For this task, the client has performed some experimentations on some trial stores (77, 86, 88) based on our last research. Let's first find out the eligible control stores out of the other ones and then, compare both trial and control stores to check how the trials went.

In [1]:
```
# Importing necessary libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime as dt
import re
from collections import Counter
import statistics
import scipy.stats as stats
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline

# Setting parameters for plots
plt.rcParams['axes.titleweight'] = 'bold'
plt.rcParams['axes.titlelocation'] = 'center'
plt.rcParams['axes.titlepad'] = 20
```

In [2]:
```
data = pd.read_csv('QVI_data.csv')
```

In [3]:
```
data.head(5)
```

Out[3]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRAND	LIFESTAGE
0	1000	2018-10-17	1	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175	NATURAL	YOUNG SINGLES/COUPLES
1	1002	2018-09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	1	2.7	150	RRD	YOUNG SINGLES/COUPLES
2	1003	2019-03-07	1	3	52	Grain Waves Sour Cream&Chives 210G	1	3.6	210	GRNWVES	YOUNG FAMILIES
3	1003	2019-03-08	1	4	106	Natural ChipCo Hony Soy Chckn175g	1	3.0	175	NATURAL	YOUNG FAMILIES
4	1004	2018-11-02	1	5	96	WW Original Stacked Chips 160g	1	1.9	160	WOOLWORTHS	OLDER SINGLES/COUPLES

In [4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264834 entries, 0 to 264833
Data columns (total 12 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   LYLTY_CARD_NBR    264834 non-null  int64  
 1   DATE              264834 non-null  object 
 2   STORE_NBR         264834 non-null  int64  
 3   TXN_ID            264834 non-null  int64  
 4   PROD_NBR          264834 non-null  int64  
 5   PROD_NAME         264834 non-null  object 
 6   PROD_QTY          264834 non-null  int64  
 7   TOT_SALES         264834 non-null  float64
 8   PACK_SIZE         264834 non-null  int64  
 9   BRAND             264834 non-null  object 
 10  LIFESTAGE         264834 non-null  object 
 11  PREMIUM_CUSTOMER  264834 non-null  object 
dtypes: float64(1), int64(6), object(5)
memory usage: 24.2+ MB
```

In [5]:
```
data['DATE'] = pd.to_datetime(data['DATE'])
```

In [6]:
```
data.describe()
```

Out[6]:

	LYLTY_CARD_NBR	STORE_NBR	TXN_ID	PROD_NBR	PROD_QTY	TOT_SALES	PACK_SIZE
count	2.648340e+05	264834.000000	2.648340e+05	264834.000000	264834.000000	264834.000000	264834.000000
mean	1.355488e+05	135.079423	1.351576e+05	56.583554	1.905813	7.299346	182.425512
std	8.057990e+04	76.784063	7.813292e+04	32.826444	0.343436	2.527241	64.325148
min	1.000000e+03	1.000000	1.000000e+00	1.000000	1.000000	1.500000	70.000000
25%	7.002100e+04	70.000000	6.760050e+04	28.000000	2.000000	5.400000	150.000000
50%	1.303570e+05	130.000000	1.351365e+05	56.000000	2.000000	7.400000	170.000000
75%	2.030940e+05	203.000000	2.026998e+05	85.000000	2.000000	9.200000	175.000000
max	2.373711e+06	272.000000	2.415841e+06	114.000000	5.000000	29.500000	380.000000

Let's find these measures and filter our control stores, which will be stores that are present throughout the pre-trial period.

- Monthly overall sales revenue
- Monthly number of customers
- Monthly number of transactions per customer

In [7]:
```
# Creating new month column
data['YEARMONTH'] = data['DATE'].dt.strftime('%Y%m')
```

In [8]:
```
data.head(3)
```

Out[8]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRAND	LIFESTAGE	PR
0	1000	2018-10-17	1	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175	NATURAL	YOUNG SINGLES/COUPLES	
1	1002	2018-09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	1	2.7	150	RRD	YOUNG SINGLES/COUPLES	
2	1003	2019-03-07	1	3	52	Grain Waves Sour Cream&Chives 210G	1	3.6	210	GRNWVES	YOUNG FAMILIES	

In [9]:
```
# For each store and month, calculate total sales, number of customers, transactions per customer,
# chips per customer and the average price per unit

measure_over_time = data.groupby(['STORE_NBR', 'YEARMONTH']).agg(
    totSales = ('TOT_SALES',sum),
    nCustomers = ('LYLTY_CARD_NBR', pd.Series.nunique),
    nAvgTxnPerCust = ('TXN_ID', lambda x: x.count()/data.loc[x.index, 'LYLTY_CARD_NBR'].nunique()),
    nChipsPerTxn = ('PROD_QTY', lambda x: x.sum()/data.loc[x.index, 'TXN_ID'].count()),
    avgPricePerUnit = ('TOT_SALES', lambda x:x.sum()/data.loc[x.index, 'PROD_QTY'].sum())
).reset_index()

measure_over_time = measure_over_time.sort_values(by=['STORE_NBR', 'YEARMONTH'])
```

In [10]:
```
# Finding stores that worked for full observation period

store_with_full_ob = list((measure_over_time['YEARMONTH'].groupby(measure_over_time['STORE_NBR']).nunique()==12).index)
```

In [11]:
```
# Filtering full observation stores in pre-trial period (Feb 2019)

pre_trial_measure = measure_over_time[(measure_over_time['YEARMONTH'] < '201902') & (measure_over_time['STORE_NBR'].isin(sto
pre_trial_measure
```

Out[11]:

	STORE_NBR	YEARMONTH	totSales	nCustomers	nAvgTxnPerCust	nChipsPerTxn	avgPricePerUnit
0	1	201807	206.9	49	1.061224	1.192308	3.337097
1	1	201808	176.1	42	1.023810	1.255814	3.261111
2	1	201809	278.8	59	1.050847	1.209677	3.717333
3	1	201810	188.1	44	1.022727	1.288889	3.243103
4	1	201811	192.6	46	1.021739	1.212766	3.378947
...	...	...	...	...	...	...	...
3159	272	201809	304.7	32	1.125000	1.972222	4.291549
3160	272	201810	430.6	44	1.159091	1.941176	4.349495
3161	272	201811	376.2	41	1.097561	1.933333	4.324138
3162	272	201812	403.9	47	1.000000	1.893617	4.538202
3163	272	201901	423.0	46	1.086957	1.920000	4.406250

1848 rows × 7 columns

In [12]:
```
pre_trial_measure.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1848 entries, 0 to 3163
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   STORE_NBR        1848 non-null   int64  
 1   YEARMONTH        1848 non-null   object 
 2   totSales         1848 non-null   float64
 3   nCustomers       1848 non-null   int64  
 4   nAvgTxnPerCust   1848 non-null   float64
 5   nChipsPerTxn     1848 non-null   float64
 6   avgPricePerUnit  1848 non-null   float64
dtypes: float64(4), int64(2), object(1)
memory usage: 115.5+ KB
```

In [13]:
```
# Let's make a function to calculate correlation between control stores and trial/comparison stores

def calculate_correlation(metric_table, metric_col, store_comparison):
    # Creating dataframe for output result
    corr_table = pd.DataFrame(columns = ['store1', 'store2', 'corr_measure'])

    # Filtering control stores
    stores = metric_table['STORE_NBR'].unique()
    control_stores = stores[~pd.Series(stores).isin([77, 86, 88])]

    for store in control_stores:

        # Creating control store data & comparison store data
        compStore_data = metric_table[metric_table['STORE_NBR'] == store_comparison][metric_col].reset_index(drop=True)
        controlStore_data = metric_table[metric_table['STORE_NBR'] == store][metric_col].reset_index(drop=True)

        # Checking both stores data have equal length for correlation
        min_len = min(len(compStore_data), len(controlStore_data))
        compStore_data = compStore_data[:min_len]
        controlStore_data = controlStore_data[:min_len]

        # Calculating correlation
        corr_measure = compStore_data.corr(controlStore_data)

        # Create a DataFrame with the result
        calculated_measure = pd.DataFrame({
            'store1': [store_comparison],
            'store2': [store],
            'corr_measure': [corr_measure]})
        corr_table = pd.concat([corr_table, calculated_measure], ignore_index = True)

    # Appending data in output DF
    return corr_table
```

In [14]:
```
# Creating a function to calculate a standardised magnitude distance for a measure

def calculate_magnitude_distance(metric_table, metric_col, store_comparison):
    # Creating dataframe for output result
    calc_dist_table = pd.DataFrame(columns = ['store1', 'store2', 'YEARMONTH', 'measure'])

    # Getting unique store numbers
    store_numbers = metric_table['STORE_NBR'].unique()

    # Loop through each store number
    for store in store_numbers:
        if store != store_comparison:

            # Extracting data for the comparison store and the current control store
            comparison_store_data = metric_table[metric_table['STORE_NBR'] == store_comparison]
            control_store_data = metric_table[metric_table['STORE_NBR'] == store]

            # Merging on YEARMONTH to ensure we are comparing the same months
            merged_data = pd.merge(comparison_store_data, control_store_data, on='YEARMONTH', suffixes=('_comparison', '_con

            # Calculating the absolute difference in the metric
            merged_data['measure'] = np.abs(merged_data[f'{metric_col}_comparison'] - merged_data[f'{metric_col}_control'])

            # Creating a DataFrame with the calculated measure
            calculated_measure = merged_data[['STORE_NBR_comparison', 'STORE_NBR_control', 'YEARMONTH', 'measure']]
            calculated_measure.columns = ['store1', 'store2', 'YEARMONTH', 'measure']

            # Appending the result to the calculation table
            calc_dist_table = pd.concat([calc_dist_table, calculated_measure], ignore_index=True)

    # Standardizing the magnitude distance so that the measure ranges from 0 to 1
    min_max_dist = calc_dist_table.groupby(['store1', 'YEARMONTH']).agg(
        minDist=('measure', 'min'),
        maxDist=('measure', 'max')
    ).reset_index()

    dist_table = pd.merge(calc_dist_table, min_max_dist, on=['store1', 'YEARMONTH'])
    dist_table['magnitude_measure'] = 1 - (dist_table['measure'] - dist_table['minDist']) / (dist_table['maxDist'] - dist_ta

    final_dist_table = dist_table.groupby(['store1', 'store2']).agg(
        mag_measure=('magnitude_measure', 'mean')
    ).reset_index()

    return final_dist_table
```

Trial Store: 77

In [15]:
```
# Calculating correlation measure and magnitude distance between trial store & control store sales and customers.

metric_table = pre_trial_measure
trial_store = 77

# Calculate correlations
corr_n_sales = calculate_correlation(metric_table, 'totSales', trial_store)
corr_n_customers = calculate_correlation(metric_table, 'nCustomers', trial_store)

# Calculate magnitude distances
magnitude_n_sales = calculate_magnitude_distance(metric_table, 'totSales', trial_store)
magnitude_n_customers = calculate_magnitude_distance(metric_table, 'nCustomers', trial_store)

# Display the results
print("Correlation of total sales:")
print(corr_n_sales)
print("\nCorrelation of number of customers:")
print(corr_n_customers)
print("\nMagnitude distance of total sales:")
print(magnitude_n_sales)
print("\nMagnitude distance of number of customers:")
print(magnitude_n_customers)
```

```
Correlation of total sales:
    store1 store2  corr_measure
0       77      1      0.075218
1       77      2     -0.263079
2       77      3      0.806644
3       77      4     -0.263300
4       77      5     -0.110652
..     ...    ...           ...
263     77    268      0.344757
264     77    269     -0.315730
265     77    270      0.315430
266     77    271      0.355487
267     77    272      0.117622

[268 rows x 3 columns]

Correlation of number of customers:
    store1 store2  corr_measure
0       77      1      0.322168
1       77      2     -0.572051
2       77      3      0.834207
3       77      4     -0.295639
4       77      5      0.370659
..     ...    ...           ...
263     77    268      0.369517
264     77    269     -0.474293
265     77    270     -0.131259
266     77    271      0.019629
267     77    272      0.223217

[268 rows x 3 columns]

Magnitude distance of total sales:
     store1  store2  mag_measure
0        77       1     0.955061
1        77       2     0.939318
2        77       3     0.354963
3        77       4     0.177414
4        77       5     0.554066
..      ...     ...          ...
265      77     268     0.962563
266      77     269     0.452903
267      77     270     0.446991
268      77     271     0.553304
269      77     272     0.886697

[270 rows x 3 columns]

Magnitude distance of number of customers:
     store1  store2  mag_measure
0        77       1     0.940321
1        77       2     0.924638
2        77       3     0.345067
3        77       4     0.189579
4        77       5     0.481199
..      ...     ...          ...
265      77     268     0.939907
266      77     269     0.343547
267      77     270     0.357725
268      77     271     0.483457
269      77     272     0.948207

[270 rows x 3 columns]
```

In [16]:
```
# let's merge sales and nCustomers table and assign 0.5 weight of correlation and 0.5 weight of magnitude to give a cumulati
weight = 0.5
score_n_sales = pd.merge(corr_n_sales, magnitude_n_sales, on = ['store1', 'store2'])
score_n_sales['score_n_sales'] = weight*(score_n_sales['corr_measure'] + score_n_sales['mag_measure'])

score_n_customers = pd.merge(corr_n_customers, magnitude_n_customers, on = ['store1', 'store2'])
score_n_customers['score_n_customers'] = weight*score_n_customers['corr_measure'] + weight*score_n_customers['mag_measure']
```

In [17]:
```
'''Now, let's combine both the scores in a single table and find our control table with highest average score
of both sales and customer measure scores'''

score_control = pd.merge(score_n_sales[['store1', 'store2', 'score_n_sales']], score_n_customers[['store1', 'store2', 'score_
score_control['final_control_score'] = 0.5*score_n_sales['score_n_sales'] + 0.5*score_n_customers['score_n_customers']

score_control.sort_values(by = 'final_control_score', ascending= False).head(5)
```

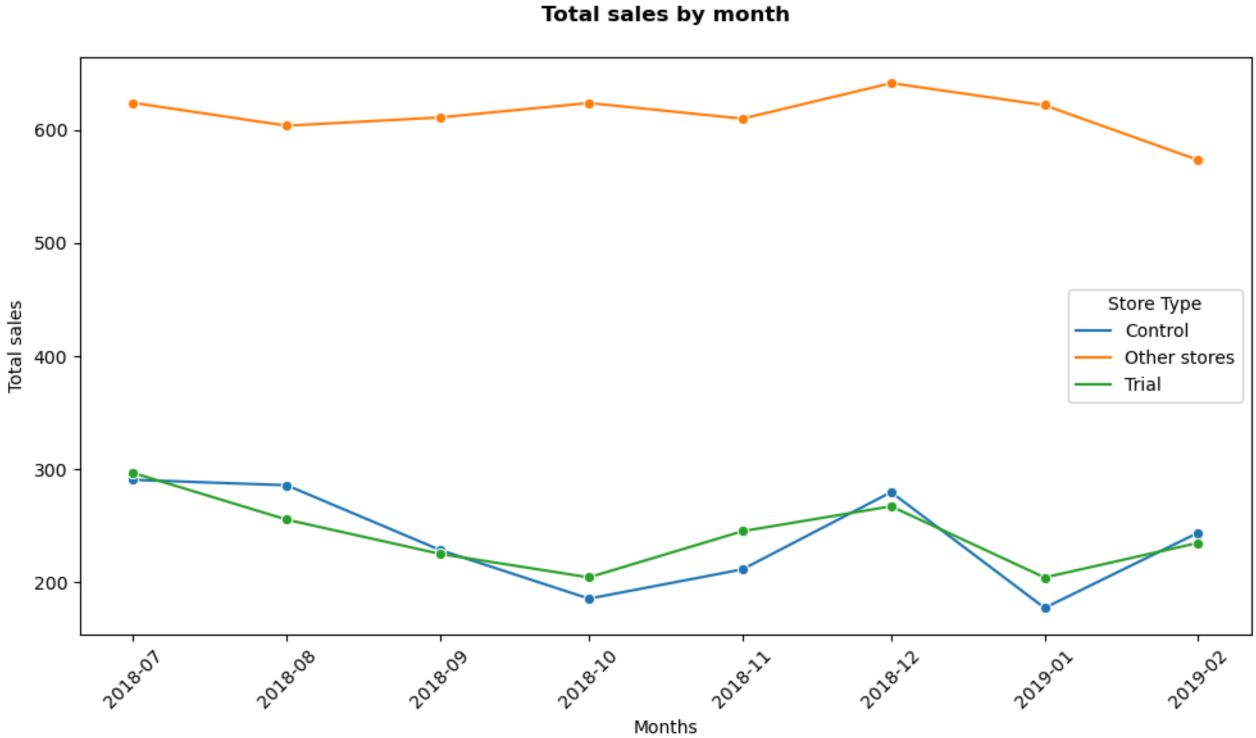
Out[17]:

	store1	store2	score_n_sales	score_n_customers	final_control_score
228	77	233	0.945433	0.991566	0.968499
40	77	41	0.875075	0.909429	0.892252
16	77	17	0.862491	0.854902	0.858696
249	77	254	0.750788	0.926670	0.838729
110	77	115	0.811868	0.842399	0.827133

We can clearly see that store #233 is the most closest to trial store #77. So we can say that store #233 is the control store for store #77

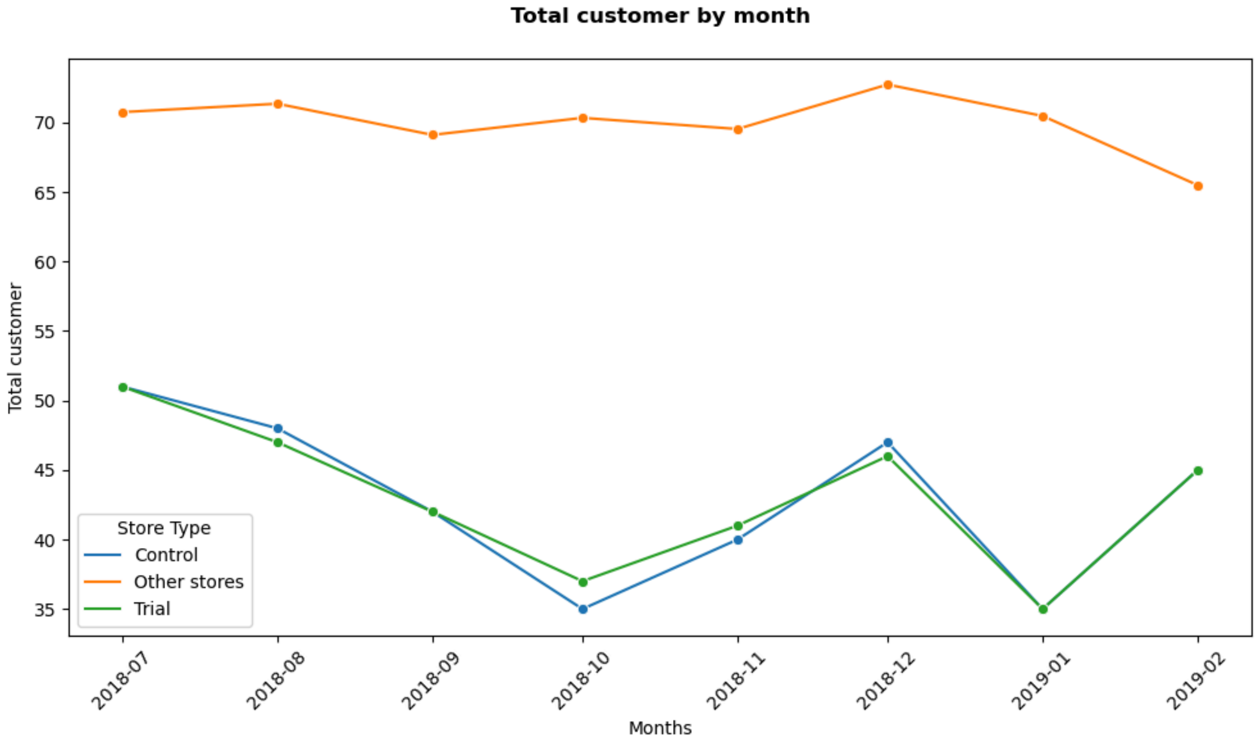
In [18]:
```
control_store = 233
trial_store = 77
```

In [19]:
```
# Let's visualize if the control store was actually similar before trial period

# Categorizing stores
measure_over_time['Store_type'] = np.where(measure_over_time['STORE_NBR'] == trial_store, 'Trial',
                                           np.where(measure_over_time['STORE_NBR'] == control_store,
                                                    'Control',
                                                    'Other stores'))

# Calculate mean of totSales by YEARMONTH and Store_type
past_sales = measure_over_time.groupby(['YEARMONTH', 'Store_type']).agg({'totSales': 'mean'}).reset_index()

# Convert YEARMONTH to datetime format
past_sales['TransactionMonth'] = pd.to_datetime(past_sales['YEARMONTH'].astype(str) + '01', format='%Y%m%d')

# Filter data for YEARMONTH < 201903
past_sales = past_sales[past_sales['YEARMONTH'] < '201903']

# Plot the data
plt.figure(figsize=(10, 6))
sns.lineplot(data=past_sales, x='TransactionMonth', y='totSales', hue='Store_type', marker='o')
plt.xlabel('Months')
plt.ylabel('Total sales')
plt.title('Total sales by month')
plt.xticks(rotation=45)
plt.legend(title='Store Type')
plt.tight_layout()
plt.show()
```



It is clearly visible that sales of both the stores show similar trends over the time.

In [20]:
```
# Let's visualize number of customer trends for both the stores

# Categorizing stores
measure_over_time['Store_type'] = np.where(measure_over_time['STORE_NBR'] == trial_store, 'Trial',
                                           np.where(measure_over_time['STORE_NBR'] == control_store,
                                                    'Control',
                                                    'Other stores'))

# Calculate mean of nCustomers by YEARMONTH and Store_type
past_customers = measure_over_time.groupby(['YEARMONTH', 'Store_type']).agg({'nCustomers': 'mean'}).reset_index()

# Convert YEARMONTH to datetime format
past_customers['TransactionMonth'] = pd.to_datetime(past_customers['YEARMONTH'].astype(str) + '01', format='%Y%m%d')

# Filter data for YEARMONTH < 201903
past_customers = past_customers[past_customers['YEARMONTH'] < '201903']

# Plot the data
plt.figure(figsize=(10, 6))
sns.lineplot(data=past_customers, x='TransactionMonth', y='nCustomers', hue='Store_type', marker='o')
plt.xlabel('Months')
plt.ylabel('Total customer')
plt.title('Total customer by month')
plt.xticks(rotation=45)
plt.legend(title='Store Type')
plt.tight_layout()
plt.show()
```



Both of the line charts follow similar trend. Therefore, we can say that our calculation results matches the visualization results.

Assessment of Trial

Trial Period -> start of February 2019 to April 2019

In [21]:
```
now want to see if there has been an uplift in overall chip sales.

lculating scaling factor to make control store sales equivalent to trial store sales
ing_factor_for_control_sales = pre_trial_measure[(pre_trial_measure['STORE_NBR'] == trial_store) &
_trial_measure['YEARMONTH'] < '201902')]['totSales'].sum()/pre_trial_measure[(pre_trial_measure['STORE_NBR'] == control_store
_trial_measure['YEARMONTH'] < '201902')]['totSales'].sum()

lculating scaled control sales using scaling factor
ed_control_sales = measure_over_time[measure_over_time['STORE_NBR'] == control_store].copy()
ed_control_sales['controlSales'] = scaled_control_sales['totSales'] * scaling_factor_for_control_sales

ial sales
l_sales = measure_over_time[measure_over_time['STORE_NBR'] == trial_store].copy()

rging trial sales and scaled control sales to find %diff
entageDiff = pd.merge(trial_sales[['STORE_NBR', 'YEARMONTH', 'totSales']],
                       scaled_control_sales[['STORE_NBR', 'YEARMONTH','controlSales']],
                      on='YEARMONTH', suffixes=['_trial', '_control'])

entageDiff['percentDiff'] = (abs(percentageDiff['totSales'] - percentageDiff['controlSales']) / percentageDiff['controlSales'
entageDiff
```

Out[21]:

	STORE_NBR_trial	YEARMONTH	totSales	STORE_NBR_control	controlSales	percentDiff
0	77	201807	296.8	233	297.565550	0.257271
1	77	201808	255.5	233	292.652187	12.694997
2	77	201809	225.2	233	233.998916	3.760238
3	77	201810	204.5	233	190.085733	7.583035
4	77	201811	245.3	233	216.597421	13.251579
5	77	201812	267.3	233	286.408121	6.671641
6	77	201901	204.4	233	181.692071	12.498029
7	77	201902	235.0	233	249.762622	5.910661
8	77	201903	278.5	233	203.802205	36.652103
9	77	201904	263.5	233	162.345704	62.307960
10	77	201905	299.3	233	352.533799	15.100339
11	77	201906	264.7	233	226.219424	17.010288

Let's check statistically if there is significant difference between sales of control stores and trial stores in trial period

Null Hypothesis: There is no difference between stores and trial stores sales

Alternate Hypothesis: There is a significant difference between stores and trial stores sales

In [22]:
```
# Assuming pre-trial period is equal to trial period.
# Standard deviation calculation for pre-trial period.
std_dev = statistics.stdev(percentageDiff[percentageDiff['YEARMONTH'] < '201902']['percentDiff'])
std_dev
```

Out[22]: 4.994076264142537

In [23]:
```
# Calculaing t-values based on percentage diff in trial period
trial_percentageDiff = percentageDiff[percentageDiff['YEARMONTH'].isin(['201902','201903','201904'])].copy()
trial_percentageDiff['tValue'] = (trial_percentageDiff['totSales'] - trial_percentageDiff['controlSales'])/std_dev
trial_percentageDiff
```

Out[23]:

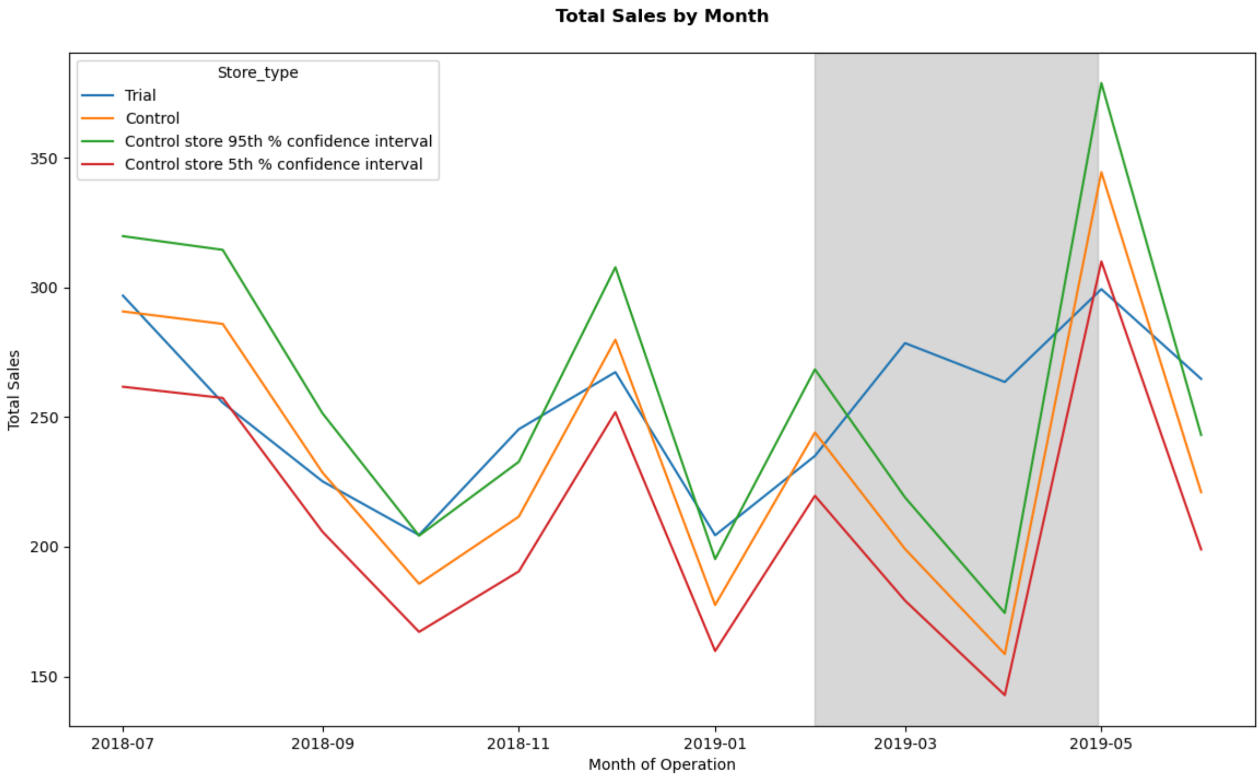
	STORE_NBR_trial	YEARMONTH	totSales	STORE_NBR_control	controlSales	percentDiff	tValue
7	77	201902	235.0	233	249.762622	5.910661	-2.956027
8	77	201903	278.5	233	203.802205	36.652103	14.957280
9	77	201904	263.5	233	162.345704	62.307960	20.254856

In [24]:
```
# Calculating critical value for 95% percentile with degrees of freedom (total months - 1)
critical_value = stats.t.ppf(0.95, 7)
critical_value
```

Out[24]: 1.894578605061305

Since t-statistic value is higher than the 95% critical value for the months March & April, we can say that sales of trial stores are significantly higher than the control stores.

In [25]:
```
''' Visualizing trial store sales, control store sales, 5% & 95% CI on store sales to check any significant difference
    in sales of trial and control stores.'''

# Calculate std_dev (standard deviation of percentage difference)
std_dev = std_dev/100

# Prepare data for plotting
measure_over_time['TransactionMonth'] = pd.to_datetime(measure_over_time['YEARMONTH'].astype(str) + '01', format='%Y%m%d')

# Filter data for trial and control stores
past_sales = measure_over_time[measure_over_time['STORE_NBR'].isin([control_store, trial_store])].copy()
past_sales = past_sales.reset_index(drop=True)

# Calculate Control store 95th and 5th percentile
past_sales_controls_95 = past_sales[past_sales['STORE_NBR'] == control_store].copy()
past_sales_controls_95['totSales'] = past_sales_controls_95['totSales'] * (1 + std_dev * 2)
past_sales_controls_95['Store_type'] = 'Control store 95th % confidence interval'
past_sales_controls_95 = past_sales_controls_95.reset_index(drop=True)


past_sales_controls_5 = past_sales[past_sales['STORE_NBR'] == control_store].copy()
past_sales_controls_5['totSales'] = past_sales_controls_5['totSales'] * (1 - std_dev * 2)
past_sales_controls_5['Store_type'] = 'Control store 5th % confidence interval'
past_sales_controls_5 = past_sales_controls_5.reset_index(drop=True)

# Combine all data
trial_assessment = pd.concat([past_sales, past_sales_controls_95, past_sales_controls_5])
trial_assessment = trial_assessment.reset_index(drop=True)

# Plotting
plt.figure(figsize=(14, 8))
sns.lineplot(data=trial_assessment, x='TransactionMonth', y='totSales', hue='Store_type')

# Highlight the trial period (Feb 2019 to Apr 2019)
plt.axvspan(dt(2019, 2, 1), dt(2019, 4, 30), color='grey', alpha=0.3, ymin=0, ymax=1)

# Mark significant differences
# Identify months where trial store sales are outside 5% to 95% confidence interval
trial_sales = trial_assessment[trial_assessment['STORE_NBR'] == trial_store]
control_95th = trial_assessment[(trial_assessment['Store_type'] == 'Control store 95th % confidence interval') &
                                (trial_assessment['STORE_NBR'] == control_store)]
control_5th = trial_assessment[(trial_assessment['Store_type'] == 'Control store 5th % confidence interval') &
                               (trial_assessment['STORE_NBR'] == control_store)]

# Mark significant points
significant_months = trial_sales[(trial_sales['totSales'] < control_5th['totSales'].min()) |
                                 (trial_sales['totSales'] > control_95th['totSales'].max())]

plt.scatter(significant_months['TransactionMonth'], significant_months['totSales'], color='red', label='Significant Differen

plt.title('Total Sales by Month')
plt.xlabel('Month of Operation')
plt.ylabel('Total Sales')
plt.show()
```



Let's analyze nCustomers now. We now want to see if there has been an uplift in number of chip customers over trial period.

In [26]:
```
# Calculating scaling factor to make control store customers equivalent to trial store customers
scaling_factor_for_control_customers = pre_trial_measure[(pre_trial_measure['STORE_NBR'] == trial_store) &
(pre_trial_measure['YEARMONTH'] < '201902')]['nCustomers'].sum()/pre_trial_measure[(pre_trial_measure['STORE_NBR'] == contro
(pre_trial_measure['YEARMONTH'] < '201902')]['nCustomers'].sum()

# Calculating scaled control customers using scaling factor
scaled_control_customers = measure_over_time[measure_over_time['STORE_NBR'] == control_store].copy()
scaled_control_customers['controlCustomers'] = scaled_control_customers['nCustomers'] * scaling_factor_for_control_customers

# Trial customers
trial_customers = measure_over_time[measure_over_time['STORE_NBR'] == trial_store].copy()

# Merging trial customers and scaled control customers to find %diff
percentageDiffCust = pd.merge(trial_customers[['STORE_NBR', 'YEARMONTH', 'nCustomers']],
                        scaled_control_customers[['STORE_NBR', 'YEARMONTH','controlCustomers']],
                       on='YEARMONTH', suffixes=['_trial', '_control'])

percentageDiffCust['percentageDiffCust'] = (abs(percentageDiffCust['nCustomers'] - percentageDiffCust['controlCustomers']) /
percentageDiffCust
```

Out[26]:

	STORE_NBR_trial	YEARMONTH	nCustomers	STORE_NBR_control	controlCustomers	percentageDiffCust
0	77	201807	51	233	51.171141	0.334448
1	77	201808	47	233	48.161074	2.410814
2	77	201809	42	233	42.140940	0.334448
3	77	201810	37	233	35.117450	5.360726
4	77	201811	41	233	40.134228	2.157191
5	77	201812	46	233	47.157718	2.454992
6	77	201901	35	233	35.117450	0.334448
7	77	201902	45	233	45.151007	0.334448
8	77	201903	50	233	40.134228	24.581940
9	77	201904	47	233	30.100671	56.142698
10	77	201905	55	233	57.191275	3.831485
11	77	201906	41	233	41.137584	0.334448

Let's check statistically if there is significant difference between nCustomers of control stores and trial stores in trial period

Null Hypothesis: There is no difference between stores and trial stores nCustomers

Alternate Hypothesis: There is a significant difference between stores and trial stores nCustomers

In [27]:
```
# Assuming pre-trial period is equal to trial period.
# Standard deviation calculation for pre-trial period.
std_dev_cust = statistics.stdev(percentageDiffCust[percentageDiffCust['YEARMONTH'] < '201902']['percentageDiffCust'])
std_dev_cust
```

Out[27]: 1.8240748558243947

In [28]:
```
# Calculaing t-values based on percentage diff in trial period
trial_percentageDiffCust = percentageDiffCust[percentageDiffCust['YEARMONTH'].isin(['201902','201903','201904'])].copy()
trial_percentageDiffCust['tValue'] = (trial_percentageDiffCust['nCustomers'] - trial_percentageDiffCust['controlCustomers'])/
trial_percentageDiffCust
```

Out[28]:

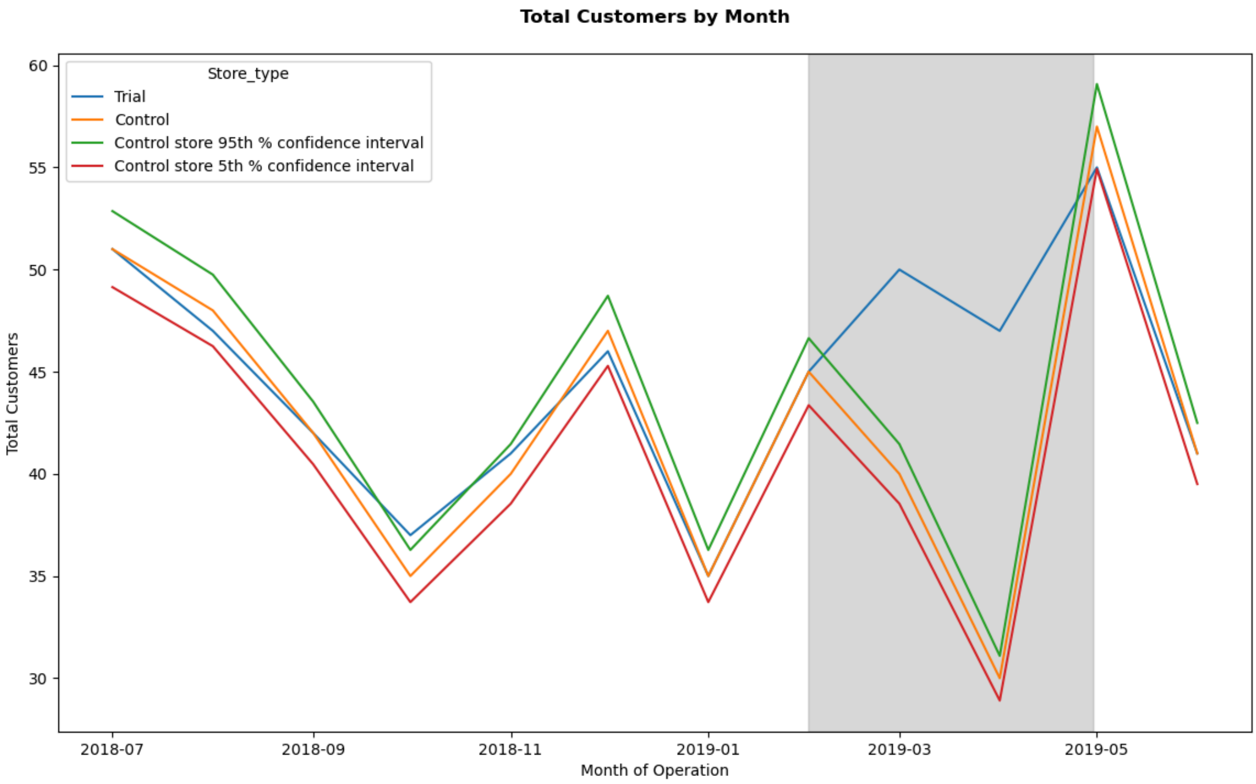
	STORE_NBR_trial	YEARMONTH	nCustomers	STORE_NBR_control	controlCustomers	percentageDiffCust	tValue
7	77	201902	45	233	45.151007	0.334448	-3.023717
8	77	201903	50	233	40.134228	24.581940	197.549482
9	77	201904	47	233	30.100671	56.142698	338.387481

In [29]:
```
# Calculating critical value for 95% percentile (1-0.05) with degrees of freedom (total pre-trial months - 1)
critical_value = stats.t.ppf(0.95, 7)
critical_value
```

Out[29]: 1.894578605061305

Since t-statistic value is higher than the 95% critical value for the months March & April, we can say that sales of trial stores are significantly higher than the control stores.

In [30]:
```
''' Visualizing trial store nCustomers, control store nCustomers, 5% & 95% CI on store nCustomers to check any significant di
    in nCustomers of trial and control stores.'''

# Calculate std_dev (standard deviation of percentage difference)
std_dev_cust = std_dev_cust/100

# Prepare data for plotting
measure_over_time['TransactionMonth'] = pd.to_datetime(measure_over_time['YEARMONTH'].astype(str) + '01', format='%Y%m%d')

# Filter data for trial and control stores
past_cust = measure_over_time[measure_over_time['STORE_NBR'].isin([control_store, trial_store])].copy()
past_cust = past_cust.reset_index(drop=True)

# Calculate Control store 95th and 5th percentile
past_cust_controls_95 = past_cust[past_cust['STORE_NBR'] == control_store].copy()
past_cust_controls_95['nCustomers'] = past_cust_controls_95['nCustomers'] * (1 + std_dev_cust * 2)
past_cust_controls_95['Store_type'] = 'Control store 95th % confidence interval'
past_cust_controls_95 = past_cust_controls_95.reset_index(drop=True)


past_cust_controls_5 = past_cust[past_cust['STORE_NBR'] == control_store].copy()
past_cust_controls_5['nCustomers'] = past_cust_controls_5['nCustomers'] * (1 - std_dev_cust * 2)
past_cust_controls_5['Store_type'] = 'Control store 5th % confidence interval'
past_cust_controls_5 = past_cust_controls_5.reset_index(drop=True)

# Combine all data
trial_assessment_cust = pd.concat([past_cust, past_cust_controls_95, past_cust_controls_5])
trial_assessment_cust = trial_assessment_cust.reset_index(drop=True)

# Plotting
plt.figure(figsize=(14, 8))
sns.lineplot(data=trial_assessment_cust, x='TransactionMonth', y='nCustomers', hue='Store_type')

# Highlight the trial period (Feb 2019 to Apr 2019)
plt.axvspan(dt(2019, 2, 1), dt(2019, 4, 30), color='grey', alpha=0.3)

# Mark significant differences
# Identify months where trial store sales are outside 5% to 95% confidence interval
trial_sales = trial_assessment_cust[trial_assessment_cust['STORE_NBR'] == trial_store]
control_95th = trial_assessment_cust[(trial_assessment_cust['Store_type'] == 'Control store 95th % confidence interval') &
                                (trial_assessment_cust['STORE_NBR'] == control_store)]
control_5th = trial_assessment_cust[(trial_assessment_cust['Store_type'] == 'Control store 5th % confidence interval') &
                                (trial_assessment_cust['STORE_NBR'] == control_store)]

# Mark significant points
significant_months_cust = trial_customers[(trial_customers['nCustomers'] < control_5th['nCustomers'].min()) |
                                 (trial_customers['nCustomers'] > control_95th['nCustomers'].max())]

plt.scatter(significant_months_cust['TransactionMonth'], significant_months_cust['nCustomers'], color='red', label='Signific

plt.title('Total Customers by Month')
plt.xlabel('Month of Operation')
plt.ylabel('Total Customers')
plt.show()
```



The results show that the trial in store 77 is significantly different to its control store 233 in the trial period as the trial store performance of both sales and nCustomers lies outside the 5% to 95% confidence interval of the control store in two of the three trial months.

Trial Store: 86

In [31]:
```
# Calculating correlation measure and magnitude distance between trial store & control store sales and customers.

metric_table = pre_trial_measure
trial_store = 86

# Calculate correlations
corr_n_sales = calculate_correlation(metric_table, 'totSales', trial_store)
corr_n_customers = calculate_correlation(metric_table, 'nCustomers', trial_store)

# Calculate magnitude distances
magnitude_n_sales = calculate_magnitude_distance(metric_table, 'totSales', trial_store)
magnitude_n_customers = calculate_magnitude_distance(metric_table, 'nCustomers', trial_store)

# Display the results
print("Correlation of total sales:")
print(corr_n_sales)
print("\nCorrelation of number of customers:")
print(corr_n_customers)
print("\nMagnitude distance of total sales:")
print(magnitude_n_sales)
print("\nMagnitude distance of number of customers:")
print(magnitude_n_customers)
```

```
Correlation of total sales:
     store1 store2  corr_measure
0        86      1      0.445632
1        86      2     -0.403835
2        86      3     -0.261284
3        86      4     -0.039035
4        86      5      0.235159
..      ...    ...           ...
263      86    268     -0.452182
264      86    269      0.697055
265      86    270     -0.730679
266      86    271      0.527637
267      86    272      0.004926

[268 rows x 3 columns]

Correlation of number of customers:
     store1 store2  corr_measure
0        86      1      0.485831
1        86      2     -0.086161
2        86      3     -0.353786
3        86      4     -0.169608
4        86      5     -0.253229
..      ...    ...           ...
263      86    268     -0.034273
264      86    269     -0.098587
265      86    270     -0.767267
266      86    271      0.267393
267      86    272     -0.353815

[268 rows x 3 columns]

Magnitude distance of total sales:
      store1  store2  mag_measure
0         86       1     0.223241
1         86       2     0.182441
2         86       3     0.763928
3         86       4     0.500566
4         86       5     0.929427
..       ...     ...          ...
265       86     268     0.253331
266       86     269     0.902364
267       86     270     0.835237
268       86     271     0.923218
269       86     272     0.448642

[270 rows x 3 columns]

Magnitude distance of number of customers:
      store1  store2  mag_measure
0         86       1     0.448607
1         86       2     0.385119
2         86       3     0.912508
3         86       4     0.775997
4         86       5     0.926931
..       ...     ...          ...
265       86     268     0.431592
266       86     269     0.917790
267       86     270     0.891428
268       86     271     0.936337
269       86     272     0.429452

[270 rows x 3 columns]
```

In [32]:

```
# Let's merge sales and nCustomers table and assign 0.5 weight of correlation and 0.5 weight of magnitude to give a cumulati
weight = 0.5
score_n_sales = pd.merge(corr_n_sales, magnitude_n_sales, on = ['store1', 'store2'])
score_n_sales['score_n_sales'] = weight*(score_n_sales['corr_measure'] + score_n_sales['mag_measure'])

score_n_customers = pd.merge(corr_n_customers, magnitude_n_customers, on = ['store1', 'store2'])
score_n_customers['score_n_customers'] = weight*score_n_customers['corr_measure'] + weight*score_n_customers['mag_measure']
```

In [33]:
```
'''Now, let's combine both the scores in a single table and find our control table with highest average score
of both sales and customer measure scores'''

score_control = pd.merge(score_n_sales[['store1', 'store2', 'score_n_sales']], score_n_customers[['store1', 'store2', 'score_
score_control['final_control_score'] = 0.5*score_n_sales['score_n_sales'] + 0.5*score_n_customers['score_n_customers']

score_control.sort_values(by = 'final_control_score', ascending= False).head(5)
```

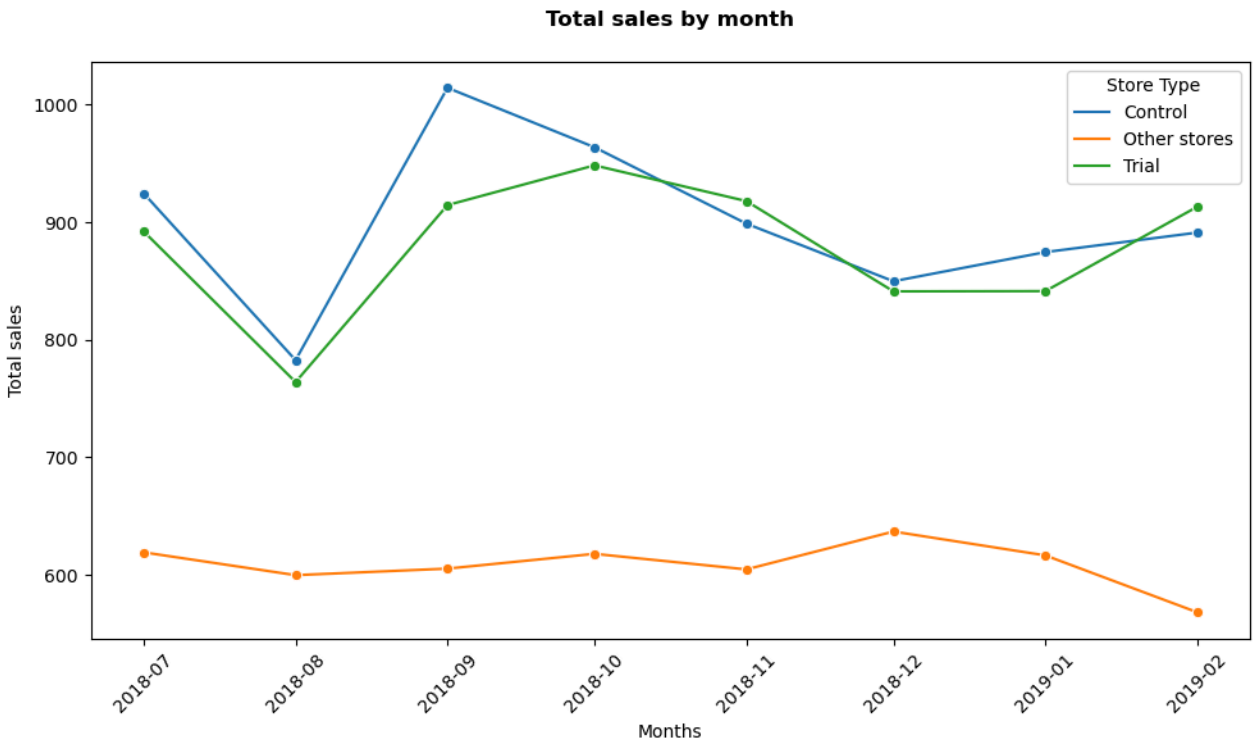
Out[33]:

	store1	store2	score_n_sales	score_n_customers	final_control_score
150	86	155	0.921422	0.964021	0.942721
104	86	109	0.876142	0.868499	0.872321
109	86	114	0.827868	0.895696	0.861782
133	86	138	0.842767	0.839141	0.840954
220	86	225	0.787889	0.850679	0.819284

We can clearly see that store #155 is the most closest to trial store #86. So we can say that store #155 is the control store for store #86

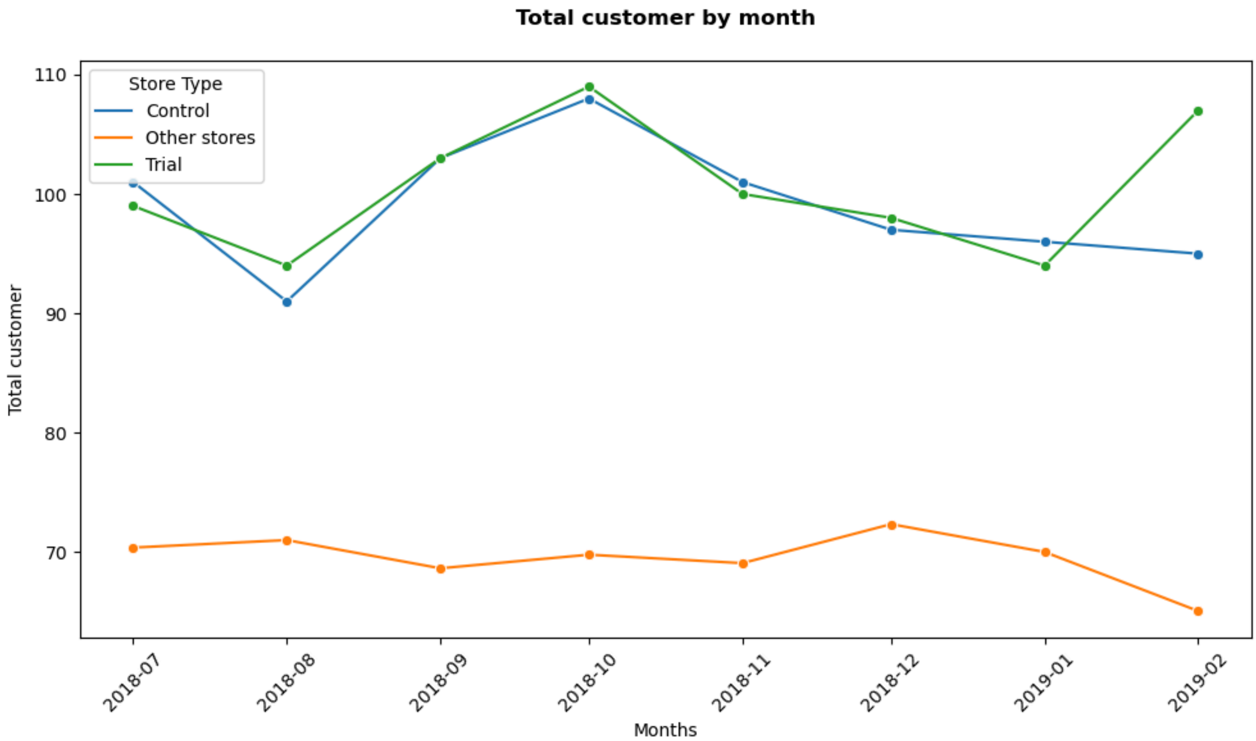
In [34]:
```
control_store = 155
trial_store = 86
```

In [35]:
```
# Let's visualize if the sales of control store and trial store were actually similar before trial period

# Categorizing stores
measure_over_time['Store_type'] = np.where(measure_over_time['STORE_NBR'] == trial_store, 'Trial',
                                           np.where(measure_over_time['STORE_NBR'] == control_store,
                                                    'Control',
                                                    'Other stores'))

# Calculate mean of totSales by YEARMONTH and Store_type
past_sales = measure_over_time.groupby(['YEARMONTH', 'Store_type']).agg({'totSales': 'mean'}).reset_index()

# Convert YEARMONTH to datetime format
past_sales['TransactionMonth'] = pd.to_datetime(past_sales['YEARMONTH'].astype(str) + '01', format='%Y%m%d')

# Filter data for YEARMONTH < 201903
past_sales = past_sales[past_sales['YEARMONTH'] < '201903']

# Plot the data
plt.figure(figsize=(10, 6))
sns.lineplot(data=past_sales, x='TransactionMonth', y='totSales', hue='Store_type', marker='o')
plt.xlabel('Months')
plt.ylabel('Total sales')
plt.title('Total sales by month')
plt.xticks(rotation=45)
plt.legend(title='Store Type')
plt.tight_layout()
plt.show()
```



It is clearly visible that sales of both the stores show similar trends over the time.

In [36]:
```
# Let's visualize number of customer trends for both the stores

# Categorizing stores
measure_over_time['Store_type'] = np.where(measure_over_time['STORE_NBR'] == trial_store, 'Trial',
                                           np.where(measure_over_time['STORE_NBR'] == control_store,
                                                    'Control',
                                                    'Other stores'))

# Calculate mean of nCustomers by YEARMONTH and Store_type
past_customers = measure_over_time.groupby(['YEARMONTH', 'Store_type']).agg({'nCustomers': 'mean'}).reset_index()

# Convert YEARMONTH to datetime format
past_customers['TransactionMonth'] = pd.to_datetime(past_customers['YEARMONTH'].astype(str) + '01', format='%Y%m%d')

# Filter data for YEARMONTH < 201903
past_customers = past_customers[past_customers['YEARMONTH'] < '201903']

# Plot the data
plt.figure(figsize=(10, 6))
sns.lineplot(data=past_customers, x='TransactionMonth', y='nCustomers', hue='Store_type', marker='o')
plt.xlabel('Months')
plt.ylabel('Total customer')
plt.title('Total customer by month')
plt.xticks(rotation=45)
plt.legend(title='Store Type')
plt.tight_layout()
plt.show()
```



Both of the line charts follow similar trend. Therefore, we can say that the trial store follows the control store trends.

Assessment of Trial

Trial Period -> start of February 2019 to April 2019

In [37]:
```
# We now want to see if there has been an uplift in overall chip sales.

# Calculating scaling factor to make control store sales equivalent to trial store sales
scaling_factor_for_control_sales = pre_trial_measure[(pre_trial_measure['STORE_NBR'] == trial_store) &
(pre_trial_measure['YEARMONTH'] < '201902')]['totSales'].sum()/pre_trial_measure[(pre_trial_measure['STORE_NBR'] == control_
(pre_trial_measure['YEARMONTH'] < '201902')]['totSales'].sum()

# Calculating scaled control sales using scaling factor
scaled_control_sales = measure_over_time[measure_over_time['STORE_NBR'] == control_store].copy()
scaled_control_sales['controlSales'] = scaled_control_sales['totSales'] * scaling_factor_for_control_sales

# Trial sales
trial_sales = measure_over_time[measure_over_time['STORE_NBR'] == trial_store].copy()

# Merging trial sales and scaled control sales to find %diff
percentageDiff = pd.merge(trial_sales[['STORE_NBR', 'YEARMONTH', 'totSales']],
                      scaled_control_sales[['STORE_NBR', 'YEARMONTH','controlSales']],
                     on='YEARMONTH', suffixes=['_trial', '_control'])
```

In [38]:
```
percentageDiff['percentDiff'] = (abs(percentageDiff['totSales'] - percentageDiff['controlSales']) / percentageDiff['controlS
percentageDiff
```

Out[38]:

	STORE_NBR_trial	YEARMONTH	totSales	STORE_NBR_control	controlSales	percentDiff
0	86	201807	892.20	155	896.922236	0.526493
1	86	201808	764.05	155	759.269991	0.629553
2	86	201809	914.60	155	984.034086	7.056065
3	86	201810	948.40	155	934.948790	1.438711
4	86	201811	918.00	155	871.894555	5.287961
5	86	201812	841.20	155	824.361363	2.042628
6	86	201901	841.40	155	848.418979	0.827301
7	86	201902	913.20	155	864.522060	5.630619
8	86	201903	1026.80	155	780.320405	31.586973
9	86	201904	848.20	155	819.317024	3.525250
10	86	201905	889.30	155	895.224622	0.661803
11	86	201906	838.00	155	831.539845	0.776891

Let's check statistically if there is significant difference between sales of control stores and trial stores in trial period

Null Hypothesis: There is no difference between stores and trial stores sales

Alternate Hypothesis: There is a significant difference between stores and trial stores sales

In [39]:
```
# Assuming pre-trial period is equal to trial period.
# Standard deviation calculation for pre-trial period.
std_dev = statistics.stdev(percentageDiff[percentageDiff['YEARMONTH'] < '201902']['percentDiff'])
std_dev
```

Out[39]: 2.583395285477237

In [40]:
```
percentageDiff[percentageDiff['YEARMONTH'].isin(['201902','201903','201904'])]['percentDiff'].std()
```

Out[40]: 15.629167059831852

In [41]:
```
# Calculaing t-values based on percentage diff in trial period
trial_percentageDiff = percentageDiff[percentageDiff['YEARMONTH'].isin(['201902','201903','201904'])].copy()
trial_percentageDiff['tValue'] = (trial_percentageDiff['totSales'] - trial_percentageDiff['controlSales'])/std_dev
trial_percentageDiff
```

Out[41]:

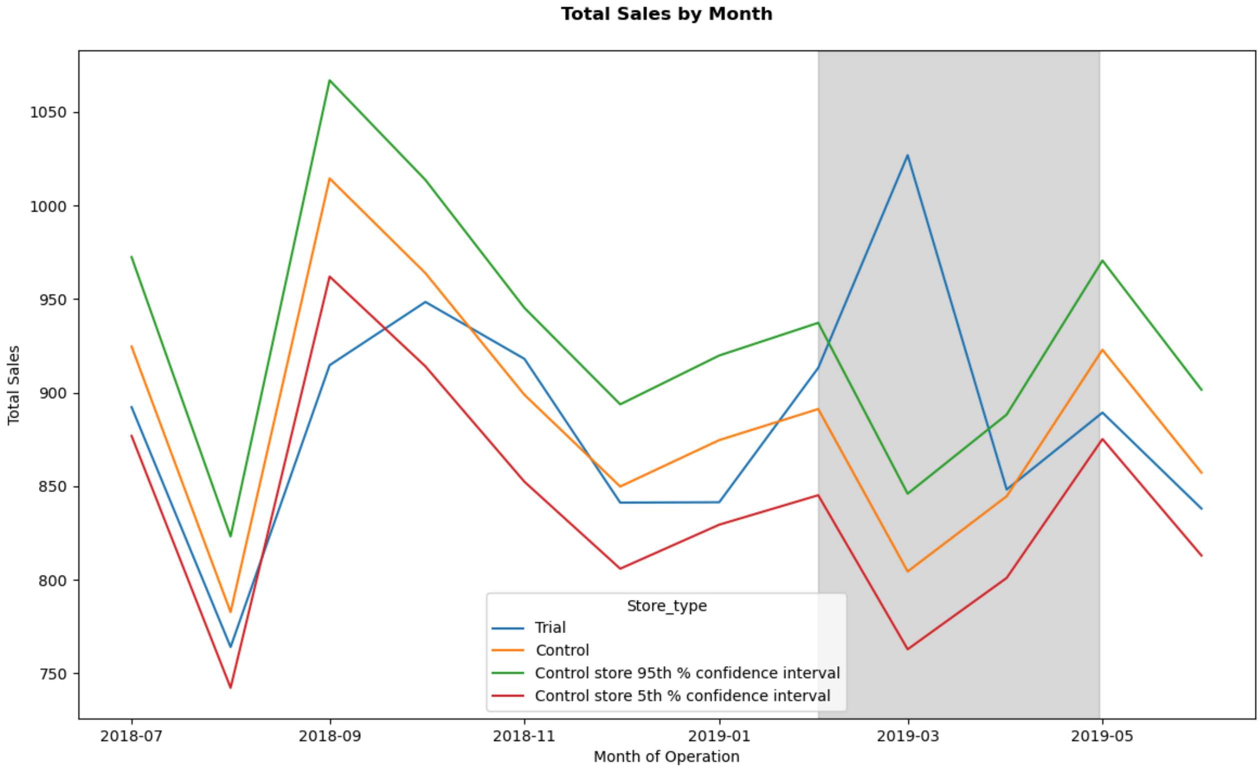
	STORE_NBR_trial	YEARMONTH	totSales	STORE_NBR_control	controlSales	percentDiff	tValue
7	86	201902	913.2	155	864.522060	5.630619	18.842622
8	86	201903	1026.8	155	780.320405	31.586973	95.409168
9	86	201904	848.2	155	819.317024	3.525250	11.180239

In [42]:
```
# Calculating critical value for 95% percentile with degrees of freedom (total months - 1)
critical_value = stats.t.ppf(0.95, 7)
critical_value
```

Out[42]: 1.894578605061305

Since t-statistic value is higher than the 95% critical value for the months Feb, Mar & Apr, we can say that sales of trial stores are significantly higher than the control stores. Let's verify with visualizing total sales now.

In [43]:
```
''' Visualizing trial store sales, control store sales, 5% & 95% CI on store sales to check any significant difference
    in sales of trial and control stores.'''

# Calculate std_dev (standard deviation of percentage difference)
std_dev = std_dev/100

# Prepare data for plotting
measure_over_time['TransactionMonth'] = pd.to_datetime(measure_over_time['YEARMONTH'].astype(str) + '01', format='%Y%m%d')

# Filter data for trial and control stores
past_sales = measure_over_time[measure_over_time['STORE_NBR'].isin([control_store, trial_store])].copy()
past_sales = past_sales.reset_index(drop=True)

# Calculate Control store 95th and 5th percentile
past_sales_controls_95 = past_sales[past_sales['STORE_NBR'] == control_store].copy()
past_sales_controls_95['totSales'] = past_sales_controls_95['totSales'] * (1 + std_dev * 2)
past_sales_controls_95['Store_type'] = 'Control store 95th % confidence interval'
past_sales_controls_95 = past_sales_controls_95.reset_index(drop=True)


past_sales_controls_5 = past_sales[past_sales['STORE_NBR'] == control_store].copy()
past_sales_controls_5['totSales'] = past_sales_controls_5['totSales'] * (1 - std_dev * 2)
past_sales_controls_5['Store_type'] = 'Control store 5th % confidence interval'
past_sales_controls_5 = past_sales_controls_5.reset_index(drop=True)

# Combine all data
trial_assessment = pd.concat([past_sales, past_sales_controls_95, past_sales_controls_5])
trial_assessment = trial_assessment.reset_index(drop=True)

# Plotting
plt.figure(figsize=(14, 8))
sns.lineplot(data=trial_assessment, x='TransactionMonth', y='totSales', hue='Store_type')

# Highlight the trial period (Feb 2019 to Apr 2019)
plt.axvspan(dt(2019, 2, 1), dt(2019, 4, 30), color='grey', alpha=0.3, ymin=0, ymax=1)

# Mark significant differences
# Identify months where trial store sales are outside 5% to 95% confidence interval
trial_sales = trial_assessment[trial_assessment['STORE_NBR'] == trial_store]
control_95th = trial_assessment[(trial_assessment['Store_type'] == 'Control store 95th % confidence interval') &
                                (trial_assessment['STORE_NBR'] == control_store)]
control_5th = trial_assessment[(trial_assessment['Store_type'] == 'Control store 5th % confidence interval') &
                                (trial_assessment['STORE_NBR'] == control_store)]

# Mark significant points
significant_months = trial_sales[(trial_sales['totSales'] < control_5th['totSales'].min()) |
                                 (trial_sales['totSales'] > control_95th['totSales'].max())]

plt.scatter(significant_months['TransactionMonth'], significant_months['totSales'], color='red', label='Significant Differen

plt.title('Total Sales by Month')
plt.xlabel('Month of Operation')
plt.ylabel('Total Sales')
plt.show()
```



Let's analyze nCustomers now. We now want to see if there has been an uplift in number of chip customers over trial period.

In [44]:
```
# Calculating scaling factor to make control store customers equivalent to trial store customers
scaling_factor_for_control_customers = pre_trial_measure[(pre_trial_measure['STORE_NBR'] == trial_store) &
(pre_trial_measure['YEARMONTH'] < '201902')]['nCustomers'].sum()/pre_trial_measure[(pre_trial_measure['STORE_NBR'] == contro
(pre_trial_measure['YEARMONTH'] < '201902')]['nCustomers'].sum()

# Calculating scaled control customers using scaling factor
scaled_control_customers = measure_over_time[measure_over_time['STORE_NBR'] == control_store].copy()
scaled_control_customers['controlCustomers'] = scaled_control_customers['nCustomers'] * scaling_factor_for_control_customers

# Trial customers
trial_customers = measure_over_time[measure_over_time['STORE_NBR'] == trial_store].copy()

# Merging trial customers and scaled control customers to find %diff
percentageDiffCust = pd.merge(trial_customers[['STORE_NBR', 'YEARMONTH', 'nCustomers']],
                        scaled_control_customers[['STORE_NBR', 'YEARMONTH','controlCustomers']],
                       on='YEARMONTH', suffixes=['_trial', '_control'])

percentageDiffCust['percentageDiffCust'] = ((percentageDiffCust['nCustomers'] - percentageDiffCust['controlCustomers']) / pe
percentageDiffCust
```

Out[44]:

	STORE_NBR_trial	YEARMONTH	nCustomers	STORE_NBR_control	controlCustomers	percentageDiffCust
0	86	201807	99	155	101.0	-1.980198
1	86	201808	94	155	91.0	3.296703
2	86	201809	103	155	103.0	0.000000
3	86	201810	109	155	108.0	0.925926
4	86	201811	100	155	101.0	-0.990099
5	86	201812	98	155	97.0	1.030928
6	86	201901	94	155	96.0	-2.083333
7	86	201902	107	155	95.0	12.631579
8	86	201903	115	155	94.0	22.340426
9	86	201904	105	155	99.0	6.060606
10	86	201905	104	155	106.0	-1.886792
11	86	201906	98	155	95.0	3.157895

Let's check statistically if there is significant difference between nCustomers of control stores and trial stores in trial period

Null Hypothesis: There is no difference between stores and trial stores nCustomers

Alternate Hypothesis: There is a significant difference between stores and trial stores nCustomers

In [45]:
```
# Assuming pre-trial period is equal to trial period.
# Standard deviation calculation for pre-trial period.
std_dev_cust = statistics.stdev(percentageDiffCust[percentageDiffCust['YEARMONTH'] < '201902']['percentageDiffCust'])
std_dev_cust
```

Out[45]: 1.9159180382211953

In [46]:
```
aing t-values based on percentage diff in trial period
rcentageDiffCust = percentageDiffCust[percentageDiffCust['YEARMONTH'].isin(['201902','201903','201904'])].copy()
rcentageDiffCust['tValue'] = (trial_percentageDiffCust['nCustomers'] - trial_percentageDiffCust['controlCustomers'])/std_dev_
rcentageDiffCust
```

Out[46]:

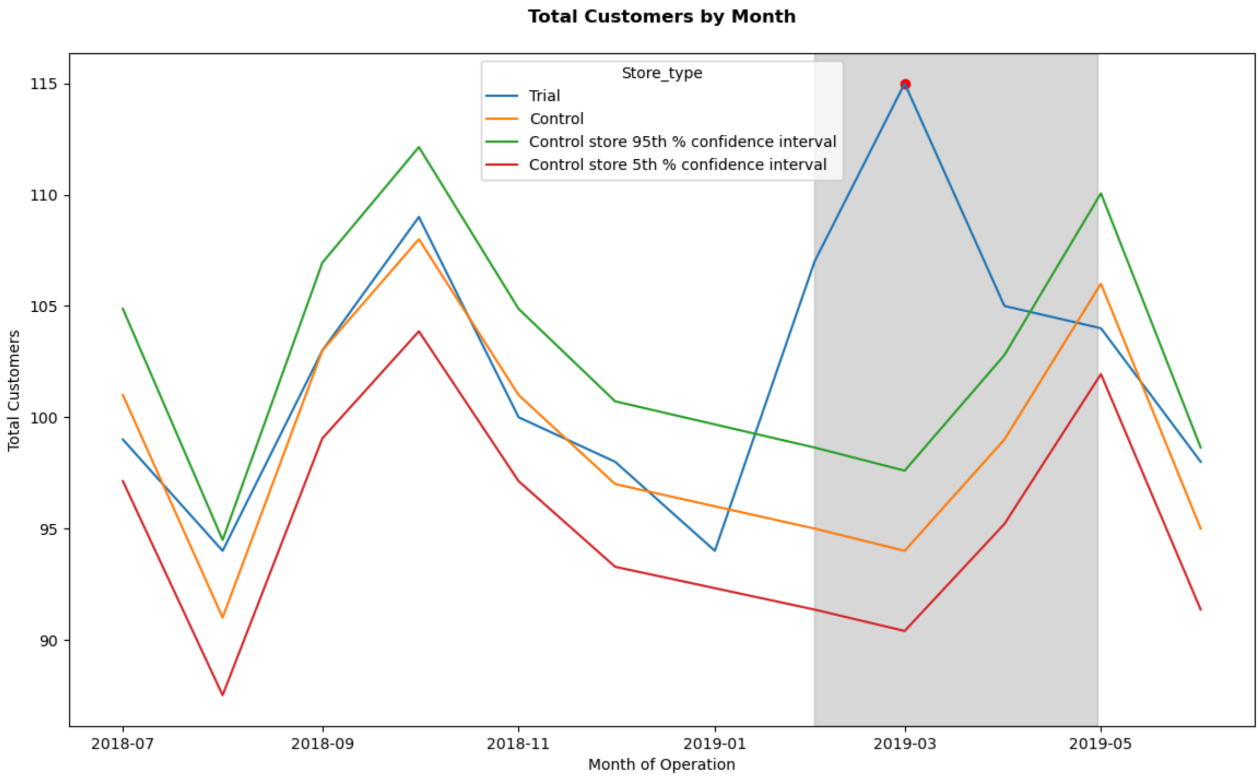
	STORE_NBR_trial	YEARMONTH	nCustomers	STORE_NBR_control	controlCustomers	percentageDiffCust	tValue
7	86	201902	107	155	95.0	12.631579	6.263316
8	86	201903	115	155	94.0	22.340426	10.960803
9	86	201904	105	155	99.0	6.060606	3.131658

In [47]:
```
# Calculating critical value for 95% confidence interval with degrees of freedom (total months - 1)
critical_value = stats.t.ppf(0.95, 7)
critical_value
```

Out[47]: 1.894578605061305

Since t-statistic value is higher than the 95% critical value for the months March & April, we can say that sales of trial stores are significantly higher than the control stores.

In [48]:
```
''' Visualizing trial store nCustomers, control store nCustomers, 5% & 95% CI on store nCustomers to check any significant di
    in nCustomers of trial and control stores.'''

# Calculate std_dev (standard deviation of percentage difference)
std_dev_cust = std_dev_cust/100

# Prepare data for plotting
measure_over_time['TransactionMonth'] = pd.to_datetime(measure_over_time['YEARMONTH'].astype(str) + '01', format='%Y%m%d')

# Filter data for trial and control stores
past_cust = measure_over_time[measure_over_time['STORE_NBR'].isin([control_store, trial_store])].copy()
past_cust = past_cust.reset_index(drop=True)

# Calculate Control store 95th and 5th percentile
past_cust_controls_95 = past_cust[past_cust['STORE_NBR'] == control_store].copy()
past_cust_controls_95['nCustomers'] = past_cust_controls_95['nCustomers'] * (1 + std_dev_cust * 2)
past_cust_controls_95['Store_type'] = 'Control store 95th % confidence interval'
past_cust_controls_95 = past_cust_controls_95.reset_index(drop=True)


past_cust_controls_5 = past_cust[past_cust['STORE_NBR'] == control_store].copy()
past_cust_controls_5['nCustomers'] = past_cust_controls_5['nCustomers'] * (1 - std_dev_cust * 2)
past_cust_controls_5['Store_type'] = 'Control store 5th % confidence interval'
past_cust_controls_5 = past_cust_controls_5.reset_index(drop=True)

# Combine all data
trial_assessment_cust = pd.concat([past_cust, past_cust_controls_95, past_cust_controls_5])
trial_assessment_cust = trial_assessment_cust.reset_index(drop=True)

# Plotting
plt.figure(figsize=(14, 8))
sns.lineplot(data=trial_assessment_cust, x='TransactionMonth', y='nCustomers', hue='Store_type')

# Highlight the trial period (Feb 2019 to Apr 2019)
plt.axvspan(dt(2019, 2, 1), dt(2019, 4, 30), color='grey', alpha=0.3)

# Mark significant differences
# Identify months where trial store sales are outside 5% to 95% confidence interval
trial_sales = trial_assessment_cust[trial_assessment_cust['STORE_NBR'] == trial_store]
control_95th = trial_assessment_cust[(trial_assessment_cust['Store_type'] == 'Control store 95th % confidence interval') &
                                (trial_assessment_cust['STORE_NBR'] == control_store)]
control_5th = trial_assessment_cust[(trial_assessment_cust['Store_type'] == 'Control store 5th % confidence interval') &
                                (trial_assessment_cust['STORE_NBR'] == control_store)]

# Mark significant points
significant_months_cust = trial_customers[(trial_customers['nCustomers'] < control_5th['nCustomers'].min()) |
                                 (trial_customers['nCustomers'] > control_95th['nCustomers'].max())]

plt.scatter(significant_months_cust['TransactionMonth'], significant_months_cust['nCustomers'], color='red', label='Signific

plt.title('Total Customers by Month')
plt.xlabel('Month of Operation')
plt.ylabel('Total Customers')
plt.show()
```



The results show that the trial in store 86 is not significantly different to its control store 155 in the trial period as the trial store performance of sales lies inside the 5% to 95% confidence interval of the control store in two of the three trial months. However, we have seen the rise in customers in all the three months of trial period. We need to check with the Category Manager as what led to decline in the total sales.

Trial Store: 88

In [49]:
```python
metric_table = pre_trial_measure
trial_store = 88

# Calculate correlations
corr_n_sales = calculate_correlation(metric_table, 'totSales', trial_store)
corr_n_customers = calculate_correlation(metric_table, 'nCustomers', trial_store)

# Calculate magnitude distances
magnitude_n_sales = calculate_magnitude_distance(metric_table, 'totSales', trial_store)
magnitude_n_customers = calculate_magnitude_distance(metric_table, 'nCustomers', trial_store)

# Display the results
print("Correlation of total sales:")
print(corr_n_sales)
print("\nCorrelation of number of customers:")
print(corr_n_customers)
print("\nMagnitude distance of total sales:")
print(magnitude_n_sales)
print("\nMagnitude distance of number of customers:")
print(magnitude_n_customers)
```

```
Correlation of total sales:
    store1 store2  corr_measure
0       88      1      0.813636
1       88      2     -0.067927
2       88      3     -0.507847
3       88      4     -0.745566
4       88      5      0.190330
..     ...    ...           ...
263     88    268     -0.021429
264     88    269     -0.172578
265     88    270     -0.723272
266     88    271     -0.103037
267     88    272     -0.772772

[268 rows x 3 columns]

Correlation of number of customers:
    store1 store2  corr_measure
0       88      1      0.305334
1       88      2     -0.452379
2       88      3      0.522884
3       88      4     -0.361503
4       88      5     -0.025320
..     ...    ...           ...
263     88    268      0.672672
264     88    269     -0.274781
265     88    270     -0.103032
266     88    271     -0.018831
267     88    272      0.026909

[268 rows x 3 columns]

Magnitude distance of total sales:
     store1  store2  mag_measure
0        88       1     0.145325
1        88       2     0.118284
2        88       3     0.806475
3        88       4     0.901628
4        88       5     0.613469
..      ...     ...          ...
265      88     268     0.163438
266      88     269     0.713431
267      88     270     0.718248
268      88     271     0.616842
269      88     272     0.292677

[270 rows x 3 columns]

Magnitude distance of number of customers:
     store1  store2  mag_measure
0        88       1     0.357367
1        88       2     0.306303
2        88       3     0.850204
3        88       4     0.931292
4        88       5     0.743585
..      ...     ...          ...
265      88     268     0.341734
266      88     269     0.853492
267      88     270     0.839872
268      88     271     0.744648
269      88     272     0.340495

[270 rows x 3 columns]
```

In [50]:
```
# let's merge sales and nCustomers table and assign 0.5 weight of correlation and 0.5 weight of magnitude to give a cumulati
weight = 0.5
score_n_sales = pd.merge(corr_n_sales, magnitude_n_sales, on = ['store1', 'store2'])
score_n_sales['score_n_sales'] = weight*(score_n_sales['corr_measure'] + score_n_sales['mag_measure'])

score_n_customers = pd.merge(corr_n_customers, magnitude_n_customers, on = ['store1', 'store2'])
score_n_customers['score_n_customers'] = weight*score_n_customers['corr_measure'] + weight*score_n_customers['mag_measure']
```

In [51]:
```
'''Now, let's combine both the scores in a single table and find our control table with highest average score
of both sales and customer measure scores'''

score_control = pd.merge(score_n_sales[['store1', 'store2', 'score_n_sales']], score_n_customers[['store1', 'store2', 'score_
score_control['final_control_score'] = 0.5*score_n_sales['score_n_sales'] + 0.5*score_n_customers['score_n_customers']

score_control.sort_values(by = 'final_control_score', ascending= False).head(5)
```

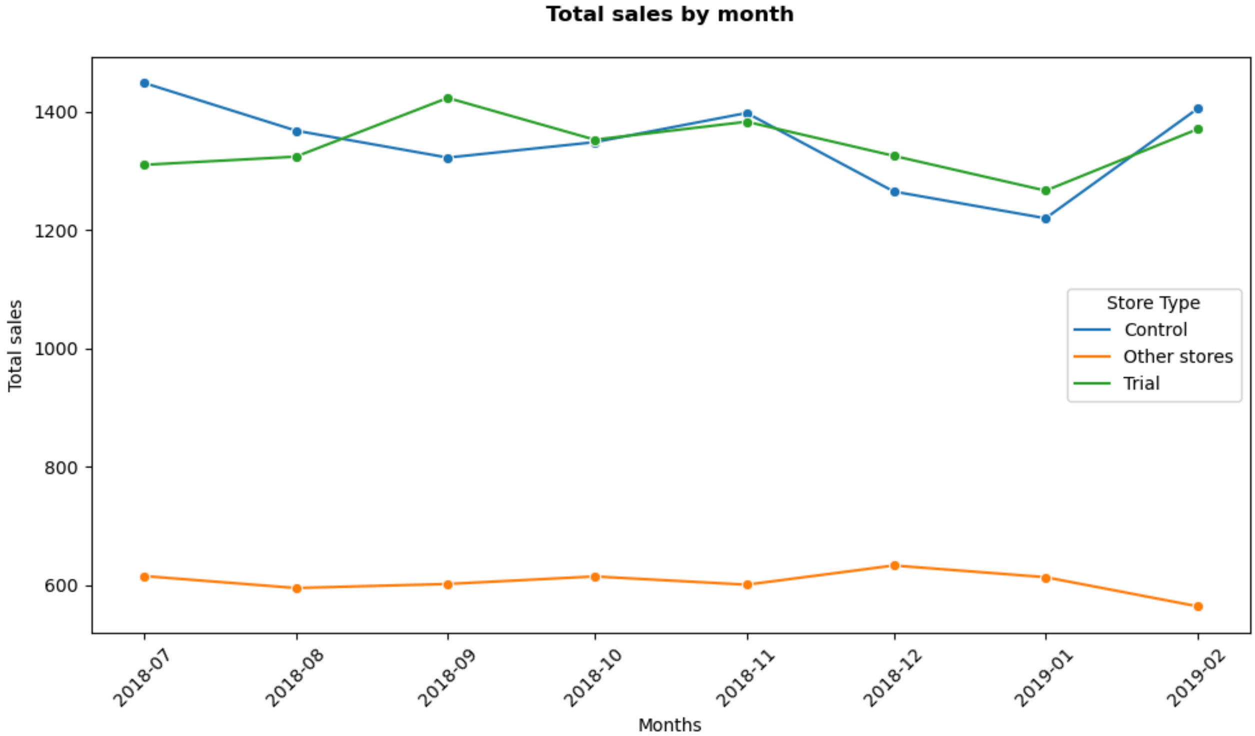
Out[51]:

	store1	store2	score_n_sales	score_n_customers	final_control_score
232	88	237	0.634304	0.970819	0.802562
173	88	178	0.715656	0.883634	0.799645
68	88	69	0.580770	0.845770	0.713270
108	88	113	0.591015	0.826644	0.708830
196	88	201	0.684850	0.719286	0.702068

We can clearly see that store #237 is the most closest to trial store #88. So we can say that store #237 is the control store for trial store #88

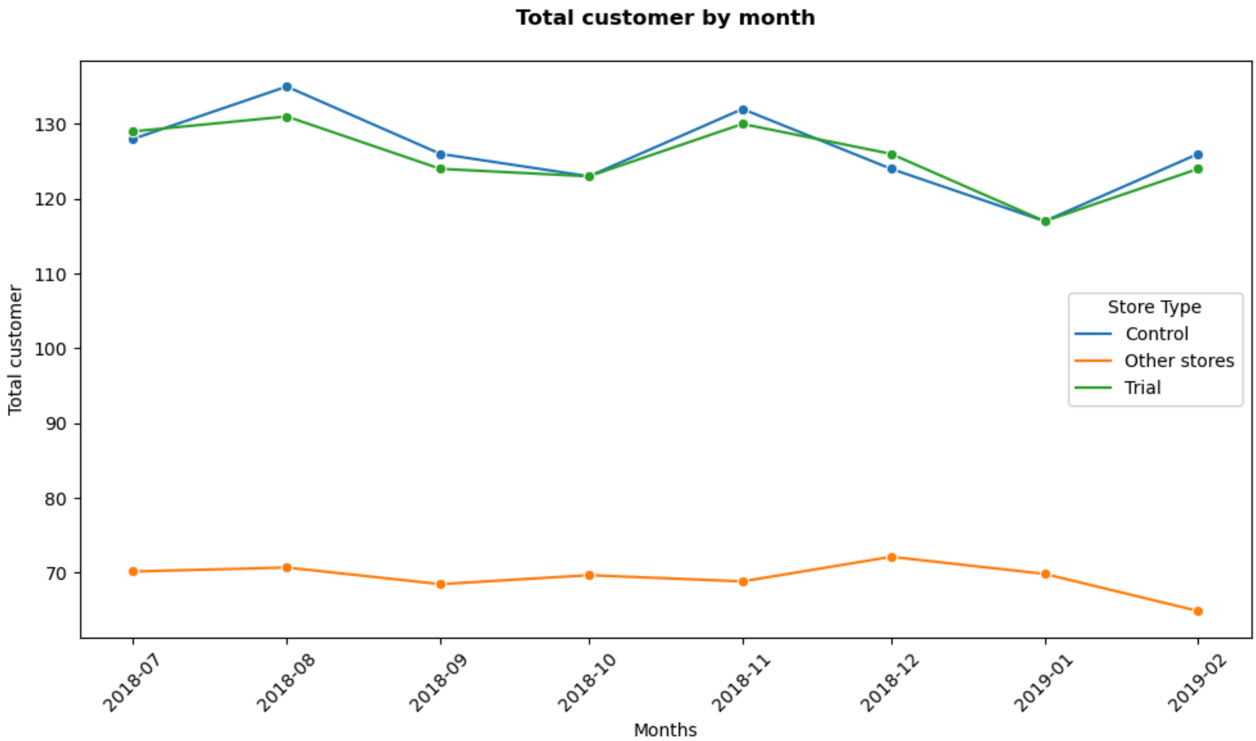
In [52]:
```
control_store = 237
trial_store = 88
```

In [53]:
```
# Let's visualize if the sales of control store and trial store were actually similar before trial period

# Categorizing stores
measure_over_time['Store_type'] = np.where(measure_over_time['STORE_NBR'] == trial_store, 'Trial',
                                           np.where(measure_over_time['STORE_NBR'] == control_store,
                                                    'Control',
                                                    'Other stores'))

# Calculate mean of totSales by YEARMONTH and Store_type
past_sales = measure_over_time.groupby(['YEARMONTH', 'Store_type']).agg({'totSales': 'mean'}).reset_index()

# Convert YEARMONTH to datetime format
past_sales['TransactionMonth'] = pd.to_datetime(past_sales['YEARMONTH'].astype(str) + '01', format='%Y%m%d')

# Filter data for YEARMONTH < 201903
past_sales = past_sales[past_sales['YEARMONTH'] < '201903']

# Plot the data
plt.figure(figsize=(10, 6))
sns.lineplot(data=past_sales, x='TransactionMonth', y='totSales', hue='Store_type', marker='o')
plt.xlabel('Months')
plt.ylabel('Total sales')
plt.title('Total sales by month')
plt.xticks(rotation=45)
plt.legend(title='Store Type')
plt.tight_layout()
plt.show()
```



It can be argued that the overall sales trends of both stores are similar, even though there is a slight divergence at the beginning.

In [54]:
```
# Let's visualize number of customer trends for both the stores

# Categorizing stores
measure_over_time['Store_type'] = np.where(measure_over_time['STORE_NBR'] == trial_store, 'Trial',
                                           np.where(measure_over_time['STORE_NBR'] == control_store,
                                                    'Control',
                                                    'Other stores'))

# Calculate mean of nCustomers by YEARMONTH and Store_type
past_customers = measure_over_time.groupby(['YEARMONTH', 'Store_type']).agg({'nCustomers': 'mean'}).reset_index()

# Convert YEARMONTH to datetime format
past_customers['TransactionMonth'] = pd.to_datetime(past_customers['YEARMONTH'].astype(str) + '01', format='%Y%m%d')

# Filter data for YEARMONTH < 201903
past_customers = past_customers[past_customers['YEARMONTH'] < '201903']

# Plot the data
plt.figure(figsize=(10, 6))
sns.lineplot(data=past_customers, x='TransactionMonth', y='nCustomers', hue='Store_type', marker='o')
plt.xlabel('Months')
plt.ylabel('Total customer')
plt.title('Total customer by month')
plt.xticks(rotation=45)
plt.legend(title='Store Type')
plt.tight_layout()
plt.show()
```



Both of the line charts follow similar trend. Therefore, we can say that our number of customers for trial stores follows trend of control stores over the time.

Assessment of Trial

Trial Period -> start of February 2019 to April 2019

In [55]:
```
# We now want to see if there has been an uplift in overall chip sales.

# Calculating scaling factor to make control store sales equivalent to trial store sales
scaling_factor_for_control_sales = pre_trial_measure[(pre_trial_measure['STORE_NBR'] == trial_store) &
(pre_trial_measure['YEARMONTH'] < '201902')]['totSales'].sum()/pre_trial_measure[(pre_trial_measure['STORE_NBR'] == control_
(pre_trial_measure['YEARMONTH'] < '201902')]['totSales'].sum()

# Calculating scaled control sales using scaling factor
scaled_control_sales = measure_over_time[measure_over_time['STORE_NBR'] == control_store].copy()
scaled_control_sales['controlSales'] = scaled_control_sales['totSales'] * scaling_factor_for_control_sales

# Trial sales
trial_sales = measure_over_time[measure_over_time['STORE_NBR'] == trial_store].copy()

# Merging trial sales and scaled control sales to find %diff
percentageDiff = pd.merge(trial_sales[['STORE_NBR', 'YEARMONTH', 'totSales']],
                         scaled_control_sales[['STORE_NBR', 'YEARMONTH','controlSales']],
                        on='YEARMONTH', suffixes=['_trial', '_control'])

percentageDiff['percentDiff'] = ((percentageDiff['totSales'] - percentageDiff['controlSales']) / percentageDiff['controlSale
percentageDiff
```

Out[55]:

	STORE_NBR_trial	YEARMONTH	totSales	STORE_NBR_control	controlSales	percentDiff
0	88	201807	1310.00	237	1450.657086	-9.696095
1	88	201808	1323.80	237	1369.931485	-3.367430
2	88	201809	1423.00	237	1324.260425	7.456205
3	88	201810	1352.40	237	1350.401097	0.148023
4	88	201811	1382.80	237	1399.777923	-1.212901
5	88	201812	1325.20	237	1266.971288	4.595898
6	88	201901	1266.40	237	1221.600696	3.667262
7	88	201902	1370.20	237	1406.989143	-2.614742
8	88	201903	1477.20	237	1210.082775	22.074294
9	88	201904	1439.40	237	1206.477165	19.306029
10	88	201905	1308.25	237	1201.168906	8.914741
11	88	201906	1354.60	237	1155.397690	17.241017

Let's check statistically if there is significant difference between sales of control stores and trial stores in trial period

Null Hypothesis: There is no difference between stores and trial stores sales

Alternate Hypothesis: There is a significant difference between stores and trial stores sales

In [56]:
```
# Assuming pre-trial period is equal to trial period.
# Standard deviation calculation for pre-trial period.
std_dev = statistics.stdev(percentageDiff[percentageDiff['YEARMONTH'] < '201902']['percentDiff'])
std_dev
```

Out[56]: 5.724965451900226

In [57]:
```
# Calculaing t-values based on percentage diff in trial period
trial_percentageDiff = percentageDiff[percentageDiff['YEARMONTH'].isin(['201902','201903','201904'])].copy()
trial_percentageDiff['tValue'] = (trial_percentageDiff['totSales'] - trial_percentageDiff['controlSales'])/std_dev
trial_percentageDiff
```

Out[57]:

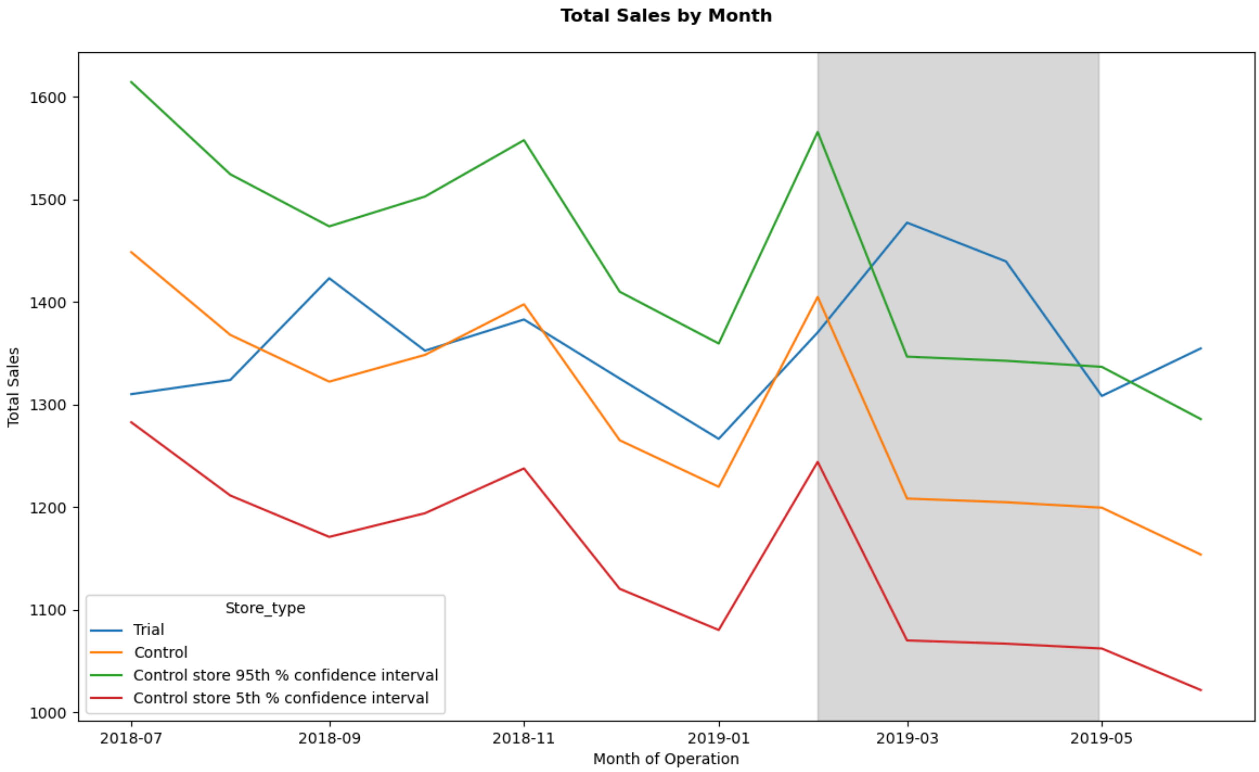
	STORE_NBR_trial	YEARMONTH	totSales	STORE_NBR_control	controlSales	percentDiff	tValue
7	88	201902	1370.2	237	1406.989143	-2.614742	-6.426090
8	88	201903	1477.2	237	1210.082775	22.074294	46.658312
9	88	201904	1439.4	237	1206.477165	19.306029	40.685457

In [58]:
```
# Calculating critical value for 95% confidence interval with degrees of freedom (total months - 1) in trial period
critical_value = stats.t.ppf(0.95, 2)
critical_value
```

Out[58]: 2.919985580355516

Since t-statistic value is higher than the 95% critical value for the months March & April, we can say that sales of trial stores are significantly higher than the control stores.

In [59]:
```
''' Visualizing trial store sales, control store sales, 5% & 95% CI on store sales to check any significant difference
    in sales of trial and control stores.'''

# Calculate std_dev (standard deviation of percentage difference)
std_dev = std_dev/100

# Prepare data for plotting
measure_over_time['TransactionMonth'] = pd.to_datetime(measure_over_time['YEARMONTH'].astype(str) + '01', format='%Y%m%d')

# Filter data for trial and control stores
past_sales = measure_over_time[measure_over_time['STORE_NBR'].isin([control_store, trial_store])].copy()
past_sales = past_sales.reset_index(drop=True)

# Calculate Control store 95th and 5th percentile
past_sales_controls_95 = past_sales[past_sales['STORE_NBR'] == control_store].copy()
past_sales_controls_95['totSales'] = past_sales_controls_95['totSales'] * (1 + std_dev * 2)
past_sales_controls_95['Store_type'] = 'Control store 95th % confidence interval'
past_sales_controls_95 = past_sales_controls_95.reset_index(drop=True)


past_sales_controls_5 = past_sales[past_sales['STORE_NBR'] == control_store].copy()
past_sales_controls_5['totSales'] = past_sales_controls_5['totSales'] * (1 - std_dev * 2)
past_sales_controls_5['Store_type'] = 'Control store 5th % confidence interval'
past_sales_controls_5 = past_sales_controls_5.reset_index(drop=True)

# Combine all data
trial_assessment = pd.concat([past_sales, past_sales_controls_95, past_sales_controls_5])
trial_assessment = trial_assessment.reset_index(drop=True)

# Plotting
plt.figure(figsize=(14, 8))
sns.lineplot(data=trial_assessment, x='TransactionMonth', y='totSales', hue='Store_type')

# Highlight the trial period (Feb 2019 to Apr 2019)
plt.axvspan(dt(2019, 2, 1), dt(2019, 4, 30), color='grey', alpha=0.3, ymin=0, ymax=1)

# Mark significant differences
# Identify months where trial store sales are outside 5% to 95% confidence interval
trial_sales = trial_assessment[trial_assessment['STORE_NBR'] == trial_store]
control_95th = trial_assessment[(trial_assessment['Store_type'] == 'Control store 95th % confidence interval') &
                                (trial_assessment['STORE_NBR'] == control_store)]
control_5th = trial_assessment[(trial_assessment['Store_type'] == 'Control store 5th % confidence interval') &
                                (trial_assessment['STORE_NBR'] == control_store)]

# Mark significant points
significant_months = trial_sales[(trial_sales['totSales'] < control_5th['totSales'].min()) |
                                 (trial_sales['totSales'] > control_95th['totSales'].max())]

plt.scatter(significant_months['TransactionMonth'], significant_months['totSales'], color='red', label='Significant Differen

plt.title('Total Sales by Month')
plt.xlabel('Month of Operation')
plt.ylabel('Total Sales')
plt.show()
```



Let's analyze nCustomers now. We now want to see if there has been an uplift in number of chip customers over trial period.

In [60]:
```
# Calculating scaling factor to make control store customers equivalent to trial store customers
scaling_factor_for_control_customers = pre_trial_measure[(pre_trial_measure['STORE_NBR'] == trial_store) &
(pre_trial_measure['YEARMONTH'] < '201902')]['nCustomers'].sum()/pre_trial_measure[(pre_trial_measure['STORE_NBR'] == contro
(pre_trial_measure['YEARMONTH'] < '201902')]['nCustomers'].sum()

# Calculating scaled control customers using scaling factor
scaled_control_customers = measure_over_time[measure_over_time['STORE_NBR'] == control_store].copy()
scaled_control_customers['controlCustomers'] = scaled_control_customers['nCustomers'] * scaling_factor_for_control_customers

# Trial customers
trial_customers = measure_over_time[measure_over_time['STORE_NBR'] == trial_store].copy()

# Merging trial customers and scaled control customers to find %diff
percentageDiffCust = pd.merge(trial_customers[['STORE_NBR', 'YEARMONTH', 'nCustomers']],
                        scaled_control_customers[['STORE_NBR', 'YEARMONTH','controlCustomers']],
                       on='YEARMONTH', suffixes=['_trial', '_control'])

percentageDiffCust['percentageDiffCust'] = ((percentageDiffCust['nCustomers'] - percentageDiffCust['controlCustomers']) / pe
percentageDiffCust
```

Out[60]:

	STORE_NBR_trial	YEARMONTH	nCustomers	STORE_NBR_control	controlCustomers	percentageDiffCust
0	88	201807	129	237	127.276836	1.353871
1	88	201808	131	237	134.237288	-2.411616
2	88	201809	124	237	125.288136	-1.028139
3	88	201810	123	237	122.305085	0.568182
4	88	201811	130	237	131.254237	-0.955579
5	88	201812	126	237	123.299435	2.190249
6	88	201901	117	237	116.338983	0.568182
7	88	201902	124	237	125.288136	-1.028139
8	88	201903	134	237	118.327684	13.244843
9	88	201904	128	237	119.322034	7.272727
10	88	201905	128	237	128.271186	-0.211416
11	88	201906	121	237	118.327684	2.258403

Let's check statistically if there is significant difference between nCustomers of control stores and trial stores in trial period

Null Hypothesis: There is no difference between stores and trial stores nCustomers

Alternate Hypothesis: There is a significant difference between stores and trial stores nCustomers

In [61]:
```
# Assuming pre-trial period is equal to trial period.
# Standard deviation calculation for pre-trial period.
std_dev_cust = statistics.stdev(percentageDiffCust[percentageDiffCust['YEARMONTH'] < '201902']['percentageDiffCust'])
std_dev_cust
```

Out[61]: 1.5837873803830578

In [62]:
```
ting t-values based on percentage diff in trial period
rcentageDiffCust = percentageDiffCust[percentageDiffCust['YEARMONTH'].isin(['201902','201903','201904'])].copy()
rcentageDiffCust['tValue'] = (trial_percentageDiffCust['nCustomers'] - trial_percentageDiffCust['controlCustomers'])/std_dev_
rcentageDiffCust
```

Out[62]:

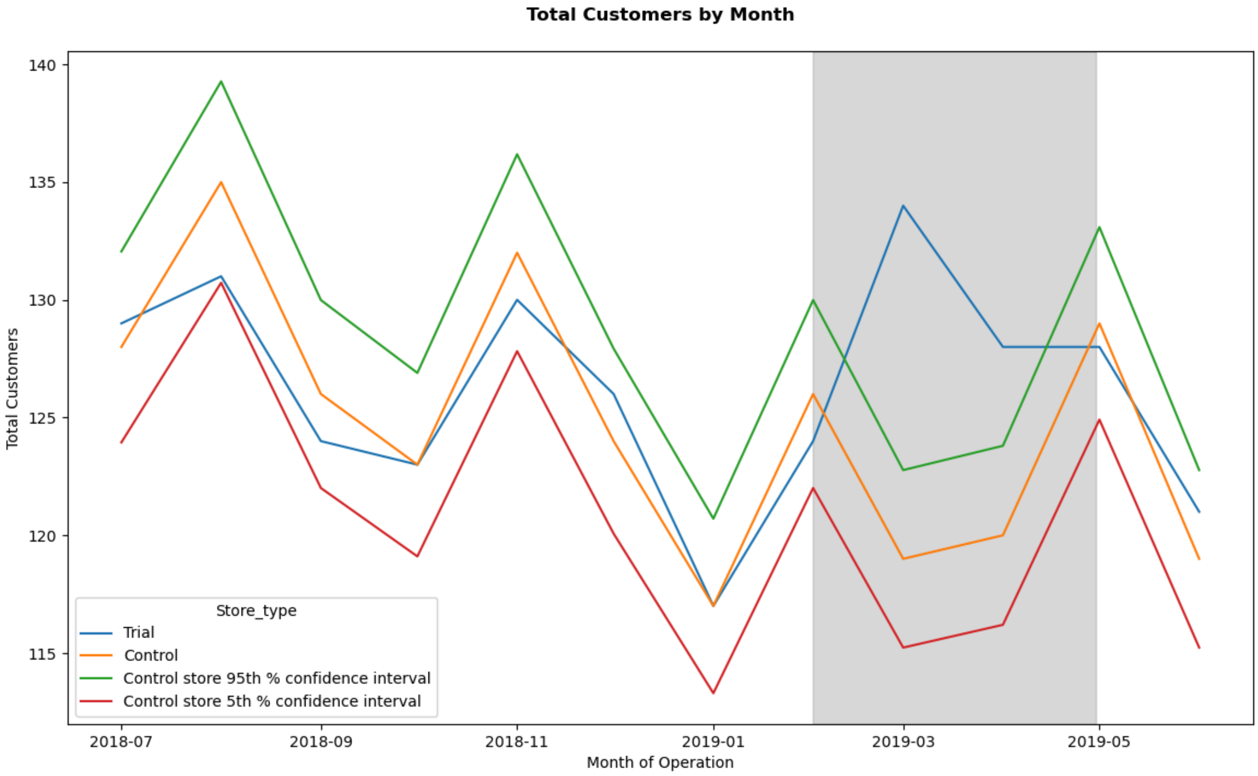
	STORE_NBR_trial	YEARMONTH	nCustomers	STORE_NBR_control	controlCustomers	percentageDiffCust	tValue
7	88	201902	124	237	125.288136	-1.028139	-0.813326
8	88	201903	134	237	118.327684	13.244843	9.895467
9	88	201904	128	237	119.322034	7.272727	5.479249

In [63]:
```
# Calculating critical value for 95% confidence interval with degrees of freedom (total months - 1)
critical_value = stats.t.ppf(0.95, 7)
critical_value
```

Out[63]: 1.894578605061305

Since t-statistic value is higher than the 95% critical value for the months March & April, we can say that sales of trial stores are significantly higher than the control stores.

In [64]:
```
''' Visualizing trial store nCustomers, control store nCustomers, 5% & 95% CI on store nCustomers to check any significant di
    in nCustomers of trial and control stores.'''

# Calculate std_dev (standard deviation of percentage difference)
std_dev_cust = std_dev_cust/100

# Prepare data for plotting
measure_over_time['TransactionMonth'] = pd.to_datetime(measure_over_time['YEARMONTH'].astype(str) + '01', format='%Y%m%d')

# Filter data for trial and control stores
past_cust = measure_over_time[measure_over_time['STORE_NBR'].isin([control_store, trial_store])].copy()
past_cust = past_cust.reset_index(drop=True)

# Calculate Control store 95th and 5th percentile
past_cust_controls_95 = past_cust[past_cust['STORE_NBR'] == control_store].copy()
past_cust_controls_95['nCustomers'] = past_cust_controls_95['nCustomers'] * (1 + std_dev_cust * 2)
past_cust_controls_95['Store_type'] = 'Control store 95th % confidence interval'
past_cust_controls_95 = past_cust_controls_95.reset_index(drop=True)


past_cust_controls_5 = past_cust[past_cust['STORE_NBR'] == control_store].copy()
past_cust_controls_5['nCustomers'] = past_cust_controls_5['nCustomers'] * (1 - std_dev_cust * 2)
past_cust_controls_5['Store_type'] = 'Control store 5th % confidence interval'
past_cust_controls_5 = past_cust_controls_5.reset_index(drop=True)

# Combine all data
trial_assessment_cust = pd.concat([past_cust, past_cust_controls_95, past_cust_controls_5])
trial_assessment_cust = trial_assessment_cust.reset_index(drop=True)

# Plotting
plt.figure(figsize=(14, 8))
sns.lineplot(data=trial_assessment_cust, x='TransactionMonth', y='nCustomers', hue='Store_type')

# Highlight the trial period (Feb 2019 to Apr 2019)
plt.axvspan(dt(2019, 2, 1), dt(2019, 4, 30), color='grey', alpha=0.3)

# Mark significant differences
# Identify months where trial store sales are outside 5% to 95% confidence interval
trial_sales = trial_assessment_cust[trial_assessment_cust['STORE_NBR'] == trial_store]
control_95th = trial_assessment_cust[(trial_assessment_cust['Store_type'] == 'Control store 95th % confidence interval') &
                                     (trial_assessment_cust['STORE_NBR'] == control_store)]
control_5th = trial_assessment_cust[(trial_assessment_cust['Store_type'] == 'Control store 5th % confidence interval') &
                                    (trial_assessment_cust['STORE_NBR'] == control_store)]

# Mark significant points
significant_months_cust = trial_customers[(trial_customers['nCustomers'] < control_5th['nCustomers'].min()) |
                                          (trial_customers['nCustomers'] > control_95th['nCustomers'].max())]

plt.scatter(significant_months_cust['TransactionMonth'], significant_months_cust['nCustomers'], color='red', label='Signific

plt.title('Total Customers by Month')
plt.xlabel('Month of Operation')
plt.ylabel('Total Customers')
plt.show()
```



The results show that the trial in store 88 is significantly different to its control store 237 in the trial period as the trial store performance of both sales and nCustomers lies outside the 5% to 95% confidence interval of the control store in two of the three trial months that is, March & April

Conclusion

We have found that control stores 233, 155, and 237 for the trial stores 77, 86, and 88 respectively. The findings have shown that trial store 77 and 88 are significantly different from the control stores, having sales of trial much higher than the control store in atleast 2 of the 3 months trial period. The store 86 shows no significant difference from its control store in terms of sales, however there is an inclined trend in the number of customers over the trial period. We need to check with the client regarding any differences in implementation of trial.

In [ ]:

```
```