive exploration and generation of arbitrary visualizations.

Future work concerns three major aspects. The first aspect entails integrating available datasets with data generated across the entire care delivery continuum, including hospitals, nursing homes and out-patient services. Second, the tool currently provides linear regression forecasts based on the values of past indicators. However, this approach does not account for complex interactions between long-term socioeconomic and demographic variables. We aim to develop a more sophisticated forecasting model. Finally, user evaluation shall take place to assess the impact of the tool on current processes.

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