MonAT: A Visual Web-based Tool to Profile Health Data Quality

Monica Noselli[1], Dan Mason[2], Mohammed A. Mohammed[2,3] and Roy A. Ruddle[1]

[1]*Department of Computing, University of Leeds, EC Stoner Building, LS2 9JT, Leeds, U.K.*

[2]*Bradford Institute for Health Research, Bradford Royal Infirmary, Bradford, U.K.*

[3]*Department of Research, University of Bradford, Bradford, U.K.*

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Abstract: Electronic Health Records (EHRs) are an important asset for clinical research and decision making, but the utility of EHR data depends on its quality. In health, quality is typically investigated by using statistical methods to profile data. To complement established methods, we developed a web-based visualisation tool called MonAT Web Application (MonAT) for profiling the completeness and correctness of EHR. The tool was evaluated by four researchers using anthropometric data from the Born in Bradford Project (BiB Project), and this highlighted three advantages. The first was to understand how missingness varied across variables, and especially to do this for subsets of records. The second was to investigate whether certain variables for groups of records were sufficiently complete to be used in subsequent analysis. The third was to portray longitudinally the records for a given person, to improve outlier identification.

1 INTRODUCTION

Clinical patient data are stored digitally in EHRs and contains a wide range of information. These data are becoming a powerful resource for secondary uses such as investigating and developing decision support systems (Coorevits et al., 2013). Clinical research results and decisions depend on the quality of EHR data.

There are three different aspects of data quality assessment: *Data profiling* defines issues in data quality, *Data wrangling* prepares the data for further investigation by transforming it into a required structure, and *Data cleansing* analyses and corrects the data (Gschwandtner et al., 2014). This paper focuses on data profiling, for which most health researchers typically adopt a statistically driven workflow and make little use of interactive data visualization.

The aim of our research is to provide new methods for profiling health data. This paper describes the design and formative evaluation of a new interactive visualization tool called MonAT, which provides users with rich functionality for data profiling, leveraging human cognitive capabilities.

2 RELATED RESEARCH

New frameworks and tools have been created to define and assess data quality (Stausberg et al., 2015). A new framework to assess health data quality (Weiskopf and Weng, 2013) provides a definition of data quality in five dimensions: completeness, correctness, concordance, plausibility and currency. In a related work (Weiskopf et al., 2013), the authors demonstrated that the completeness depends on the type of tasks. Moreover, completeness and correctness are considered the important dimensions to assess first since the others depend on the quality of these (Dungey et al., 2014).

A data quality ontology has been defined (Johnson et al., 2015) based on the above data quality definition (Weiskopf and Weng, 2013). The ontology describes concepts and measures of data quality (Table 1 and 2).

Another aspect of the completeness is the *Missing Data Mechanisms* (Rubin, 1976). Data are missing for several reasons. Understanding the reasons for missingness is important for evaluating the rest of the data and for generating accurate results (Nakagawa and Freckleton, 2008), (Farhangfar et al., 2008).

Visualization techniques are powerful tools for knowledge discovery. In the work (West et al., 2014), the authors state that "EHR data are complicated by missing values, inaccurate data entry, and mixed data

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Table 1: Concept and Description of (Johnson et al., 2015)'s ontology for Completeness Dimension.

	Concept	Description
a	DomainCoverage	Data represents Domain Concepts
b	DomainComplete	Presence or absence of expected information
c	RepresentationComplete	Data is not missed without consider the Domain
d	Sufficiency	Longitudinal data is sufficient to investigate a given Task
e	Relevance	Data complies the Domain and is sufficient to investigate a given Task
f	TaskCoverage	Variables used to investigate a given Task appears in the data
g	Flexibility	Data is sufficient to investigate different Tasks

Table 2: Concept and Description of (Johnson et al., 2015)'s ontology for Correctness Dimension.

	Concept	Description
h	RepresentationIntegrity	Data is not corrupted, no data entry errors
i	Reliability	The data can be used because it is correct
l	RepresentationCorrectness	The data is complete and accurate

types that must be considered in developing visualization techniques" and "users wants to see both categorical and numerical data when interactively exploring the data, and they like to look at the detail in the record".

There is a huge amount of data quality investigations specifically in health care and medical research (Stausberg et al., 2015) but tackling data quality assessment with a visual analytic perspective is quite novel (Kohlhammer et al., 2011).

Two examples of visual analytic tools are TimeCleanser (Gschwandtner et al., 2014) and Profiler (Kandel et al., 2012). TimeCleanser is a visual analytics system that helps to clean time-oriented data. Profiler adopts visualization and statistical analysis for data quality assessment. The cleansing job is driven by summaries and automated detection of anomalies and then visualizes and interacts with the results.

MonAT aims to help experts detect and flag completeness and correctness data quality issues by providing interactive and connected visualizations.

We designed MonAT to cater to the (Weiskopf and Weng, 2013)'s data quality definitions and considering the (Johnson et al., 2015)'s ontology (Table 1 and Table 2). MonAT offers a visualization that can help to classify the data in the (Rubin, 1976)'s categories and considers the longitudinal characteristic of health data.

3 BORN IN BRADFORD

Born in Bradford (BiB) is a longitudinal multi-ethnic birth cohort study aiming to examine the impact of environmental, psychological and genetic factors on maternal and child health and wellbeing (Raynor, 2008). Bradford is a city in the North of England with high levels of socio-economic deprivation and ethnic diversity. Women were recruited at the Bradford Royal Infirmary at 26-28 weeks gestation. The full BiB cohort recruited 12,453 women comprising 13,776 pregnancies between 2007 and 2010 and the cohort is broadly characteristic of the city's maternal population. The mothers and children are followed up longitudinally through direct surveys and linkage to routine healthcare records. Ethical approval for the data collection was granted by the Bradford Research Ethics Committee (Ref 07/H1302/112).

We obtained access to a subset of the BiB children's growth variables (Wright et al., 2013) in two flat files. The first file contains 500 records with children's raw observations (Table 3). There are 360 children. The greatest number of records per child is 21. The greatest number of height observations per child is 3. The greatest number of weight observations per child is 20. On average, there are 0.51 height observations and 1.38 weight observations per child. The second file contains the same information cleaned by statisticians following an established cleansing method (see Section 3.1).

3.1 Data Cleansing Process

We met several times with BiB statisticians. The aim of the meetings was to understand their cleansing method, detect deficiencies, and establish requirements for our tool.

The BiB method uses STATA and goes through the following steps to clean height and weight variables:

- Implausible values. Weight observations greater than 25kgs are removed.

Table 3: Variables in the anthropometric data set that was used to evaluate MonAT.

Variables			
Name	Type	Description	#Categories
ChildID	Encoding	Child's ID to identify longitudinal data	360
age	Numerical (Integer)	Child's age calculate in days	
weight	Numerical (Float)	Child's weight calculated in kilograms	
height	Numerical (Float)	Child's height calculated in centimeter	
gender	Categorical	Child's sex	2
eth0ethall	Categorical	Child's ethnicity category	22
eth0eth9gp			9
eth0ethgrp			6
ethgrp4			4
eth0eth3gp			3
source	Categorical	Information about the data provenance	3

- Outliers. Data are divided by baby's sex and mother's ethnicity group. Four Standard Deviation (4SD) from mean is calculated separately for the groups over intervals of two months. Values greater than +4SD and smaller than -4SD are considered as outliers and deleted from the data set.
- Negative Increment. Weight and height observations are checked by comparing two consecutive numerical observations and deleting the second observation if it does not follow certain criteria. Weight observations are also compared with the subsequent measurement. Weight values between the first two weeks of age with a drop of more than 10% and weight and height values with a drop of more than 5% in the other intervals are removed.
- Plot. Any further outlier is analyzed by plotting weight and height against age by sex and the three ethnicity categories.
- Combine height and weight observations. Another plot shows weight against height to check for further outliers.
- Ponderal Index (a ratio of a person's height to weight) is calculated and plotted against age by sex and ethnicity to check for further outliers.

3.2 Limitations

Our analysis highlighted three key limitations in the BiB data cleansing process. First, the process does not consider missing data at all, which prevents feedback being given to data providers and places the onus for investigating missingness solely on the users of BiB data.

Second, the process only cleans a subset of the variables that are in a given data set. For example, BiB only cleaned the weight and height variables in the anthropometric dataset. There may also be data quality issues with the age and ethnicity variables. An assumption that underlies categorical variables such as ethnicity is that they do not change over the time. However, a child's ethnicity may not be present for each data record, or ethnicity may be recorded differently over time, indicating that some data are not consistent.

Third, numerical longitudinal variables (weight and height, in the case of the anthropometric data set) are only cleaned in a pair-wise fashion, rather as a whole. The sequence of points in a plot defines the overall weight (or height) profile of a child. Inspection of individual points in the context of the children's overall profile can help researchers to identify outliers. Such profiles are even more useful for investigating negative increments, because a visual check can identify which point is suspicious rather than always assuming that the second observation in a pair is wrong, as is the case with the current BiB process.

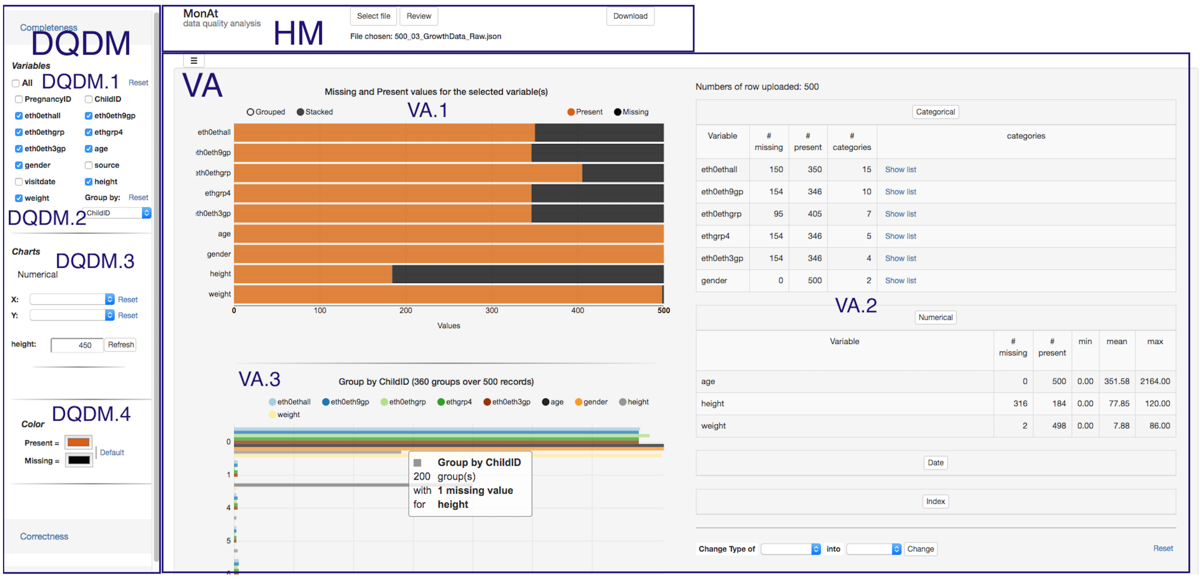
4 MonAT

This section list the requirements and describes the design and implementation of novel visualization tool, MonAT, which allows researchers to profile data by combining basic computations and human cognitive capabilities.

4.1 Requirements

Based on the limitations discussed in 3.2, we identify two key requirements for our tool.

Profiling Completeness. A normal statistical approach to deal with missingness is to remove records containing missing data. However, this can lead to biased results. Missing data profiling (Table 1) can help



Group by: ChildID

height: 450

File chosen: 500_03_GrowthData_Raw.json

Group by ChildID
200 group(s)
with 1 missing value
for height

Numbers of row uploaded: 500

Variable	# missing	# present	# categories	categories
eth0ethall	150	350	15	Show list
eth0eth9gp	154	346	10	Show list
eth0ethgrp	95	405	7	Show list
ethgrp4	154	346	5	Show list
eth0eth3gp	154	346	4	Show list
gender	0	500	2	Show list

Variable	# missing	# present	min	mean	max
age	0	500	0.00	351.58	2164.00
height	316	184	0.00	77.85	120.00
weight	2	498	0.00	7.88	86.00

Change Type of into

Figure 1: Screen shot showing the three main areas of MonAT. The *Horizontal Menu* (*HM*) is on the top. The *Data Quality Dimension Menu* (*DQDM*) on the left shows the Completeness sub-menu expanded. It contains the four filters: the *List of Variables Filter* (DQDM.1), the *Group Filter* (DQDM.2), the *Chart Filter* (DQDM.3), and the *Color Filter* (DQDM.4). The *Visualization Area* (VA) in the middle-right-bottom shows *Present-Missing Overview* bar chart (VA.1), *Tables overview* (VA.2), and *Grouped Present-Missing Data* (VA.3).

to mitigate bias when researchers are defining data inclusion criteria.

Profiling Correctness. Abnormal observations can lead to misleading findings. Outliers can occur in categorical variables due to erroneous free input text or data processing errors. In numeric variables outliers can be due to mistyping, measurement errors, or data processing errors. When observations are related to each other, longitudinal data profiling can improve outlier identification.

Other, general requirements were as follows. First, a tabular view showing summary statistics (e.g., minimum, maximun and mean of numerical observations, and the number of categories in categorical variables) is important to provide an overview of data. Second, MonAT needs to be accessible to researchers without specialist knowledge of statistical tools and programming languages (e.g., STATA and R). Third, the interface should be user friendly and intuitive, and support workflows that are easy to learn and follow. Fourth, researchers should find that MonAT provides added value for data profiling.

4.2 Design and Implementation

MonAT is a web-base tool implemented using Django Rest Framework, AngularJS, and Krispo's nvd3 (D3) reusable charts.

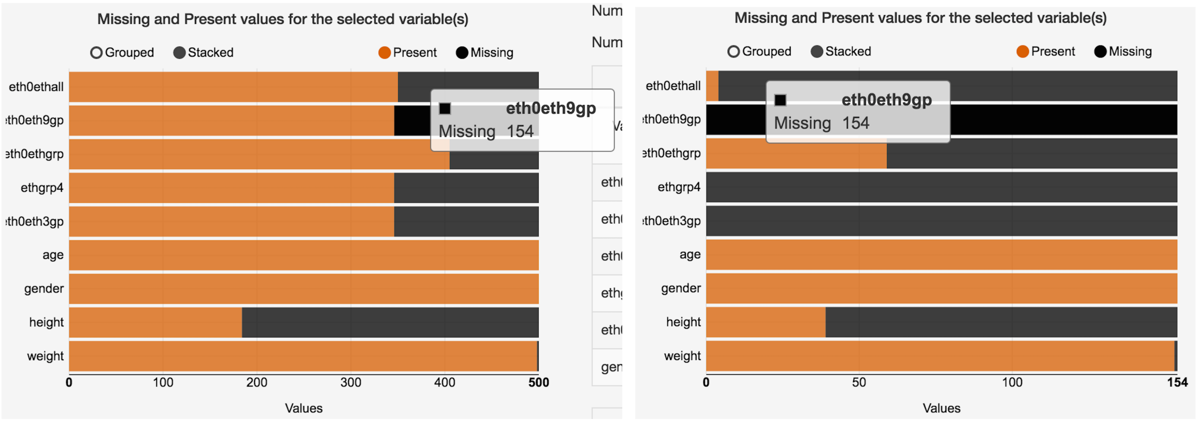
The architecture of MonAT follows the concepts of Single Page Application (SAP) and Model View Control (MVC). MonAT web interface (Figure 1) is divided into three main areas: the *Horizontal Menu* (*HM*), the *Data Quality Dimension Menu* (*DQDM*), and the *Visualization Area* (*VA*).

The *HM* contains a function to select a local flat file. Statistical information and some additional variables for managing page layout are automatically calculated.

This menu stores the data in local memory in JSON format object. The type of variable (numerical, categorical, index or date), number of present and missed observations per each variable are precalculated and stored in the JSON object. For numerical variables, minimum, mean, and maximum are calculated. For categorical variables, a list of categories is created. The scope of all this information is the root: the variables can be accessed from every component. Some additional variables are added with a root scope to allow flexible layouts to be created.

The *DQDM* is a dynamic menu that maps the dimensions of data quality (Weiskopf and Weng, 2013) to sub-menus. The application automatically creates this menu when user upload a file. Currently there are two sub-menus - one for ‘Completeness’ and one for ‘Correctness’.

The *VA* is the core of MonAT, and where it shows visualization and tabular output in response to users’ interactions. We designed different *VA* components for profiling completeness and correctness.



(a) (b)

Figure 2: The *Present-Missing Overview* bar chart, showing the number of present and missing observations (orange and black bars, respectively) for nine variables. The plots show missingness for: (a) all 500 records in the data set, and (b) the 154 records where the 'eth0eth9grp variable is missing (selected by clicking on the black bar for that variable in (a)).

4.2.1 Completeness

Interactions with the Completeness *DQDM* creates *VA* components to explore different levels of missingness (Table 1).

The checkbox *List of Variables Filter* (Figure 1 - DQDM.1) represents the Domain of the data (Table 1.a). It allows users to understand what tasks can be answered with the set of variables (Table 1.f).

Interactions with the checkbox list create a *Present-Missing Overview* (Figure 1 - VA.1), and *Tables Overview* (Figure 1 - VA.2).

The *Present-Missing Overview*, a grouped/stacked interactive bar chart, shows missing and present values, calculated over all the entries (Table 1.b). It allows analysis of data quantity (Table 1.c and Figure 2).

The *Tables Overview* shows four tables, one for each type of variable (numerical, categorical, index, and date) with the number of present and missing observations, categories and statistical information.

The *Group Filter* (Figure 1 - DQDM.2) is a drop-down menu for selecting a variable to group the data. It creates the *Grouped Present-Missing Data* (Figure 1 - VA.3), a grouped bar chart, which shows information about number of groups that miss variables selected in the *List of Variables Filter* (Figure 1 - DQDM.1). The *y* axis represents the number of missing observations and the bar length represents a variable. Each barsize represents the number of groups missing a variable. It is useful for inclusion criteria giving information of sufficiency and relevant observations (Table 1.b and 1.e).

The *Chart Filter* (Figure 1 - DQDM.3) is a combination of two drop-down menu allowing selection of two numerical variables that create a plot (Figure 3.a). The two variables are respectively the *x* and *y* axes of the plot. The filter automatically creates a contextual menu (Figure 3.b), a series of checkboxes that allows users to visualize *Data in Context* and *Distributions*.

The *Data in Context* (Figure 3.a) can be analyzed to evaluate sufficiency, task coverage and variable flexibility (Table 1.d, 1.f, and 1.g) by interacting with the contextual menu (Figure 3.b) and *Logic Function Filter* (3.c).

The *Logic Function Filter* allows investigation of variables' missingness with 'AND' and 'OR' operations.

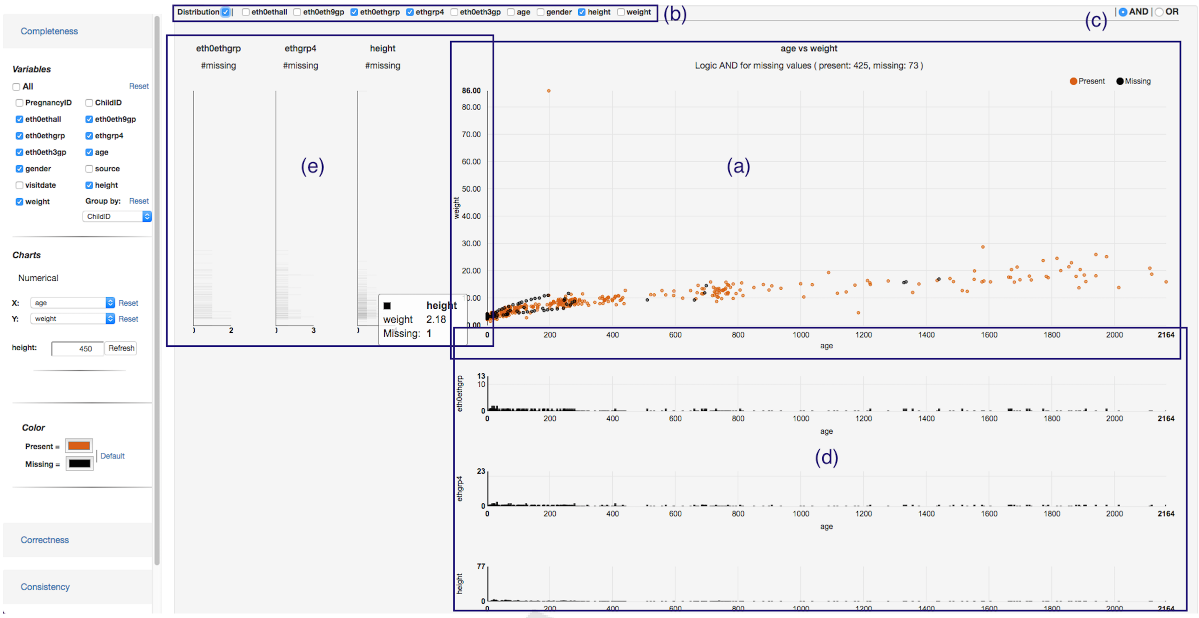
The *Distribution* (Figure 3.d and 3.e) shows the number of missing values of selected variable, in respect of the two axes of the scatterplot to investigate correlation of missingness between variables. It can be used to evaluate the *Missing Data Mechanisms*.

4.2.2 Correctness

Users may analyze correctness by interacting with the Correctness *DQDM*. The set of filters is similar to the Completeness *DQDM*, but the *VA* components change.

Interactions with the *Distribution Filter*, a checkbox list of variables, shows a boxplot for each selected variable, allowing users to detect outliers for numerical values (points above or below the upper and lower whiskers) (Table 2.h and 2.i).

The *Chart Filter* creates a *Data in Context* view to let users detect outliers and analyze negative increment on longitudinal data. It helps to analyze correctness and suitability of the data for a given task (Table 2.i and Table 2.l). It can also be used to spot variation



Completeness

Variables

☐ All Reset

☐ PregnancyID ☐ ChildID

☑ eth0ethall ☑ eth0eth9gp

☑ eth0ethgrp ☑ ethgrp4

☑ eth0eth3gp ☑ age

☑ gender ☐ source

☐ visitdate ☑ height

☑ weight Group by: ChildID Reset

Charts

Numerical

X: age Reset

Y: weight Reset

height: 450 Refresh

Color

Present = 🟧

Missing = ⬛ Default

Correctness

Consistency

Distribution ☑ | ☐ eth0ethall ☐ eth0eth9gp ☑ eth0ethgrp ☑ ethgrp4 ☐ eth0eth3gp ☐ age ☐ gender ☑ height ☐ weight

| ● AND | ○ OR

Figure 3: The *VA* shows *Data in Context*. A contextual menu (b) allows show missing and present observations of selected variables (eth0thgrp, ethgrp4, and height) in the age against weight scatterplot (a) with an *AND* operation (*Logic Function Filter* c). The contextual menu also contains a check box button to show/hide *Distributions* (d, e) of the selected variables.

in categories (i.e., variation of ethnicity category for a given child) (Table 2.h).

5 MonAT EVALUATION

This section describes a formative evaluation of MonAT, using the BiB Project anthropometric data set. We carried out a formative evaluation to list a minimum set of functions that end-users would benefit while using the tool.

The aims of the evaluation were to assess the value of MonAT's existing functionality for investigating data completeness and correctness, and to identify important additional functionality for the tool.

5.1 Method

This section presents information on recruited participants, materials and procedure for the evaluation.

5.1.1 Participants

We recruited four participants aged between 28 and 51. One of them had worked at the Bradford Institute for Health Research (BIHR) for two years and was knowledgeable about the BiB Data Collection (BiB DC). Two of them were post-doctoral researchers, with experience of visual analytics and data analysis, respectively. The fourth participant was a PhD student with experience in data analysis.

5.1.2 Materials

A set of exercises were created with the aim to highlight issues in the tool and identify new functions for the release version of MonAT. The exercises tested the main functions of Completeness (4.2.1) and Correctness (4.2.2) dimensions. Examples of the Visualization Components are shown in Figures 1 and 3.

5.1.3 Procedure

At the start of the evaluation, participants were given an information sheet about the aims of the evaluation, a description of the data set, and a brief description of the MonAT functionality. Then participants were asked to think aloud while they completed some data completeness and correctness exercises. If they were uncertain about anything, participants were encouraged to ask the experimenter questions during the exercises. At the end of the exercises the experimenter conducted a semi-structured interview to gain further feedback about MonAT and identify additional functionality that participants thought would be beneficial.

The first set of exercises required the use of MonAT to investigate the completeness functionality.

Participants started by selecting a subset of variables listed in the completeness *DQDM* and evaluated the *Present-Missing Overview* and the *Tables*

Overview. Then, they used the *Group Filter* to investigate missingness in the groups.

The next steps were to plot a chart, select some variables in the *Contextual Menu* and evaluate the differences between visualizing values in *logic AND* and *logic OR*. Finally, they visualized the *Distribution* charts.

The second set of exercises focused on the correctness functionality. Participants interacted with the Correctness *DQDM* to dynamically create the visualizations and detect outliers.

5.2 Results

Overall, participants were impressed by the novel capabilities of MonAT. This section reports participants main comments and suggestions.

Participants found the *Present-Missing Overview* (Figure 1 VA.1) useful for understanding how missingness varied across variables, and especially having the possibility to select a subset of the records. For example, the chart shows that there is a similar amount of missing data for the ethnicity variables (first five black bars). By selecting one of these bars, the participant can explore that similarity, and an example is shown in Figure 2. Participants preferred stacked bars for that rather than grouped bars.

The participants liked the *Tables Overview* (Figure 1 VA.2). However they recommended that it was shown in a separate panel to leave the focus on the visual chart.

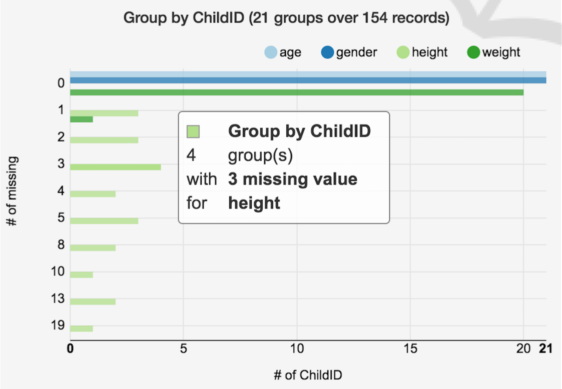


Figure 4: The x axis shows the number of groups having missing data for selected variables (age, gender, height, weight). In this example there are 21 children (groups) over 154 records. The y axis shows the number of missing values per variable. In this example, there are four children missing exactly three observations for the height. A mouse over on bar displays a tooltip that shows related information.

The *Grouped Present-Missing Data* (Figure 1 VA.3 and Figure 4) shows the number of missing observations for selected variables (in this case eth0eth9gp and height), grouped by the value of another variable (in this case 'childID'). Participants initially found it difficult to understand the meaning of this visualization but, once they did, they considered it to be useful for investigating whether groups had sufficient values for a given task (Table 1.d and 1.e).

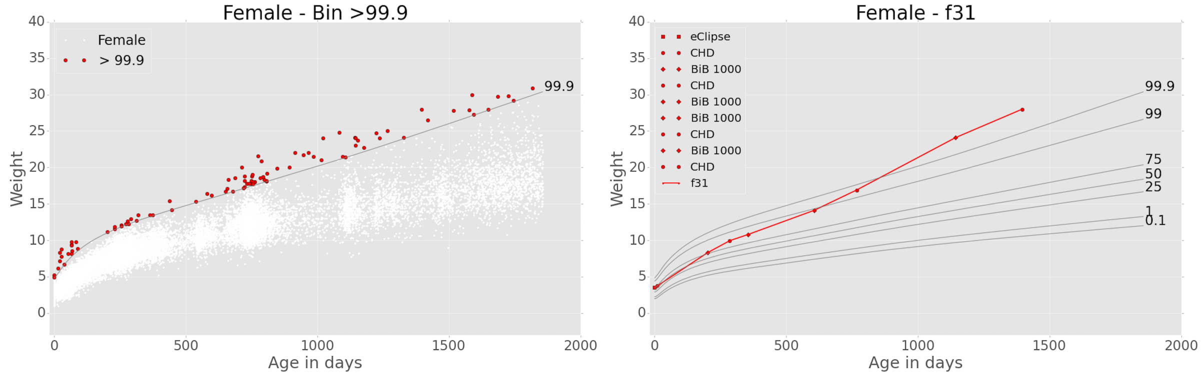
Participants suggested being able to interact with bars in the *Grouped Present-Missing Data* (as it is for the *Present-Missing Overview*) to show frequency distributions of missing values. They also said they would like to be able to select more than one group. For example to include in the further analysis groups having no missing values or not more than one value missed for a given variable.

The scatterplot (Figures 3) shows missing and present *Data in Context*. The contextual menu (at the top of the Figure 3) allows users to include variables in the scatterplot. Participants found it useful to visualize how categorical missing observations relate to the scatterplot variables. For example (Figure 3a) the three selected variables (eth0ethgr, ethgrp4 and height) shown in AND, present missing data mostly in early children days (from 0 to 300). Participants considered it useful to be able to 'AND' or 'OR' the selected variables, and suggested that 'XOR' (only one of the selected variables is missing) would also be useful.

Participants made a number of other comments, which were as follows. The *Distributions* that are shown in the bar charts of Figure 3 are difficult to see, which could be addressed by binning the data to reduce the number of bars that are drawn.

Referring to the correctness exercises, the scatterplot and the scatterplot with lines (Figure 5) show *Data in Context* to reveal outliers. Investigating the data as single points may lead to some of them being defined as outliers because they lie above the 99.9th percentile (Figure 5a). However, a longitudinal visualization indicates that some of those points are correct because they are from a single child and follow a reasonable curve (Figure 5b). Participants found these scatterplots useful to visualize the longitudinal data to explore correctness. However, to improve the legibility of a plot they suggested the use of bins to visualize a subset of the data. The number of groups (children) should be low to avoid confusion. Moreover, the longitudinal groups should be smartly selected to avoid overlaps in the visualization.

Overall, participants found MonAT useful for profiling the quality of the data. They suggested adding 'print' and 'download' function for each visualization, so the visualizations can be easily included in presentations and reports. Moreover, the tool can be



(a) (b)

Figure 5: *Data in Context* for outlier identification, showing: (a) all of the height data for female children (the red points lie above the 99.9th percentile), and (b) the height profile of a single child (the red line and points).

used to create a subset of data set that satisfies inclusion criteria for further investigations.

6 CONCLUSIONS

This paper describes the design and formative evaluation of a novel tool called MonAT for visual data profiling. The tool was developed in conjunction with researchers from the BiB Project, and designed to address limitations in the statistical data profiling methods that are commonly used with EHR.

MonAT involves automatic and human analysis to compute the complex task of profiling different dimensions of data quality of medical data. The tool is novel in providing multiple and connected interactive visualizations to investigate completeness and correctness in longitudinal data such as EHRs. It answers the need of profiling data for different tasks and different dimensions of data quality.

The tool was positively received, and provided three advantages as a complement to statistical methods. These were to understand how missingness varied across variables, investigate whether certain variables were sufficiently complete to be used in subsequent analysis, and improve outlier identification.

A revised version of MonAT is being developed and will be deployed for use in the BiB Project. Further functionality is planned, to combine interactive visualisation with a data mining capability.

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