Building an Integrated Relational Database from Swiss Nutrition's (menuCH) and Multiple Swiss Health Datasets Acquired from 1992 to 2012 for Data Mining Purposes

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Abstract: **Objective:** The objective of the study was to integrate a large database from Swiss nutrition national survey (menu-CH) with 5 extensive databases derived from 5 consecutive Swiss health national surveys from 1992 to 2012 for data mining purposes. Each database has additionally a demographic base data. An integrated Swiss database is built to later discover critical food consumption patterns linked with lifestyle diseases known to be strongly tied with food consumption and compare the derived rules with the rules resulted with a previous study which used a significantly smaller database. **Design:** Swiss nutrition national survey (menu-CH) with approx. 2000 respondents from two different surveys, one by Phone and the other by questionnaire along with Swiss health national surveys from 1992 to 2012 with over than 100000 respondents were pre-processed, cleaned, transformed and finally integrated to a unique relational database. **Results:** The result of this study is an integrated relational database from the Swiss nutritional and 20 years of Swiss health data.

1 INTRODUCTION

Lifestyle diseases aka chronical diseases are a key determinant of global public health. These diseases are diseases of long-term duration and include obesity, hypertension, type 2 diabetes, high cholesterol, cancer, mental disorders, cardiovascular diseases (including hypertension and stroke), and osteoporosis. They are different from communicable diseases (CD) like Ebola or Corona since they are non-contagious and are often related to nutritional habits (WHO, 2003). Nevertheless, chronical diseases are no longer a disease of developed countries, the prevalence of chronical diseases is steadily increasing everywhere, most markedly in the world's middle-income countries (WHO, 2019). Moreover already 79% of deaths attributable to chronic diseases are occurring in developing countries (WHO, 2019). According to WHO report in 2017, 11 million (95% uncertainty interval) deaths and 255 million DALYs were attributable to dietary risk factors (WHO, 2018). Another report of WHO states that an estimated 422 million adults were living with diabetes in 2014, compared to 108 million in 1980 (WHO, 2018). Furthermore, part of the 2030 Agenda of WHO is to reduce premature mortality from non-communicable diseases (NCD) – including diabetes – by one third [(WHO, 2018). The role of nutritional habits like the role of low-glycaemic index (GI) and low-carbohydrate diets in Chinese patients with type 2 diabetics has shown that a low-carbohydrate diet can improve blood glucose more than a low-fat diet (Wang, 2018). Denova-Gutierrez et al. report in (Denova-Gutiérrez, 2018) of assessing the relationship between the dietary inflammatory index and the prevalence of type 2 diabetes among the adult population in Mexico City. A total of 1174 participants were involved in this study, and the data from a semi-quantitative food questionnaire were used to calculate the dietary inflammatory index scores for each of the subjects of dietary Inflammatory Index and Type 2 Diabetes Mellitus in adults of Mexico City. Sanchez-Rodriguez et al has demonstrated in (Sanchez-Rodriguez, 2018) that a Mediterranean diet supplemented with virgin olive oil may exert beneficial effects in people with

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cardiovascular disease in populations who are at high risk of developing the condition. Klimova and Valis report in (Klimova, 2018) of different types of nutritional interventions and their impact in preventing and delaying cognitive decline in healthy older adults. Leyvraz et al noted in (Leyvraz, 2018) that a high intake of salt was a major risk factor in the development of hypertension and cardiovascular diseases, and observed that improving the knowledge, attitudes, and practices in relation to salt intake was a useful strategy in mitigating the impact of these chronic diseases. Thus, Leyvraz et al. conducted a survey involving 588 participants aged 25 to 65 years in five sub-Saharan African countries, namely Benin, Guinea, Kenya, Mozambique, and Seychelles. Sugizaki and Naves evaluated in (Sugizaki, 2018) the potential prebiotic properties of nuts and edible seeds, and their relationship to obesity.

Applying data mining techniques and pattern recognition algorithms to extract nutritional patterns have been reported by several researchers. A´ine P Hearty et al. propose in (Hearty, 2008) a coding system at the meal level that might be analyzed by using data mining techniques. These researchers used data from an existing conducted survey. M. Sulaiman Khan et al. in (Sulaiman, 2008) introduced a framework for mining market basket data to generate nutritional patterns (NPs) and a method for analyzing generated nutritional patterns using Fuzzy Association Rule Mining. The database used by Sulaiman Khan et al. was a synthetic grocery basket database from IBM Almaden (Agarwal,1993). Lydia Manikonda et al. in (Manikonda, 2011) focused on an application of mining questionnaires of such kind to determine the current knowledge of participants and how this knowledge improved after the training session. Nikolaos Katsaras et al carried out a study described in (Kinsey, 2002) using a nationwide survey of consumer preferences. J. Michael Harris et al. reported in (Harris, 2002) a study that aimed at quantifying food expenditures by age groups and contrast elderly expenditure patterns with other age groups, test for significant differences between elderly food-expenditures and younger age groups, and test for differences in food expenditures between two elderly age groups (age 65-74 versus age 75 and over).

To gain understanding about the impact of using data mining techniques for the analysis of lifestyle diseases that can be influenced by nutrition, we have conducted a preliminary study (Einsele, 2015) to show the proof of our concept. For this purpose, a publicly on-line available grocery store dataset (Google, 2009) served as our data source along with the publicly available health data from the same region. Recently, we have conducted a consecutive research study (Mewes, 2021) in which we firstly have built a real-world integrated database from a nationwide Swiss survey about nutritional habits linked with a Swiss nationwide health database from 2012 (Mewes, 2021) and secondly conducted a study of applying data mining on this database to gain interesting association rules along with their interpretation that show the link between nutrition and chronical diseases. In this paper we present building an extended database including a vast amount of Swiss health data from Swiss health surveys dated from 1992 to 2012 (BAG, 2021) that is integrated with the Swiss nutritional Survey database menuCH (BLV, 2021). The concept and Scheme of this extended database is fundamentally different with the previous reported database in (Mewes, 2021), which is the reason, why we decided to report on this database separately it in this article.

2 SELECTED DATASETS

2.1 Swiss Nutrition Database menuCH

The menu-CH National Nutrition Survey (BLV, 2021) is the first to provide representative data on the food consumption and eating habits of the population living in Switzerland. National Nutrition Survey (menu-CH) diet and exercise have a direct impact on health and quality of life.

From January 2014 to February 2015, around 2000 people from the Swiss resident population were interviewed. Men and women between the ages of 18 and 75 provided information about their food consumption and about their cooking, eating and exercise along with some demographical behaviour.

The survey was conducted as a questionnaire in the first stage and orally by phone in the second stage. Three tables resulted from the survey:

- The table with the data from the questionnaire provides information on eating and drinking and cooking behaviour, as well as intake of additives and salts, avoided foods and reasons for avoiding food. Additionally, the survey provides basic knowledge of healthy eating, activity patterns, body measurements, weight satisfaction, diet behaviour, social structure of the interviewed persons
- The table with the data from the oral survey provides information on the interview and the interview context; Age and body information; Food consumed (preparation, category,

nutritional values, amount, and time of taking the food
- The third table contains data on the demographic classification of the respondents. Telephone number, year of birth, age group, gender, relationship status, nationality, country of birth, household size, residence in the major Swiss regions

Figure 1: Swiss Demography.

2.2 Lifestyle-Diseases Database

Since 1992, the Swiss Federal Statistical Office has been collecting health data every five years from the population living in Switzerland using a written and telephone questionnaire. As part of this study, representative data from around 85,000 people from 1992, 1997, 2002, 2007 and 2012 are available (BAG, 2021).

2.3 Demographic Database

As mentioned above, two demographic tables from the above databases were obtained. The first database from the database Menu-CH included appx. 2000 individuals and the second one 85000 individuals. Therefore, a third table as the profile table with the following categories was built and linked to the two existing demographic tables to this table.

3 SELECTION, CLEANING, TRANSFORMATION OF THE DATASETS

3.1 Selection

The relevant data was identified and selected from the tables. The positive criteria were freedom from redundancy, completeness, consistency, and relevance (for the question). In the database of nutritional data, 60 table columns were selected from the oral survey data, and 125 table columns were selected from the questionnaire data.

3.2 Cleaning

3.2.1 Cleaning menu-CH Database

The menuCH database was largely represented by codes. menuCH database included occasionally the same content, which was mapped with two different codes. This inconsistency was corrected by defining one coding type and overwriting the second coding type with the one specified. If there were no data cells, it was checked whether the data record was still usable. If not (for example the absence of the Person-ID), the entire data record was deleted.

3.2.2 Cleaning Health Database

For the issues with the highest link and priority to the health and nutrition were extracted and reduced to a table with 9 subject areas: Alcohol consumption, age problems, disability, cholesterol, chronic diseases, diabetes, drug use, nutrition, health status. This allowed the data volume to be massively reduced and the performance by data processing to be increased. Redundant data in the tables have been removed as well as missing data.

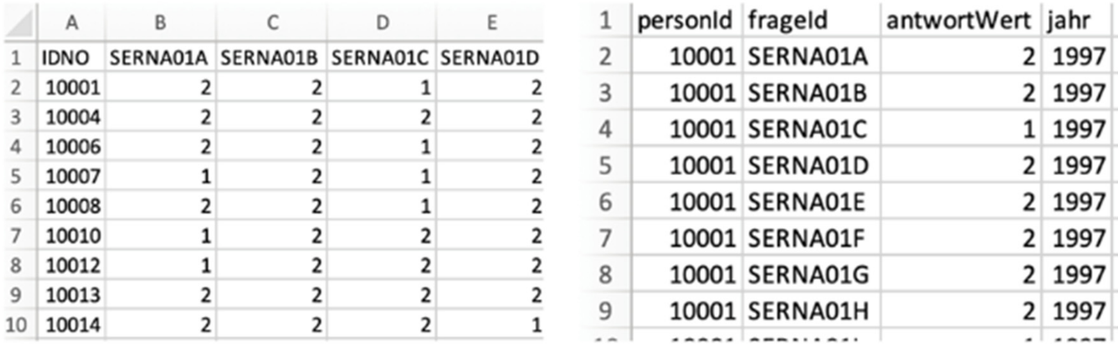
3.3 Transformation

3.3.1 menuCH Database

The setup of the menuCH database was done in three stages. First, a database was created for the database of the questionnaire. Another database was then created for the database of the oral survey. A personal profile was created with the third database (data on demographic characteristics). The personal profile has the characteristics age group, gender, household size, marital status, language. This personal profile connects the other two menuCH databases. Finally, a relational database scheme was designed, and menuCH database was implemented into mySQL.

3.3.2 Health Database

Health data needed some further steps to be finally transformed. First, the various questions were sorted out from the selected subject areas and saved in separate tables. A comparison with the Word files was necessary for each topic. During this process it became clear that the number of questions varies greatly from year to year (1992, 1997,2002, 2007,



	A	B	C	D	E
1	IDNO	SERNA01A	SERNA01B	SERNA01C	SERNA01D
2	10001	2	2	1	2
3	10004	2	2	2	2
4	10006	2	2	1	2
5	10007	1	2	1	2
6	10008	2	2	1	2
7	10010	1	2	2	2
8	10012	1	2	2	2
9	10013	2	2	2	2
10	10014	2	2	2	1

1	personId	frageId	antwortWert	jahr
2	10001	SERNA01A	2	1997
3	10001	SERNA01B	2	1997
4	10001	SERNA01C	1	1997
5	10001	SERNA01D	2	1997
6	10001	SERNA01E	2	1997
7	10001	SERNA01F	2	1997
8	10001	SERNA01G	2	1997
9	10001	SERNA01H	2	1997

Figure 2: An example of unpivoting.

2012). For the two different types of survey - by telephone and questionnaire - the questions were also separated for each topic. This resulted in a total of 49 different Excel tables. Since the questions asked in prose together with the possible answers were only available as Word files and this data format is not suitable for a relational database, the data had to be brought into a database compatible form. For this purpose, all questions were copied together with the associated QuestionID numbers and the survey year and saved in an Excel file. The same was done with the answer options and their answer values. In response to the question "Have you ever used drugs in your life?" interview participants were able to answer, for example, "yes", "no" or "no answer". The corresponding answer values was coded as 1, 2 and 9. Due to the structure of the Word files, this copying process could not be automated, which is why all questions and answer options were copied manually. The structure of the relational database did not provide for a separation of questions and answers according to subject area, which is why all telephone and questionnaire questions as well as answers to all the selected topics could then be listed in a table and made available for unpivoting. The Azure Data Factory was used to unpivot the matrix tables. The Azure Data Factory is a SaaS service and is available and usable as part of the Azure Cloud (Microsoft, 2020a). Figure 2 shows an example of our data unpivoting.

3.3.3 Linking Table for the Integration of Datasets

For the integration of the nutrition and health databases, a third person profile table had to be created, which connects the person profile tables of the nutrition database and the health database. Six attributes were selected which were available in both databases for the personal description:

a) Gender (m / f)
b) age group (15-29 / 30-39 / 40-49 / 50-64 / 65+)
c) Household size (1/2/3/4/5 / 6+)
d) Marital status (single / married or registered / widowed / divorced / other)
e) Language (de / fr / it)

The selected attributes and their categories resulted in 720 different categories of people. The PersonIDs in the Menu-CH database and the PersonIDs in the Health database were each assigned to a person category in the PersonProfil table as shown in Figure 3.

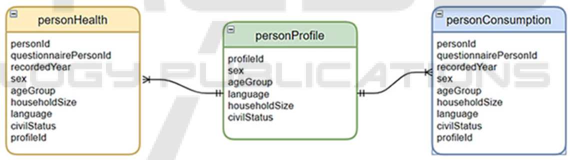


Figure 3: Integrated database design vial linking table.

4 INTEGRATION

A database schema was developed beforehand to structure the integrated database. When developing the scheme, it was considered that redundancies and inconsistencies should be avoided. Fig. 4 shows the scheme of the integrated database with the personal profile (colored green) as the central link, the structure of the health data (yellow) and the connection to the nutritional data (blue). The database scheme on the nutritional data side is shown as a black box (blue), as this scheme was already created in the previous study (Mewes, 2021). By creating the database scheme, care was taken to ensure that no relevant information is lost, but that referential integrity between the tables is still ensured.

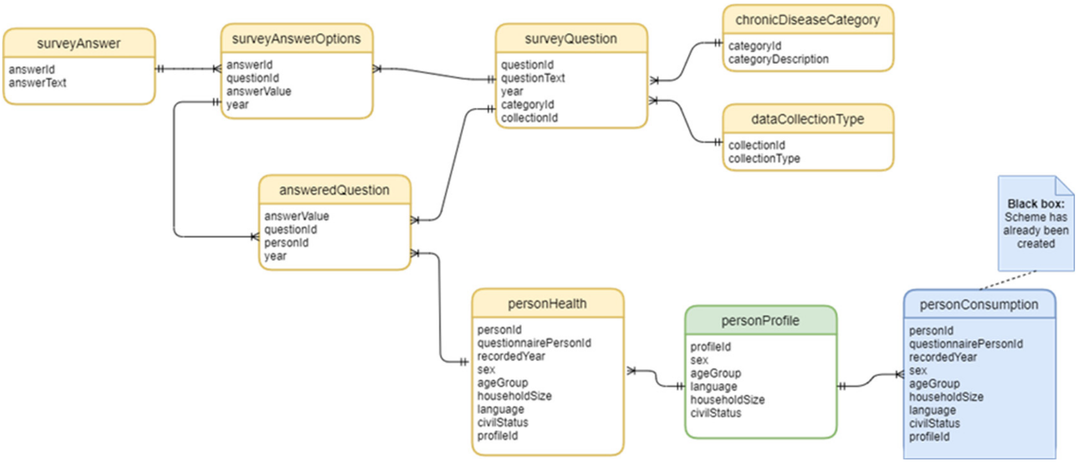


Figure 4: RDB scheme of new health database (1992-2012).

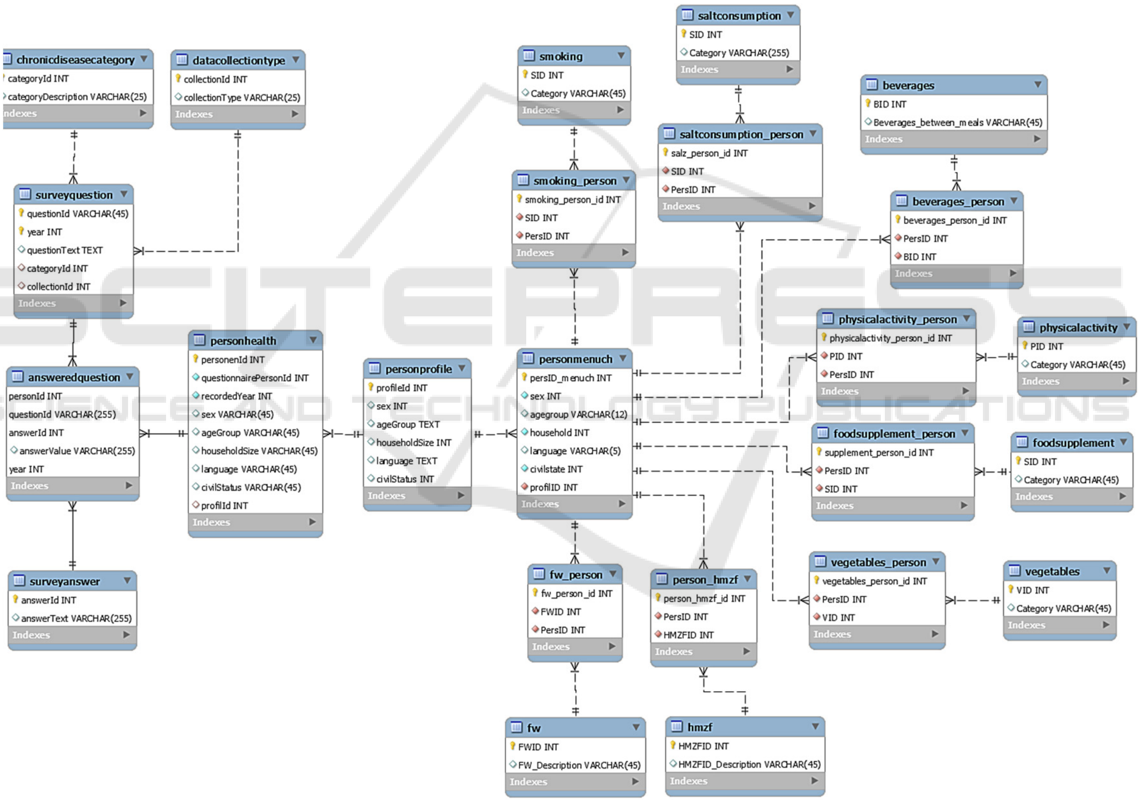


Figure 5: The final version of integrated health & nutrition database.

The final database is structured as follows:

- For each subject of the menuCH database, a combination of two tables is used. One table contains the subject area with the categorization and the other table represents the assignment table of person and response to the topic. In total, 16 tables contain the data from the menuCH «Questionnaire» database of which include 8 tables the data from the menuCH «Nutritional values» database.
- 6 tables contain the data from multiple "Health" databases from 1992 to 2012. Contrary to the menuCH database, the used categories of chronic diseases (alcohol, age problems, disabilities, health status, cholesterol, chronic diseases, diabetes, drug consum-

ption, nutrition) are stored in one single table “chronicdiseasecategory”. Moreover, all answers of the respondents are stored in one single table "answeredquestion" and are connected to the corresponding question in the survey, to the chosen answer and to the person. The big advantage of this new structure is, that the database can simply be extended with additional topics in the future, without modifying the scheme. This will be enormously efficient and timesaving if in the future years the questionnaires are expanded, and more lifestyle topics are added and evaluated.

- Central to the integrated database are the three person profiles of the data base nutrition the data base health and the person profile which connects the two person profiles, as shown in Fig. 4. Finally, Fig. 5 illustrates the resulted integrated menuCH and health database from Switzerland.

5 CONCLUSION AND FUTURE WORK

The present study aimed at linking data sources of a nutritional database to demographical and health statistics come from 5 surveys in a 20 years’ time frame from 1992 to 2012. The aim of building this integrated database is twofold: firstly, to address the influence of food consumption patterns on lifestyle diseases such as obesity, hypertension, cardio-vascular diseases, cancer, type 2 diabetes, and mental disorder. Secondly we aim at comparing the gained association rules with the previously gained ones coming from our previous study [19], which was based on health data from a single Swiss health survey in 2012 to see the differences of additional Swiss health data to the integrated database.

According to the World Health Organization (WHO, 2018) “lifestyle diseases are among the main causes of premature death and disability in industrialized countries and in most developing countries. Developing countries are increasingly at risk, as are the poorer populations in industrialized countries “

For our future work, we intend to use data mining techniques to discover patterns. Moreover, we intend to compare the gained patterns and rules with the gained one from our previous study to see the impact of adding 4 times more health data to the integrated database. We aim at extending further the database first with the new Swiss federal health survey from 2017 and later with the ones of European countries to receive accurate demographical and health data which should help us derive interesting and ground-breaking hidden patterns. Our goal is to find valid rules to be able to predict and prevent lifestyle diseases by detecting critical food consumption patterns. We intend to use association mining algorithms that will allow us to help reach our goal without the common limitations of the previous research efforts, which used the classical statistical hypothesis-bound methods.

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