Analysis of Accidental Drug-Related Deaths in CT & Other States (US) (2012-2021)

Introduction:

Drug-related accidental deaths have been a significant public health concern in the United States for several decades. This analysis aims to explore drug-related accidental deaths in Connecticut from 2012 to 2021, as well as in other states across the US.

Throughout history, drug overdoses have been a significant problem in the US, with a steady increase in the number of drug overdose deaths since the early 2000s, as reported by the Centers for Disease Control and Prevention (CDC). In recent years, there has been a sharp increase in the number of deaths involving opioids, which has been a major driver of the increase in drug-related deaths.

Prescription opioids, such as oxycodone and hydrocodone, have been overprescribed and misused, leading to addiction and overdose. Illicit opioids, such as heroin and fentanyl, have also become more prevalent, contributing to the rise in overdose deaths.

In response to the opioid epidemic, many states have implemented policies and programs aimed at reducing the number of drug-related deaths. These include expanding access to addiction treatment, increasing the availability of overdose-reversing drugs like naloxone, and cracking down on the illicit drug trade.

Despite these efforts, drug-related accidental deaths and overdoses continue to be a major public health concern in the US. Understanding the trends and patterns of these deaths is essential for developing effective prevention and intervention strategies.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as stats
```

Part 1 : Data Pre-proceesing

In [2]:
```
df=pd.read_csv('Accidental_Drug_Related_Deaths_2012-2021.csv')
df.head()
```

Out[2]:

	Date	Date Type	Age	Sex	Race	Description of Injury	Death City	Death County	Death State	Cause of Death	...	Tramad
0	5/29/2012	Date of death	37.0	Male	Black	Used Cocaine	NaN	NaN	NaN	Cocaine Toxicity	...	NaN
1	6/27/2012	Date of death	37.0	Male	White	Drug Use	NORWICH	NEW LONDON	NaN	Heroin Toxicity	...	NaN
2	3/24/2014	Date of death	28.0	Male	White	Drug Use	MARLBOROUGH	NaN	NaN	Heroin Intoxication	...	NaN
3	12/31/2014	Date	26.0	Female	White	NaN	BALTIC	NEW	NaN	Acute	...	NaN

		of death						LONDON		Heroin Intoxication		
4	1/16/2016	Date of death	41.0	Male	White	Drug Use	BRIDGEPORT	NaN	NaN	Acute Fentanyl Intoxication	...	NaN

5 rows × 34 columns

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9202 entries, 0 to 9201
Data columns (total 34 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   Date                            9202 non-null   object 
 1   Date Type                       9202 non-null   object 
 2   Age                             9200 non-null   float64
 3   Sex                             9194 non-null   object 
 4   Race                            9178 non-null   object 
 5   Description of Injury           8411 non-null   object 
 6   Death City                      9197 non-null   object 
 7   Death County                    8090 non-null   object 
 8   Death State                     6873 non-null   object 
 9   Cause of Death                  9202 non-null   object 
 10  Manner of Death                 9193 non-null   object 
 11  Heroin                          3347 non-null   object 
 12  Heroin death certificate (DC)   740 non-null    object 
 13  Cocaine                         3171 non-null   object 
 14  Fentanyl                        5672 non-null   object 
 15  Fentanyl Analogue               728 non-null    object 
 16  Oxycodone                       877 non-null    object 
 17  Oxymorphone                     148 non-null    object 
 18  Ethanol                         2470 non-null   object 
 19  Hydrocodone                     155 non-null    object 
 20  Benzodiazepine                  2238 non-null   object 
 21  Methadone                       814 non-null    object 
 22  Meth/Amphetamine                127 non-null    object 
 23  Amphet                          285 non-null    object 
 24  Tramad                          258 non-null    object 
 25  Hydromorphone                   56 non-null     object 
 26  Morphine (Not Heroin)           49 non-null     object 
 27  Xylazine                        441 non-null    object 
 28  Gabapentin                      182 non-null    object 
 29  Opiate NOS                      119 non-null    object 
 30  Heroin/Morph/Codeine            1952 non-null   object 
 31  Other Opioid                    90 non-null     object 
 32  Any Opioid                      6281 non-null   object 
 33  Other                           654 non-null    object 
dtypes: float64(1), object(33)
memory usage: 2.4+ MB
```

In [4]:
```
df.isna().sum()
```

Out[4]:
```
Date                                 0
Date Type                            0
Age                                  2
Sex                                  8
Race                                24
Description of Injury              791
Death City                           5
Death County                      1112
Death State                       2329
Cause of Death                       0
```

```
Manner of Death                  9
Heroin                        5855
Heroin death certificate (DC)    8462
Cocaine                       6031
Fentanyl                      3530
Fentanyl Analogue             8474
Oxycodone                     8325
Oxymorphone                   9054
Ethanol                       6732
Hydrocodone                   9047
Benzodiazepine                6964
Methadone                     8388
Meth/Amphetamine              9075
Amphet                        8917
Tramad                        8944
Hydromorphone                 9146
Morphine (Not Heroin)         9153
Xylazine                      8761
Gabapentin                    9020
Opiate NOS                    9083
Heroin/Morph/Codeine          7250
Other Opioid                  9112
Any Opioid                    2921
Other                         8548
dtype: int64
```

In [5]:

```
columns_to_modify = [
    "Heroin", "Heroin death certificate (DC)", "Cocaine", "Fentanyl", "Fentanyl Analogue
    "Oxymorphone", "Ethanol", "Hydrocodone", "Benzodiazepine", "Methadone", "Meth/Amphet
    "Amphet", "Tramad", "Hydromorphone", "Morphine (Not Heroin)", "Xylazine", "Gabapenti
    "Opiate NOS", "Heroin/Morph/Codeine", "Other Opioid",'Any Opioid'
]

for col in columns_to_modify:
    df[col] = df[col].apply(lambda x: "Present" if x == "Y" else "Not Present")



def mark_drugs_present_or_not(column):
    if pd.isna(column) or str(column).strip() == "":
        return 'Not Present'
    else:
        return 'Present'

df['Other'] = df['Other'].apply(mark_drugs_present_or_not)

df.isna().sum()
```

Out[5]:

```
Date                             0
Date Type                        0
Age                              2
Sex                              8
Race                            24
Description of Injury          791
Death City                       5
Death County                  1112
Death State                   2329
Cause of Death                   0
Manner of Death                  9
Heroin                           0
Heroin death certificate (DC)    0
Cocaine                          0
Fentanyl                         0
Fentanyl Analogue                0
Oxycodone                        0
Oxymorphone                      0
```

```
Ethanol                                0
Hydrocodone                            0
Benzodiazepine                         0
Methadone                              0
Meth/Amphetamine                       0
Amphet                                 0
Tramad                                 0
Hydromorphone                          0
Morphine (Not Heroin)                  0
Xylazine                               0
Gabapentin                             0
Opiate NOS                             0
Heroin/Morph/Codeine                   0
Other Opioid                           0
Any Opioid                             0
Other                                  0
dtype: int64
```

In [6]:

```
df['Description of Injury'].replace(np.nan, 'Unknown', inplace=True)
df.isna().sum()
```

Out[6]:

```
Date                                   0
Date Type                              0
Age                                    2
Sex                                    8
Race                                  24
Description of Injury                  0
Death City                             5
Death County                        1112
Death State                         2329
Cause of Death                         0
Manner of Death                        9
Heroin                                 0
Heroin death certificate (DC)          0
Cocaine                                0
Fentanyl                               0
Fentanyl Analogue                      0
Oxycodone                              0
Oxymorphone                            0
Ethanol                                0
Hydrocodone                            0
Benzodiazepine                         0
Methadone                              0
Meth/Amphetamine                       0
Amphet                                 0
Tramad                                 0
Hydromorphone                          0
Morphine (Not Heroin)                  0
Xylazine                               0
Gabapentin                             0
Opiate NOS                             0
Heroin/Morph/Codeine                   0
Other Opioid                           0
Any Opioid                             0
Other                                  0
dtype: int64
```

In [7]:

```
#Dropping unneccessary columns

columns_to_drop=['Death City','Death County','Death State','Heroin death certificate (DC
df.drop(columns_to_drop, axis=1,inplace=True)
df
```

Out[7]:

	Date	Date Type	Age	Sex	Race	Description of Injury	Cause of Death	Manner of Death	Heroin	Cocaine	...	Ampl

0	5/29/2012	Date of death	37.0	Male	Black	Used Cocaine	Cocaine Toxicity	Accident	Not Present	Present	...	N Pres
1	6/27/2012	Date of death	37.0	Male	White	Drug Use	Heroin Toxicity	Accident	Present	Not Present	...	N Pres
2	3/24/2014	Date of death	28.0	Male	White	Drug Use	Heroin Intoxication	Accident	Present	Not Present	...	N Pres
3	12/31/2014	Date of death	26.0	Female	White	Unknown	Acute Heroin Intoxication	Accident	Present	Not Present	...	N Pres
4	1/16/2016	Date of death	41.0	Male	White	Drug Use	Acute Fentanyl Intoxication	Accident	Not Present	Not Present	...	N Pres
...	...	...	...	...	...	...	...	...	...	...	...	
9197	10/19/2021	Date of death	56.0	Male	Black or African American	Substance abuse	Acute Intoxication by the Combined Effects of ...	Accident	Not Present	Present	...	N Pres
9198	5/4/2021	Date of death	48.0	Male	Black or African American	Substance Use	Complications of Acute Substance Intoxication ...	Accident	Not Present	Present	...	N Pres
9199	5/15/2021	Date of death	59.0	Male	White	Substance Abuse	Acute Intoxication by the Combined Effects of ...	Accident	Not Present	Present	...	N Pres
9200	5/28/2021	Date of death	68.0	Male	Black or African American	Substance Abuse	Acute Cocaine Intoxication	Accident	Not Present	Present	...	N Pres
9201	12/24/2021	Date of death	29.0	Male	White	Substance abuse	Acute Intoxication by the Combined Effects of ...	Accident	Not Present	Not Present	...	N Pres

9202 rows × 29 columns

In [8]:
```
df.columns
```

Out[8]:
```
Index(['Date', 'Date Type', 'Age', 'Sex', 'Race', 'Description of Injury',
       'Cause of Death', 'Manner of Death', 'Heroin', 'Cocaine', 'Fentanyl',
       'Fentanyl Analogue', 'Oxycodone', 'Oxymorphone', 'Ethanol',
       'Hydrocodone', 'Benzodiazepine', 'Methadone', 'Meth/Amphetamine',
       'Amphet', 'Tramad', 'Hydromorphone', 'Morphine (Not Heroin)',
       'Xylazine', 'Gabapentin', 'Opiate NOS', 'Other Opioid', 'Any Opioid',
       'Other'],
      dtype='object')
```

In [9]:
```
df.isna().sum()
```

Out[9]:
```
Date                          0
Date Type                     0
Age                           2
```

```
Sex                          8
Race                        24
Description of Injury        0
Cause of Death               0
Manner of Death              9
Heroin                       0
Cocaine                      0
Fentanyl                     0
Fentanyl Analogue            0
Oxycodone                    0
Oxymorphone                  0
Ethanol                      0
Hydrocodone                  0
Benzodiazepine               0
Methadone                    0
Meth/Amphetamine             0
Amphet                       0
Tramad                       0
Hydromorphone                0
Morphine (Not Heroin)        0
Xylazine                     0
Gabapentin                   0
Opiate NOS                   0
Other Opioid                 0
Any Opioid                   0
Other                        0
dtype: int64
```

In [10]:

```
Columns=['Race','Sex','Manner of Death']


for col in Columns:
    df[col].replace(np.nan,'Unknown',inplace=True)


# Calculating the meean for replaing the missing twol values for age

mean=df.Age.mean().astype(int)
df['Age'].replace(np.nan,mean,inplace=True)
```

In [11]:

```
df.isna().sum()
```

Out[11]:

```
Date                        0
Date Type                   0
Age                         0
Sex                         0
Race                        0
Description of Injury       0
Cause of Death              0
Manner of Death             0
Heroin                      0
Cocaine                     0
Fentanyl                    0
Fentanyl Analogue           0
Oxycodone                   0
Oxymorphone                 0
Ethanol                     0
Hydrocodone                 0
Benzodiazepine              0
Methadone                   0
Meth/Amphetamine            0
Amphet                      0
Tramad                      0
Hydromorphone               0
Morphine (Not Heroin)       0
```

```
Xylazine         0
Gabapentin       0
Opiate NOS       0
Other Opioid     0
Any Opioid       0
Other            0
dtype: int64
```

In [12]:
```
df.head()
```

Out[12]:

	Date	Date Type	Age	Sex	Race	Description of Injury	Cause of Death	Manner of Death	Heroin	Cocaine	...	Amphet	Tran
0	5/29/2012	Date of death	37.0	Male	Black	Used Cocaine	Cocaine Toxicity	Accident	Not Present	Present	...	Not Present	I Pres
1	6/27/2012	Date of death	37.0	Male	White	Drug Use	Heroin Toxicity	Accident	Present	Not Present	...	Not Present	I Pres
2	3/24/2014	Date of death	28.0	Male	White	Drug Use	Heroin Intoxication	Accident	Present	Not Present	...	Not Present	I Pres
3	12/31/2014	Date of death	26.0	Female	White	Unknown	Acute Heroin Intoxication	Accident	Present	Not Present	...	Not Present	I Pres
4	1/16/2016	Date of death	41.0	Male	White	Drug Use	Acute Fentanyl Intoxication	Accident	Not Present	Not Present	...	Not Present	I Pres

5 rows × 29 columns

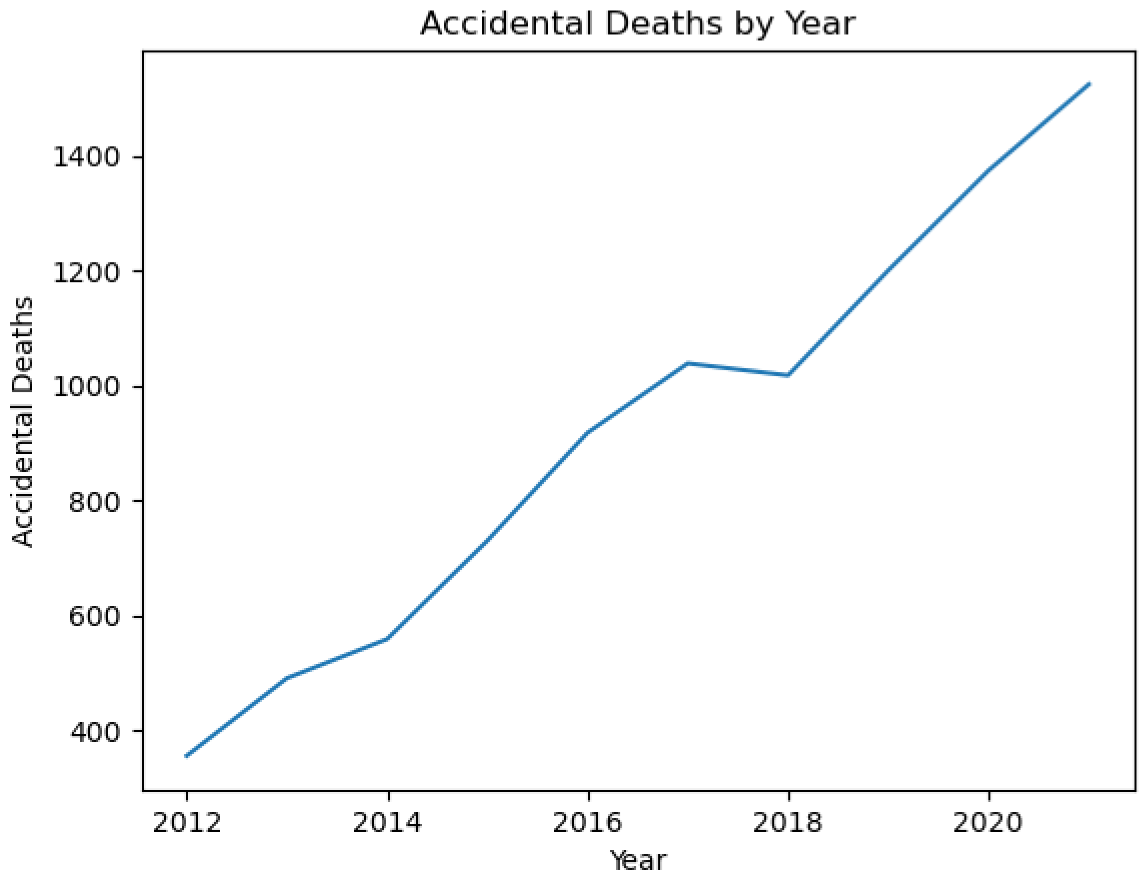
In [13]:
```
# As there two types of rows 'Black' and 'Black or African American' , so I am making th
df['Race'] = df['Race'].replace('Black', 'Black or African American')
```

Part 2 : Analyzing Data

Has the total number of overdose deaths increased or decreased from 2012 to 2021?

In [14]:
```
# Convert the date column to a datetime object.
df['Date'] = pd.to_datetime(df['Date'])
df['Year'] = df.Date.dt.year

grouped = df.groupby('Year')['Manner of Death'].value_counts().sum(level=0)

# Plot the results as a line graph.
plt.plot(grouped)
plt.xlabel('Year')
plt.ylabel('Accidental Deaths')
plt.title('Accidental Deaths by Year')
plt.show()
```

```
C:\Users\ttgmo\AppData\Local\Temp\ipykernel_36712\2955435196.py:5: FutureWarning: Using
the level keyword in DataFrame and Series aggregations is deprecated and will be removed
in a future version. Use groupby instead. df.sum(level=1) should use df.groupby(level=
1).sum().
  grouped = df.groupby('Year')['Manner of Death'].value_counts().sum(level=0)
```



What percentage change was there in the number of overdose deaths from 2012 to 2021?

In [15]:
```
# Percent chnage from year to year
grouped.pct_change()
```

Out[15]:
```
Year
2012         NaN
2013    0.380282
2014    0.138776
2015    0.306452
2016    0.257888
2017    0.131952
2018   -0.020231
2019    0.179941
2020    0.145000
2021    0.109170
Name: Manner of Death, dtype: float64
```

In [16]:
```
# Percent change from 2012 to 2021

Total_Percent= (grouped.loc[2021] / grouped.loc[2012] -1) * 100

print('The percent change from 2012 to 2021 is',Total_Percent.astype(int),'%')
```

```
The percent change from 2012 to 2021 is 329 %
```

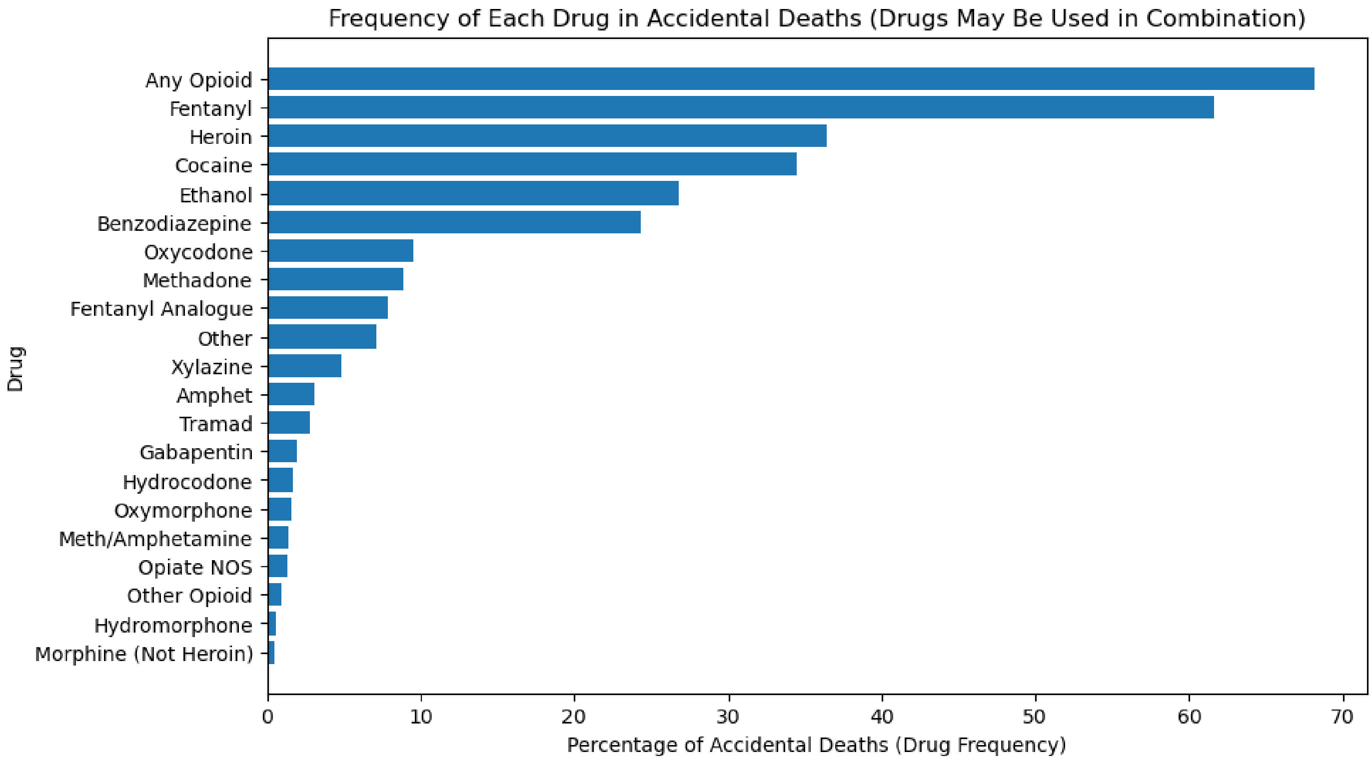
Based on the data, from 2012 to 2021, there has been a significant increase of 329% in the number of overdose deaths. This alarming trend highlights the growing severity of the opioid crisis and the need for immediate action. The data reveals that various substances, such as heroin, fentanyl, cocaine, and oxycodone, have contributed to these fatalities. As an analyst, it is crucial to identify patterns and raise awareness of the substances causing the most harm, so that policymakers and healthcare professionals can create targeted strategies to combat this critical public health issue.

Which drug is most commonly associated with accidental deaths?

In [17]:
```
drug_columns = ['Heroin', 'Cocaine', 'Fentanyl', 'Fentanyl Analogue', 'Oxycodone', 'Oxym

# Calculate the percentages and values for each drug
percentages = {drug: {'percentage': (len(df[df[drug] == 'Present']) / len(df) * 100), 'v

# Print the percentages and values
for drug, stats in percentages.items():
    print(f'{drug}: {stats["percentage"]:.2f}% ({stats["value"]}  Accidental Deaths)')
```

```
Heroin: 36.37% (3347  Accidental Deaths)
Cocaine: 34.46% (3171  Accidental Deaths)
Fentanyl: 61.62% (5670  Accidental Deaths)
Fentanyl Analogue: 7.91% (728  Accidental Deaths)
Oxycodone: 9.53% (877  Accidental Deaths)
Oxymorphone: 1.61% (148  Accidental Deaths)
Ethanol: 26.83% (2469  Accidental Deaths)
Hydrocodone: 1.68% (155  Accidental Deaths)
Benzodiazepine: 24.32% (2238  Accidental Deaths)
Methadone: 8.85% (814  Accidental Deaths)
Meth/Amphetamine: 1.38% (127  Accidental Deaths)
Amphet: 3.10% (285  Accidental Deaths)
Tramad: 2.80% (258  Accidental Deaths)
Hydromorphone: 0.61% (56  Accidental Deaths)
Morphine (Not Heroin): 0.50% (46  Accidental Deaths)
Xylazine: 4.79% (441  Accidental Deaths)
Gabapentin: 1.98% (182  Accidental Deaths)
Opiate NOS: 1.29% (119  Accidental Deaths)
Other Opioid: 0.98% (90  Accidental Deaths)
Other: 7.11% (654  Accidental Deaths)
Any Opioid: 68.17% (6273  Accidental Deaths)
```

In [18]:
```
sorted_percentages = dict(sorted(percentages.items(), key=lambda x: x[1]['percentage']))



drug_names = list(sorted_percentages.keys())
drug_percentages = [sorted_percentages[drug]['percentage'] for drug in drug_names]



plt.figure(figsize=(10, 6))
plt.barh(drug_names, drug_percentages)
plt.xlabel('Percentage of Accidental Deaths (Drug Frequency)')
plt.ylabel('Drug')
plt.title('Frequency of Each Drug in Accidental Deaths (Drugs May Be Used in Combination

plt.show()
```



The analysis of drug occurrences in accidental deaths reveals several insights. Fentanyl, a highly potent synthetic opioid, emerges as the most prevalent drug, being involved in a striking 61.62% (5670) of accidental deaths in the dataset. This finding underscores the significant concern surrounding Fentanyl abuse and its deadly consequences.

Further investigation shows that Heroin and Cocaine, both illicit substances, also contribute considerably to accidental deaths, with occurrences at 36.37% (3347) and 34.46% (3171), respectively. These results serve as a reminder of the ongoing challenges in addressing the repercussions of illicit drug use on public health. It is important to note that the "Morphine (Not Heroin)" category, with 0.50% (46) occurrences, refers to cases where the Medical Examiner could not conclusively determine whether the morphine detected was from Heroin or prescription Morphine.

Prescription drugs like Oxycodone and Hydrocodone are implicated in accidental deaths as well, although at lower rates than illicit drugs, with occurrences at 9.53% (877) and 1.68% (155), respectively. This observation highlights the necessity for prudent prescription practices and monitoring to avert misuse and overdose.

Besides opioids and stimulants, other substances such as Benzodiazepines and Ethanol have been found to be involved in a sizeable proportion of accidental deaths, with occurrences standing at 24.32% (2238) and 26.83% (2469), respectively. This finding indicates that efforts to mitigate drug-related accidental deaths must take into account a broad spectrum of substances and their potential interactions.

Some drugs display relatively low occurrences in accidental deaths, including Hydromorphone, Other Opioids, and those classified under "Other." Despite their lower prevalence in the dataset, it remains essential to stay alert to the possible risks associated with any drug.

The "Any Opioid" category, with 68.17% (6273) occurrences, represents cases where the Medical Examiner could not conclusively determine whether the opioid detected was prescription Morphine or heroin-based Morphine.

What is the average age of death? Has the average age changed from 2012 to 2021?

In [19]:
```
print('The mean age for all these years is',df.Age.mean().astype(int),'years')
```

```
The mean age for all these years is 43 years
```

Checking the weight mean average as the number of people for each year are different.

In [27]:
```python
weighted_mean_age_grouping = df.groupby('Year').apply(lambda x: np.average(x['Age'], wei
weighted_mean_age_grouping
```

Out[27]:
```
Year
2012    44
2013    44
2014    45
2015    46
2016    45
2017    45
2018    46
2019    46
2020    47
2021    49
dtype: int32
```

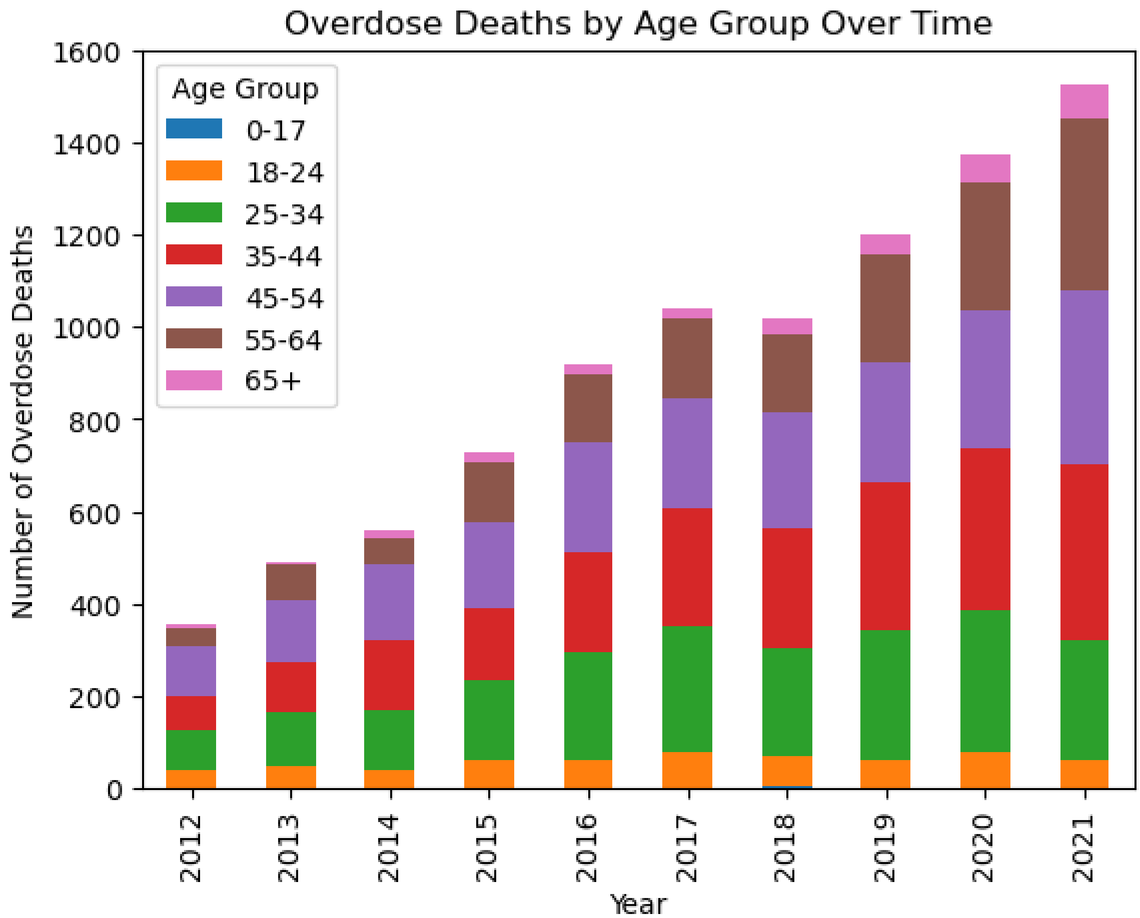
Now to check whether there is a significance difference between the mean of these groups or not

In [21]:
```python
from scipy.stats import kruskal

grouped_data = df.groupby('Year')

weighted_ages_by_year = []

for year, group in grouped_data:
    weighted_ages = np.repeat(group['Age'].values, group['Age'].values.astype(int))
    weighted_ages_by_year.append(weighted_ages)


stat, p_value = kruskal(*weighted_ages_by_year)

print("p-value:", p_value)
if p_value < 0.05:
    print("Reject null hypothesis: The distributions are significantly different.")
else:
    print("Fail to reject null hypothesis: The distributions are not significantly diffe
```

```
p-value: 0.0
Reject null hypothesis: The distributions are significantly different.
```

Which age groups are most affected by overdose deaths, and how has this changed over time?

In [22]:
```python
bins = [0, 17, 24, 34, 44, 54, 64, 100]
labels = ['0-17', '18-24', '25-34', '35-44', '45-54', '55-64', '65+']

df['Age Group'] = pd.cut(df['Age'], bins=bins, labels=labels)

age_group_overdose = df.groupby(['Year', 'Age Group']).size().reset_index(name='Deaths')

age_group_overdose_pivot = age_group_overdose.pivot_table(index='Year', columns='Age Gro

age_group_overdose_pivot.plot.bar(stacked=True)
plt.xlabel('Year')
plt.ylabel('Number of Overdose Deaths')
plt.title('Overdose Deaths by Age Group Over Time')
plt.legend(title='Age Group')
plt.show()
```



In [23]:
```
bins = [0, 17, 24, 34, 44, 54, 64, 100]
labels = ['0-17', '18-24', '25-34', '35-44', '45-54', '55-64', '65+']

df['Age Group'] = pd.cut(df['Age'], bins=bins, labels=labels)
age_group_overdose = df.groupby(['Year', 'Age Group']).size().unstack()

age_group_percent = age_group_overdose.div(age_group_overdose.sum(axis=1), axis=0) * 100

for year in age_group_percent.index:
    print(f'Percentage of overdose deaths in {year} by age group:')
    print(age_group_percent.loc[year])
```

```
Percentage of overdose deaths in 2012 by age group:
Age Group
0-17      0.845070
18-24    10.422535
25-34    24.225352
35-44    20.281690
45-54    30.704225
55-64    10.985915
65+       2.535211
Name: 2012, dtype: float64
Percentage of overdose deaths in 2013 by age group:
Age Group
0-17      0.000000
18-24     9.795918
25-34    24.285714
35-44    21.632653
45-54    27.959184
55-64    15.102041
65+       1.224490
Name: 2013, dtype: float64
Percentage of overdose deaths in 2014 by age group:
Age Group
0-17      0.358423
```

```
18-24     7.168459
25-34    23.118280
35-44    27.240143
45-54    29.211470
55-64    10.035842
65+       2.867384
Name: 2014, dtype: float64
Percentage of overdose deaths in 2015 by age group:
Age Group
0-17      0.274348
18-24     8.230453
25-34    23.593964
35-44    21.262003
45-54    25.788752
55-64    17.969822
65+       2.880658
Name: 2015, dtype: float64
Percentage of overdose deaths in 2016 by age group:
Age Group
0-17      0.109051
18-24     6.761178
25-34    25.408942
35-44    23.336968
45-54    25.954198
55-64    16.357688
65+       2.071974
Name: 2016, dtype: float64
Percentage of overdose deaths in 2017 by age group:
Age Group
0-17      0.096339
18-24     7.707129
25-34    26.107900
35-44    24.470135
45-54    22.928709
55-64    16.955684
65+       1.734104
Name: 2017, dtype: float64
Percentage of overdose deaths in 2018 by age group:
Age Group
0-17      0.393314
18-24     6.588004
25-34    22.713864
35-44    25.860374
45-54    24.778761
55-64    16.224189
65+       3.441495
Name: 2018, dtype: float64
Percentage of overdose deaths in 2019 by age group:
Age Group
0-17      0.083333
18-24     5.166667
25-34    23.333333
35-44    26.666667
45-54    21.583333
55-64    19.416667
65+       3.750000
Name: 2019, dtype: float64
Percentage of overdose deaths in 2020 by age group:
Age Group
0-17      0.218341
18-24     5.676856
25-34    22.270742
35-44    25.545852
45-54    21.688501
55-64    20.232897
65+       4.366812
```

```
Name: 2020, dtype: float64
Percentage of overdose deaths in 2021 by age group:
Age Group
0-17      0.196850
18-24     3.937008
25-34    16.863517
35-44    25.000000
45-54    24.868766
55-64    24.278215
65+       4.855643
Name: 2021, dtype: float64
```

The data presented demonstrates the distribution of overdose deaths among different age groups over the years, from 2012 to 2021. It has been observed that the age group with the consistently highest proportion of overdose deaths is the 45-54 age group. However, a decreasing trend in the percentage of overdose deaths in this group has been noticed, particularly from 2012 to 2021.

Significant proportions of overdose deaths have also been found in the 25-34 and 35-44 age groups. These percentages have shown some fluctuations but have remained relatively stable throughout the years. In comparison, the 18-24 and 55-64 age groups have lower proportions of overdose deaths. A decrease in the percentage of overdose deaths in the 18-24 age group has been identified, while an increase in the 55-64 age group's percentage has been observed over the years.

It is noteworthy that the lowest proportions of overdose deaths are consistently found in the 0-17 and 65+ age groups. Their percentages have remained relatively stable and low across the years.

What are the proportions of individuals by sex and race ?

In [24]:
```
# Proportion of overdose deaths by sex
sex_counts = df['Sex'].value_counts(normalize=True)
print("Proportions by Sex:")
print(sex_counts)

# Proportion of overdose deaths by race
race_counts = df['Race'].value_counts(normalize=True)
print("Proportions by Race:")
print(race_counts)
```

```
Proportions by Sex:
Male       0.741795
Female     0.257335
Unknown    0.000869
Name: Sex, dtype: float64
Proportions by Race:
White                               0.864051
Black or African American           0.118779
Unknown                             0.007824
Other                               0.003151
Asian, Other                        0.002608
Asian Indian                        0.002282
Other Asian                         0.000652
Chinese                             0.000217
American Indian or Alaska Native    0.000109
Hawaiian                            0.000109
Native American, Other              0.000109
Korean                              0.000109
Name: Race, dtype: float64
```

An analysis of the data reveals the distribution of proportions by sex and race. Regarding sex, males constitute the majority with a proportion of 74.18%, while females account for 25.73%. A small percentage, 0.09%, is categorized as unknown.

In terms of race, the data indicates that the White population represents the largest proportion at 86.41%. The Black or African American group comes in second with 11.88%. Other racial groups have significantly smaller proportions, with the Unknown category at 0.78%, Other at 0.32%, Asian, Other at 0.26%, and Asian Indian at 0.23%. The remaining groups, including Other Asian, Chinese, American Indian or Alaska Native, Hawaiian, Native American, Other, and Korean, each account for less than 0.1% of the total. The data provides insight into the distribution of proportions across different sex and race categories, offering a basis for further investigation and analysis.

What are the trends in drug involvement in overdose deaths between 2012 and 2021 for various substances ?

In [25]:

```
drug_columns = ['Heroin', 'Cocaine', 'Fentanyl', 'Fentanyl Analogue', 'Oxycodone', 'Oxym

# Convert "Present" and "Not Present" to binary values
df_binary = df.replace({"Present": 1, "Not Present": 0})

# Group the data by year
grouped_by_year = df_binary.groupby('Year')

# Calculate the number of overdose deaths for each year
yearly_overdose_deaths = grouped_by_year.size()

# Calculate the number of overdose deaths involving each drug for each year
yearly_drug_counts = grouped_by_year[drug_columns].sum()

# Calculate the percentage of overdose deaths involving each drug for each year
yearly_drug_percentages = (yearly_drug_counts.div(yearly_overdose_deaths, axis=0)) * 100

print("Percentage of Overdose Deaths Involving Each Drug by Year:")
print(yearly_drug_percentages)
```

```
Percentage of Overdose Deaths Involving Each Drug by Year:
         Heroin    Cocaine   Fentanyl  Fentanyl Analogue  Oxycodone  \
Year
2012  49.014085  29.577465   3.661972           0.000000  19.718310
2013  52.448980  30.000000   7.346939           0.000000  15.102041
2014  58.243728  22.759857  13.440860           0.000000  18.100358
2015  57.201646  24.279835  25.925926           0.000000  13.031550
2016  53.871320  29.989095  52.562704           0.000000  11.995638
2017  45.664740  33.429672  65.125241          13.391137   9.152216
2018  38.446411  33.923304  74.729597          24.975418   6.096362
2019  32.250000  38.583333  81.583333          12.166667   7.666667
2020  19.068413  38.500728  84.352256           4.221252   6.914119
2021  10.892388  43.044619  85.367454           8.595801   5.446194

      Oxymorphone    Ethanol  Hydrocodone  Benzodiazepine  Methadone  ...  \
Year                                                                  ...
2012     8.450704  17.183099     4.225352       13.802817   9.295775  ...
2013     3.265306  16.938776     3.877551       15.918367   9.591837  ...
2014     5.197133  22.580645     2.688172       28.136201   9.139785  ...
2015     0.823045  24.142661     2.743484       30.315501   9.876543  ...
2016     0.763359  27.808070     2.181025       26.390403   9.160305  ...
2017     0.770713  27.938343     1.445087       31.791908   9.537572  ...
2018     1.573255  25.073746     1.376598       26.253687   8.652901  ...
2019     1.666667  28.500000     1.166667       24.166667   7.666667  ...
2020     0.727802  29.403202     0.946143       22.343523   8.733624  ...
2021     0.393701  31.299213     0.656168       19.488189   8.398950  ...

        Amphet    Tramad  Hydromorphone  Morphine (Not Heroin)   Xylazine  \
Year
2012  1.971831  2.253521       0.000000               0.000000   0.000000
2013  0.816327  1.428571       0.000000               0.000000   0.000000
```

```
2014  2.329749  2.688172         0.000000                    0.000000   0.000000
2015  2.743484  2.194787         0.000000                    1.371742   0.000000
2016  2.071974  1.853871         0.000000                    1.635769   0.000000
2017  3.853565  2.697495         1.541426                    1.156069   0.000000
2018  0.000000  3.834808         0.884956                    0.294985   0.000000
2019  0.000000  1.250000         1.166667                    0.166667   0.000000
2020  6.914119  4.585153         0.873362                    0.000000  10.189229
2021  5.708661  3.280840         0.328084                    0.262467  19.750656

      Gabapentin  Opiate NOS  Other Opioid      Other  Any Opioid
Year
2012    0.000000    0.000000      0.000000  10.985915    0.000000
2013    0.000000    0.000000      0.000000   9.795918    0.000000
2014    0.000000    0.000000      0.000000  10.752688    0.000000
2015    0.000000    4.115226      0.000000  10.562414   90.397805
2016    0.000000    3.489640      0.000000   8.396947   93.020720
2017    0.000000    1.156069      0.000000   6.358382    0.000000
2018    0.000000    1.278269      0.000000   6.686332   93.215339
2019    0.000000    1.000000      0.000000  11.500000   93.916667
2020    0.000000    0.946143      6.550218   0.000000   92.649199
2021   11.942257    0.459318      0.000000   5.314961   92.716535

[10 rows x 21 columns]
```

The analysis of overdose death data between 2012 and 2021 highlights several important trends in drug involvement. Over the years, there has been a notable decrease in the percentage of overdose deaths involving heroin, dropping from 49.01% in 2012 to 10.89% in 2021. In contrast, the involvement of cocaine has increased, with percentages rising from 29.58% in 2012 to 43.04% in 2021. Fentanyl has seen a significant surge in its contribution to overdose deaths, skyrocketing from 3.66% in 2012 to 85.37% in 2021. While the percentage of overdose deaths involving fentanyl analogues has fluctuated, oxycodone has consistently declined, falling from 19.72% in 2012 to 5.45% in 2021. Notably, there has been an increase in the involvement of amphetamines in the latter part of the data, particularly from 2019 to 2021. Additionally, the presence of xylazine in overdose deaths has dramatically risen, surging from 0% before 2020 to 19.75% in 2021. These trends emphasize the importance of continuous monitoring and targeted interventions to address the evolving landscape of drug involvement in overdose deaths.

Conclusion

The analysis presented reveals several key insights into drug involvement in accidental deaths:

- Fentanyl is the most prevalent drug involved in accidental deaths, with occurrences rising from 3.66% in 2012 to 85.37% in 2021. Heroin and cocaine also contribute considerably to accidental deaths, with occurrences at 36.37% and 34.46%, respectively. Prescription drugs like oxycodone and hydrocodone are implicated in accidental deaths at lower rates, with occurrences at 9.53% and 1.68%, respectively. Benzodiazepines and ethanol are involved in a sizeable proportion of accidental deaths, with occurrences standing at 24.32% and 26.83%, respectively. Additionally, xylazine has emerged as a concerning new trend, with occurrences rising from 0% before 2020 to 19.75% in 2021. Xylazine is a sedative and muscle relaxant used in veterinary medicine that has been increasingly found in illicit drugs, particularly in combination with fentanyl. This combination of drugs can be extremely dangerous and potent, leading to an increased risk of overdose and death.
- The age group with the consistently highest proportion of overdose deaths is the 45-54 age group, while the lowest proportions of overdose deaths are consistently found in the 0-17 and 65+ age groups. The 25-34 and 35-44 age groups have significant proportions of overdose deaths, while the 18-24 and 55-64 age groups have lower proportions of overdose deaths. The percentage of overdose

deaths in the 45-54 age group has been decreasing over the years, while the percentage in the 55-64 age group has been increasing.
- Males constitute the majority of overdose deaths, with a proportion of 74.18%, while females account for 25.73%. A small percentage, 0.09%, is categorized as unknown. In terms of race, the White population represents the largest proportion of drug involvement at 86.41%, followed by the Black or African American group at 11.88%. Other racial groups have significantly smaller proportions.

To address the issue of drug-related accidental deaths, several strategies can be implemented:

- Increase access to addiction treatment and recovery programs to assist individuals struggling with substance abuse.
- Expand the availability of overdose-reversing drugs like naloxone to prevent fatalities.
- Promote targeted interventions and prevention strategies tailored to the substances causing the most harm, such as fentanyl and the emerging trend of xylazine use.
- Enhance prescription drug monitoring programs to prevent overprescription and misuse.
- Raise awareness among healthcare professionals, policymakers, and the public to reduce the stigma surrounding substance abuse and encourage early interventions.

Limitations

While the analysis provides valuable insights into drug involvement in accidental deaths, there are some limitations to consider. First, the dataset may not be comprehensive as it only includes accidental deaths that were reported and recorded in the system. There may be cases of accidental deaths that were not reported or recorded and therefore not included in the dataset, resulting in an underestimation of the true number of drug-related accidental deaths. Additionally, the accuracy of the data may be limited by inconsistencies or errors in the recorded information such as the description of injury or cause of death. Furthermore, the dataset only includes information on specific drugs such as heroin, cocaine, and fentanyl but may not capture the full range of substances involved in accidental deaths. For example, the emerging trend of xylazine use, which has been found in combination with fentanyl, may not be fully captured in the data. Therefore, while the analysis provides valuable insights, it is important to acknowledge the limitations of the data and conduct further research to fully understand the scope and nature of drug-related accidental deaths and develop effective prevention and intervention strategies.

In [26]:

In [ ]:

In [ ]: