Visualizing Clinical Data of Patients at the Child and Adolescent Psychiatric Emergency Unit: Final Report

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Abstract—With the increasing digitization of healthcare, more and more clinical data is available to researchers and care providers. Given the complexity and size of these data, well thought-out visualization is key to abstract and understand this data. Past work has primarily focused on visualizing the data of a specific patient, and most of the focus has been on quantitative data such as blood pressure or heart rate. In this design study, we visualize clinical data from a child and adolescent psychiatry ward. Our system, implemented in Tableau, focuses on summarizing and exploring categorical data such as diagnoses and medications. Data is explored at the cohort level, not at the individual, reducing privacy concerns and allowing more macro trends of care to be investigated. We use simple idioms such as bar and pie charts to increase legibility for a wide range of users. We also aggregate categorical attribute values to aid abstraction, and utilize intuitive interactive features to allow detail exploration. Our system features further scalability to incorporate data from more patients and with more measures. It also provides a framework for future work to visualizing automatically extracted and cleaned data.

1 Introduction

As healthcare becomes more digitized, more and more clinical data becomes available to clinicians and health care researchers. Given the complexity and size of these data, well thought-out visualization is key. Most of these data are text-based or provided in spreadsheets, making it difficult to detect patterns, trends and correlations. Data visualization helps make this process simpler and allows decision-makers to more easily analyze information.

Our project seeks to visualize the clinical data of patients admitted to the Child and Adolescent Psychiatric Emergency Unit (CAPE) at BC Childrenâs Hospital (BCCH). We designed our visualisation to be usable by different users with different roles, clinical interests, and information technology familiarity. We also consider how to show a varied set of data with complexities such as, for example, categorical attributes with hundreds of different values. We build our design around visualizing patient's diagnoses and medications, and use different views to allow these data to be further filtered. Our design ends up combining attribute value aggregation with relatively simple visual and interaction idioms. Initial user studies comment on the design's intuitive nature. Despite our use of simple idioms, our project may contribute to medical visualisation, being one of the first visualization projects we could find seeking to visualize this domain at the non-individual level, and one of the first visualizing psychiatric data.

1.1 Related work

Information visualization has a long history of application to clinical data, which we distinguish from other data used in biology/medicine such as omics (RNA, DNA...) and imaging (MRI, CT, xrays). Early examples, dating from mid-19th century, include Charles Mindard's graph showcasing the losses of Napoleonâs army as they marched to and from Moscow [3], and Florence Nightingale's radial bar chart showing causes of death during the Crimean War [20]. The amount of clinical data generated and potentially available to visualize is steadily increasing, owning to widespread adoption of Electronic Medical Records (EMRs) and the digitization of insurance records [12].

Early examples of visualizing these new data sources focused on showing the time series data of a single patient, such as the adoption of *LifeLines* [17]. This application uses the horizontal axis to represent time and the vertical axis to fit labelled bars representing distinct events which happen over periods of time. Similarly, the *KNAVE* system helps users choose and view a patientâs attributes using time-series small-multiple views [24]. Refinement of such work, in the *LifeLines2* [26] and *VISITORS* [11] systems respectively, allowed users to view data from multiple patients. *LifeLines2* was primarily designed to visualize temporal categorical data, of up to double-digit number of both subjects and attributes. Vertical space is divided for each patient. The patientâs data is then shown through horizontal distance which codes data, with the color channel used on labelled glyphs to the time of several categorical events. The *VISITORS* system used different views to allow both more subjects and more attributes. Users make selections of subjects, attributes, and time periods, and different views are used accordingly. For examples, the system uses a scatter plot to show quantitative time-series of only one attribute, while it uses parallel coordinates to show multiple attributes from multiple subjects at discrete time points.

Recent work has continued explore different visualization techniques, though most applications remain centered around visualizing data as a time-series. One exception is the *DICON* system [6] is centered around visualization clusters of similar patients. Each cluster is shown by a tree map, with color coding of the regions inside the tree map corresponding to different diseases. The regions representing different disease are in turn divided into regions corresponding to an individual patient having a certain disease. Another application eschews time-series to instead display the current state of an ICU patient [10]. Unsupervised machine learning is used to produce a quantitative measure for a set of attributes which are then visualized using a radial line graph. Another visualization

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used a web-based "pictorial visualization system" [9] which allows spatial/body system interactivity through glyphs of the human body, and temporal interactivity through interconnected time axes. Unlike most visualization systems mentioned which focus on professional users, this last system is also designed for patients to use.

A few examples of previous work have focused more on visualizing patient data in the aggregate instead of the individual. Smith et al [25] developed *HospMapper* to investigate the spread of infections through hospital wards. *HospMapper* uses a heatmap of hospital wards over time to show this spread, though other detail views also individual patients' infections over time. *VisAGE* [8] is a tool to visualize information extracted from clinical documents, as this project will eventually seek to do. Huang et al's system combined many low-level features for each patient, such as whether a drug is prescribed or a genetic test result. They then use t-distributed stochastic neighbor embedding [15] to reduce dimensionality and allow users to investigate patient clusters.

In the only prior work we could find specifically visualizing psychiatric data, Ha et al [7] conduct a design study to visualize dementia patients' EMR data. An initial design in this study allowed users to select different variables to be displayed using parallel coordinates. However, psychiatrists interviewed found this difficult to understand. Their eventual system combined a parallel coordinate view with a cylindrical 3D view for clustering patients. Radial positioning encodes a patient's summarized position amongst fifteen attributes evenly distributed around the circumference, while height encodes a different calculated value representing how advanced overall a patient's dementia is.

Work from other domains explores some of the design choices used in this project. For example, Kosara [13] compare different use cases for pie charts, stacked bar chart, and heat maps in different scenarios. They find that these charts are mostly useful when the user aims to answer part-to-whole questions using the multiple slices and different distributions of values. They also comment that stacked bar charts are useful to show deep hierarchies, while treemaps are increasingly used as pie chart alternatives. Redmond [22] further quantifies these design choices by performing experiments to compare the performance of pie charts and horizontal bar charts with various segment sizes, with and without additional visual cues. They find that bar charts are generally more accurate, especially when augmented by internal visual cues which act as anchors. The findings of both works are found in our design choices, such as our incorporation of numerical anchors into overlay interactions, and our general use of detailed views, part-to-whole views, and filtering using these idioms.

Prior work from other domains also suggests ways to utilize our chosen tool. As an example, Morton et al. [18] show the use of a drill down menu in Tableau to allow users to continually modify the visualization by viewing more fine grained details without disrupting their analytical flow. Our work also uses such a feature.

1.2 Contribution

Our work seeks to build on this prior work in both domain explored and the granularity of clinical data visualized. Instead of focusing on the individual patient, we show the summarized data of hundreds of patients. This allows a broader range of clinical questions to be investigated and permits comparisons between different groups in order to better understand how attributes interact. While prior work has often primarily visualized the quantitative data from EMRs, our work is centered upon visualizing categorical attributes such as medications and diagnoses. This is important for visualizing data in psychiatry, where common quantitative attributes are less important than complex, categorical attributes. This pattern is born out in the dearth of prior visualization for psychiatric data, with the only example we found visualizing mostly quantitative attributes of dementia patients. Our project represents a first attempt to visualize more general and categorical psychiatric data, but can be easily adopted to visualize patients from other fields of medicine.

From a technical perspective, our project shows the potential of using Tableau to visualize health care data, a modern tool proposed to fit this domain [12]. In addition, instead of visualizing structured EMR data, our project is designed to visualize data output from a natural language processing (NLP) pipeline which analyzes free text physician dictations. Such systems will be crucial to understand many aspects of patient data not captured by structured EMR fields.

2 Data and Task

This work visualizes data from a child and adolescent psychiatry ward. However, little of our design choices are specific to child and adolescent psychiatry, and our system could easily be incorporated to visualize data from patients in other sub-fields of psychiatry, or of patients in other fields of medicine.

2.1 Domain/Who

Child and adolescent psychiatry is the sub-specialty of psychiatry working with patients generally younger than 18 years of age. Clinicians practising in this area typically acquire additional training, owing to the differences in disease and treatment of patients in this age group. For instance, social factors such as home and school life are especially important for this population, while many psychiatric diseases only start to develop during these ages and may present atypically [1]. Patients requiring inpatient treatment typically stay in specific wards for this age group, which can be located at either general hospitals, or those focusing on the care of children. Like other fields of psychiatry, the quantitative attributes that are important in most fields of medicine, such as vital signs or lab work, are of less importance. Instead, categorical attributes are especially important and can be complex. For instance, patients can often suffer from multiple psychiatric diagnoses. Understanding categorical demographic and social data can also be key.

Our visualization thus focuses on allowing various types of users to explore and understand data of this type. We have a wide range of intended users, which can vary in training, role, intent and comfort with visualization or technology in general. The intended users include those in a managerial role such as chief psychiatrists, hospital administrators, and nurse managers. It also includes clinicians who work in the ward or this field, such as the psychiatrists, other physicians, nurses, and other allied health professionals. We also expect the tool to be used for researchers, such as clinician-scientists, graduate students or resident physicians. Example questions the user groups may have can be found in Table 1.

Use Case	Users	Example Questions
Management	Administrators Nurse Managers Head psychiatrists	How do staffing needs change with the seasons?
Clinical	Physicians Nurses Allied Health	Do my prescribing practices match others?
Research	Graduate students Clinician scientists Resident Physicians	What are some interesting patient sub-populations to further investigate?

Table 1: The different use cases of our visualization, the intended users, and some examples of questions they may have.

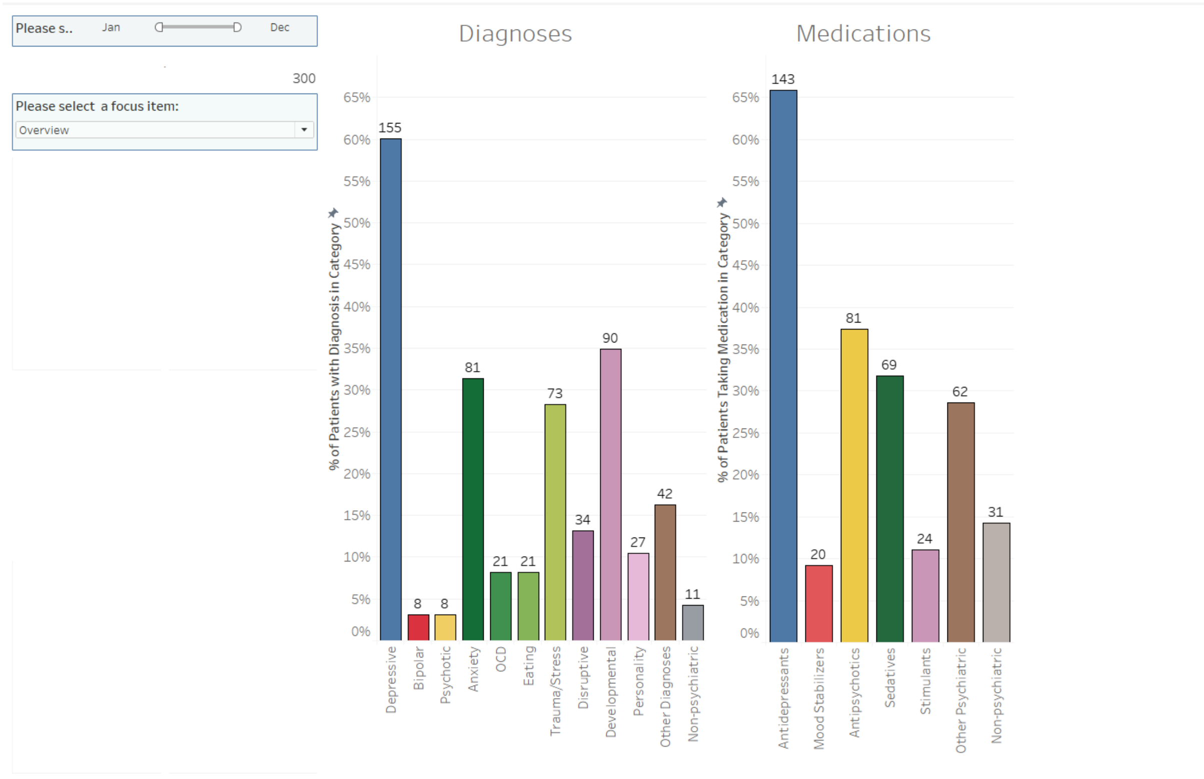

Fig. 1: The initial view presented to users. This overview features bar charts representing unfiltered diagnosis and medication information.

2.2 Task/Why/Actions

Our work's facilitation of these tasks can be abstracted in the following manner, using the framework from Visualizing Analysis and Design (VAD) [19].

Analyze: Primarily our task is to discover and analyze aggregated patient data. While not an explicit feature, the tool can currently be used to produce static visualizations by screenshot to present data, though discovery remains the main task.

Search: An important feature of our visualization is to facilitate the various search functions. We can abstract searching in our task as "targets" being patients, and "location" being various attribute spaces. Tasks where users want to search for a specific set of patients are therefore a *locate* task. Just as important is when users want to view data for patients with a certain attribute, such as those admitted during a specific season; this would be an example of *browse*. Users may have neither in mind, which would be *explore*. Knowing both, *lookup*, is also something we allow, but only to a certain granularity. Due to privacy concerns, we do not allow viewing of a single patient's attributes, which would be the most granular *lookup* search.

Query: *Summarizing* is a central action of our tool, setting it apart from much prior work in this domain. Instead of visualizing an individual patient's attributes, our work summarizing these attributes over all or subsets of the patients. Again, this in place of *identifying* a single patient's data. *Comparing* actions are an important part of the task, as users may want to compare how the summarized attributes differ between different target subsets. For example, users may want to compare the age break down of patients with different disorders.

2.3 Data/What

Our data consists of 333 items (patients) each with a consistent and numerous set of attributes, summarized in Table 2. While much of our visualization is for categorical data, certain ordinal and quantitative attributes are still important, such as a patient's age or school grade.

Of the categorical attributes, a patient's diagnoses and medications are central, but also present a challenge for visualization due to their number of possible values. However, both of these attributes do have a hierarchical nature that allows aggregation. For example, "schizophrenia" and "schizoaffective disorder" are both psychotic disorders [2], and "olanzapine" and "risperidone" both medications of the antipsychotic class [1]. Both medication and diagnoses attributes are also available at two time points, at patient's admission to hospital, and at their discharge, though we did not have time to implement viewing both.

Other categorical attributes generally have fewer values, such as what substances a patient uses or who brought them to hospital. Both of these categorical values have single-digit numbers of possible values.

An important consideration of our data is that each item may have only one value of certain attributes, but may have multiple values of others. For instance, a patient may have multiple ethnicities in the categorical ethnicity attribute, or may have multiple diagnoses. On the other hand, other attributes can only have one value per item; a patient may only have one age, or be in a single grade at school.

An additional consideration for our data is the need to maintain patient privacy. Our visualization must not allow an individual patient's attributes to be observed, as this could allow identification, an example of an external regulatory constraint as explored in prior work [5].

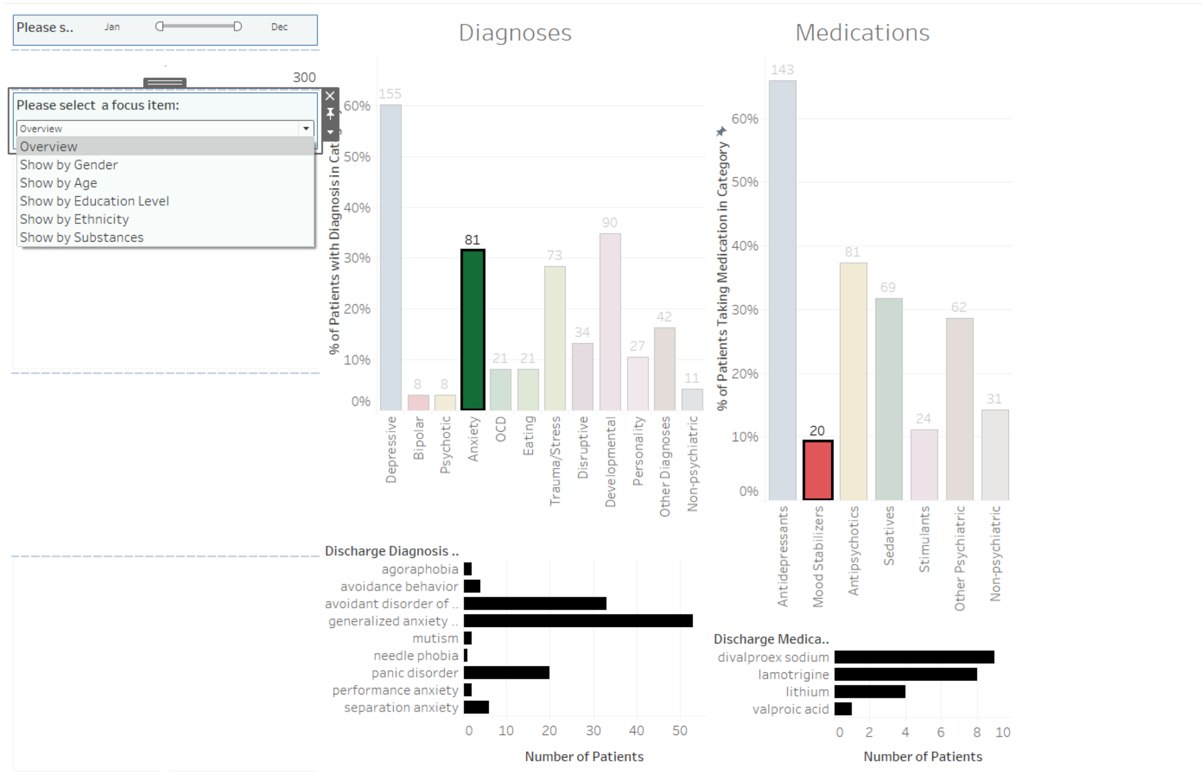

Fig. 2: The Overview panel showing some of the possible interactive features. This figure shows detail views of the *Anxiety* diagnosis group and of the *mood stabilizer* medication group, triggered by clicking on these bars respectively. The drop-down menu shows the different views users can switch to.

3 INFOVIS SOLUTION

Our solution attempts to balance usability and simplicity with still allowing users to access more detailed views. We also took into consideration designing a system that could visualize a data set with both more items and more attributes, at least to the magnitudes that could be expected for clinical data.

3.1 Attribute Value Aggregation

Our visualization depends upon aggregating values for diagnoses, medication, ethnicity and other attributes to facilitate usability and clarity. However, this aggregation is done in a domain-sensitive manner that may help reduce of the noise of hand-coded or NLP generated data. Diagnoses are grouped based on their category in the Diagnostical and Statistical Manual, Fifth Edition, a widely used psychiatric resource both clinically and in research. These groupings also help reduce the noise from data recording; for instance, “bipolar affective disorder type one" may be recorded as this full term in our data, or as “bipolar disorder", but both would be included in the general bipolar disorder grouping. We similarly aggregate medications by their broad pharmacological class, and ethnicities by broader geographical regions. We also reduce the range of age and grade level, to combine non-adolescent patients into one age and grade level. These younger patients are rarer and differentiating their age is less relevant due to the emergence of many psychiatric disorders in adolescence [1].

3.2 Visual Encoding Idioms

Bar chart: The main idiom of our visualization is the simple bar chart, which in some views can become a stacked bar chart. We used bar charts for the more important attributes, compared to pie charts for the less important attributes that are only viewed in certain views. A prime reason for this choice was its widespread familiarity, and its use of the relatively accurate length channel to allow users to make accurate comparisons between bars. Moreover, stacked bar chart allows users to explore the part-to-whole relationships, particularly important for many possible research questions

Pie chart: We generally implemented these as donuts, to allow space saving by featuring labels in the center. Again, a factor in this choice was familiarity with many users, including those with less familiarity with visualization. We used donuts for viewing more ancillary attributes, as a way to differentiate it from the more important attributes (medications, diagnoses). While the radial channel is known to be less accurate for comparisons [19], we rationalize this choice by using this idiom for attributes where more accurate comparisons are less likely to be needed. Multiple donut charts are needed when exploring some groups of attributes due to it being possible for multiple values to be present for one item. For example, ethnicity is visualized as multiple donut charts, with one for ethnicity; one pie chart could not be used, as patients may have multiple ethnicities so the sum would be greater than one. We augment both pie and bar charts with additional information, such as numerical labels showing specific percentages, accessible by both hover and by clicking on parts of the charts.

3.3 Marks and Channels

Horizontal Position: For the main view consisting of the diagnosis and medication bar charts, vertical position encodes percentage as part of the bar chart. However, the horizontal positioning of the diagnosis and medication groupings was available to incorporate into the design. As such, we used it to arrange the diagnoses in relative groupings, and along a general trend of more episodic disorders on the left, and more long-lasting ones to the right. Medication groupings are then arranged to be in a similar order as the diagnoses.

Hue: To avoid confusion, we try to use hue sparingly. On initial overview, hue is used to encode yet another level of hierarchy between the diagnosis groupings; for instance, green groups are related to anxiety, while those of a pink hue are related to development. Depressive and manic disorders are coloured blue and red respectively; depression can be thought of being emotionally “cold" and is described as “feeling blue", while mania is the opposite and so is coloured red to convey being “hot". Medication groupings are then matched with hue based on what disorders they typically are used to treat.

Luminance: A black vs white contrast is used when conveying a binary attribute, such as whether someone is of “white" ethnicity or not. A grey-scale gradient is used to for ordinal attributes such as age. While gradients could also be shown with colour, we instead reserve that channel as described above.

Size: Our visualisation also features a different version of a detailed view which encodes the number of patients who use a recreational substance by the Size of circles.

3.4 Interaction Idioms

Slider: A simple horizontal slider is used to filter patients by their month-of-admission attribute. We believe this is an intuitive and simple choice, as users are likely to be interested in continuous periods.

Drop-down menu: We use this idiom for its familiarity and space-saving nature. It allows users to transition between views, such as from the overview to views detailing certain sets of attributes. The drop-down menu also serves as a title to inform users of what view they are looking at. The different views are detailed in Table 3.

Click for detailed view: While we expect that the diagnosis and medication groupings will likely be sufficient granularity for most use cases, users may also want to have a detail breakdown of what specific diagnoses or medications are within a group. This is facilitated by the user clicking on a bar, which then brings up an additional detail view showing the breakdown of specific medications or diagnoses. When in a view utilizing a stacked bar chart, this detail view will show the detail view for only the data of patients within that layer of the stacked bar.

Click for filtering: Clicking on an area of a donut chart filters the diagnosis and medication bar charts. Clicking on the black portion, which correspond to the percentage that have this attribute value, filters patients that also have this value. Clicking on the white portion, which shows percentage without this attribute value, similarly filters users without this value.

Clicking on legend items: Click on a category in a legend shows an overlay with the specific percentages for each bar.

Hover: Users can hover above portions of the bar and pie charts to trigger an overlay with additional information about that portion, such as number of patients, percentage, and the full text label.

3.5 Obfuscation

Our visualization inherently accomplishes the need for obfuscation. By only allowing one or two filters at a time, users cannot select individual patients. Even if there was only one patient that would fit a filter set, users could not obtain additional information on that single patient. If future work allows more filtering steps, obfuscation would need to be considered explicitly; for instance, results fewer than a certain cut-off could all be shown with the same glyph.

4 Implementation

Our project may have differed from others in the amount of front-loaded work needed before visualization could take place.

4.1 Obtaining the Data

Before starting the project, we needed to attend multiple meetings to discuss using this data for visualization. We consulted multiple stakeholders ,and we needed to decide on what data would be available for the visualization. This involved negotiating with stakeholders to obtain a dataset that would minimize privacy concerns, but still allow meaningful visualization. As we needed different sorts of data, we needed to combine data from different datasets. Similarly, we also needed to decide on a method of data de-identification. We ended up deciding on scrambling identifying information: age, sex, gender, and ethnicity. Again, this was a trade-off between privacy and still visualizing something meaningful. Our project is designed such that the non-scrambled data could be easily used instead.

4.2 Processing the Data

The raw data was provided in a CSV format. We performed initial data processing using the pandas library [16] in Python 3.7. This involved white-space and delimiter unification, missing data handling, and filtering out unneeded or mislabelled data. The next step was to convert the data from medical ontology coding to English strings. This step proved to be more difficult than anticipated, as the encoding was done with multiple ontologies including RxNorm [14], the Systematised Nomenclature of Human and Veterinary Medicine: Clinical Terms (SNOMED-CT) [4], and the International statistical classification of diseases and related health problems: 10th revision (ICD-10) [21]. The encoding was done somewhat noisily, with different ontologies for different patients, sometimes encoding single items or attributes with multiple ontologies, and some encoding have their numbers switched requiring manual coding to the correct ontology.

Following encoding conversion, we needed to convert various versions of drug names to a unique generic form. We then aggregated medications, diagnoses, substances and ethnicities based on known groupings from literature sources such as the DSM-5 [2]. We initially attempted to do this automatically using the ontologies, but eventually settled on hand coding due to time constraints and the often messy nature of these ontolgoies.

Finally, we needed to prepare the data so that it could be used by Tableau. A particular difficult was the attributes that patients could have more than one value of, such as diagnoses and medications. The raw data had these entries in separate columns, while in Python they could be placed in an array. We ended up converting these attributes to separate pivot tables in Tableau. However, this ended up causing performance issues likely due to Tableau adding rows in an exponential fashion with each pivot table added.

4.3 Implementation in Tableau

We chose Tableau as it has many built-in data analysis features and native support of visualizations created in the form of dashboards and worksheets.

Visualizing the data required multiple steps. First, we joined different data source tables on the patient’s id numbers. Next, we implemented attribute value aggregation for different values in the age, medication, ethnicity, education-level, and diagnoses attributes.

Attributes	Type	Simultaneous?	Distinct Values	Aggregated?	Distinct Values After Aggregation	Aggregation Criteria
Sex	Categorical	N	2	N	N/A	N/A
Age	Quantitative	N	15	Y	6	12 or less combined
School Grade	Ordinal	N	13	Y	5	Grade 8 or less combined
Ethnicity	Categorical	Y	11	Y	7	Geographical groups
Substance Use	Categorical	Y	8	Y	5	Pharmacological groups
Diagnoses	Categorical	Y	110	Y	12	Diagnostic groups
Medications	Categorical	Y	70	Y	7	Pharmacological groups
Discharge and Admission Details	Categorical	Y	13	Y	8	Filtered on relevance

Table 2: Summary of attributes visualized. *Simultaneous?* entails whether a single item can have multiple of such values. *Distinct Values* describes the number of possible unique values before and after aggregation, which the last column details how such aggregation was done.

Detail View	Sub-bar Encoding
Show by Sex	Sex
Show by Age	Age Groups
Show by Education level	Grade Group
Show by Ethnicity	Ethnicity Groups
Show by Substances	Any substance use
Show by Admission & Discharge Info*	Number of Admissions

Table 3: The different detail views of our visualization, and how the stacked bar charts for medications and diagnoses are portioned in each view. *Not implemented by code freeze.

Task	J.J.N.	M.F.
Data Acquisition, Ethics Training and Privacy Considerations	80%	20%
Project Proposal	80%	20%
Initial Data Processing in Python	90%	10%
Tableau Data Integration	40%	60%
Overview and detail views: static	40%	60%
Medication and Diagnosis Detail View and Interaction	80%	20%
Detail View Filterting	10%	90%
Presentation and Videos	70%	30%
Final Report	65%	35%

Table 4: Estimated breakdown of each author's contribution.

This reduced the complexity of the data for visualization. We then created the bar charts for these aggregated medication and diagnosis attributes. We followed by then implementing the interaction to allow these nested hierarchies to be expanded for the medication and diagnosis aggregations by using "attribute" and "action" settings in Tableau.

Next, we developed the detail views to allow the diagnoses and medications to be viewed according to other attributes such as age, sex, medication, substances and education-level. This involved developing new donut charts, as well as functionality to convert the medication and diagnosis bar charts to stacked bar charts, again using a combination of Tableau "parameters" and "attributes". Our next step was to further refine the filtering across all charts to ensure the proper filtering functionality occurred. We then implemented additional interactivity, such as the month selection slider, hovering and some other overlay features.

4.4 Team Breakdown

When possible, our team sought to ensure both partners were involved in all steps of the project, and that types of work, such as programming or designing, were generally split evenly. Some factors of our project interfered with this. As Tableau has no native version control support, it was difficult to simultaneously work on the visualization, and one partner adding features sometimes broke the other's work. Partner preference also played a role, as did M.F. becoming sick during the last week of the project. A detailed breakdown is available in Table 4. We estimate spending at least 160 hours on the project between both partners.

5 Results

Our visualization starts by showing an overview as seen in Fig 1. Two groups of stacked bar charts are centered in the screen, encoding their importance. The left bar charts shows the percentages of patients who have a diagnosis from each of the different diagnostic groups. Similarly, the bar chart on the left shows the percentage of patients on a medication from each of the different medication groups. A slider on the top left allows users to only visualize data from patients admitted for a specified time period, while a counter below shows the number of patients that results; this slider in action can be seen in Figure 4. The hue of the diagnosis bar corresponds to a further level of grouping, such as green-diagnosis groups pertaining to an anxious process. Horizontal ordering of the diagnoses confers how transient a diagnosis group typically presents (depressive episodes, on the left, usually happen only occasionally, while developmental disorders, on the right, affect patients their entire lives). Medication groups are coloured and ordered to correspond to the diagnosis group they typical treat.

Users are able to click on the bars of the medication or diagnosis charts to see detailed breakdowns of these diagnoses or medications in these groups, as show in Figure 2. Users can also click on the drop-down menu to switch to detailed views, as also shown in Fig 2. The different views are detailed in Table 3. Unfortunately, our view does not yet allow users to view data from the different detail views at the same time, nor to have persistent filters between views. Similarly, users can not filter medication use by diagnoses or vice versa.

The detail views generally adopt a consistent design to show

Fig. 3: The Show by Sex view, showing male patients in turquoise and female in purple. Donuts on the right hand side show total gender breakdowns, and can filter the stacked bar charts upon click. Note that the drop-down menu's text is mistaken and should say sex, not gender.

additional attributes. As can be seen in the "Show by Gender" view in Figure 3, the bar charts from the overview are changed to stacked bar charts with the subsections defining proportions as detailed in Table 3. On the right hand side, donut charts show the percentage of patients with specific attribute values. Clicking on the black part of such donuts filters the medication and diagnosis bar charts by only patients with this attribute value, while clicking on the white portion filters only patients without this attribute value. Clicking on a specific value in the legend overlays the specific percentage of patients in each diagnosis or medication group as seen in Figure 4. This figure also shows an example of the stacked bar charts using a grey-scale gradient to represent the ordinal attribute age. Figure 4 also shows that the medication and diagnosis detail views can be brought up for sub-portions, with appropriate filtering. We also implemented some alternative design choices in the "Show by Substance Use View" as shown in Figure 5. Instead of the donuts previously used, the view's added attributes shown by circles, with the number of patients using a substance encoded by circle size. Clicking on the circles again triggers filtering as before. Instead of the black and white scheme used elsewhere for showing binary values, a blue vs orange scheme is used for contrast.

5.1 Example Use Scenario

A possible user could be a clinician-scientist specializing in developmental disorders who works as an outpatient psychiatrist at BC Children's Hospital. She wants to understand more details about which patients are admitted to the CAPE unit. She may want to know this information both from a research and clinical perspectives; admissions represent unsuccessful outpatient treatment, and she may want to both improve her clinical practice and conduct research to prevent such admissions.

The psychiatrist initially views the overview. She notices that a relatively large proportion of patients have a developmental disorder relative to other diagnostic groupings. Her attention is caught by the bar for personality disorders, which can be related or mistaken for developmental disorders, aided by the proximity and similar hue of this category. The psychiatrist compares the proportion of patients with developmental disorders to the percentage on stimulants, noticing it is lower. She then clicks on developmental disorders to learn that only a portion of these have diagnoses treated by stimulants. She notices the relatively large number of patients on antipsychotics, realizing that this may represent many of her patients with developmental disorders. The psychiatrist then wants to determine how many of these patients on this type of medication have developmental disorders, a feature that would be easy to add and hopefully included in future version of this visualization.

Finished with the overview, she noticed the drop down menu and clicks it to explore other views. She goes through the different views to look for different patterns for her patient group. The ethnicity view's filtering allows her to notice different diagnostic pattern amongst ethnic groups, leading her to think about barriers to access. Similarly, the age view allows her to compare age distributions, which is of interest owing to the misdiagnoses of other diagnoses that may actually represent development disorders at younger ages. She explores the breakdown of developmental diagnoses at different ages using the detail view, as show in Fig 4. However, needs to switch back and forth between views to remember trends, hoping that future version can allow direct comparisons between these views or

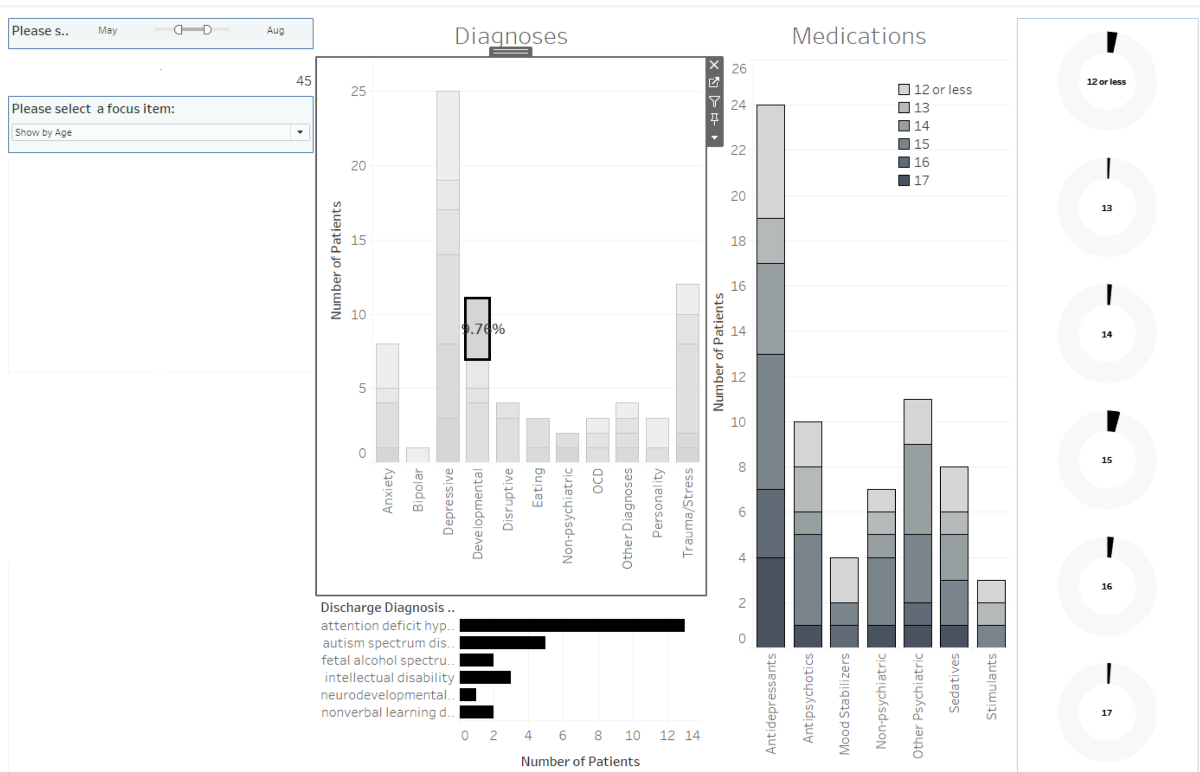

Fig. 4: The Show by Age view, after a user has clicked on the *Developmental Disorders* bar. This results in the detail view shown, which only includes patients of the selected age group (12 years old or younger).

persistent filters.

5.2 User Studies

We sought feedback from possible users on two occasions. The first, with an earlier version of the visualization, was shown to Drs. E.P-C. and A.E. The former is a PhD researcher and clinical informatics lead at BCCH, while the later is a psychiatrist, researcher, and manager at BCCH including at the CAPE unit. Their research assistant S.N. also joined. None previously viewed the visualization, but are involved with the larger research group which provided the data. Their immediate feedback was that the visualization was easy to understand, and they almost immediately started to use it to look at the data, using the time slider to observe how many patients with developmental disabilities were admitted over the summer months. They asked for additional capabilities, such as being able to use it for different data sets. They also showed a visualization being used by the clinical informatics team to track workload tickets, pointing out a similarity in idioms used.

Dr. P.Z. was also invited to try out the final visualization. She is a psychiatry resident in the same resident program as author J.J.N., but otherwise is not involved with the project and had not seen prior versions. She was asked to provide general feedback, but was also given a task to use the tool to discover an interesting aspect of the CAPE data that could lead to a resident research project. A brief verbal explanation was given regarding functionality.

When asked for general feedback, this user explained that the visualization is "really easy to use, the visuals are helpful". Constructive feedback included that the grade and age views are somewhat redundant, and that ages could likely be binned more coarsely. She also asked for more filtering features, such as being able to select one or more diagnosis groups, and having the medication bar charts update accordingly. She also suggested a view to show how many medications patients were on, as well as an ability to view what medications are prescribed together.

Despite using the tool for less than ten minutes, she was able to come up with multiple possible research questions. For instance, she noted that CAPE admitted a large number of patients aged 12 or under for depressive disorders, and then used the detail view to find out that many did not have a diagnosis of suicidal ideation; she finds this surprising, noting that these patients can often avoid a hospital admission, and would like to do a case review of some of these patients. She was also surprised at the rate of antipsychotic use given the total diagnostic breakdown of the patients, and wanted to know more about the diagnoses of those prescribed these medications. Similarly, she was also surprised at the rate of sedative prescription, and wanted to know more about how long the physicians prescribed these for; she thought this would make an interesting quality improvement project.

6 Discussion

Our project seeks to visualize summarized psychiatric clinical in a manner that is intuitive, not overwhelming, and legible to a wide range of users, but in a manner that can still convey detail when required. We made design choices in this vein, including choosing relatively simple visual and interactive idioms, and using relatively few channels. However, the design choices to lead to questions about balancing simplicity with functionality, as well as to the extent our project represents a visualization contribution.

Fig. 5: The Show by Substance Use view. This view shows some alternative design choices, such as using size-encoded circles to show the number of patients who use each substance. Additionally, the y-axis of the bar charts show number of patients, while a hover overlay shows an exact percentage of the patients in a sub-bar.

Based on some initial user feedback, a strength of the project is obtaining this desired simplicity and ease-of-use. Users needed little explanation, and were able to understand and explore data easily. While perhaps an obvious step, our aggregation of attribute values, such as grouping diagnoses by DSM-5 section, increases interpretability, while our interaction mitigates the loss information from this aggregation. We were also able to interpret and process our data to allow our detailed views to maintain a consistent set of visual idioms and interaction, increasing usability.

While we needed to spend a relatively large amount of the project's time on obtaining and processing data, it allowed us make a visualization with some novelty, being the first work we could find visualizing broad psychiatric data, and one of the first focusing on clinical data summarized over a large group of patients. Our visualization provides a framework for item and attribute scalability to the extent that is likely clinically relevant, though some data fixes are required to support the needed computational scalability.

However, some of our design choices also lead to weaknesses that may question the contribution of our work. Namely it is unclear to what extent our visualization represents something that truly adds to usersâ ability to know and explore their data, as opposed to simply being a 'chart generator'. For instance, our use of a drop-down menu requires a user to explicitly realize they would like to few certain details, instead of our visualization helping a user realize such a view might be helpful. Viewing the different views also entails some cognitive load to remember what was seen in prior views. The current project also errs on the side of likely being too simple, and could likely feature more idioms, interactions, and attribute views without being substantially more difficult to use. In its current state, some bugs, issues with uniformity, and performance issues also exist. Some of these weaknesses are inherent in our design choices. However, others could be mitigated in future work, and represent the time limitations of a class project.

6.1 Future Work

Many avenues exist to improve and extend our project. In a sense, it serves as a prototype, with different directions possible to allow better visualization, visualization of other data, and automated visualization.

Bug Fixes and Immediate Improvements: The day or two before code freeze were difficult due to some laryngitis and unfortunately timed hospital shifts affecting the partners respectively. As such, our current visualization has some bugs and other needs for quick fixes that we did not have to chance to implement. For instance, the "View by Substances" view uses size-encoded circles to show how many patients used each subject, while similar encoding in other views uses donut charts; this should be unified to use the same idiom across all. Similarly, the "View by Substance View" stacked charts use color encoding to differentiate those who do or do not use substances; this should be unified to black vs white as used elsewhere. The "View by Ethnicity" view currently uses the stacked bar charts to show ethnicity composition, though this is incorrect owing to some patients having more than one ethnicity. Instead, the stacked sub-proportions could show the proportion of patients with non-white ethnicity. As well, the current "View by Gender" view is mislabelled, and should instead state "View by Sex". Lastly, some views currently use percentage as an axis, while others show total number of patients; this should also be uniform between views.

Partially implemented and planned additions: Again due to illness and time constraints, two additions to the project barely missed being included. The first was an extra view, “View by Admission and Discharge Info", contained details such as whether patients have prior admissions, were transferred from a community hospital, or have psychiatric follow up. We also planned to include a stacked line chart, to show the number of patients admitted per month. This stacked line chart’s stacks would change depending on the view, and would update would other filtering. We also planned a simple toggle to choose whether the displayed medication and diagnoses data are from admission or diagnosis; this was deferred due to it requiring optimizing our data and replacing our pivot solution. One-hot encoding certain attributes would likely be such a solution.

Expanding functionality: Many other functions or features could be added to improve our visualization. One addition would allow more filters at once may improve functionality; this could be added via allowing the detailed views to set persistent filters between sheets. Filtering between medications and diagnoses could easily be added to the current click interaction. Users would also likely want to be able to change the level of attribute value aggregation depending on their data set. For instance, if viewing patients across the hospital, a coarser aggregation like “Psychiatric Diagnosis" would likely be appropriate, while a user using a dataset of only patients with psychotic disorders would appreciate a finer granularity. A simple interaction could allow such changes if the data contained details of such corresponding levels. Another idea we had was to add clustering to the visualization, to allow users to explore similarities between groups of patients.

Automation and Pipeline Integration: The impetus for this project was to build a visualization step as one of the final outputs of a natural language processing (NLP) pipeline being developed by the larger group looking at this data. The current pipeline produces data similar to what is visualized in this project. Our visualization can be used to visualize this data, and compare the hand-coded and NLP-produced data. Full integration would likely involve adding more automation to the data processing steps, such as using the medical ontologies to automatically aggregate attribute vales.

6.2 Lessons Learned

Some of the planned improvements likely require more time than is feasible in a class project. However, some many have been possible had we learned the various lessons we did over this project. These lessons can be explained in the context of the pitfalls enumerated by Sedlmair, Meyer, and Munzner [23], even though this work was read before embarking on this project .

Non-rapid prototyping was a definite mistake; we took too long for the first visualization. While this was partly was due to time needed for obtaining data, data processing and tool familiarization, we should have used familiar visualization tools in pandas or Microsoft Excel for parts of the data as soon as it was obtained. We could have also made a synthetic dataset quite easily, as recommended by prior work commenting on using data subject to regulatory constraints [5].

Rapid prototyping may have prevented the next pitfall, *Premature design commitment*. We focused on an initial design idea before any other data was visualized. This design was obviously flawed after some initial visualization. A focus on rapid visualization may have also helped with determining the scope of the project; focusing on visualizing only a few attributes at first, and then adding, may have lead to smoother progress compared to trying to visualize a large set and then having to narrow scope.

Our decision to use Tableau had both pros and cons. Once we gained familiarity, it allowed rapid deployment and development. We were easily able to change design decisions, and the built-in and automatic features of the program were often helpful. It was also a valuable learning experience to familiarize with a tool commonly used in industry.

On the other hand, we switched to this tool later in the project, which imposed a significant time cost to become familiar. The learning curve may have been smaller had we stuck with the initial idea to use Python’s Plotly library, given that both of us have substantial experience with Python. A Python implementation would also likely facilitate better version control and collaboration, and not involved copyrighted software. However, it may also have taken more time to produce our visualization due to more manual work being needed for the actual visualizations and any changes, so it is unclear which option would have allowed quicker development in total.

7 Conclusion

In this project, we visualize clinical data from a child and adolescent psychiatric ward, a novel domain not explored in prior work. We visualize the summarized data of 333 patients, instead of focusing on visualizing single patient as is common in health visualization. Special considerations are needed for this data, such as attending to privacy concerns, and the wide range of potential users with varied information technology familiarity. The data are also varied, with complexities such as categorical attributes with up to hundreds of possible values. Our design solution incorporates simple design idioms and interactivity to achieve a visualization that initial users have found intuitive and easily understood. Careful use of attribute value aggregation contributes to interpretability, but is paired with interactivity that allows more detailed views. The contribution of the current project is limited by its functionality and possibly over-simplistic design choices. However, it nevertheless represents an attempt to visualize clinical data from a yet unexplored domain, at a scale also rarely attempted. Based on positive feedback from initial users, with some additional work our visualization may provide a meaningful benefit to the researchers, clinicians, and managers trying to improve the health of mental health patients.

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