ROAD ACCIDENT ANALYSIS IN UNITED KINGDOM -POWERBI

A PROJECT REPORT

Submitted by

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for

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DEPARTMENT OF ARTIFICIAL INTELLIGENCE

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Department of Artificial Intelligence

20ADF01 – Data Analysis Project Report

Signature of course in-charge Signature of the HOD

Submitted for the continuous Assessment viva voce examination held on ____________________

EXAMINER I **EXAMINER II**

ABSTRACT

This study provides an in-depth analysis of the road accidents in the United Kingdom using Power BI, outlining general trends, causes, and patterns associated with the occurrence of the accidents. A database containing accident reports over a number of regions has been provided with variables such as accidents time, meteorological condition, categories of involved vehicles, types of roadways, and severity of accidents. This project will provide relevant insights into accident hotspots, peak incidence times, and exogenous variables like weather conditions and road infrastructure utilizing interactive dashboards and visualizations. Through the utilization of Power BI's data visualization and analytical features, the project underscores significant domains for possible enhancements in road safety. Additionally, it supports data-informed decision-making for policymakers and relevant stakeholders, thereby playing a crucial role in decreasing accident occurrences and improving overall road safety throughout the UK.

This projects road accident data across the United Kingdom and uses Power BI, mainly to uncover key trends and patterns. The factors visualized here are accident locations, times, and weather conditions besides vehicle types to identify critical insights on accident-prone areas and their peak periods. The target is to provide data-driven strategies in efforts aimed at improving road safety as well as reducing accident rates, considering clear, interactive dashboards which inform policies together with public safety initiatives.

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Project Overview: Analysis of Road Accidents Using Power BI for Enhanced Road Safety

Road accidents are among the primary causes of fatalities and injuries globally, presenting substantial social, economic, and public health challenges. The repercussions extend beyond individual losses, affecting communities, healthcare systems, and economic stability. Analyzing road accident data is crucial in identifying trends, underlying risk factors, and potential preventive measures to improve road safety and save lives. This project leverages Power BI—a versatile business intelligence and data visualization tool—to conduct an in-depth analysis of road accident data. Through Power BI's capabilities, we aim to uncover insights related to the frequency, locations, timing, and contributing factors of road accidents, including weather conditions, types of vehicles involved, and demographics of drivers. These insights enable us to recommend data-driven interventions to make roads safer.

The primary objective of this project is to provide a comprehensive analysis of road accident data through Power BI, which empowers users to explore complex data interactively. Power BI enables the creation of dynamic dashboards and detailed reports that make it easier to visualize various elements associated with road accidents. By examining factors like accident-prone locations, peak hours, seasonal trends, and risk-prone conditions, we can draw conclusions about high-risk scenarios and recurring issues that may contribute to road accidents.

Our analysis begins with understanding the distribution of accidents by location. By mapping accident data, we can highlight areas with high accident frequency, commonly referred to as "hotspots." These hotspots often correlate with specific infrastructure characteristics such as high traffic density, intersections, or highway junctions. The visualization of these areas helps traffic authorities and urban planners prioritize improvements to infrastructure, signage, and other traffic management strategies.

Next, we analyze the timing of accidents to identify patterns related to time of day, week, and year. For instance, our analysis may reveal that a significant number of accidents occur during rush hours or at night when visibility is low. Similarly, seasonal changes such as rainfall or snow in certain regions can affect road safety, which Power BI allows us to track through filtering and drill-down capabilities. By isolating these patterns, stakeholders can implement targeted awareness campaigns during high-risk periods and consider adjusting speed limits or deploying additional safety measures.

1.2 DATA COLLECTION

The data for this project was sourced from a preprocessed dataset on Kaggle, containing essential details about road accidents such as date, location, vehicle type, weather conditions, and driver demographics. The Kaggle dataset provided a robust foundation with historical data, covering a range of accident-related variables necessary for comprehensive analysis. To ensure the dataset remains relevant and reflects current trends, we further enhanced it by integrating updated data from an API. This API connection enabled us to pull recent accident records, adding an additional layer of real-time context to our analysis.

The API provided consistent updates, helping capture trends that might have emerged post-pandemic, including changes in traffic flow and accident frequency. By combining the static dataset from Kaggle with real-time data from the API, we achieved a hybrid data model that balances historical perspective with recent trends. This approach enhances the accuracy and relevance of our findings, as it allows us to observe shifts in accident patterns over time. The enriched dataset forms the basis for visualizations and trend analyzes in Power BI, enabling stakeholders to make well-informed decisions grounded in both historical data and current insights.

ABOUT DATASET :

The dataset used in this road accident analysis project contains detailed information on various incidents occurring on roadways over a specific period and across multiple geographic locations. This rich dataset is a collection of attributes that provide insights into multiple aspects of road accidents, including spatial and temporal factors, accident severity, weather conditions, types of vehicles involved, and driver demographics. Each row in the dataset represents an individual accident, providing a comprehensive view of the circumstances surrounding each event. By analyzing this dataset, we can gain valuable insights into patterns and factors contributing to road safety risks, ultimately aiding efforts to enhance road safety measures and reduce accident rates.

The primary attributes of the dataset include the date and time of each accident, which allow us to identify patterns related to the time of day, day of the week, or seasonal trends in accidents. For example, this information helps pinpoint high-risk periods such as rush hours or specific times of the year when accidents are more frequent. Additionally, the dataset records geographical coordinates or the location of each accident, enabling the identification of accident-prone areas or "hotspots." This spatial data is crucial for urban planners and traffic authorities to implement targeted interventions in high-risk zones.

The dataset also provides critical data on the contributing conditions for each accident, such as weather, road surface, and visibility conditions. These factors are known to influence accident likelihood and severity, with adverse weather like rain, fog, or snow posing additional risks to drivers. Other attributes include information on the type of vehicles involved, which may range from personal cars and motorcycles to larger vehicles like trucks and buses. Examining vehicle types helps determine if certain types are more prone to accidents, which can guide focused safety regulations or public awareness campaigns.

1.3 PROBLEM STATEMENT

This project aims to analyze road accidents in the United Kingdom, focusing on how different vehicle types contribute to accident rates. By examining accident patterns related to vehicle types such as cars, motorcycles, buses, and trucks. We seek to identify high-risk categories and underlying factors that lead to collisions. This analysis leverages historical data to reveal trends, helping authorities and policymakers understand how vehicle type influences accident frequency and severity. With these insights, targeted strategies can be developed to improve road safety, reduce accident occurrences, and ultimately contribute to a safer transportation environment for all road users in the UK.

1.4 BUSINESS OBJECTIVE

The objective of this analysis is to leverage data-driven insights to reduce road accidents in the United Kingdom, with a particular focus on the impact of different vehicle types on accident rates. Road accidents have significant financial, social, and economic implications, including medical costs, property damage, and lost productivity. By understanding the patterns and factors associated with various vehicle types in accidents, this analysis aims to provide actionable recommendations that can inform targeted safety interventions, policy changes, and urban planning strategies.

Our primary goal is to empower traffic authorities, insurance companies, transportation agencies, and policymakers with insights into the relationship between vehicle type and accident risk. For example, we seek to identify which types of vehicles—such as motorcycles, trucks, or buses—are more prone to accidents under specific conditions. Knowing this information allows authorities to allocate resources effectively, such as implementing stricter regulations for high-risk vehicle types, designing specialized safety programs, and considering modifications in road infrastructure to accommodate different vehicle needs.

For insurance companies, the analysis can contribute to more accurate risk assessments and pricing models. Understanding which vehicle types are more susceptible to accidents helps insurers better predict claim probabilities, which can lead to more tailored insurance policies and premium adjustments. Similarly, transportation companies and fleet managers can use these insights to optimize vehicle maintenance schedules, driver training programs, and risk management strategies, thereby enhancing safety and reducing operating costs.

Furthermore, urban planners can incorporate findings from this analysis to design safer road networks, adjusting lanes, signage, and other infrastructure elements to minimize accident risks associated with certain vehicle types. Ultimately, by addressing these issues proactively, the analysis contributes to creating safer roadways, lowering accident rates, and fostering a culture of safe and responsible driving across the United Kingdom

ABOUT POWER BI :

1. Power BI, a business analytics tool from Microsoft, offers interactive data visualization BI features that let users see and share information throughout their organization. By using data interactively and visualizing it, Power BI offers insight data. Utilize the data models to produce reports and visuals.

2. A business user can use it to centralize measurements and significant company goals so they can track their progress. In addition, it promotes cooperation and interaction on the site while being simple to use and aesthetically pleasing.

3. In the modern world people are very busy with their duties so they don't have enough time to look into the entertainment especially looking into cricket score and analysis takes more time so it is necessary to summarize all the events that happened in a cricket needed to be visualized attractively and understand to everyone easily.

4. So, for this purpose it is necessary to prepare a dashboard. Power BI is a tool that helps users easily visualize dynamic and interactive Reports/Dashboards by utilizing its Business Intelligence Capabilities.

5. Power BI is a tool that makes decision-making easier as it offers a wide range of interactive visualizations along with Business Intelligence Capabilities.

CHAPTER 2

DATA PREPARATION AND MODELING

2.1 DATA CLEANING

Data cleaning is a critical step in preparing the road accident dataset for analysis, ensuring accuracy and consistency in the insights derived. For this project, we first handled missing values, particularly for fields like weather conditions, vehicle type, and accident location, which are essential for identifying patterns. Duplicate records were removed to avoid skewed results, and we standardized formats for date, time, and categorical variables like vehicle type. Additionally, inconsistent entries and outliers such as unrealistic speeds or duplicate coordinates were carefully reviewed and corrected or removed. This cleaning process ensures a reliable dataset, providing a solid foundation for analyzing accident patterns by vehicle type**.**

Accident_Index	Accident Date	Day_of_Week	Junction_Control	Junction_Detail	Accident_Severit	Latitude	Light_Conditions	Local_Authority_(District	Carriageway_Hazards	Longitude	Number_of_Casualties	Number_of_Vehicles	Police_For
BS0000001	01-01-2021	Thursday	Give way or uncontroll	T or staggered junction	Serious	51.512273	Daylight	Kensington and Chelsea	None	-0.201349	1	2	Metropolit
BS0000002	05-01-2021	Monday	Give way or uncontroll	Crossroads	Serious	51.514399	Daylight	Kensington and Chelsea	None	-0.199248	11	2	Metropolit
BS0000003	04-01-2021	Sunday	Give way or uncontroll	T or staggered junction	Slight	51.486668	Daylight	Kensington and Chelsea	None	-0.179599	1	2	Metropolit
BS0000004	05-01-2021	Monday	Auto traffic signal	T or staggered junction	Serious	51.507804	Daylight	Kensington and Chelsea	None	-0.20311	1	2	Metropolit
BS0000005	06-01-2021	Tuesday	Auto traffic signal	Crossroads	Serious	51.482076	Darkness - lights lit	Kensington and Chelsea	None	-0.173445	1	2	Metropolit
BS0000006	01-01-2021	Thursday	Give way or uncontroll	T or staggered junction	Slight	51.493415	Daylight	Kensington and Chelsea	None	-0.185525	3	2	Metropolit
BS0000007	08-01-2021	Thursday	Give way or uncontroll	T or staggered junction	Serious	51.480177	Daylight	Kensington and Chelsea	None	-0.178561	1	2	Metropolit
BS0000008	02-01-2021	Friday	Auto traffic signal	Crossroads	Slight	51.491957	Daylight	Kensington and Chelsea	None	-0.178524	1	1	Metropolit
BS0000009	07-01-2021	Wednesday	Give way or uncontroll	T or staggered junction	Slight	51.49646	Daylight	Kensington and Chelsea	None	-0.167395	2	1	Metropolit
BS0000010	10-01-2021	Saturday	Auto traffic signal	Crossroads	Slight	51.48115	Daylight	Kensington and Chelsea	None	-0.183275	1	1	Metropolit
BS0000011	07-01-2021	Wednesday	Auto traffic signal	Crossroads	Slight	51.482076	Darkness - lights lit	Kensington and Chelsea	None	-0.173445	1	2	Metropolit
BS0000012	16-01-2021	Friday	Auto traffic signal	Crossroads	Slight	51.494995	Darkness - lights lit	Kensington and Chelsea	None	-0.183013	1	1	Metropolit
BS0000013	12-01-2021	Monday	Data missing or out of	Not at junction or withi	Slight	51.498778	Daylight	Kensington and Chelsea	None	-0.206779	1	2	Metropolit
BS0000014	09-01-2021	Friday	Give way or uncontroll	T or staggered junction	Slight	51.506187	Daylight	Kensington and Chelsea	None	-0.209082	1	2	Metropolit
BS0000015	17-01-2021	Saturday	Give way or uncontroll	T or staggered junction	Slight	51.493077	Daylight	Kensington and Chelsea	None	-0.169548	1	2	Metropolit
BS0000016	25-01-2021	Sunday	Auto traffic signal	Crossroads	Serious	51.482076	Darkness - lights lit	Kensington and Chelsea	None	-0.173445	1	2	Metropolit
BS0000017	26-01-2021	Monday	Give way or uncontroll	Crossroads	Slight	51.488673	Darkness - lights lit	Kensington and Chelsea	None	-0.169724	1	2	Metropolit
BS0000018	26-01-2021	Monday	Data missing or out of	Not at junction or withi	Slight	51.482363	Darkness - lights lit	Kensington and Chelsea	None	-0.186108	1	1	Metropolit
BS0000019	19-01-2021	Monday	Give way or uncontroll	T or staggered junction	Slight	51.49391	Daylight	Kensington and Chelsea	None	-0.176861	1	2	Metropolit
BS0000020	27-01-2021	Tuesday	Data missing or out of	Not at junction or withi	Slight	51.509296	Darkness - lights lit	Kensington and Chelsea	None	-0.194837	1	1	Metropolit
BS0000021	21-01-2021	Wednesday	Give way or uncontroll	T or staggered junction	Slight	51.50228	Darkness - lights lit	Kensington and Chelsea	None	-0.188919	1	1	Metropolit
BS0000022	22-01-2021	Thursday	Give way or uncontroll	T or staggered junction	Slight	51.507588	Darkness - lights lit	Kensington and Chelsea	None	-0.194905	1	1	Metropolit
BS0000023	31-01-2021	Saturday	Auto traffic signal	Crossroads	Serious	51.488585	Daylight	Kensington and Chelsea	None	-0.193063	2	2	Metropolit
BS0000024	03-02-2021	Tuesday	Give way or uncontroll	T or staggered junction	Slight	51.528344	Daylight	Kensington and Chelsea	None	-0.217295	1	2	Metropolit
BS0000025	31-01-2021	Saturday	Give way or uncontroll	T or staggered junction	Slight	51.499201	Darkness - lights lit	Kensington and Chelsea	None	-0.164404	2	2	Metropolit
BS0000026	31-01-2021	Saturday	Give way or uncontroll	T or staggered junction	Serious	51.517081	Daylight	Kensington and Chelsea	None	-0.204042	2	1	Metropolit
BS0000027	29-01-2021	Thursday	Auto traffic signal	Crossroads	Slight	51.48944	Daylight	Kensington and Chelsea	None	-0.190148	1	1	Metropolit
BS0000028	31-01-2021	Saturday	Give way or uncontroll	Crossroads	Slight	51.494521	Daylight	Kensington and Chelsea	None	-0.158397	1	2	Metropolit
BS0000029	29-01-2021	Thursday	Auto traffic signal	Crossroads	Slight	51.508624	Daylight	Kensington and Chelsea	None	-0.203799	1	2	Metropolit
BS0000030	31-01-2021	Saturday	Auto traffic signal	Crossroads	Slight	51.491173	Darkness - lights lit	Kensington and Chelsea	None	-0.18014	1	2	Metropolit
BS0000031	28-01-2021	Wednesday	Give way or uncontroll	T or staggered junction	Slight	51.495478	Daylight	Kensington and Chelsea	None	-0.202731	1	1	Metropolit
BS0000032	27-01-2021	Tuesday	Auto traffic signal	Crossroads	Serious	51.495658	Daylight	Kensington and Chelsea	None	-0.173622	1	2	Metropolit
BS0000033	31-01-2021	Saturday	Give way or uncontroll	T or staggered junction	Slight	51.499727	Daylight	Kensington and Chelsea	None	-0.163518	1	2	Metropolit
BS0000034	22-01-2021	Thursday	Give way or uncontroll	T or staggered junction	Slight	51.507802	Darkness - lights lit	Kensington and Chelsea	None	-0.202966	1	2	Metropolit
BS0000035	29-01-2021	Thursday	Auto traffic signal	T or staggered junction	Slight	51.508972	Darkness - lights lit	Kensington and Chelsea	None	-0.197156	1	1	Metropolit
BS0000036	20-01-2021	Tuesday	Auto traffic signal	T or staggered junction	Slight	51.513036	Daylight	Kensington and Chelsea	None	-0.204201	1	1	Metropolit
BS0000037	17-01-2021	Saturday	Give way or uncontroll	Crossroads	Slight	51.512443	Daylight	Kensington and Chelsea	None	-0.206531	1	2	Metropolit
BS0000038	15-01-2021	Thursday	Give way or uncontroll	T or staggered junction	Serious	51.491908	Daylight	Kensington and Chelsea	None	-0.192787	1	1	Metropolit

Fig1 : Dataset Preview

DATA PREPROCESSED :

- ❖ Handling Missing values (if any)
- ❖ Rename Columns
- ❖ Data Type Conversion
- ❖ Separate Data Component.
- ❖ Outlier Detection and smoothing (optional).

2.2 DATA TRANSFORMATION

1. The process of changing data from one format or structure to another is known as data transformation. It is a crucial component of the majority of data management and integration jobs, including
2. application integration, data wrangling, data warehousing, and data integration. Depending on the required modifications to the data between the source (initial data) and the destination (final data), data transformation can be straightforward or difficult. The process of data transformation often involves both manual and automated procedures.
3. Depending on the format, structure, complexity, and amount of the data being changed, a broad range of tools and technologies may be employed. For decades, corporations have benefited greatly from using conventional data transformation techniques.
4. Since the development of the various tools and technologies (data profiling, data visualization, data purification, data integration, etc.), most (if not all) businesses now transform massive volumes of data that feed internal and external applications, data warehouses, and other data repositories.
5. So, Data Transformation is a required process inorder to preprocess the loaded data set as per our requirement and apply those changes for future use. It is while Data Analysis and creating DAX functions of those relations respectively.

PROCEDURE

STEP 1

1. Go to the HOME tab in the ribbon.

2. Click on GET DATA and select data from the system or from any platform where it resides.

3. Here select 2 different tables of CSV format from the system and load it to POWER BI.

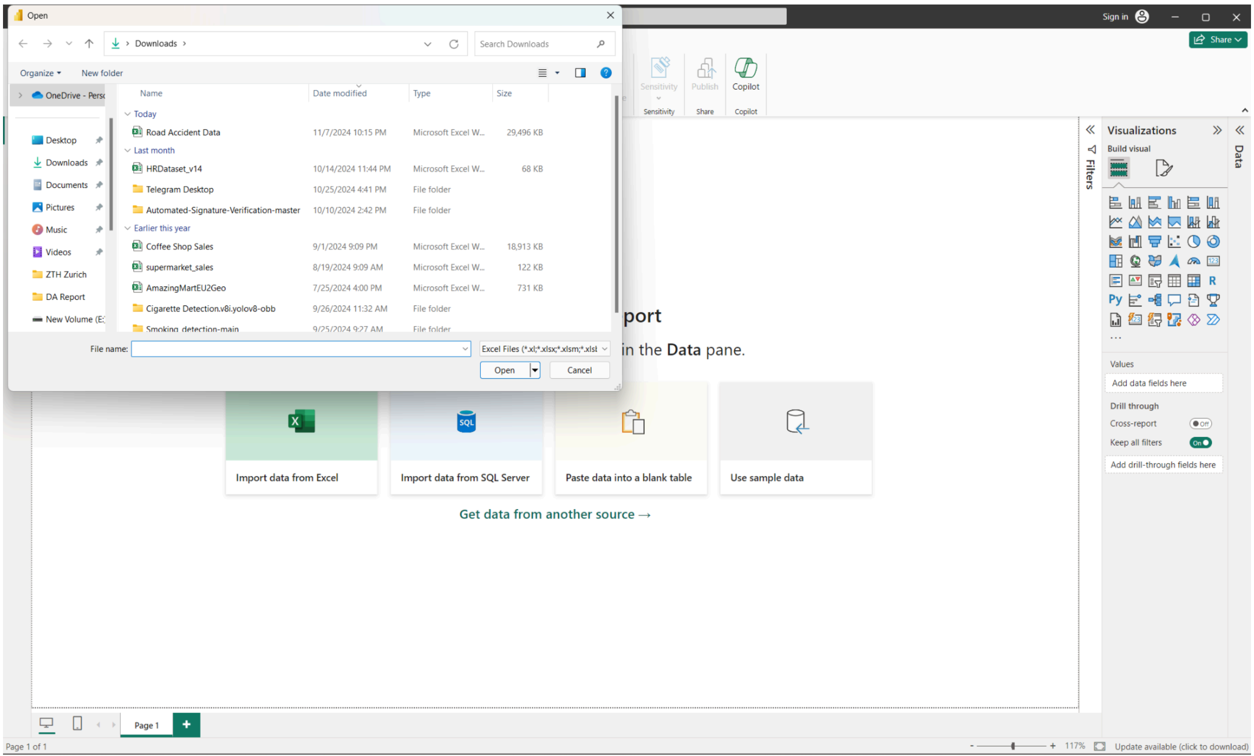

Figure 2.2.1 Select Dataset

STEP 2

1. From the ribbon of the HOME tab select TRANSFORM DATA in order to clean and transform data.

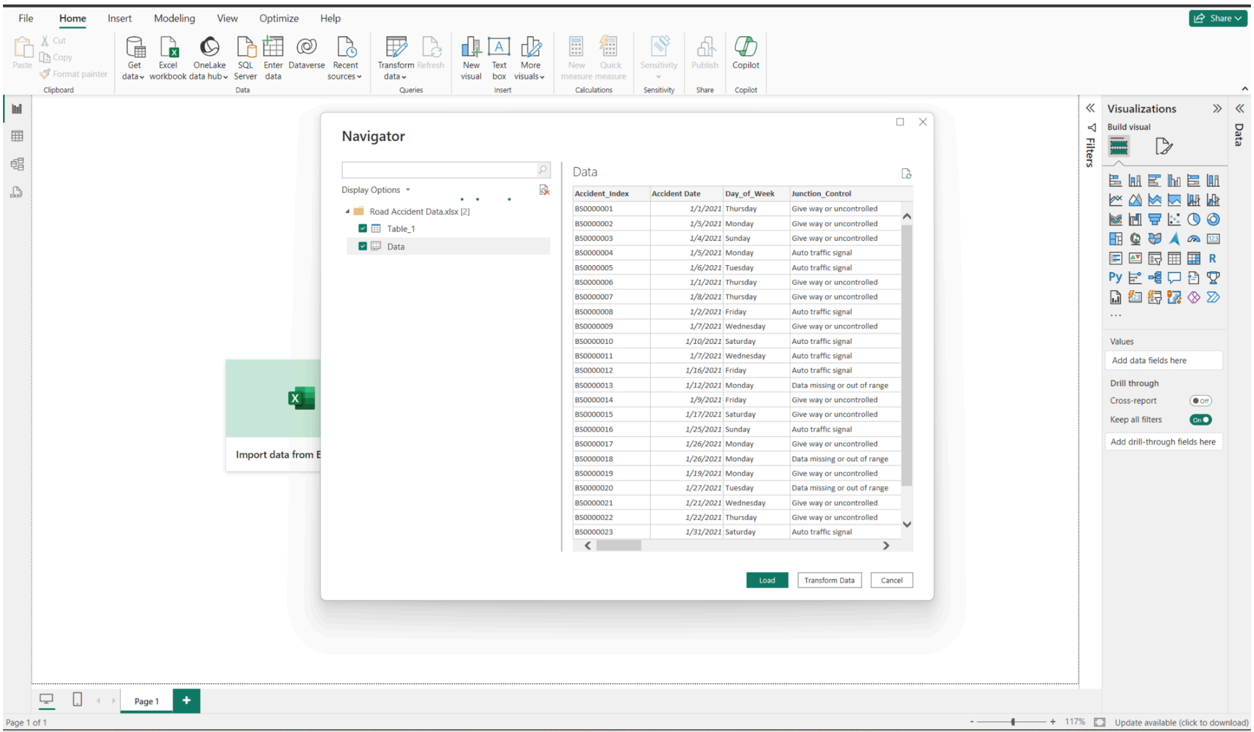

Figure 2.2.2 Transform Data

STEP 3

1. After choosing transforming data all the loaded tables and opened in POWER QUERY EDITOR, so that we can make any changes as per our wish.

2. Then open the SUMMARY table and replace the values which are blank.

3. Then try to add NULL values to the rows in which the matches are canceled due to some reasons.

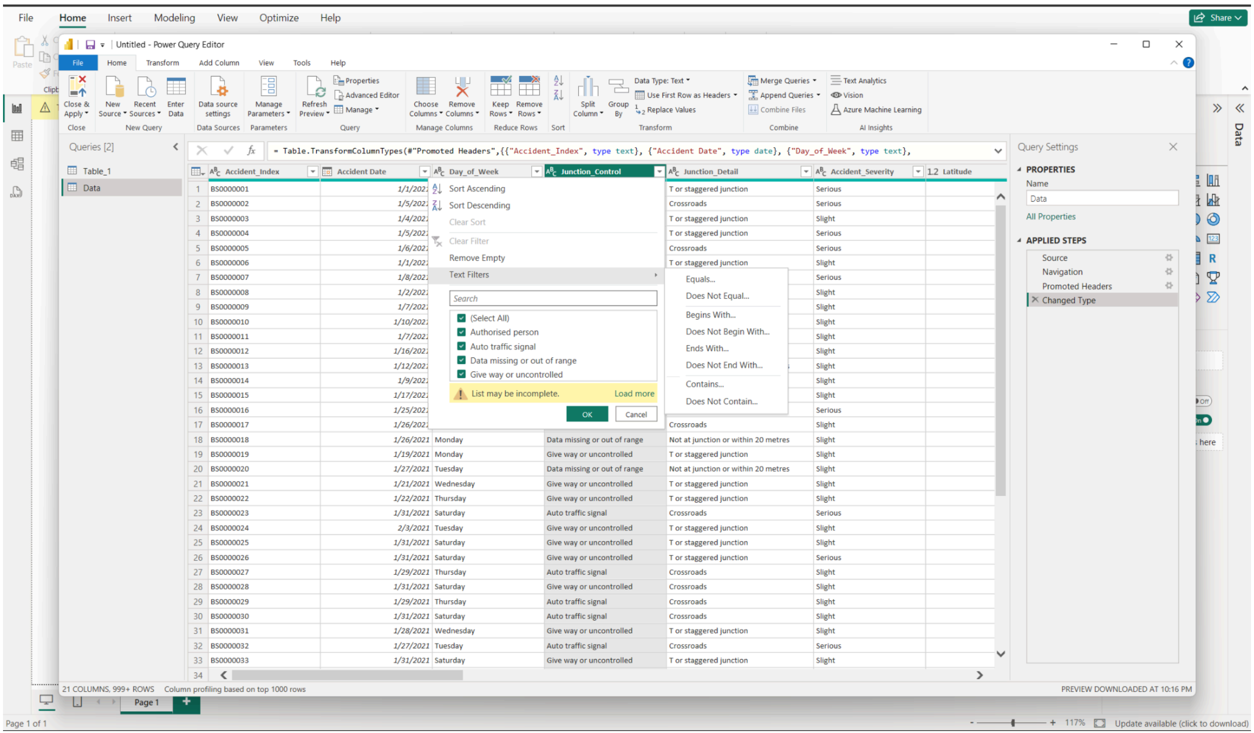

Figure 2.2.3 Power Query Editor

STEP 4

1. Then on the same SUMMARY table apply REPLACE VALUES.

2. In this select any column that needs new values to be replaced for further processing.

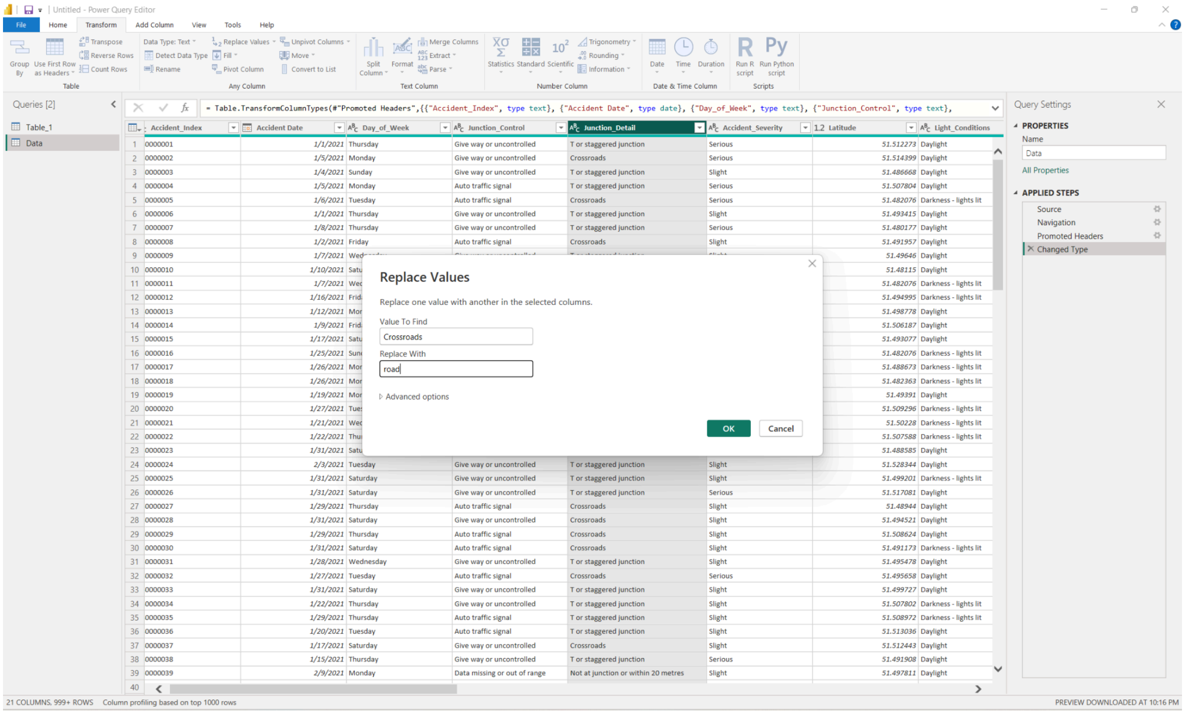

Figure 2.2.4 Replace Value

STEP 5

1. Now select the Accident DATA table to clean it.

2. Here apply change datatype so click the column that needed to change the datatype.

3. Select the “Accident” column then change its datatype to minutes.

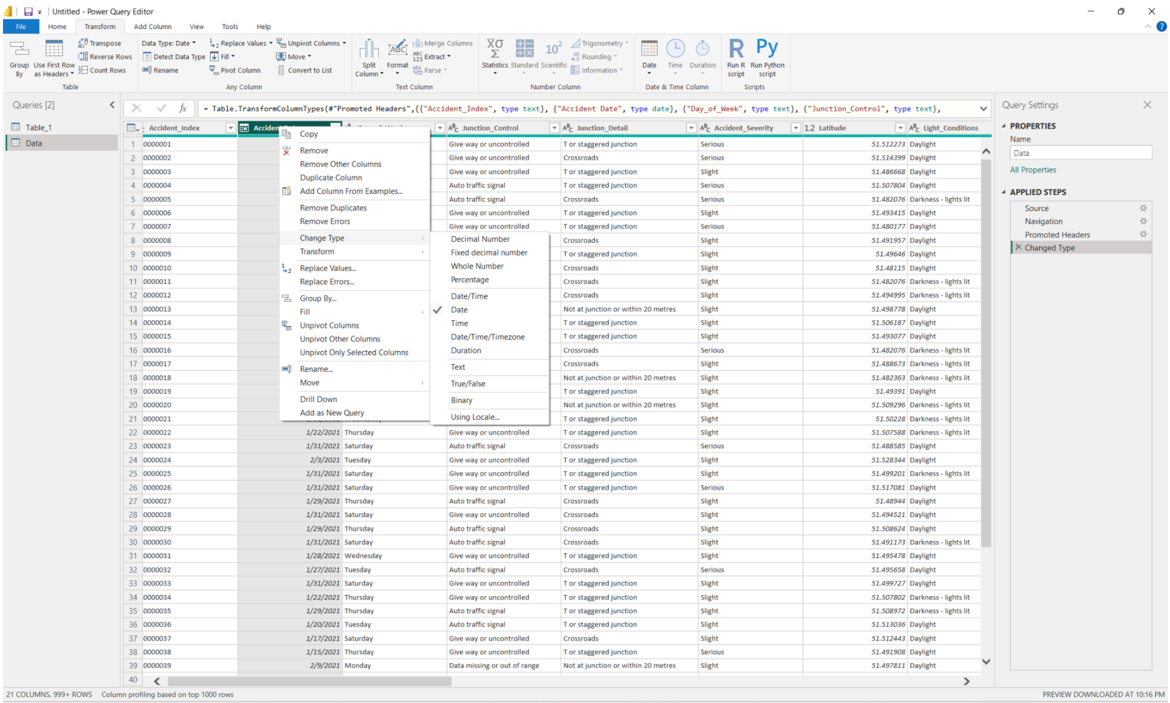

Figure 2.2.5 Change Column Type

STEP 6

1. Now select the Light Condition table inorder to apply SPLIT COLUMN.

2. It is needed to split a particular column so that data can be accessed easily.

3. Select column to be splitted, RIGHT CLICK the column.

4. Drop down the list displays and select SPLIT COLUMN.

5. Then select the split column by DELIMITER.

6. Similarly, we can also split columns by using delimiters such as comma, colon, semi solon, hyphen, etc...

7. Now split the column “Accident” from the Accident Data table into three different columns by using the delimiter “comma”.

8. Then rename the newly created columns as “description1”, “Light Condition” and “Cause of Accident”.

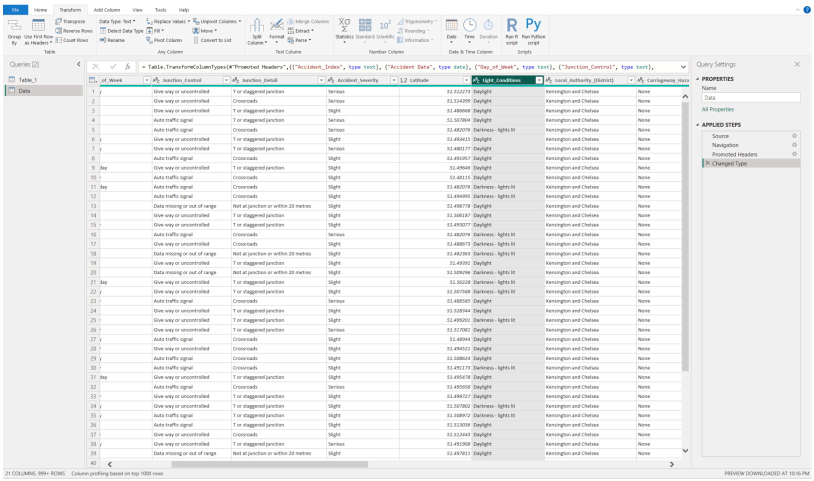

Figure 2.2.6 Split Column Selection

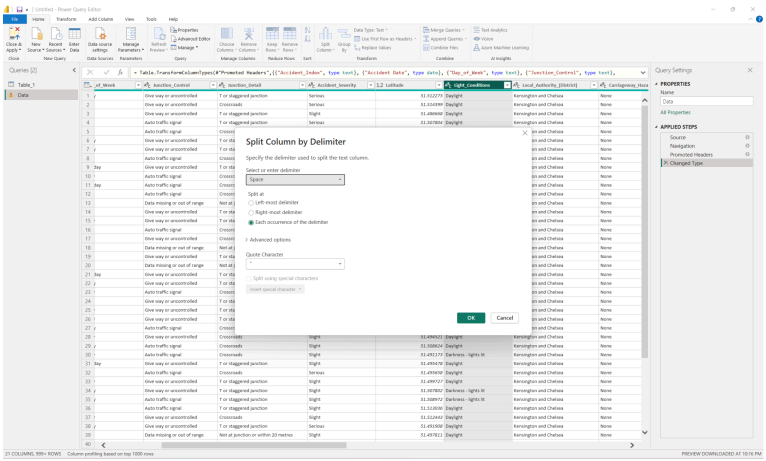

Figure 2.2.7 Split Column by Delimiter

STEP 7

1. Then select the split column by DELIMITER.

2. Similarly, we can also split columns by using delimiters such as comma, colon, semi solon, hyphen, etc...

3. Now split the column “Accident” from the Accident Data table into three different columns by

using the delimiter “comma”.

4. Then rename the newly created columns as “description1”, “Light Condition” and “Cause of Accident”.

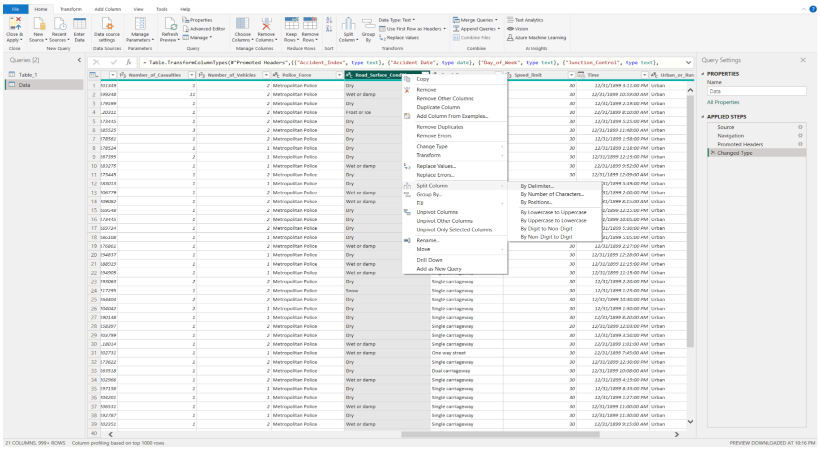

Figure 2.2.8 Split Column by Delimiter

STEP 8:

1. Select SUMMARY table to change data type.

2. Select Accident Index and change the data type from TEXT to DATA.

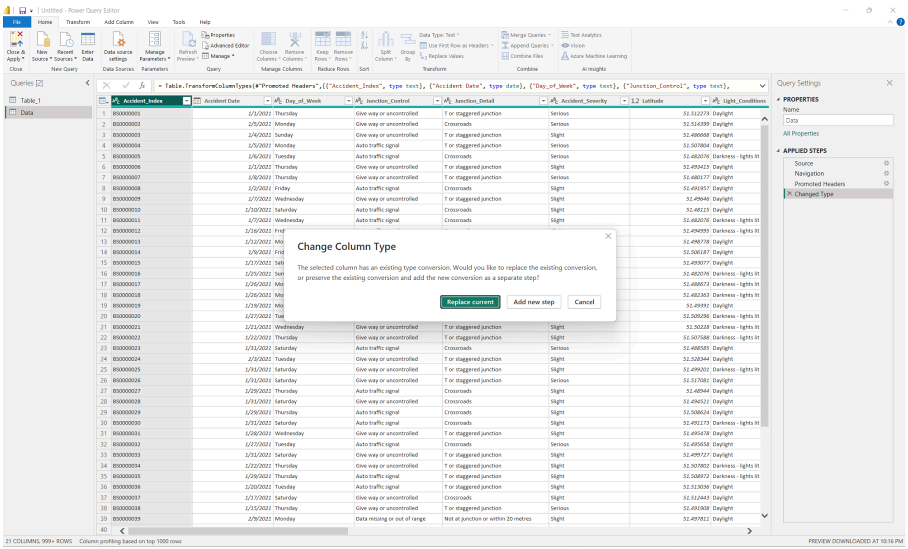

Figure 2.2.9 Change the Column Type

2.3 DATA MODELLING

For road accident analysis by vehicle type, a well-structured data model is essential for extracting actionable insights. The data model integrates multiple tables representing key aspects of the accident data, enabling efficient querying and visualization in Power BI.

- **Fact Table – Accident Events**

The main fact table, “Accident Events,” contains unique records for each accident, with fields such as Accident ID, Timestamp, Location, Weather Conditions, Vehicle Type, Accident Severity, and Casualty Count. This table captures the essential event data, which can be analyzed across various dimensions.

- **Dimension Table – Vehicle Types**

The “Vehicle Types” dimension categorizes vehicle types (e.g., Car, Motorcycle, Bus, Truck) to allow for simplified filtering and analysis. Each type can be mapped to multiple model numbers in cases where model-specific information is available.

- **Dimension Table – Time**

A “Time” dimension table breaks down the timestamp into detailed attributes such as Year, Month, Day, and Hour, enabling temporal analysis. This allows us to examine accident patterns by season, month, day, or time of day.

- **Dimension Table – Locations**

The “Locations” dimension table provides information on accident locations, including fields for Area, City, and specific accident-prone zones. This supports geospatial analysis of high-risk areas and location-based trend insights.

- **Dimension Table – Weather**

A “Weather” dimension captures weather conditions during each accident event. This table includes attributes like Weather Type (e.g., Rainy, Clear), Temperature, and Visibility, which are critical for understanding environmental influences on accident risk.

- **Dimension Table – Severity Levels**

This dimension defines accident severity categories (e.g., Minor, Major, Fatal), allowing us to analyze and visualize the severity distribution across vehicle types. These relationships, primarily based on common keys such as Accident ID, Timestamp, or Location ID, establish a relational data model. This data structure enables a range of analyses, from accident frequency by vehicle type and time to severity analysis by weather and location.

2.4 DAX (Data Analysis Expressions)

DAX is a special function that contains a collection of operators, formulae, functions, expressions to calculate, process and execute the values from the existing table and return one or more values as the result of respective functions. So, it is used to create new information from the data that already exists in the table while creating models and analyzing them. DAX measured of Power Bi are special functions or Programming Language that are used to create the following such as

- ➢ Calculated columns
- ➢ New measures
- ➢ Customized tables
- ➢ Quick measures
- ➢ Implement Time Intelligence

There exist many formulae for creating the new columns, measures. The time intelligence are special functions that are applicable only for the Time-based columns only. So, from these formulae and expressions we can find results like maximum, minimum, average, count, sum, filters, difference, total, variance, percentage, addition, subtraction, division, etc.….

CHAPTER 3

DATA ANALYSIS AND INTERPRETATION

3.1 DATA ANALYSIS

The analysis of road accidents in the United Kingdom by vehicle type reveals critical patterns and insights that inform safety strategies. By examining historical accident data, we identified key factors contributing to accident frequency and severity. Data visualization techniques, such as bar charts and heatmaps, highlighted the distribution of accidents across different vehicle categories, showing that motorcycles and heavy trucks are often associated with higher severity outcomes. Time-series analysis demonstrated notable trends in accident occurrences during specific hours and seasons, indicating peak risk periods. Additionally, weather conditions were analyzed to understand their impact on accident rates, revealing that adverse weather significantly correlates with increased incidents. Data analysis includes the following results

- ❖ Used to create various charts from Power Bi visuals
- ❖ Select datas from various tables, analyze it and convert it into visuals.
- ❖ From the analyzed result infer the result or final solution.

3.2 CHARTS

1) How many total casualties occurred in the current year (CY)?

i.Select table CASUALTIES

ii.Include calculated measure "COUNT OF CASUALTIES"

iii.. Then select a card chart for visualization.

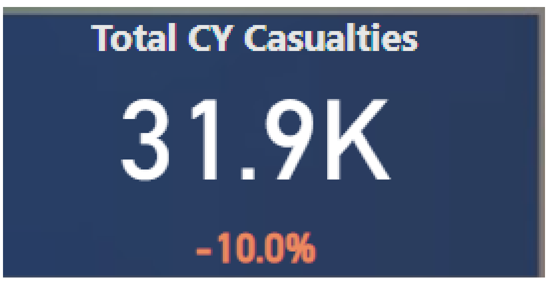

Figure 3.2.1 Total CY Casualties

2) What is the percentage of accidents occurring during the day versus night?

i.Select table CASUALTIES.

ii Include "DARK", "DAY"

iii. Then select the donut chart for visualization.

iv. Then use the previously created slicer for selecting each accident name.

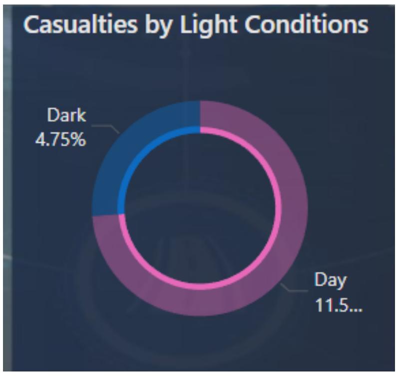

Figure 3.2.2 **Casualties by Light conditions**

3) How many casualties occurred on dual carriageways?

i. Select table summary.

ii. Include "CASUALTIES" AND "ROAD_TYPE"

iii. Then select stacked bar chart for visualization.

Figure 3.2.3 **Casualties by Road type**

4) What is the total number of slight casualties in the current year (CY)?

i.Select table CASUALTIES

ii.Include calculated measure "COUNT OF SLIGHT CASUALTIES"

iii.. Then select a card chart for visualization.

Figure 3.2.4 Total CY Slight Casualties

5) Which vehicle type had the lowest number of casualties?

i.Select table CASUALTIES

ii.Include calculated measure "COUNT OF CASUALTIES BY VEHICLE TYPE"

iii.. Then a standard card chart for visualization.

Figure 3.2.5 Count of casualties in by vehicle type

6) What is the total number of CY casualties in the current year (CY)?

i.Select table CASUALTIES

ii.Include calculated measure "COUNT OF CY CASUALTIES"

iii.. Then select a card chart for visualization.

Figure 3.2.6 Total CY Accidents

7) Which months show the highest difference between CY and PY casualties?

i.Select table CASUALTIES

ii.Include calculated measure "COUNT OF CY CASUALTIES" AND "COUNT OF PY CASUALTIES".

iii.. Then stacked graph chart for visualization.

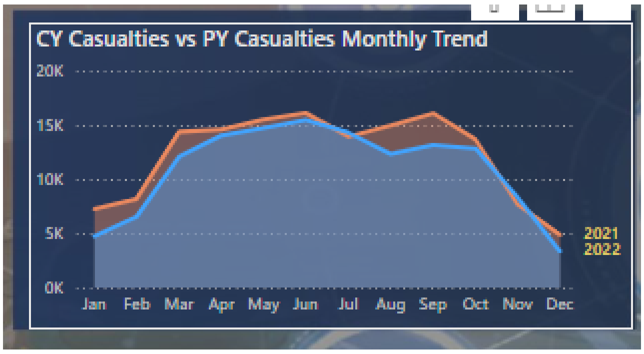

Figure 3.2.7 Difference between CY and PY casualties

8) Which regions have the highest concentration of casualties in dry areas?

i.Select table CASUALTIES

ii.Include calculated measure "COUNT OF CASUALTIES BY LOCATION"

iii.. Then map chart for visualization.

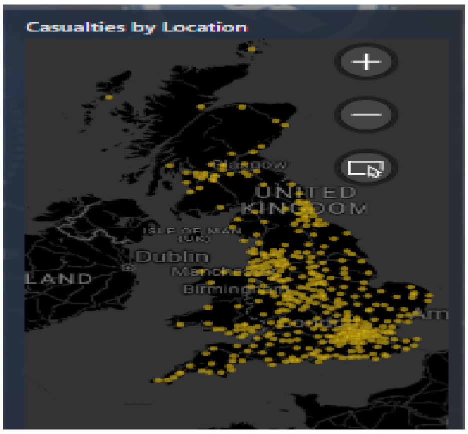

Figure 3.2.8 **Concentration of casualties in dry areas**

9) What measures can be taken to reduce casualties in urban areas where the majority of incidents occur?

i.Select table CASUALTIES.

ii Include “RURAL”, “URBAN”

iii. Then select the donut chart for visualization.

iv. Then use the previously created slicer for selecting each accident name.

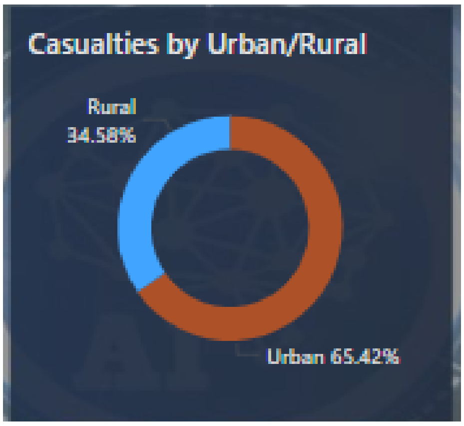

Figure 3.2.9 **Casualties in rural and urban areas**

10) Which months have the lowest casualties for both CY and PY in the snow/Ice region?

i.Select table CASUALTIES

ii.Include calculated measure “COUNT OF CY CASUALTIES” AND “COUNT OF PY CASUALTIES” BY MONTH TREND.

iii.. Then stacked graph charts for visualization.

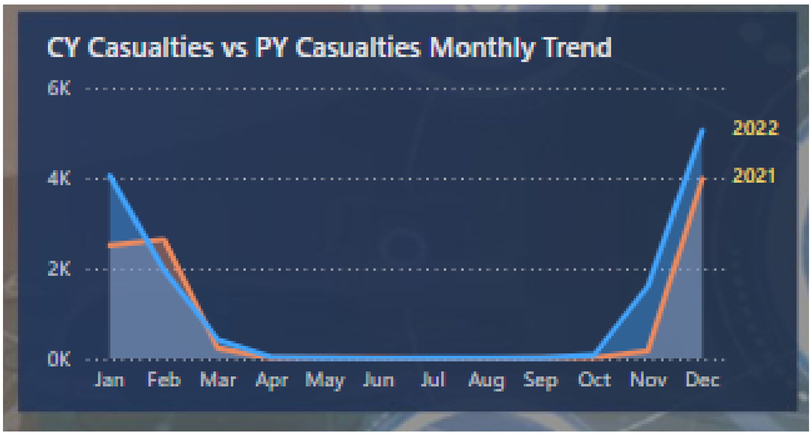

Figure 3.2.10 **CY and PY casualties in monthly trend**

11) What are the common factors in areas with a high density of casualties in snow/Ice areas?

i.Select table CASUALTIES

ii.Include calculated measure "COUNT OF CASUALTIES BY LOCATION"

iii.. Then map charts for visualization.

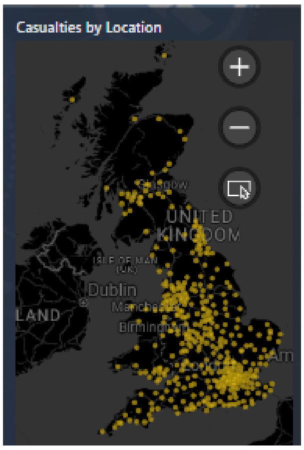

Figure 3.2.11 **Casualties by Locations**

12) How many total casualties occurred in the current year (CY) in Snow/Ice climate?

i.Select table CASUALTIES

ii.Include calculated measure "COUNT OF CY CASUALTIES"

iii.. Then select a card chart for visualization.

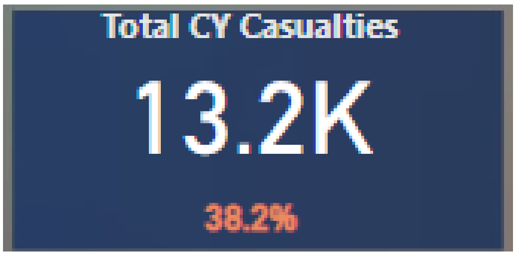

Figure 3.2.12 Total CY Casualties

13) Which vehicle type had the lowest number of casualties?

i.Select table CASUALTIES

ii.Include calculated measure “COUNT OF CASUALTIES BY VEHICLE TYPE”

iii.. Then a standard card chart for visualization.

Figure 3.2.13 Count of casualties in by vehicle type

14) Have interventions (like traffic calming measures, road improvements) had different impacts on casualty rates in urban and rural areas in Snow/Ice climate?

i.Select table CASUALTIES.

ii Include “RURAL”, “URBAN”

iii. Then select the donut chart for visualization.

iv. Then use the previously created slicer for selecting each accident name.

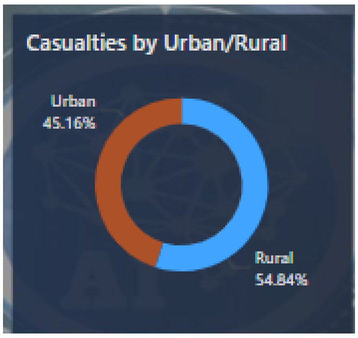

Figure 3.2.14 **Casualties in rural and urban areas**

15) Are there any noticeable patterns in casualty locations in relation to major cities?

i.Select table CASUALTIES

ii.Include calculated measure “COUNT OF CASUALTIES BY LOCATION”

iii.. Then map chart for visualization.

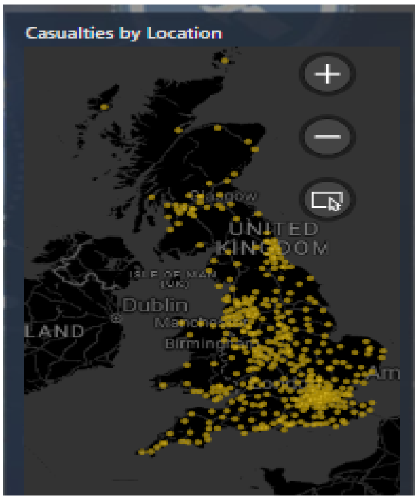

Figure 3.2.15 **Casualties by Locations**

3.3 PUBLISHING DASHBOARD

➢ This dashboard focuses on dissecting accident data by vehicle type, offering a clear understanding of how different vehicles contribute to road safety challenges.

➢ Utilizing data sourced from preprocessed datasets and real-time updates, the dashboard enables users to explore patterns and trends in accident occurrences, severities, and contributing factors.

- ➢ The dashboard features interactive charts and graphs that facilitate in-depth analysis, allowing stakeholders, policymakers, and researchers to identify high-risk vehicle categories, peak accident times, and the influence of environmental conditions.

- ➢ By leveraging this data, we aim to support informed decision-making, enhance public safety initiatives, and ultimately reduce the incidence of road accidents.

- ➢ With an intuitive user interface, the dashboard serves as a valuable resource for driving data-driven discussions around road safety and fostering collaboration among various entities dedicated to improving traffic safety in the UK.

Process of creating Dashboard :

STEP 1

1. Open Power Bi serviced in a web browser.
2. From that interface click on get data at the left bottom.
3. Select import data from device or local disk.
4. Then import the created Power Bi file of Road Accident Analysis.

STEP 2

1. Now select visuals from the Power Bi file created and imported to the dashboard.
2. Create a new dashboard named “Road Accident Analysis”.
3. Then pin them to the dashboard.

Figure 3.3.1 Dashboard for Road Accident Analysis

3.4 INFERENCE

1. **What is the percentage of accidents occurring during the day versus night?**

   It is mostly 4.75 % of accidents that happen in Dark and 11.5 % in Day time.

2. **How many casualties occurred on dual carriageways?**

   It is in the massive number of 32075 casualties that happened in the Dual Carriageways.

3. **What is the total number of slight casualties in the current year (CY)?**

   The total number of 27275 casualties had slight accidents in the current year.

4. **Which vehicle type had the lowest number of casualties?**

   Agricultural vehicles have the least casualties in the current year.

5. **What is the total number of CY casualties in the current year (CY)?**

   There are 21,463 accidents in casualties in the current year.

6. **Which months show the highest difference between CY and PY casualties?**

   September in 2021 and June in 2022 shows the highest difference between CY and PY casualties.

7. **Which regions have the highest concentration of casualties in dry areas?**

   London has the highest concentration of casualties in dry areas.

8. **What measures can be taken to reduce casualties in urban areas where the majority of incidents occur?**

   By improving the standards of roads and signals may reduce the accidents occurring in rural and urban areas.

9. **Which months have the lowest casualties for both CY and PY in the snow/Ice region?**

   May to September has the fewest casualties on both CY and PY in snow/Ice region.

10. **What are the common factors in areas with a high density of casualties in snow/Ice areas?**

    Excess snowfall is the major reason for the casualties that happen during the snow/ice region.

11. **How many total casualties occurred in the current year (CY) in Snow/Ice climate?**

    In total, 13294 casualties occurred in the current year (CY) in Snow/Ice climate.

12. **Which vehicle type had the lowest number of casualties?**

    Agricultural vehicle types had the lowest number of casualties.

13. **Have interventions (like traffic calming measures, road improvements) had different impacts on casualty rates in urban and rural areas in Snow/Ice climate?**

Yes, It shows a difference in the impact on casualty rates in urban and rural areas in Snow/Ice climate.

14. Are there any noticeable patterns in casualty locations in relation to major cities?

Yes, there are noticeable patterns in casualty locations in relation to major cities.

15. How many total casualties occurred in the current year (CY)?

In total, 13294 casualties occurred in the current year (CY) .

INFERENCE OF DASHBOARD

1. Total Casualties: The total road casualties for the current year (CY) stand at approximately 195.7K, reflecting an 11.9% decrease.

2. Total Accidents: There have been around 144.4K accidents, with an 11.7% decrease from previous figures.

3. Severity of Accidents: Fatal casualties are at 2.9K, while serious casualties are 27K, showing respective changes of -9.3% and -8.2%.

4. Vehicle Type Impact: Different vehicle types, such as agriculture, motorcycles, bicycles, and cars, have varying contributions to casualty counts, with cars showing the highest impact.

5. Casualties by Month: Monthly trends display fluctuations in casualty numbers, useful for identifying high-risk periods.

6. Urban vs. Rural Distribution: The data shows a breakdown of casualties in urban versus rural areas, which can help in targeted safety measures.

7. Impact of Light Conditions: Casualties are segmented by light conditions (day vs. night), highlighting how lighting influences accident severity.

8. Geographic Distribution: A map visualizes casualty locations across the UK, indicating regional hotspots for accidents.

3.5 INTEGRATING WITH WEB APPLICATION

To develop a future-focused application that leverages the insights from our road accident analysis, integrating this analysis within a Flutter framework presents a versatile and user-friendly approach. Flutter allows for the creation of cross-platform applications with a single codebase, ensuring that the insights and visualizations can be accessible on both Android and iOS devices.

The application can feature interactive dashboards similar to those created in Power BI, enabling users to explore data visualizations such as accident trends by vehicle type, heat maps of accident-prone areas, and real-time updates on road safety metrics. By utilizing APIs to fetch updated accident data, the app can provide users with the latest insights, facilitating timely decision-making for road safety authorities and the public. Furthermore, the application can include functionalities such as personalized alerts for accident hotspots based on user location, educational resources on safe driving practices tailored to vehicle types, and a reporting tool for users to submit accident observations. By incorporating machine learning algorithms, the app could also predict potential accident risks based on historical data and current conditions, enhancing proactive safety measures. Ultimately, this integration not only enhances user engagement and awareness but also contributes to a data-driven culture around road safety, paving the way for a future with reduced road accidents and improved traffic management

CHAPTER 4

CONCLUSION AND FUTURE WORK

4.1 RECOMMENDATIONS

Our analysis indicates that certain vehicle types, such as motorcycles and trucks, have higher accident frequencies or severity levels. To address this, targeted safety initiatives should be introduced for these high-risk vehicles. Programs could include specialized training, enhanced safety features, and strict compliance checks, particularly focusing on vehicles prone to severe accidents.

Launching public awareness campaigns during peak accident hours and adverse weather conditions could significantly reduce road incidents. These campaigns should emphasize safe driving practices and caution drivers about the elevated risks during challenging conditions. Additionally, stricter regulations, such as speed limits and vehicle inspections for high-risk categories, could further mitigate accident risks.

Improving road infrastructure, like adding separate lanes or installing safety barriers for high-risk vehicles, can enhance safety on frequently affected routes. Such infrastructure changes will help minimize the impact of accidents by providing safer road environments for vehicles that are more prone to severe crashes.

To gain a more comprehensive understanding of road accidents, future analysis could integrate real-time traffic and weather data. These additional data sources would provide insights into dynamic risk factors, offering a more nuanced view of the conditions under which accidents occur.

Using machine learning to develop predictive models could help forecast accident probabilities based on factors like time, weather, and road conditions. This proactive approach would enable authorities to anticipate high-risk scenarios and implement preventive measures, potentially reducing accident rates even further.

Expanding the data analysis to include driver demographics, such as age and driving experience, could allow for tailored interventions. Understanding demographic risk factors could inform targeted safety measures that cater to specific driver groups more effectively.

Incorporating advanced visualization techniques and AI-driven anomaly detection in tools like Power BI could reveal emerging patterns in road safety data. Enhanced visualizations would make it easier for stakeholders to identify accident trends, enabling faster, data-informed decision-making to improve road safety across the UK.

4.2 CONCLUSION

In conclusion, this analysis of road accidents in the United Kingdom by vehicle type has highlighted critical insights into patterns and risk factors contributing to road safety issues. By examining the frequency and severity of accidents associated with various vehicle types, we have identified high-risk categories and the influence of external factors such as time and weather conditions. The findings underscore the need for targeted safety measures, public awareness campaigns, and infrastructure improvements to mitigate accidents effectively. Our recommendations, informed by data-driven insights, aim to support policymakers, traffic authorities, and stakeholders in making informed decisions to enhance road safety. Future work, including the integration of real-time data and advanced predictive modeling, will further enrich our understanding of road accident dynamics, enabling proactive interventions. Ultimately, by leveraging data analysis, we can contribute to creating safer roadways and reducing the incidence of accidents, fostering a more secure environment for all road users in the UK.

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