**Data Visualisation with given dataset using Tableau.**

# Introduction

## Data Visualisation:

What is data visualization, nowadays type of information (multi-dimensional data?)

Many businesses intelligent companies nowadays are slowly acknowledging the value of data and often require more advanced visualisation technologies to extract insightful information from various data sources. As discussed by Kelleher and Wagener (2011), visualisation is effective in terms of conveying and presenting information. Hence, many applications of data visualisation have come into real-world practice to help people gain more insights.

Data visualisation is the graphical representation of information about a set of data, Tableau (n.d.). Throughout various uses of visual components such as, graphs, charts, or even geographical graphing like maps that a dataset can be visualised with. There are multiple tools that supports data visualisation, such as Power BI, Excel, Tableau, and data visualisation tools developed by Java developers. However, the most common used tool is Tableau because of its high functionality and simplicity. In this paper, Tableau will be used for analysis and visualisation of data.

Things about Tableau:

J. Buhler et al (2016) discussed about the visualisation tool like Tableau, that it is a rapid-analytics and powerful data-visualisation software that provides users with the ability to query, explore and visualise quantitative data with dynamic, interactive dashboards and papers. There are a lot of ways to convince your data with Tableau when working with across categories, Tableau (n.d). Some of the available graphing methods are Mapping Spatial data with geographical locations, Bar Charts, Line Charts, Text Table, Scatterplot, TreeMap, etc

## Guide on visualisation:

“Visualisation process is a sequence of transformation that converts a data set into a displayable image” – Senay, H and Ignatius, E., 1994. To support for the statement, Senay, H. and Ignatius has proposed the following steps to help perform effective visualisation:

* Data Manipulation
* Visualisation mapping and Rendering

On the other hand, traditional data manipulation process and visualisation methods are not effective enough in terms of handling big data nowadays. To help with a newer approach to Big Data Visualisation Analysis, Ben Fry (2008) also proposed more steps to interact with large data set:

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Figure 1: Ben Fry’s Seven-Steps for Information Visualisation

As a stepwise information visualisation, Ben Fry (2008) defines each step as follows:

1. Acquire: Acquire the data from a certain source, which could be disk, storages, or over network
2. Parse: Exploring the data’s meaning and reorganising the data structures
3. Filter: Filters the data of interests for future analysis
4. Mine (aka Data Mining): Using knowledge-based statistics and other mathematical techniques to find any significant patterns in the data that is noteworthy.
5. Represent: From there, implementation of data through visualisation mapping can be done with basic modelling graphs, e.g. bar, tree, scatterplot, etc.
6. Refine: From basic graphing of data, further implementation through techniques, for examples, colour sizes and shapes.
   1. Thus, these techniques can improve the basic representation to be more transparent and visually engaged.
7. Interact: hands-on interaction can help users experiencing, manipulating, and controlling what features they want to see in the visualisation (Fry, 2008), Fry, B. 2008, July. Data Visualisation.

## Multidimensional data and data file:

According to Virtualitics (n.d), a dataset with different columns, called features or attributes, is referred as multidimensional data. For example, healthcare data has numerous variables such as, blood pressure, weight, cholesterol level, etc. Consecutively, the more attributes a dataset contains, the more likely a dataset will have more information for potential discovery.

The dimensionality of the data can cause issues in analysis, so it is essential to parse and reorganise the data before planning on data mining and visualisation, Finney D.J. (1977). In this paper, the data file **2022\_mpi\_statistical\_data\_table\_1\_and\_2\_en** was obtained from online sources, the file contained unformatted information of data in the form of Excel Spreadsheet; hence it requires to go through some cleaning process. Finally, the cleaned data file will be store in **Final\_data\_for\_assignment**, which is a new Excel spreadsheet. The cleaning process will be further provided in the section below

## MPI Dataset (2022\_mpi\_statistical\_data\_table\_1\_and\_2\_en) and Parsing steps:

**General information about Multidimensional Poverty Index:**

In this paper, the Multidimensional Poverty Index dataset acquired from Human Development Paper website will be used for discussion. According to research from Global Multidimesional Poverty Index (2022)*,* Multidimensional Poverty Index (MPI), is often known as the key international resource that measures multidimensional poverty across countries, *Nation. U (2022)*. It begins by measuring each household’s deprivation profile and person in it, including indicators on health, education and standard of living (see figure 1). MPI values are the consequence of poverty incidences and the intensity of poverty. The higher the MPI value on a scale from 0 to 1, the higher poverty rate the country is. The MPI papers have been taken under surveying for at least 10 years, ranging from 2010 to 2020/2021 and it showed that there has some improvement in reducing national poverty, seen in some countries, e.g. In India, approximately 415 million people exited poverty between 2005/2006 and 2019/2021, demonstrating that the Sustainable Development Goals target 1.2 of halving the proportion of people living in poverty by the start of 2030 is achievable, UNODC Regional Office for Southeast Asia and the Pacific (n.d.).

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Figure 2: Structure of the Global Multidimensional Poverty Index, by *Nation. U (2022)*

**Parsing MPI data with Excel Spreadsheet:**

Originally, the MPI paper was poorly formatted in form of a Excel Spreadsheet, and it contained columns with NULL observations and table names were incorrectly formatted for Tableau recognition. Hence, a new file was created, where the old dataset had been cleaned and rearranged in a new Tableau-readable data frame format. The following changes have been made in the file to acquire a more efficient data:

1. *Multiple titles recognition problem:*

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As shown in the figure above, the original dataset contains multiple titles on multiple rows, for example, there is a header on row 1 to identify the context of the information below. Meanwhile, the next 3 rows are the variable names categorising the distinctive nature of data, e.g, the column **Country** shows name of each country. On the one hand, Excel professionals will find this useful for organising data and easy to read. On the other hand, Tableau will not be able to capture the data in this format, since it can only recognise multidimensional data in a single data frame structure, which is as shown in the figure below when the data is rearranged.

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Hence, a modification of titles was made to simplify the data structure. For example, in the original data, the row that was classified as *Multidimensional Poverty Index* then *Value* on the next row, is then renamed into one single title on one single cell as *Multidimensional Poverty Index – Value*. This led to the results shown in the figure above.

1. *Removed unnecessary categorisation of data:*

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There is an additional row that categorises data based on year of survey called **Estimates based on survey for 2010 – 2015**. However, it is not needed since the column **Multidimensional Poverty Index - Year of survey (2010 – 2021)**have included any data from 2010 to 2021. Hence, the row name was removed and the rows below it was joined to the rows above, resulting in a complete, unseparated dataset as shown below:

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Furthermore, it can be seen in that there are characters in between columns annotating the reason behind the numbers or characters of the left column, e.g. f, g, d,g,k, etc. This will be filtered out since we are only interested in the exploration of data and the mathematical insight it provides.

1. *Separation of distinguishable rows:*

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There are rows as shown above, like **Developing countries** and **Regions***,* which does not belong to the column **Country***.* Hence, to further distinguish data, two spreadsheets were created for **Developing countries** and **Regions***,* each with the same data structure as discussed in the section *1 – Multiple Recognition problem.*

Repetitively, this whole process will also be applied to the second spreadsheet, *table2*, which is **Table2: Multidimensional Poverty Index: changes over time based on harmonised estimates***.* As a result, we will have a complete data frame as shown in the following figure.

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Among the columns, there are some significant attribute variables of the dataset that can be looked at later in the analysis section, such as, health (%), Multidimensional Poverty Index, Education, etc, which will help us understanding more about issues behind the countries’ multidimensional poverty.

# Visualisation and Analysis on the given dataset

To begin exploring the dataset, there are two original datasets that require to combine to give a complete analysis of human poverty. The first dataset is stored in the spreadsheet **MPI dev counts (2010- 2021)**, while the second dataset is stored in the sheet **Harmonised (2010-2021)**. To join two table of data frame, we will perform left join on tables, as every values belong in *Harmonised (2010-2021)* equal to values in *MPI dev counts (2010-2021)* will be selected.

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During the process of joining table, there occurred some missing values in the table. For example, the most recent data estimation survey on Afghanistan’s MPIs was during 2015/2016, with further details only about general Poverty scores, such as, MPI values, Headcounts, Intensity of deprivations, Population shares (%), Contribution of deprivation in dimension to overall multidimensional poverty (%). However, detail information about the contribution the health, education, and standard of livings deprivation for each household and person were not recorded, as shown as in the table below. This is due to the differences in ways of measuring poverty in country like Afghanistan. “Poverty in Afghanistan is multidimensional: it varies by region, by gender and by access to exit pathways”, NSIA (n.d.). Therefore, for a more suitable way of measuring poverty in Afghanistan, the Islamic Republic of Afghanistan developed their own scale of multidimensional measurements. From the publishment of A-MPI (Afghanistan Multidimensional Poverty Index), there are over 34 groups of people in Afghanistan, in which the poorest those groups is Badghis with over 85.5% of poor people. The intensity of multidimensional poverty is deprived from 18 weighted indicators, ranging from Food security, assisted delivery, Access to water, Sanitation, Electricity, Cooking fuel, to Youth NEET, Production, Security and more. The reason to create more indicators on the measurement of poverty is because there are more problems to concern about than basic human needs in Afghanistan. As similar to Afghanistan, each country in the NULL table gave various number of ways to indicate their country’s MPI data, based on their current situations of livings and major problems revolving around their daily basis. Or simply just because there isn’t any available information about them.

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## Using GeoVisualisation to show MPI values across countries:

After exploring on the dataset, we could start with a GeoVisualisation to show the Global MPI values across nations around the world. On the graph below, there are over 100 nations recorded the MPI values during the past 10 years. Among the nations shown, the Sub-Saharan region of Africa, coloured in Orange, seems to be the regions of most impact by poverty among the people. For example, the MPI indicator shows that South Sudan had reached over 0.50 marks of MPI values, with an overall value of 0.5802 (surveyed in 2010). Meaning the multidimensional deprivation rate in Sudan was in a high scale danger and Sudan people was living in serious poverty at the time. Moreover, It can be noticed that MPI values tended to be higher in countries that clusters around the centre of Africa, it declined from West to East. Countries such as South Africa in the South, or Algeria and Libya (both are coloured in green), had a much lower MPI values compared to Sudan:

* South Africa with MPI value of 0.0249, measured in 2016.
* Algeria with MPI value of 0.0054, measured in 2018, and
* Libya with MPI value of 0.0074, measured 2014.

Furthermore, outside the Sub-Saharan region of Africa (which filtered in Green), there are major areas in South and South-east Asia where the MPI values are slightly significant comparing to countries in Sub Saharan Africa, such as Afghanistan, Pakistan, Nepal, Bhutan, Bangladesh.

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Using GeoVisualisation for the analysis of Spatio-temporal data is widely acceptable. According to Laurini (2017), GeoVisualisation enhances the recognition of patterns or trends. Hence, in the previous example, by applying geographical modelling on the MPI values onto the global map, it was able to effectively show a highly recognisable pattern of high MPI values clustering across Sub-Saharan regions. Meanwhile, other MPI values in various location were either infrequent or as significant as the cluster within Sub-Saharan region. By that, it also gives a global vision of the situation of MPI values in countries.

To implement pattern recognition in GeoVisualisation, we created a set to separate any country in and out from Sub-Saharan Africa, and by highlighting the inner countries with Orange and the outer countries with Green, since Orange is more colour-expressive than Green (Note: The process of separation of country was done manually through Visual grouping on the GeoVisualisation graph). Kobourov et al (2015) mentioned about the theory of Gestalt laws of Similarity, that things can be grouped together by their colour, shapes, or size; and hence, by implementing colours and sizes on the set of countries that was grouped, it can identify which countries have higher number of MPI values. This not only aids in creating a boundary detection layer between the inner and outer area of Sub-Saharan Africa, making the Visualisation clearer and more visually reactive, but also give us another angle to investigate on.

However, there is a drawback on using GeoVisualisation. We cannot embed too many details information on a graph because it might cause a confliction in reading the data. For example, if we added the survey year to the GeoVisualisation, the information will be mixed, and the text will overlap with the other text. Therefore, there must not be many texts information displayed on the graph except showing the MPI values of the countries. To eliminate the issue, we added a tooltip that shows the information of the survey year of the country when user interacts with the map. As shown in the figure below:

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## Using Bar chart to address the poverty issues based on the ranking of a country’s MPI value:

In accompanying with the data in the table below which shows the MPI Values across developing countries in Sub-Saharan Africa, countries with MPI values above 0.50 threshold are Niger, South Sudan, Burkina Faso and Chad. From the survey data, Niger reached the MPI value of 0.60 in 2012, whereas South Sudan and Burkina Faso reached 0.58016 and 0.52342 during 2010. And Chad despite was measured during late 2019, Chad still got a high MPI value of 0.516701.

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In the next figure, bar chart was able to effectively provide the statistical number behind the MPI value of each country within the Sub-Saharan Region. The colours were used to represent the year of survey. For instance, pink is 2010, green is 2018, etc. Furthermore, a filter was featured with the bar chart to help user narrowing down the range of MPI values. In the case below, the graph returned the results with countries that had the MPI values smaller than 0.50. The graph shows a total of 39 countries that their MPI value is smaller than 0.50. The only country with the smallest MPI value is Seychelles, 0.0030, which was recorded in 2019.

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Overall, bar chart provides a very efficient method to show an attribute over many observations, like in the example above, it visualised the MPI value of each country, showing which value is the highest or lowest among them and the country with it. However, the limitation using bar charts is that it is not effective to have many observations and many attributes at once. A bar chart can only present a limited amount of information to users Keim el al. (2002). And ROM (n.d.) also said a bar graph is not suitable for large scale visualisation, since the graph will extend and will cause confusion in the observation of values. The best way to fix this is to implement colours and filtering as shown in the figure above, it allows users to compare information and as well as gaining more data insight through interaction with the graph. The bar chart above, despite having two different attributes, **Country** and **Multidimensional Poverty Index – Value**, by applying colours to show the Survey year and using filter to extract MPI values that are below 0.50. It has successfully shown more information about the MPI values of each country, such as the information about the Survey Year of the countries. Potentially, we could also add more filtering on the Survey Year to show the MPI value of the filtered countries based on the Survey Year. This will help extracting more insightful information about the countries in Sub-Saharan Africa.

## Using Pie chart to summarise the total contribution of multidimensional poverty of Sub-Saharan countries in comparison with the global contribution:

During the discussion on the GeoVisualisation, it was mentioned that there was a large cluster of significant MPI values in Sub-Saharan, meaning that there were many countries suffering from poverty. To see how much percentage of total contribution of deprivation in Sub-Saharan countries contributed to the Global contributions of deprivation (including all countries), We used pie chart, to indicate the total contribution of each attribute of multidimensional poverty. This includes Standard of Living (measured in % and coloured in Orange), Education (%, coloured in Red), and Health (%, coloured in Blue). In this example below, the total contribution of Standard of Living deprivation is 2,043; while the global total contribution of deprivation of Standard of Living is 4,159.4. Meaning that approximately 49% of the global deprivation of Standard of Living were from Sub-Saharan countries (. Similarly, about 35.68% of the global deprivation of Education were from Sub-Saharan countries (. And lastly, about 29.35% of the global deprivation of Health were added by Sub-Saharan countries (. This suggests that Sub-Saharan countries has been in dire need of humanitarian assistance.

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An update on the development program by Australia to support Sub-Saharan Africa (n.d.), a total of $88.8 million was raised during 2021-2022 to the Australian ODA (Official Development Assistance) for humanitarian missionary in Sub-Saharan Africa, in order to help advance stability, growth and prosperity.

Using Pie Charts allows effective visualisation of large multidimensional dataset, because it summarise the data of each attribute very well, Data presentation (2022, May 6). In this example above, are the total summation of each attribute of the multidimensional poverty in Sub-Saharan countries, which are health, education, and standard of living. Pie chart also summarised the data of each attribute perfectly when there is the addition of tooltip, which shows related data from other sheet. We used tooltip to combine data information from **“Sheet 5”** with **“Sheet5-sup1”** to capture the overall contribution percentage of deprivation of Sub-Saharan countries compared to the global deprivation. The tooltip feature is added to the pie chart as shown in the figure below. A screenshot of a pie chart

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There are advantages and disadvantages from using Pie chart. On one side, It can summarise a large data set in visual form very well. On the other side, it fails to reveal any major pattern within the dataset. For example, it doesn’t show more details about how a country contributed to each deprivation; it only displays show the total deprivation contributed by every country in the set. Hence, further interaction features could be added to the chart to unlock more data insight behind the dataset.

Eells (1926), suggested to use Pie charts instead of Bar charts due to the accuracy of pie charts was better than bar charts and people tend to read pie chart faster than reading bar charts. If the graph was introduced with a bar chart, it is harder to make assumptions based on each column. But if we used pie charts, it can clearly be generally seen that the deprivation of Standard of Living dominated over the other two deprivations. We tend to make more accurate judgements in perceptual task that involves length, angle and area, Cleveland et al (1984). In the pie chart, Area and angle were considered.

To further improving pie chart, instead of keeping original pie chart, we could implement it to Doughnut-50 (meaning a doughnut shape chart with hole having radius of 50% of the pie radius). From the result of experimentation on data recognition with different pie chart shape conducted by Harri et al (n.d.), it showed Doughnut-50 had the lowest mean task time when the Index of Difficulty is the highest, there is a trend that people make faster judgment and faster sight reading with pie chart that has hole other than variations, including the standard pie chart.

## Using Stacked Bar charts to see how much an attribute contributes to the total poverty of a country.

To explore deeper into the cause of poverty, lets view the three main attributes of multidimensional poverty of each country with stacked bar chart. Each colour on the graph represents a deprivation profile that contributes to the overall deprivation of that country. Yellow stands for deprivation of Standard of Living, Cyan is deprivation of Health, and Red is deprivation of education. Each country has different levels of difficulty on each aspect. From figure below on the left, it shows Kenya, Lesotho, …, were among the top 10 countries concerned about Standard Livings most, and the percentage of deprivation which was the highest across Sub-Saharan country was 61.51%, which is Kenya. While the figure on the right demonstrates countries with top issues regarding to Education concerns. Senegal, Mauritania, Mali, …, belongs to the top 10 countries with the highest rates of Education deprivation. Senegal has contributed the highest deprivation rate of about 48.45% to the overall multidimensional poverty of the country. Furthermore, Countries within the top 10 highest Health Deprivation were Seychelles, South Africa, Gambia, Gabon, Namibia, Nigeria, Botswana, Kingdom of Eswatini, Cameroon and Uganda. Meanwhile, Seychelles was among the poorest in Health, with an overall percentage of 66.83%.

However, in comparison, those countries with lowest value of MPI for each deprivation profile (Standard of Living, Health, and Education) consecutively are Seychelles, South Sudan and South Africa. Seychelles despite having issue with Health most, Standard of Living was the least among the type of deprivation, it has an overall percentage of 1.06%. On the other hand, the total contribution of deprivation on Health by South Sudan was 13.99%. Finally, South Africa faced approximately 13.11% of total deprivation on Education.

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Classical Stacked bar charts are effective for presenting the sums of data attributes while allowing to see how the values of the attributes contribute to the totals, Streit et al (2014). A Great thing about Stacked bar chart is that it can show multiple rows of observations and its contribution values; Which is better than Pie chart in terms of presenting how much an observation contributes to the whole, whereas a classical pie chart generally cannot perform that. For future analysis, instead of using classical Stacked Bar Chart, we could implement inverting stacked bar chart in replacement of classical Stacked bar to help reducing the completion time of reading data, Indratmo et al (2018).

In the next figure, a stacked bar graph was used to show the overview of deprivation profiles of each country in Sub-Saharan region. There were Null values in the graph as there were further records of information was described in the dataset (as it can be seen in the sheet **Null\_value** in Tableau). As usual, Niger was the country that suffers most based on the 10 indicators shown in the graph below. Then we had Chad, Central African Republic, etc. Among that there were null value, meaning there were no available information indicating more about the country.

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## Using Bar Charts to visualise the differences in number of poor people in the survey year and number of poor people in 2020

To track the overall changes in population in multidimensional poverty since the survey year to 2020 by each country. We used side-by-side bar chart for comparison of value significance. From the figure below, Column coloured in red represents data measured in survey year and Columns coloured in blue represents data measured in 2020. It can be observed that Nigeria had the highest population in multidimensional poverty during the time of surveying as well as after the survey year, which is in 2020. About 92,085 million people lived in poverty in Nigeria in 2018 and the number had increased to 96,699 million in 2020. As similar to Nigeria, some countries had shown a dramatic increase in number of people living in poverty in the survey data.

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A new parameter was set up to calculate the difference in the number of people living in poverty since the survey year to 2020. The figure below, shows the parameter as the difference between population in multidimensional poverty in survey year and population in multidimensional poverty in 2020 in the mentioned country in **Sheet\_9/ Bar diff**. In the graph, it demonstrates that the majority of countries’ population in multidimensional poverty seemed to increase after the survey year; whereas only a minor group of countries has a downward or unchanged trend, for instance, Mauritania had successfully reduced the number of people living in poverty by 68 thousand people within two years, from 2019 to 2020. Meanwhile, Rwanda, Malawi, Liberia, Gambia, Seychelles, Sao Tome and Principe had not changed at during and after the survey year.

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# Discussion:

There are other analysis techniques that are helpful to support the visualisation of multidimensional data, which include:

* Data Processing
* Data Automated analysis,
* Machine learning algorithms
* Clustering
* Support vector machine
* Dimension Reduction,
* Filtering of Data
* Etc.

In the analysis section above, we have performed some of the key steps in data analysis techniques to help visualise data and extract meaningful insights, such as going through steps of data processing to help preparing a cleaned data file, Using Filter to focus on interested information.

Overall, there are many more potential areas of research could have been done to further assess the issues faced by countries in each region around the world. Furthermore, this paper overall has only been focusing on only the Sub-Saharan region, there are more related information could have been done on other regions than the Sub-Saharan regions, such as the Arab States, East Asia and the Pacific or Europe and Central Asia, etc. Aside, from the graphs shown in this paper, there are other visualisation which can be seen in the below section **Further Visualisation**. For those in the below section, those were potential visualisation that could be used in discussion in this paper. However, there wasn’t enough time to explain on these visualisations.

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# Conclusion

To have a better understanding of a large set of data through visualisation, a careful planning and preparation step must be undertaken precisely to produce the most accurate representation of the dataset. Ben Fry (2008) has proposed the steps that can be taken seriously to help further interacting with large dataset. This paper has explained and gone through every step from data acquiring to visualising data, with the support of visualisation tools like Tableau and Data handling tool like Excel.

This paper also developed several visualisation techniques to view Multidimensional data. And throughout the process, various meaningful analysis was conducted using different visualisation techniques, such as Geospatial Modelling, Bar Charts, Pie Charts, Stacked Bar Charts. Furthermore filtering, subsetting the data, creating parameters to calculate the differences are additional steps that were used to extract more detailed information about the dataset, finding more patterns or trends about a country and as well as to effectively use the graphing techniques like Bar Charts despite its limitation in visualising large amounts of data.

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