In [6]:

```
# Import dependencies
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans

# Import and display the dataset
df = pd.read_csv("data/exploratory_sorted_data.csv")
df
```

Out[6]:

	Unnamed: 0	school_name	applications	acceptances	per_pupil_spending	avg_class_size	a
0	304	THE CHRISTA MCAULIFFE SCHOOL\I.S. 187	251	205	17403.0	27.71	
1	324	MARK TWAIN I.S. 239 FOR THE GIFTED & TALENTED	336	196	16814.0	30.51	
2	33	J.H.S. 054 BOOKER T. WASHINGTON	257	150	17359.0	25.47	
3	241	M.S. 51 WILLIAM ALEXANDER	280	122	16145.0	25.36	
4	22	NEW YORK CITY LAB MIDDLE SCHOOL FOR COLLABORAT...	163	113	15853.0	31.83	
...	...	...	...	...	...	...	
589	441	EAGLE ACADEMY FOR YOUNG MEN III	0	0	22617.0	17.25	
590	211	EAST BRONX ACADEMY FOR THE FUTURE	14	0	22509.0	16.92	
591	443	COMMUNITY VOICES MIDDLE SCHOOL	9	0	18845.0	20.26	
592	210	BRONX LATIN	0	0	19742.0	18.16	
593	0	P.S. 034 FRANKLIN D. ROOSEVELT	6	0	24890.0	20.15	

594 rows × 26 columns

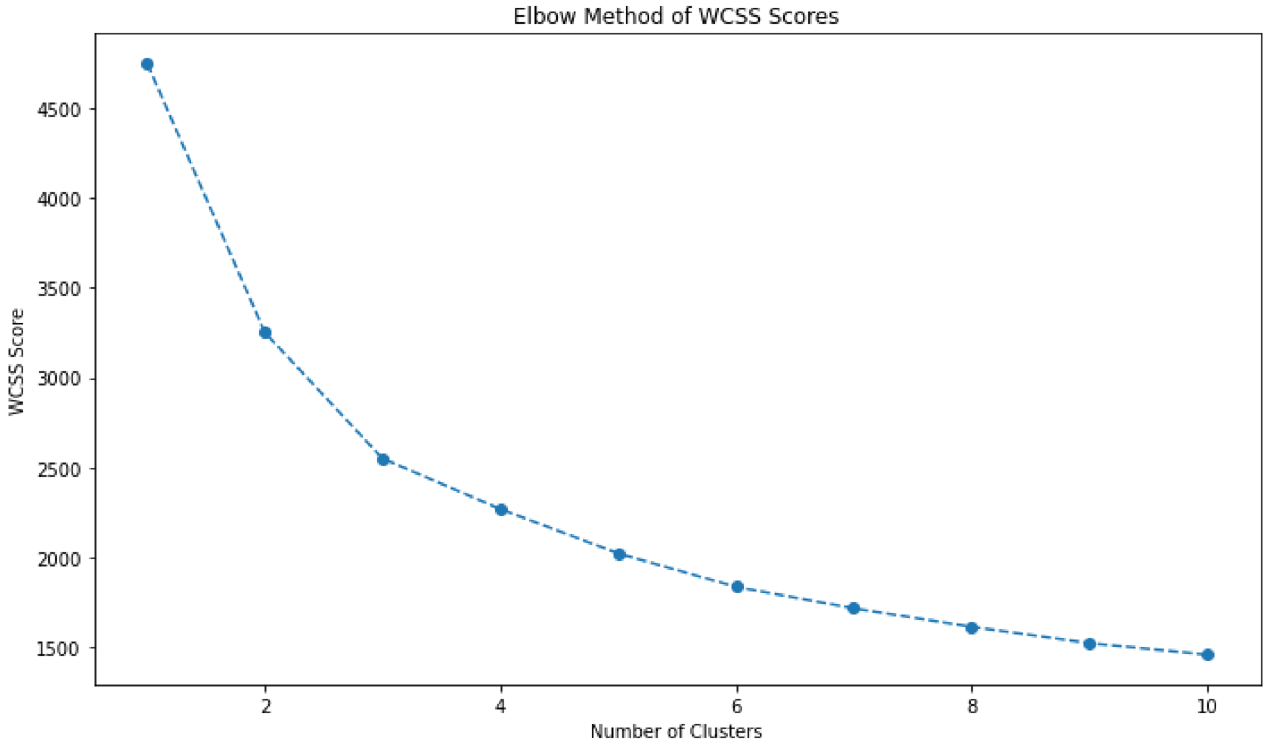
Constructing a Clustering Model to Determine School Success Metrics

In [5]:
```
# Create list of features which measure student success metrics
success_metrics = ["applications", "acceptances", "per_pupil_spending", "avg_cla
                  "school_size", "student_achievement", "reading_scores_exceed",

# Separate success metric features from the rest of the dataset
X = df[success_metrics]
# Standardize the success metric features
scaler = StandardScaler()
X_scale = scaler.fit_transform(X)
# Display shape of scaled features to determine if properly standardized
X_scale.shape
```

Out[5]: (594, 8)

Determining Optimal Number of Clusters Using Elbow Method

In [8]:
```
# Determine optimal number of clusters using Elbow Method
wcss = []
for i in range(1,11):
    kmeans = KMeans(n_clusters = i, init = "k-means++", max_iter = 300, n_init =
    kmeans.fit(X_scale)
    wcss.append(kmeans.inertia_)

# Plotting the Elbow method WCSS scores
plt.figure(figsize = (10,6))
plt.plot(range(1,11), wcss, marker = "o", linestyle = "--")
plt.title("Elbow Method of WCSS Scores")
plt.xlabel("Number of Clusters")
plt.ylabel("WCSS Score")
plt.tight_layout()
plt.show();
```



From the WCSS scores, it seems as if the **optimal number of clusters** to build a KMeans model on is **3 clusters**. This is because after 3 clusters, the WCSS scores decreases at a much slower rate. Therefore I decided to train my KMeans model with these 3 clusters to segment the schools. I first trained the KMeans clustering model before analyzing the centroids in order to **determine which school features are the most significant in predicting educational outcomes**.

Training the KMeans Model on Educational Features

In [10]:

```
# Train KMeans clustering model with 3 clusters
kmeans = KMeans(n_clusters = 3, init = "k-means++", max_iter = 300, n_init = 10)
clusters = kmeans.fit_predict(X_scale)
# Add cluster labels to the DataFame
df["cluster"] = clusters

# Analyze the centroids
centroids = pd.DataFrame(scaler.inverse_transform(kmeans.cluster_centers_),
                         columns = success_metrics)
# Display the KMeans centroids
centroids
```

Out[10]:

	applications	acceptances	per_pupil_spending	avg_class_size	school_size	student_achieveme
0	42.100418	4.627615	19332.309623	23.992218	748.056485	3.6225
1	207.744681	64.574468	16949.659574	26.728936	1269.744681	3.778
2	17.931818	1.038961	22196.224026	19.640942	425.556818	3.1751

Analyzing the KMeans Centroids

Comparing the three centroids, I noticed **key differences** between each of the three clusters:

- **Cluster 0:** Cluster 0 schools are characterized as a **moderate number** of both **acceptances** and **applications**, with **average class size* around** 25 students **and a** relatively high per pupil spending**. Additionally these schools have** student achievement scores **of around** 3.30 **as well as around** 36% **of students** exceeding reading expectations **and** 30% **of students** exceeding math expectations**.

- **Cluster 1:** Cluster 1 schools are characterized as having the **highest number** of both **acceptances** and **applications**, as well as having the **largest class sizes** and **highest per pupil spending**. Additionally these schools have the **highest student achievement scores** and the **highest percentage of students exceeding both reading and math expectations**.

- **Cluster 2:** Cluster 2 schools are characterized as having the **lowest number** of **acceptances, applications, smallest class sizes,** and **least per pupil spending**. Additionally these schools have the **lowest student achievement scores** and the **lowest percentage of students exceeding both reading and math expectations**.

However in order to determine which school features contributed the most to these objective measures of success, I analyzed the **spread between centroids** for each educational feature across the clsuters.

Essentially features with a **wider spread between centroids** are more likely to be **significant** in **differentiating clusters**.

Calculating Spread Between KMeans Centroids

In [11]:

```
# Calculate spread between centroids for each educational feature
spread = centroids.max() - centroids.min()
# Create a spread DataFrame for the featuresF
spread_df = spread.reset_index()
spread_df.columns = ["feature", "spread"]
# Sort the spread DataFrame according to descending values of spread
spread_df.sort_values(by = "spread", ascending = False)
```

Out[11]:

	feature	spread
2	per_pupil_spending	5246.564452
4	school_size	844.187863
0	applications	189.812863
1	acceptances	63.535507
3	avg_class_size	7.087995
5	student_achievement	0.603316
7	math_scores_exceed	0.431875
6	reading_scores_exceed	0.373745

From analyzing the DataFrame of spread values, it is clear that the feature that explains the difference between centroids the most is **per pupil spending**. This definitely makes sense as increased student spending would contribute significantly to student success. However a **suprising observation** is that **school size** and **average class size** are so much less meaningful in regards to student success metrics than just overall spending.