Bushfire Brigade

DATA MANAGEMENT PLAN

Group TA30 - Next Gen Innovators:

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Table of Contents

1. Dataset Overview..2

2. Data Usage...3

3. Data Preparation..4

4. Data Storage...5

5. Database Design..6

6. Data Analytics..7

7. Ethical, Legal & Privacy Issues...12

1. Dataset Overview

Dataset	*Source*	*Physical Access*	*Granularity*	*Licence*	*User Story*
Dataset 01: School locations in Victoria	*https://discover.data.vic.gov.au/dataset/school-locations-2023/resource/92fdd072-4666-4cc6-a28a-749c826297a7*	*CSV*	*High*	*Open source data*	*U4.1, U4.2*
Dataset 02: Enrollments in schools in Victoria	*https://discover.data.vic.gov.au/dataset/all-schools-fte-enrolments-feb-2023-victoria/resource/64c14b8a-dbe9-4c28-9f75-c5689a727b80*	*CSV*	*High*	*Open source data*	*U1.9*
Dataset 03: Bushfire risk school registry	*https://www.vic.gov.au/bushfire-risk-register-barr*	*CSV*	*High*	*Open source data*	*U4.1, U4.2*
Dataset 04: Bushfire scar history	*https://discover.data.vic.gov.au/dataset/fire-history-records-of-fires-across-victoria-showing-the-fire-scars1*	*shapefile*	*High*	*Open source spatial data*	*U4.1, U4.2*

2. Data Usage

We plan to use the above mentioned datasets as below:

- **School locations in Victoria:** The school locations dataset provides detailed information about schools across Victoria, including their coordinates, address, and contact details. This data can be used to create interactive maps that visualise each school's proximity to bushfire-prone areas. By overlaying bushfire risk zones on these maps, students can better understand the specific risks their school faces and level of alertness they need to maintain. Additionally, the dataset can inform the creation of tailored bushfire preparedness plans and evacuation routes for each school, ensuring that educational content is relevant and practical for the students' local environment.

- **Enrollments in schools in Victoria:** The enrollment data for schools in Victoria provides a detailed breakdown of student numbers across different grade levels within each school. This data will be used to assess the potential impact of bushfire education programs on the student population. By analysing enrollment figures, the program can tailor educational content to specific age groups and ensure that resources are allocated effectively. Additionally, understanding the distribution of students across grades helps in effective targeting, designing age-appropriate materials and activities, ensuring that the bushfire education program is both engaging and relevant for students at different stages of their schooling.

- **Bushfire risk school registry:** The bushfire risk school registry, which includes the Fire Risk Category for 2023-24, will be used to identify and prioritise schools and educational facilities that are at higher risk of bushfire incidents. By categorising schools according to their fire risk, the bushfire education program can focus on delivering targeted content to those in high-risk areas, ensuring that students and staff are well-prepared for potential emergencies. An interactive map will be developed for the first time with the schools overlaid on bushfire scar areas with kid friendly insights highlighting the level of alert required.

- **Bushfire scar history:** This dataset includes information on areas that have been affected by bushfires in the past. By analysing historical bushfire scars, we can identify patterns and trends in bushfire activity over time. This information will be used to create interactive child-friendly visualisations that show how bushfire scars have changed over time. These visualisations can help students understand the impact of bushfires on the environment and recognize areas that have experienced multiple incidents.

3. Data Preparation

The data preparation process began by examining the entities and attributes contained within each CSV and shapefile file. We have 5 datasets that we need to clean and combine in order to establish the database for the project. Upon examination, we found that the datasets needed to be filtered based on the target audience, which are kids ages between 8 to 12 years old, living in the bushfire prone area. This filtering process will make the database lighter and improve querying efficiency.

To clean and wrangle the data, we used Python and the pandas library. One significant benefit of using pandas is its efficiency in handling tabular data, which is the format we are working with. We used pandas to clean column names, transform enrollment data into a long format, and perform initial data wrangling. Additionally, QGIS was employed to read and convert shapefile data into GeoJSON format for mapping historical bushfire risks that will be later used for mapping the fire-scaring history.

A crucial part of the data preparation involved geocoding school addresses to obtain latitude and longitude coordinates. If the latitude and longitude were not provided in the data, we utilised a geocoding function to acquire these coordinates. Schools from the datasets were matched based on their names and addresses, and latitude and longitude mappings were validated through name-address similarity mapping. Schools with matching identifiers were cross-referenced for accuracy, and discrepancies were addressed by checking coordinates against Google Maps. The cleaning is mainly to connect all datasets, those including School, Risk Category, School_BARR, Enrollment, the School_No (school number). For schools without existing identifiers, new keys were created to ensure a seamless integration of data.

4. Data Storage

Creating a robust data storage plan for a project involving NEXT.js, Prisma, and PostgreSQL requires a detailed approach to ensure efficient data management, security, and scalability. The first step is to define the data requirements and design the database schema based on the provided ERD. This schema includes attributes such as `School_No`, `School_Name`, `Risk_Cat_No`, and `Enroll_Code`, among others, with well-defined relationships like the connection between `School_Barr` and `Risk_Category`, ensuring data integrity.

The PostgreSQL database setup is facilitated using Prisma, where models corresponding to the tables in the ERD are defined in the Prisma schema. Each model includes attributes relevant to its entity, such as `School_No` and `Risk_Cat_No` in `School_Barr`, and these models are then used to generate the necessary tables in the PostgreSQL database. The Prisma schema's attributes ensure that all necessary data points are captured and maintained accurately.

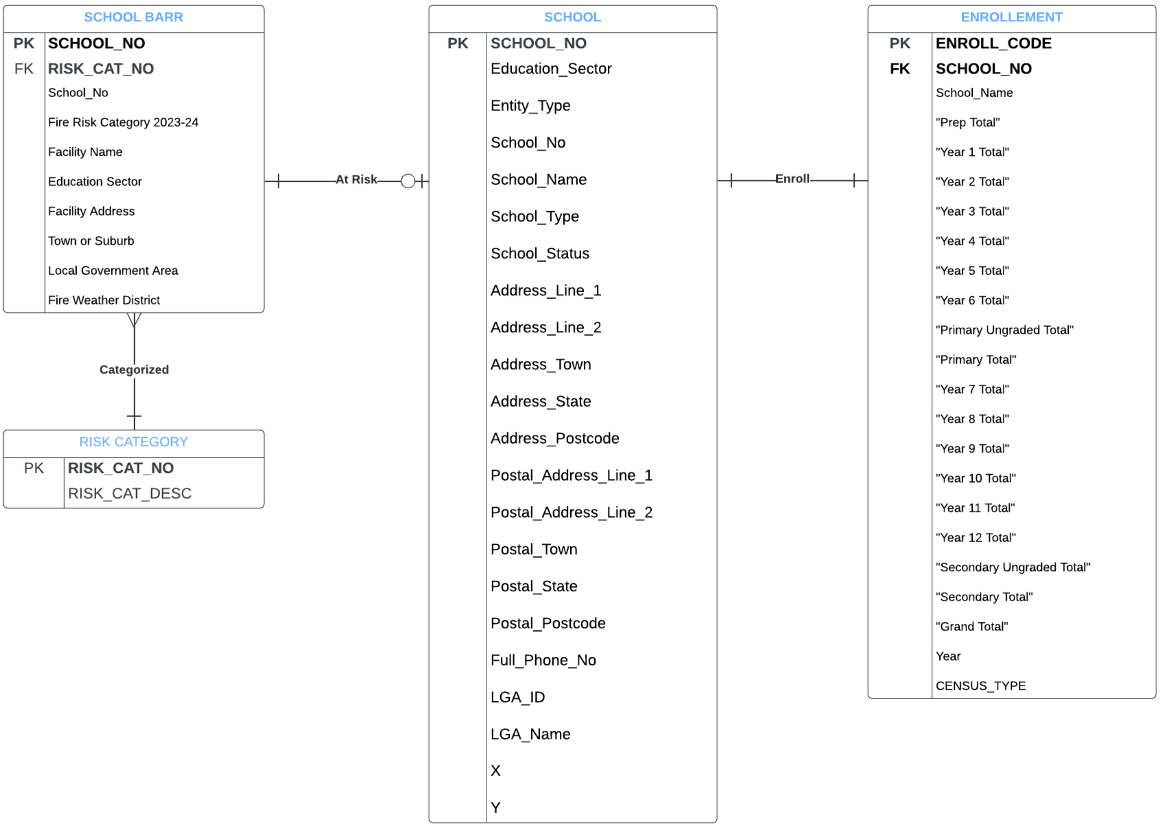
Integration with NEXT.js involves creating a `prismaClient` within the application, which interacts with the database to perform CRUD operations. API routes are developed in NEXT.js to handle operations for each entity, such as `School`, `School_Barr`, `Enrollment`, and `Risk_Category`, with these routes utilizing the specific attributes defined in the schema, like `School_No` for identifying schools and `Risk_Cat_No` for categorizing risk levels.

Security measures are critical in this plan, where environment variables securely store database credentials, and API routes are protected with authentication and authorization strategies like JWT or OAuth. Each operation within these routes ensures the security of the attributes and the overall data integrity.

Finally, deployment is carried out on platforms such as Vercel or AWS, with the PostgreSQL database hosted securely, possibly on AWS RDS. Performance is optimized using Prisma’s query optimization features and indexing the database on crucial attributes like `School_No` and `Risk_Cat_No` to enhance retrieval times. Regular monitoring of both the application and database ensures that the attributes and data remain secure, accurate, and efficiently managed, fulfilling the goals of scalability and robust performance in the data storage plan.

5. Database Design

Identifying the primary and foreign keys, the team utilised found in the metadata available on the website Victorian Government (please refer to the link in the Data Overview section) to guide the establishment of our Entity-Relationship (ER) schema. However, we refined some attributes that were not relevant to the project to ensure efficiency and relevance. The high level schema is firstly focused on the school and risk category.



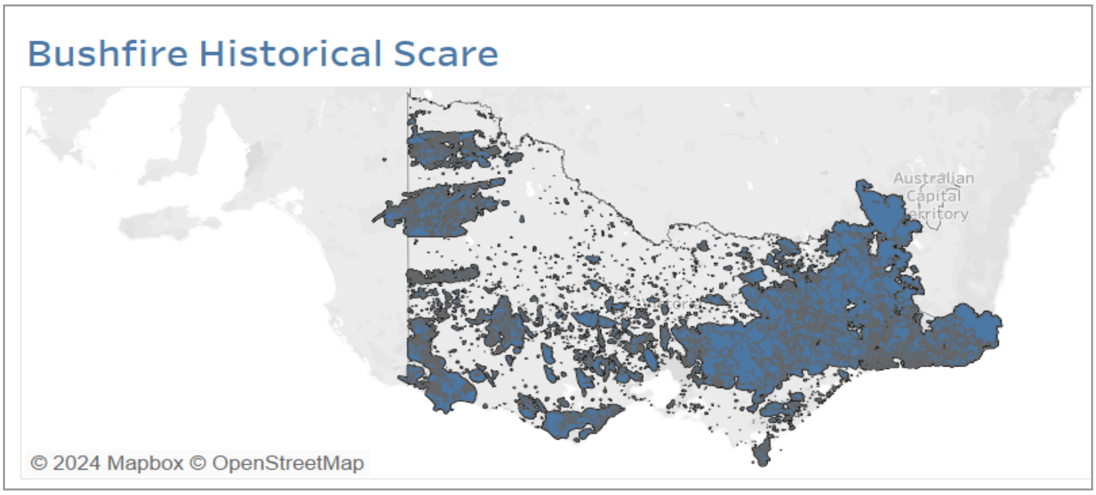
6. Data Analytics

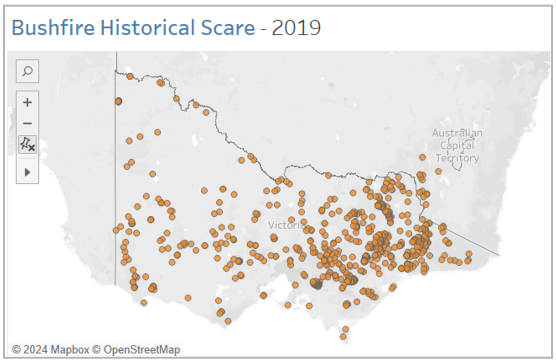
The data science team utilised the cleaned dataset to conduct an exploratory data analysis (EDA) to uncover critical insights related to bushfire risk and its impact on schools across Victoria. Our primary analysis focuses on understanding the potential bushfire risks that pose a threat to educational institutions and the number of schools and children affected by these risks. We aim to answer the following key questions:

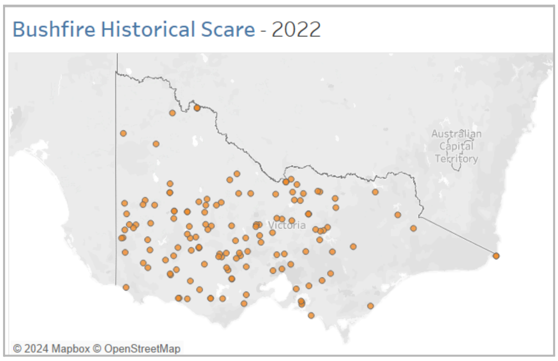
- **Which** schools are located in the highest bushfire risk zones?
- **Who** is affected in these risk areas?
- **What** are the distributions of schools across various fire risk categories?
- **Where** does the bushfire risk vary in different local government areas and weather districts?

By addressing these questions, we aim to provide valuable insights into the vulnerability of schools to bushfires. This information is essential for structuring the storytelling on the homepage of the website, allowing us to present data-driven narratives effectively. The following section highlights and reveals the insights extracted from the datasets, offering a comprehensive overview of the bushfire risks facing schools in Victoria.

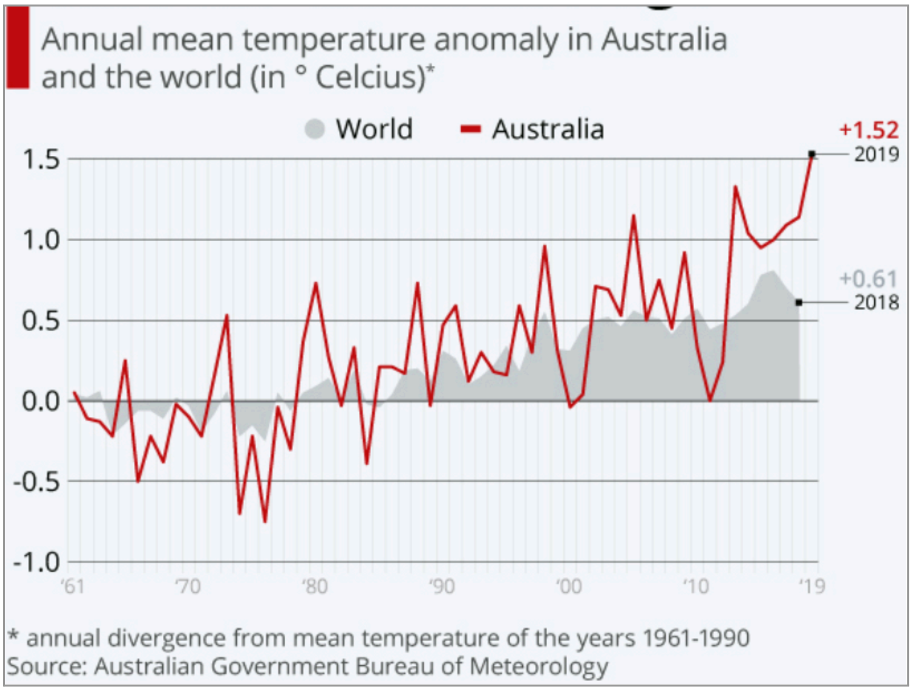
Insight

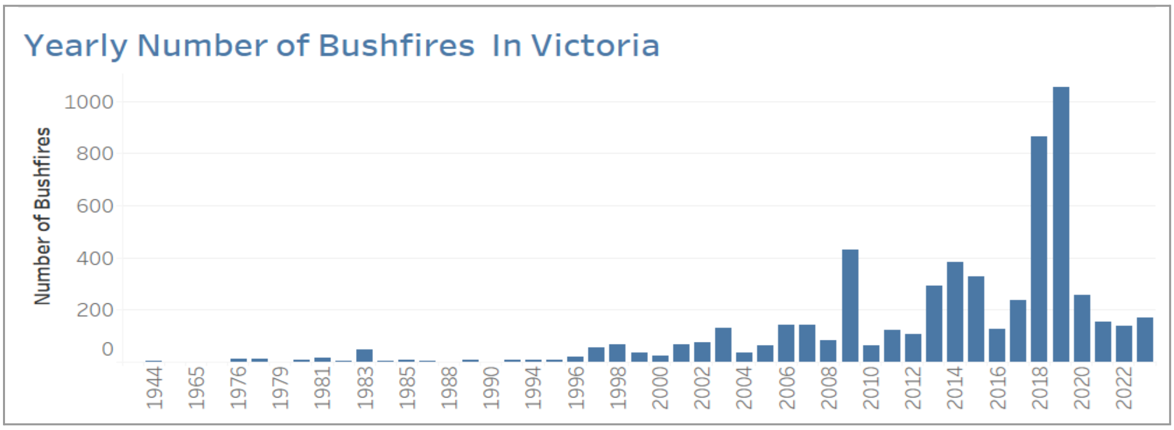




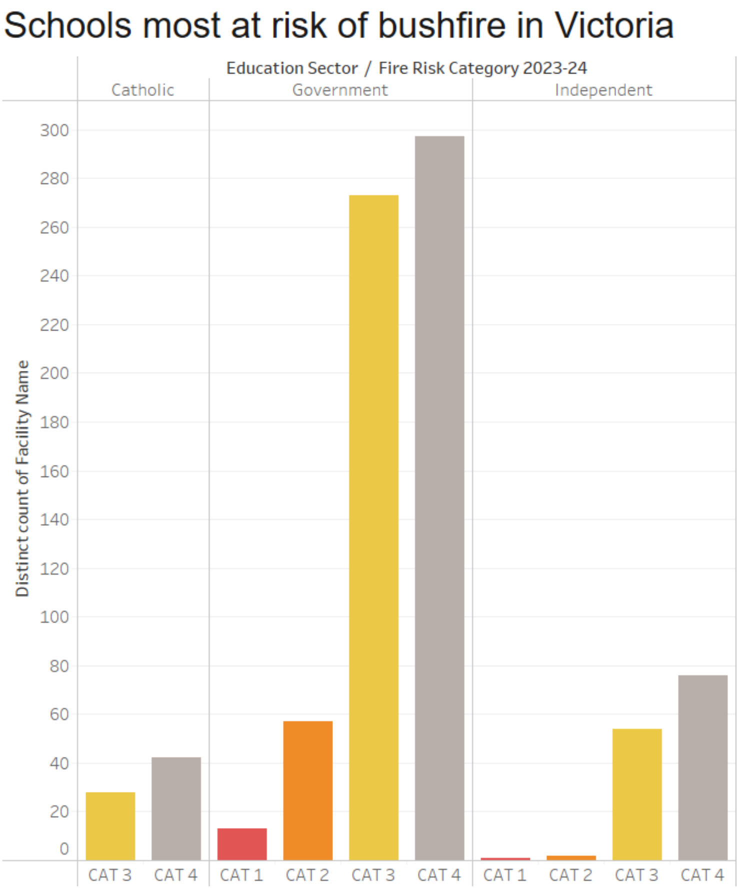


The historical data shows that bushfire activity in Victoria has evolved significantly over time and has scattered across the state. In the early 1900s, bushfires were relatively occasional. Over the years, there has been a marked **increase in both the frequency and intensity of these fires**. Initially, fire activity was more concentrated around the Australian Capital Territory (ACT), but **recent data indicates a significant shift, with fires now becoming more concentrated in the central regions of Victoria**. This trend highlights the need for targeted fire management and increased preparedness in these newly affected areas.

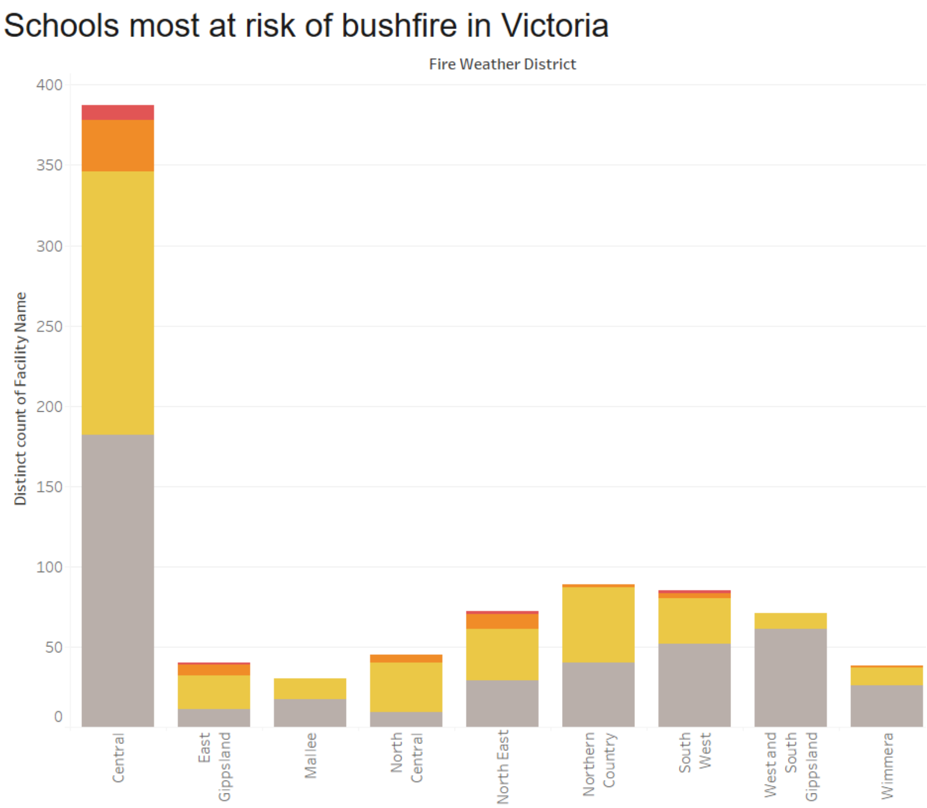




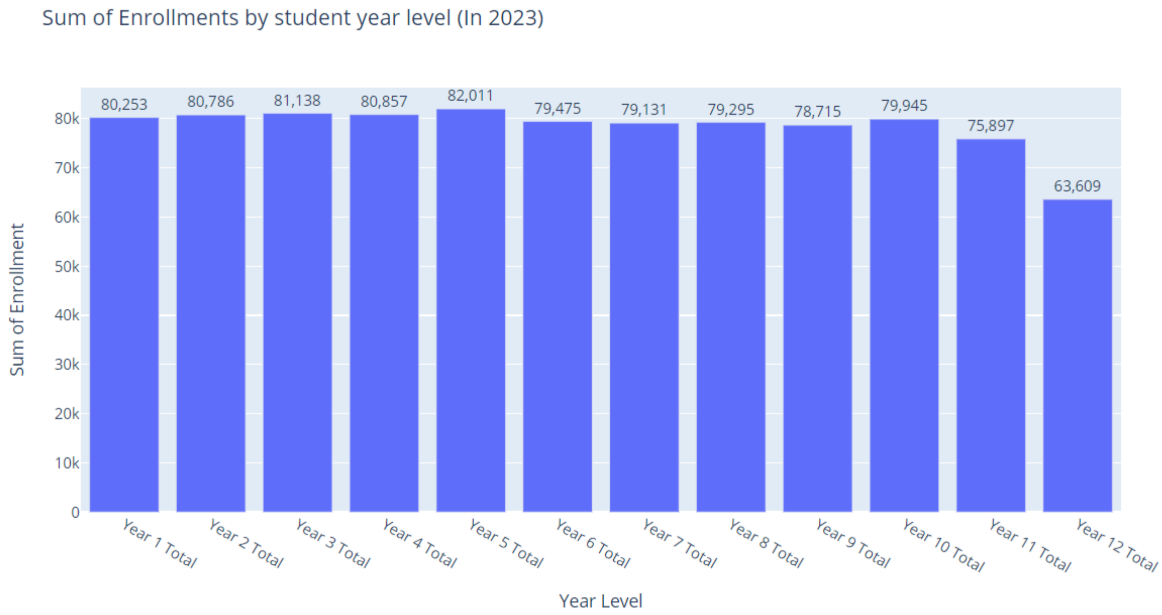
The bar chart displays **a significant upward trend in the yearly number of bushfires in Victoria**, starting from the year 2000. Notably, there are dramatic peaks in 2003, 2009, 2014, and 2019, indicating **a pattern of increased sudden occurrences**, particularly in the past two decades. According to the Australian Bureau of Meteorology, **Australia is warming faster than the global average**, a factor that likely contributes to the growing severity of fire seasons. The spike in 2019 is especially alarming, with nearly 1,000 bushfires recorded, signifying the **growing severity of fire seasons in the 21st century**. This trend suggests an escalating risk of bushfires, emphasising the urgent need for enhanced fire management strategies, preparedness measures, and climate resilience efforts to mitigate the impact of these increasingly frequent and intense bushfire events.



A **total of 839 schools have been identified as being in bushfire risk zones** in Victoria, highlighting the critical need for strategic intervention. The distribution of these schools across various risk levels, with Category 1 representing the highest risk, highlights the urgency of the situation. While most Government schools are situated in lower-risk categories, particularly CAT 3 and CAT 4, with over 270 and 300 schools respectively, the presence of schools in higher-risk zones cannot be overlooked. Catholic and Independent schools also predominantly fall into CAT 3 and CAT 4, though in smaller numbers.



However, the few schools that are classified under the highest-risk category, **CAT 1, require immediate attention.** Specifically the **Central district appears to be a hotspot** for bushfires. This distribution indicates a **pressing need for targeted preparedness and risk mitigation strategies**, particularly for those schools in the highest-risk zones, to ensure the safety of students and staff. Proactive measures must be prioritised to address vulnerabilities and enhance bushfire resilience across all education sectors.



The graph indicates a **stable enrollment of around 80,000 students** across various years, with a clear **drop in enrollments from year 10 to year 12, suggesting a potential issue with student retention**. A study by Towers in 2015 **identified gaps and misconceptions in bushfire education among children aged 8-12**. Furthermore, **nearly 27,000 of these students are located in high-risk bushfire areas**, representing about 8% of the total. This overlap suggests that addressing educational gaps and improving bushfire preparedness in these high-risk zones could be crucial in enhancing student retention and safety.

7. Ethical, Legal & Privacy Issues

Some important aspects to consider when designing the 'Bushfire Brigade' web application are the ethical, legal and privacy issues associated with the team's use of open data. We understand the importance of identifying and mitigating these issues and have incorporated this aspect into every step of the data management process for this project.

Ethical Considerations

Our team is determined to develop a project with ethical considerations at its core, with every effort taken to adhere to guidelines governing privacy and data protection:

- Transparency: We make every effort to be transparent about the way in which data is collected, stored and used for the purposes of this project through extensive documentation regarding the data sources used as well as the decisions made regarding the data.
- Personally Identifiable Information (PII): We are committed to ensuring that no PII is collected or stored, including information that may enable anonymous individuals from the datasets to be identified.

Legal Considerations

The Data management approach for the project has been developed in line with all relevant laws and regulations:

- Licences: All the datasets used by the team are governed by the Creative Commons Attribution 4.0 International Licence (Creative Commons, n.d.), and we are committed to adhering to all the terms outlined in the Licence including giving appropriate credit.

- Acts/Principles: We are determined to uphold each of the Australian Privacy Principles (Office of the Australian Information Commissioner, n.d.) and protect individuals' privacy when working with open data.

Privacy Considerations

Our team is dedicated to protecting individuals' privacy and managing data in a way that prioritises the protection of sensitive information:

- Necessary data collection: To avoid engaging in privacy violations, we only focus on collecting data that is directly relevant to the project.
- Security: We have put in place various security measures including data access controls to ensure that data is only accessible to authorised personnel, and encryption to ensure that the data cannot be read by any unauthorised parties even if it is accessed.

The 'Bushfire Brigade' project is determined to abide by all guidelines, laws and regulations governing ethics, legality and privacy. Through incorporating these principles into our approach to data management for this project, we hope to protect individuals' privacy while simultaneously boosting the 'Bushfire Brigade' web application's legitimacy and dependability. Through upholding legal obligations, prioritising privacy, and preserving transparency, our goal is to construct a reliable and efficient solution that facilitates more child-friendly and impactful bushfire safety education in Victoria.

Load Packages

In [42]:
```
import time
from geopy.exc import GeocoderTimedOut
from geopy.geocoders import Nominatim
import plotly.express as px
import pandas as pd
import os
!pip install geopy
```

```
Requirement already satisfied: geopy in c:\users\thinithi\anaconda3\lib\site-packa
ges (2.4.1)
Requirement already satisfied: geographiclib<3,>=1.52 in c:\users\thinithi\anacond
a3\lib\site-packages (from geopy) (2.0)
```

In [6]:
```
# Get the current working directory
current_directory = os.getcwd()
current_directory
```

Out[6]:
```
'C:\\Users\\Thinithi\\Monash\\Sem4_2023\\FIT5120 INDUSTRY EXP\\onboarding\\ITERATI
ON_DATA'
```

Data Exploration

In [31]:
```
file_path = 'dv355-VIC All Schools Enrolments 2023.csv'

# Read the CSV file into a DataFrame with a different encoding
df = pd.read_csv(file_path, encoding='ISO-8859-1')

# describe data
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2290 entries, 0 to 2289
Data columns (total 26 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Education_Sector             2290 non-null   object 
 1   Entity_Type                  2290 non-null   int64  
 2   School_No                    2290 non-null   int64  
 3   School_Name                  2290 non-null   object 
 4   School_Type                  2290 non-null   object 
 5   School_Status                2290 non-null   object 
 6   "Prep Total"                 2290 non-null   float64
 7   "Year 1 Total"               2290 non-null   float64
 8   "Year 2 Total"               2290 non-null   float64
 9   "Year 3 Total"               2290 non-null   float64
 10  "Year 4 Total"               2290 non-null   float64
 11  "Year 5 Total"               2290 non-null   float64
 12  "Year 6 Total"               2290 non-null   float64
 13  "Primary Ungraded Total"     2290 non-null   float64
 14  "Primary Total"              2290 non-null   float64
 15  "Year 7 Total"               2290 non-null   float64
 16  "Year 8 Total"               2290 non-null   float64
 17  "Year 9 Total"               2290 non-null   float64
 18  "Year 10 Total"              2290 non-null   float64
 19  "Year 11 Total"              2290 non-null   float64
 20  "Year 12 Total"              2290 non-null   float64
 21  "Secondary Ungraded Total"   2290 non-null   float64
 22  "Secondary Total"            2290 non-null   float64
 23  "Grand Total"                2290 non-null   float64
 24  Year                         2290 non-null   int64  
 25  CENSUS_TYPE                  2290 non-null   object 
dtypes: float64(18), int64(3), object(5)
memory usage: 465.3+ KB
None
```

In [18]:

```
# Check for nulls in columns
df.isnull().sum()
```

Out[18]:
```
Education_Sector               0
Entity_Type                    0
School_No                      0
School_Name                    0
School_Type                    0
School_Status                  0
"Prep Total"                   0
"Year 1 Total"                 0
"Year 2 Total"                 0
"Year 3 Total"                 0
"Year 4 Total"                 0
"Year 5 Total"                 0
"Year 6 Total"                 0
"Primary Ungraded Total"       0
"Primary Total"                0
"Year 7 Total"                 0
"Year 8 Total"                 0
"Year 9 Total"                 0
"Year 10 Total"                0
"Year 11 Total"                0
"Year 12 Total"                0
"Secondary Ungraded Total"     0
"Secondary Total"              0
"Grand Total"                  0
Year                           0
CENSUS_TYPE                    0
dtype: int64
```

In [33]:
```
# describe data
print(df.describe())
```

```
       Entity_Type    School_No  "Prep Total"  "Year 1 Total"  "Year 2 Total"  \
count  2290.000000  2290.000000   2290.000000     2290.000000     2290.000000   
mean      1.316157  3531.783843     34.494236       35.045066       35.277773   
std       0.465077  2518.851970     37.715966       38.869626       38.632585   
min       1.000000     1.000000      0.000000        0.000000        0.000000   
25%       1.000000  1554.000000      3.000000        3.000000        3.000000   
50%       1.000000  2602.000000     24.000000       24.000000       25.000000   
75%       2.000000  5239.750000     54.000000       54.000000       54.000000   
max       2.000000  8917.000000    316.000000      355.000000      357.000000   

       "Year 3 Total"  "Year 4 Total"  "Year 5 Total"  "Year 6 Total"  \
count     2290.000000     2290.000000     2290.000000     2290.000000   
mean        35.431354       35.308734       35.812533       34.705153   
std         38.808744       38.645317       39.338791       38.477236   
min          0.000000        0.000000        0.000000        0.000000   
25%          4.000000        3.125000        3.000000        3.000000   
50%         25.000000       25.000000       26.000000       25.000000   
75%         54.000000       54.000000       54.000000       52.000000   
max        383.000000      394.000000      425.000000      385.000000   

       "Primary Ungraded Total"  ...  "Year 7 Total"  "Year 8 Total"  \
count               2290.000000  ...     2290.000000     2290.000000   
mean                   2.793100  ...       34.554891       34.626463   
std                   18.821981  ...       77.200670       77.210002   
min                    0.000000  ...        0.000000        0.000000   
25%                    0.000000  ...        0.000000        0.000000   
50%                    0.000000  ...        0.000000        0.000000   
75%                    0.000000  ...        8.000000        8.000000   
max                  305.200000  ...      600.000000      561.000000   

       "Year 9 Total"  "Year 10 Total"  "Year 11 Total"  "Year 12 Total"  \
count     2290.000000      2290.000000      2290.000000      2290.000000   
mean        34.373275        34.910480        33.142620        27.776638   
std         76.201101        78.469754        79.575126        68.478003   
min          0.000000         0.000000         0.000000         0.000000   
25%          0.000000         0.000000         0.000000         0.000000   
50%          0.000000         0.000000         0.000000         0.000000   
75%          8.000000         5.000000         2.000000         0.000000   
max        511.000000       600.000000       968.200000       776.100000   

       "Secondary Ungraded Total"  "Secondary Total"  "Grand Total"    Year  
count                 2290.000000        2290.000000    2290.000000  2290.0  
mean                     2.481310         201.865677     450.733624  2023.0  
std                     16.295483         437.426883     481.084346     0.0  
min                      0.000000           0.000000       0.000000  2023.0  
25%                      0.000000           0.000000     132.650000  2023.0  
50%                      0.000000           0.000000     305.400000  2023.0  
75%                      0.000000          98.400000     584.250000  2023.0  
max                    253.000000        3317.000000    4610.000000  2023.0  

[8 rows x 21 columns]
```

Data Cleaning &Transformation

Student Enrollment Data

In [35]:

```python
# Clean column names by stripping extra characters
df.columns = df.columns.str.strip().str.replace('"', '')

# Clean column names
df.columns = df.columns.str.strip().str.replace('"', '', regex=False)
```

In [36]:
```
# Convert the DataFrame from wide format to long format using the melt() function
long_df = df.melt(
    id_vars=['Education_Sector', 'Entity_Type', 'School_No', 'School_Name',
             'School_Type', 'School_Status', 'Year', 'CENSUS_TYPE'],
    value_vars=['Prep Total', 'Year 1 Total', 'Year 2 Total', 'Year 3 Total', 'Year
                'Year 6 Total', 'Primary Ungraded Total', 'Primary Total', 'Year 7
                'Year 9 Total', 'Year 10 Total', 'Year 11 Total', 'Year 12 Total',
                'Secondary Total', 'Grand Total'],
    var_name='Year_Level',
    value_name='Enrollment'
)

# Display the first few rows of the transformed DataFrame
print(long_df.head())
```

```
  Education_Sector  Entity_Type  School_No                    School_Name  \
0         Catholic            2         20                 Parade College
1         Catholic            2         25        Simonds Catholic College
2         Catholic            2         26     St Mary�s College Melbourne
3         Catholic            2         28  St Patrick's College Ballarat
4         Catholic            2         29             St Patrick's School

  School_Type School_Status  Year CENSUS_TYPE  Year_Level  Enrollment
0   Secondary             O  2023           F  Prep Total         0.0
1   Secondary             O  2023           F  Prep Total         0.0
2   Secondary             O  2023           F  Prep Total         0.0
3   Secondary             O  2023           F  Prep Total         0.0
4     Primary             O  2023           F  Prep Total        28.0
```

In [38]:
```
# Verify the column names
print(long_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41220 entries, 0 to 41219
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Education_Sector  41220 non-null  object 
 1   Entity_Type       41220 non-null  int64  
 2   School_No         41220 non-null  int64  
 3   School_Name       41220 non-null  object 
 4   School_Type       41220 non-null  object 
 5   School_Status     41220 non-null  object 
 6   Year              41220 non-null  int64  
 7   CENSUS_TYPE       41220 non-null  object 
 8   Year_Level        41220 non-null  object 
 9   Enrollment        41220 non-null  float64
dtypes: float64(1), int64(3), object(6)
memory usage: 3.1+ MB
None
```

In [39]:
```
# Group by 'Year' and calculate the sum of 'Year 3 Total'
yearly_sum = long_df.groupby('Year_Level')['Enrollment'].sum().reset_index()

# Filter to include only 'Year' levels
yearly_sum = yearly_sum[yearly_sum['Year_Level'].str.contains('Year')]

# Define the order of categories
order = ['Year 1 Total', 'Year 2 Total', 'Year 3 Total', 'Year 4 Total', 'Year 5 To
         'Year 7 Total', 'Year 8 Total', 'Year 9 Total', 'Year 10 Total',
         'Year 11 Total', 'Year 12 Total']

# Convert 'Year_Level' to categorical with a specified order
```

```
yearly_sum['Year_Level'] = pd.Categorical(
    yearly_sum['Year_Level'], categories=order, ordered=True)

# Sort the DataFrame by 'Year_Level'
yearly_sum = yearly_sum.sort_values('Year_Level')

# Create the bar chart
fig = px.bar(yearly_sum, x='Year_Level', y='Enrollment',
             title='Sum of Enrollments by student year level (In 2023)',
             labels={'Year_Level': 'Year Level',
                     'Enrollment': 'Sum of Enrollment'},
             text='Enrollment')


# Update the text formatting to include commas
fig.update_traces(texttemplate='%{text:,.0f}', textposition='outside')


# Show the plot
fig.show()
```

School Bushfire risk Data

In [48]:
```
file_path = 'Website-BARR-2023-24-updated.xlsx'

# Read the Excel file into a DataFrame
df2 = pd.read_excel(file_path)
```

In [49]:
```
# Display the first few rows of the DataFrame
print(df2.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 868 entries, 0 to 867
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   row                        868 non-null    int64  
 1   SCHOOL_NO2                 868 non-null    int64  
 2   flag                       868 non-null    int64  
 3   Fire Risk Category 2023-24  868 non-null    object 
 4   Facility Name              868 non-null    object 
 5   Education Sector           868 non-null    object 
 6   Facility Address           868 non-null    object 
 7   Town or Suburb             868 non-null    object 
 8   Local Government Area      868 non-null    object 
 9   Fire Weather District      867 non-null    object 
 10  LATITUDE                   868 non-null    float64
 11  LONGITUDE                  868 non-null    float64
dtypes: float64(2), int64(3), object(7)
memory usage: 81.5+ KB
None
```

A) Geocoding the School address

In [50]:
```
# Initialize geocoder
geolocator = Nominatim(user_agent="myGeocoder")

# Function to geocode addresses


def geocode_address(address):
    try:
        # Attempt to get the geographic coordinates (latitude and longitude) of the
        # Timeout is set to handle cases where the service is slow
        location = geolocator.geocode(address, timeout=10)
        if location:
            # If the location is found, return the latitude and longitude
            return location.latitude, location.longitude
        else:
            # If no location is found, return (None, None)
            return None, None
    except GeocoderTimedOut:
        # If the geocoding service times out, retry the geocoding request
        return geocode_address(address)  # Recursive call to retry
    except Exception as e:
        # If any other exception occurs, print the error and return (None, None)
        print(f"Error: {e}")
        return None, None
```

In [51]:
```
# Concatenate 'Facility Address' with 'Town or Suburb'
df2['Full Address'] = df2['Facility Address'].str.strip(
) + ', ' + df2['Town or Suburb'] + ', ' + df2['Local Government Area'].str.strip()

# Display the DataFrame to check the Full Address
df2.head(5)
```

Out[51]:

	row	SCHOOL_NO2	flag	Fire Risk Category 2023-24	Facility Name	Education Sector	Facility Address	Town or Suburb	Loca Governmen Are
0	1	1098	2	CAT 3	Advance College of Education Incorporated - Ha...	Independent	1973 Frankston Flinders Road	Hastings	Morningto Peninsul
1	2	5566	1	CAT 2	Aireys Inlet Primary School	Government	13 Anderson Street	Aireys Inlet	Surf Coas
2	3	2101	2	CAT 2	Alice Miller School	Independent	110 Bailey Road	Macedon	Macedo Range
3	4	366	1	CAT 3	Alice Miller School - Candlebark	Independent	83 Kerrie Road	Romsey	Macedo Range
4	5	1906	1	CAT 3	Al-Taqwa College - Camp	Independent	10 Cranswick Road	Banksia Peninsula	Eas Gippslan

In [ ]:

```
# Create a DataFrame to store the geocoded results
results = pd.DataFrame(df2['Full Address'], columns=['Full Address'])

# Apply geocoding with a delay to handle rate limits


def apply_geocoding(address):
    time.sleep(1)  # Adding delay to handle rate limits
    return geocode_address(address)


# Apply geocoding to addresses and create Latitude and Longitude columns
results[['Latitude', 'Longitude']] = results['Full Address'].apply(
    lambda x: pd.Series(apply_geocoding(x)))

# Merge the geocoded results with the original DataFrame
final_df = pd.concat([df2, results[['Latitude', 'Longitude']]], axis=1)

# Display the DataFrame with geocoded coordinates
final_df.head()
```

In [58]:

```
# Write the DataFrame to a CSV file
final_df.to_csv('geocoded_facilities.csv')
```

School register and location data

In [53]:
```
file_path = 'dv346-schoollocations2023.csv'

# Read the CSV file into a DataFrame with a different encoding
df3 = pd.read_csv(file_path, encoding='ISO-8859-1')

# Display the structure
df3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2302 entries, 0 to 2301
Data columns (total 25 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   Education_Sector       2302 non-null   object 
 1   Entity_Type            2302 non-null   int64  
 2   School_No              2302 non-null   int64  
 3   count                  2302 non-null   int64  
 4   School_Name            2302 non-null   object 
 5   School_Type            2302 non-null   object 
 6   School_Status          2302 non-null   object 
 7   Address_Line_1         2302 non-null   object 
 8   Address_Line_2         11 non-null     object 
 9   Address_Town           2302 non-null   object 
 10  Address_State          2302 non-null   object 
 11  Address_Postcode       2302 non-null   int64  
 12  Postal_Address_Line_1  2302 non-null   object 
 13  Postal_Address_Line_2  15 non-null     object 
 14  Postal_Town            2302 non-null   object 
 15  Postal_State           2302 non-null   object 
 16  Postal_Postcode        2302 non-null   int64  
 17  Full_Phone_No          2302 non-null   object 
 18  LGA_ID                 2302 non-null   int64  
 19  LGA_Name               2302 non-null   object 
 20  X                      2301 non-null   float64
 21  Y                      2301 non-null   float64
 22  X.1                    2302 non-null   float64
 23  Y.1                    2302 non-null   float64
 24  lat-lon                2302 non-null   object 
dtypes: float64(4), int64(6), object(15)
memory usage: 449.7+ KB
```

In [54]:
```
# Display the first few rows of the DataFrame
df3.head()
```

Out[54]:

	Education_Sector	Entity_Type	School_No	count	School_Name	School_Type	School_Status	Ac
0	Government	1	1	2	Alberton Primary School	Primary	O	
1	Government	1	3	1	Allansford and District Primary School	Primary	O	
2	Government	1	4	1	Avoca Primary School	Primary	O	
3	Government	1	8	1	Avenel Primary School	Primary	O	
4	Government	1	12	1	Warrandyte Primary School	Primary	O	

5 rows × 25 columns

In [55]:

```
# Load geocoded data
file_path = 'geocoded_facilities.csv'

# Read the CSV file into a DataFrame with a different encoding
df4 = pd.read_csv(file_path, encoding='ISO-8859-1')

# Display the first few rows of the DataFrame
print(df4.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 868 entries, 0 to 867
Data columns (total 12 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Unnamed: 0                   868 non-null    int64  
 1   row                          868 non-null    int64  
 2   Fire Risk Category 2023-24   868 non-null    object 
 3   Facility Name                868 non-null    object 
 4   Education Sector             868 non-null    object 
 5   Facility Address             868 non-null    object 
 6   Town or Suburb               868 non-null    object 
 7   Local Government Area        868 non-null    object 
 8   Fire Weather District        867 non-null    object 
 9   Full Address                 868 non-null    object 
 10  Latitude                     818 non-null    float64
 11  Longitude                    818 non-null    float64
dtypes: float64(2), int64(2), object(8)
memory usage: 81.5+ KB
None
```

B) Matching schools using longitude and latitude

In [60]:

```
# Filter out rows with NaN in the Coordinates columns
df4 = df4.dropna(subset=['Latitude', 'Longitude'])
df3 = df3.dropna(subset=['Y', 'X'])

# Extract latitudes and longitudes
df4['Coordinates'] = list(zip(df4['Latitude'], df4['Longitude']))
```

```
df3['Coordinates'] = list(zip(df3['Y'], df3['X']))
df4.head()
```

Out[60]:

	Unnamed: 0	row	Fire Risk Category 2023-24	Facility Name	Education Sector	Facility Address	Town or Suburb	Local Government Area	F Weatl Distı
0	0	3	CAT 3	Advance College of Education Incorporated - Ha...	Independent	1973 Frankston Flinders Road	Hastings	Mornington Peninsula	Cen
1	1	4	CAT 2	Aireys Inlet Primary School	Government	13 Anderson Street	Aireys Inlet	Surf Coast	Cen
2	2	5	CAT 2	Alice Miller School	Independent	110 Bailey Road	Macedon	Macedon Ranges	Cen
3	3	6	CAT 3	Alice Miller School - Candlebark	Independent	83 Kerrie Road	Romsey	Macedon Ranges	Cen
4	4	9	CAT 3	Al-Taqwa College - Camp	Independent	10 Cranswick Road	Banksia Peninsula	East Gippsland	E Gippsla

Reference: https://geopy.readthedocs.io/en/stable/#geopy.distance.GeodesicDistance

In [61]:

```
from geopy.distance import geodesic

# Filter out rows with Null in the Coordinates columns
df3 = df3.dropna(subset=['Y', 'X'])
df4 = df4.dropna(subset=['Latitude', 'Longitude'])

# Extract latitudes and longitudes
df4['Coordinates'] = list(zip(df4['Latitude'], df4['Longitude']))
df3['Coordinates'] = list(zip(df3['Y'], df3['X']))

# Ensure no extra spaces in column names
df3.columns = df3.columns.str.strip()
df4.columns = df4.columns.str.strip()

# Function to find the closest school in dataset A for a given facility in dataset
def find_closest_school(facility_coords, school_coords):
    closest_school = None
    min_distance = float('inf')
    for i, school_coord in enumerate(school_coords):
        distance = geodesic(facility_coords, school_coord).kilometers
```

```
        if distance < min_distance:
            min_distance = distance
            closest_school = i
    return closest_school

# Ensure 'School_No' exists in df3
if 'School_No' not in df3.columns:
    raise KeyError("The column 'School_No' is not present in df3")

# Find the closest school for each facility
df4['Closest_School_No'] = df4['Coordinates'].apply(
    lambda x: df3.iloc[find_closest_school(x, df3['Coordinates'])]['School_No']
    if find_closest_school(x, df3['Coordinates']) is not None
    else None
)

# Define the path and filename for the CSV file
csv_file_path = 'output_data_with_school_no.csv'

# Save the DataFrame to a CSV file
df4[['row','Facility Name', 'Closest_School_No']].to_csv(csv_file_path, index=False
```

In [64]:

```
# reload dataset with all long and lat, remap schools
file_path = 'Website-BARR-2023-24-updated.xlsx'

# Read the Excel file into a DataFrame
df5 = pd.read_excel(file_path)
```

In [65]:

```
# Extract latitudes and longitudes
df5['Coordinates'] = list(zip(df5['LATITUDE'], df5['LONGITUDE']))

# Ensure no extra spaces in column names
df5.columns = df5.columns.str.strip()

# Find the closest school for each facility
df5['Closest_School_No'] = df5['Coordinates'].apply(
    lambda x: df3.iloc[find_closest_school(x, df3['Coordinates'])]['School_No']
    if find_closest_school(x, df3['Coordinates']) is not None
    else None
)

# Define the path and filename for the CSV file
csv_file_path = 'output_data_with_school_no2.csv'

# Save the DataFrame to a CSV file
df5[['row','Facility Name', 'Closest_School_No']].to_csv(csv_file_path, index=False
```

C) Matching schools between the datasets based on name and city

In [69]:

```
!pip install fuzzywuzzy
!pip install python-Levenshtein
```

```
Collecting fuzzywuzzy
  Obtaining dependency information for fuzzywuzzy from https://files.pythonhosted.
org/packages/43/ff/74f23998ad2f93b945c0309f825be92e04e0348e062026998b5eefef4c33/fu
zzywuzzy-0.18.0-py2.py3-none-any.whl.metadata
  Downloading fuzzywuzzy-0.18.0-py2.py3-none-any.whl.metadata (4.9 kB)
Downloading fuzzywuzzy-0.18.0-py2.py3-none-any.whl (18 kB)
Installing collected packages: fuzzywuzzy
Successfully installed fuzzywuzzy-0.18.0
Collecting python-Levenshtein
  Obtaining dependency information for python-Levenshtein from https://files.pytho
nhosted.org/packages/72/8e/559c539e76bc0b1defec3da39a047fe151258efc9b215bf41db41e2
c7922/python_Levenshtein-0.25.1-py3-none-any.whl.metadata
  Downloading python_Levenshtein-0.25.1-py3-none-any.whl.metadata (3.7 kB)
Collecting Levenshtein==0.25.1 (from python-Levenshtein)
  Obtaining dependency information for Levenshtein==0.25.1 from https://files.pyth
onhosted.org/packages/47/19/4528246e25bb79fa8d4adae6640251c613f05eb310d79307d1ac53
c7bf28/Levenshtein-0.25.1-cp311-cp311-win_amd64.whl.metadata
  Downloading Levenshtein-0.25.1-cp311-cp311-win_amd64.whl.metadata (3.4 kB)
Collecting rapidfuzz<4.0.0,>=3.8.0 (from Levenshtein==0.25.1->python-Levenshtein)
  Obtaining dependency information for rapidfuzz<4.0.0,>=3.8.0 from https://files.
pythonhosted.org/packages/aa/bb/cdd512d40f8ea67692deee6b0da4f7235c6a0f9e126fdded32
b62c5d91fe/rapidfuzz-3.9.6-cp311-cp311-win_amd64.whl.metadata
  Downloading rapidfuzz-3.9.6-cp311-cp311-win_amd64.whl.metadata (12 kB)
Downloading python_Levenshtein-0.25.1-py3-none-any.whl (9.4 kB)
Downloading Levenshtein-0.25.1-cp311-cp311-win_amd64.whl (98 kB)
   ---------------------------------------- 0.0/98.4 kB ? eta -:--:--
   ------------------------------------- -- 92.2/98.4 kB 2.6 MB/s eta 0:00:01
   ---------------------------------------- 98.4/98.4 kB 1.9 MB/s eta 0:00:00
Downloading rapidfuzz-3.9.6-cp311-cp311-win_amd64.whl (1.7 MB)
   ---------------------------------------- 0.0/1.7 MB ? eta -:--:--
   --------- ------------------------------ 0.4/1.7 MB 11.9 MB/s eta 0:00:01
   ---------------- ----------------------- 0.7/1.7 MB 9.3 MB/s eta 0:00:01
   ------------------------------ --------- 1.2/1.7 MB 9.9 MB/s eta 0:00:01
   ---------------------------------------- 1.7/1.7 MB 10.5 MB/s eta 0:00:00
Installing collected packages: rapidfuzz, Levenshtein, python-Levenshtein
Successfully installed Levenshtein-0.25.1 python-Levenshtein-0.25.1 rapidfuzz-3.9.
6
```

Reference: https://stackoverflow.com/questions/32055817/python-fuzzy-matching-fuzzywuzzy-keep-only-best-match

In [80]:

```python
from fuzzywuzzy import fuzz
from fuzzywuzzy import process
import pandas as pd

# Ensure no extra spaces in column names
df2.columns = df2.columns.str.strip()
df3.columns = df3.columns.str.strip()

# Combine 'Facility Name' and 'Town or Suburb' into a single string
df2['Name_City'] = df2['Facility Name'] + ", " + df2['Town or Suburb']

# Combine 'School_Name' and 'Address_Town' into a single string
df3['Name_City'] = df3['School_Name'] + ", " + df3['Address_Town']

# Function to find the best match for a facility in df2 with the school in df3


def find_best_school_match(facility_name_city, school_name_cities, threshold=80):
    best_match = process.extractOne(
        facility_name_city, school_name_cities, scorer=fuzz.ratio)
    if best_match and best_match[1] >= threshold:
        # return the best matching school name if the match is above the threshold
```

```
        return best_match[0]
    else:
        return None


# Ensure 'School_No' and 'Name_City' exist in df3
if 'School_No' not in df3.columns or 'Name_City' not in df3.columns:
    raise KeyError(
        "The column 'School_No' or 'Name_City' is not present in df3")

# Create a dictionary to map Name_City to their corresponding School_No
name_city_to_no = df3.set_index('Name_City')['School_No'].to_dict()

# Find the best matching school name for each facility and get its School_No
df2['Closest_School_Name_City'] = df2['Name_City'].apply(
    lambda x: find_best_school_match(x, df3['Name_City'], threshold=80)
)
df2['Closest_School_No'] = df2['Closest_School_Name_City'].map(name_city_to_no)

# Define the path and filename for the CSV file
csv_file_path = 'output_data_with_school_no3.csv'

# Save the DataFrame to a CSV file
df2[['row', 'Facility Name', 'Town or Suburb', 'Closest_School_No']].to_csv(
    csv_file_path, index=False)
```

Longitude and latitude mappings were further validated through name-address similarity mapping to identify whether the same school appears in both datasets. A unique identifier was assigned to each school to facilitate this process. This approach ensured that schools with matching geographic coordinates were accurately linked, while discrepancies were addressed by verifying names and addresses to confirm or correct the data..

In [ ]:

```
```