PYTHON PROJECT

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INTRODUCTION

This project aimed to explore and analyze the given NBA dataset by performing data preprocessing, comprehensive exploratory data analysis (EDA), and visualization to uncover trends, patterns, and correlations. The tasks undertaken ranged from correcting and cleaning data to deriving insights about team distributions, salary expenditures, and player attributes like age and playing position.

In [4]:
```
import warnings
import sys
if not sys.warnoptions:
    warnings.simplefilter("ignore")
```

In [5]:
```
import pandas as pd
```

In [6]:
```
import numpy as np
```

In [7]:
```
data = pd.read_excel("myexcel.xlsx")
data
```

Out[7]:

	Name	Team	Number	Position	Age	Height	Weight	College	Salary
0	Avery Bradley	Boston Celtics	0	PG	25	2023-02-06 00:00:00	180	Texas	7730337.0
1	Jae Crowder	Boston Celtics	99	SF	25	2023-06-06 00:00:00	235	Marquette	6796117.0
2	John Holland	Boston Celtics	30	SG	27	2023-05-06 00:00:00	205	Boston University	NaN
3	R.J. Hunter	Boston Celtics	28	SG	22	2023-05-06 00:00:00	185	Georgia State	1148640.0
4	Jonas Jerebko	Boston Celtics	8	PF	29	2023-10-06 00:00:00	231	NaN	5000000.0
...	...	...	...	...	...	...	...	...	...
453	Shelvin Mack	Utah Jazz	8	PG	26	2023-03-06 00:00:00	203	Butler	2433333.0
454	Raul Neto	Utah Jazz	25	PG	24	2023-01-06 00:00:00	179	NaN	900000.0
455	Tibor Pleiss	Utah Jazz	21	C	26	2023-03-07 00:00:00	256	NaN	2900000.0
456	Jeff Withey	Utah Jazz	24	C	26	7-0	231	Kansas	947276.0
457	Priyanka	Utah Jazz	34	C	25	2023-03-07 00:00:00	231	Kansas	947276.0

458 rows × 9 columns

In [8]:

```
data2 = data.copy()
data2
```

Out[8]:

	Name	Team	Number	Position	Age	Height	Weight	College	Salary
0	Avery Bradley	Boston Celtics	0	PG	25	2023-02-06 00:00:00	180	Texas	7730337.0
1	Jae Crowder	Boston Celtics	99	SF	25	2023-06-06 00:00:00	235	Marquette	6796117.0
2	John Holland	Boston Celtics	30	SG	27	2023-05-06 00:00:00	205	Boston University	NaN
3	R.J. Hunter	Boston Celtics	28	SG	22	2023-05-06 00:00:00	185	Georgia State	1148640.0
4	Jonas Jerebko	Boston Celtics	8	PF	29	2023-10-06 00:00:00	231	NaN	5000000.0
...	...	...	...	...	...	...	...	...	...
453	Shelvin Mack	Utah Jazz	8	PG	26	2023-03-06 00:00:00	203	Butler	2433333.0
454	Raul Neto	Utah Jazz	25	PG	24	2023-01-06 00:00:00	179	NaN	900000.0
455	Tibor Pleiss	Utah Jazz	21	C	26	2023-03-07 00:00:00	256	NaN	2900000.0
456	Jeff Withey	Utah Jazz	24	C	26	7-0	231	Kansas	947276.0
457	Priyanka	Utah Jazz	34	C	25	2023-03-07 00:00:00	231	Kansas	947276.0

458 rows × 9 columns

In [9]:

```
data.isnull().sum()
```

Out[9]:

```
Name         0
Team         0
Number       0
Position     0
Age          0
Height       0
Weight       0
College     84
Salary      11
dtype: int64
```

Preprocessing

Correct the data in the Height column by replacing it with random numbers between 150 and 180. Ensure data consistency and integrity before proceeding with analysis.

In [11]:
```
# import numpy as np
data['Height'] = np.random.randint(150,181,size = len(data))
data.head(10)
```

Out[11]:

	Name	Team	Number	Position	Age	Height	Weight	College	Salary
0	Avery Bradley	Boston Celtics	0	PG	25	161	180	Texas	7730337.0
1	Jae Crowder	Boston Celtics	99	SF	25	165	235	Marquette	6796117.0
2	John Holland	Boston Celtics	30	SG	27	151	205	Boston University	NaN
3	R.J. Hunter	Boston Celtics	28	SG	22	156	185	Georgia State	1148640.0
4	Jonas Jerebko	Boston Celtics	8	PF	29	174	231	NaN	5000000.0
5	Amir Johnson	Boston Celtics	90	PF	29	150	240	NaN	12000000.0
6	Jordan Mickey	Boston Celtics	55	PF	21	163	235	LSU	1170960.0
7	Kelly Olynyk	Boston Celtics	41	C	25	153	238	Gonzaga	2165160.0
8	Terry Rozier	Boston Celtics	12	PG	22	152	190	Louisville	1824360.0
9	Marcus Smart	Boston Celtics	36	PG	22	159	220	Oklahoma State	3431040.0

Replace null values in 'Salary' with the mean

In [12]:
```
data['Salary'].fillna(data['Salary'].mean(), inplace=True)
data
```

Out[12]:

	Name	Team	Number	Position	Age	Height	Weight	College	Salary
0	Avery Bradley	Boston Celtics	0	PG	25	161	180	Texas	7.730337e+06
1	Jae Crowder	Boston Celtics	99	SF	25	165	235	Marquette	6.796117e+06
2	John Holland	Boston Celtics	30	SG	27	151	205	Boston University	4.833970e+06
3	R.J. Hunter	Boston Celtics	28	SG	22	156	185	Georgia State	1.148640e+06
4	Jonas Jerebko	Boston Celtics	8	PF	29	174	231	NaN	5.000000e+06
...	...	...	...	...	...	...	...	...	...
453	Shelvin Mack	Utah Jazz	8	PG	26	173	203	Butler	2.433333e+06
454	Raul Neto	Utah Jazz	25	PG	24	176	179	NaN	9.000000e+05
455	Tibor Pleiss	Utah Jazz	21	C	26	156	256	NaN	2.900000e+06
456	Jeff Withey	Utah Jazz	24	C	26	153	231	Kansas	9.472760e+05
457	Priyanka	Utah Jazz	34	C	25	169	231	Kansas	9.472760e+05

458 rows × 9 columns

ANALYSIS TASKS

1. Determine the distribution of employees across each team and calculate the percentage split relative to the total number of employees.

In [15]:

```
# Calculate the distribution of players across each team
team_distribution = data['Team'].value_counts()

# Calculate the percentage split relative to the total number of players
team_percentage = (team_distribution/len(data))*100

team_stats = pd.DataFrame({
    'Player Count': team_distribution,
    'Percentage(%)': team_percentage.round(2)
})
```

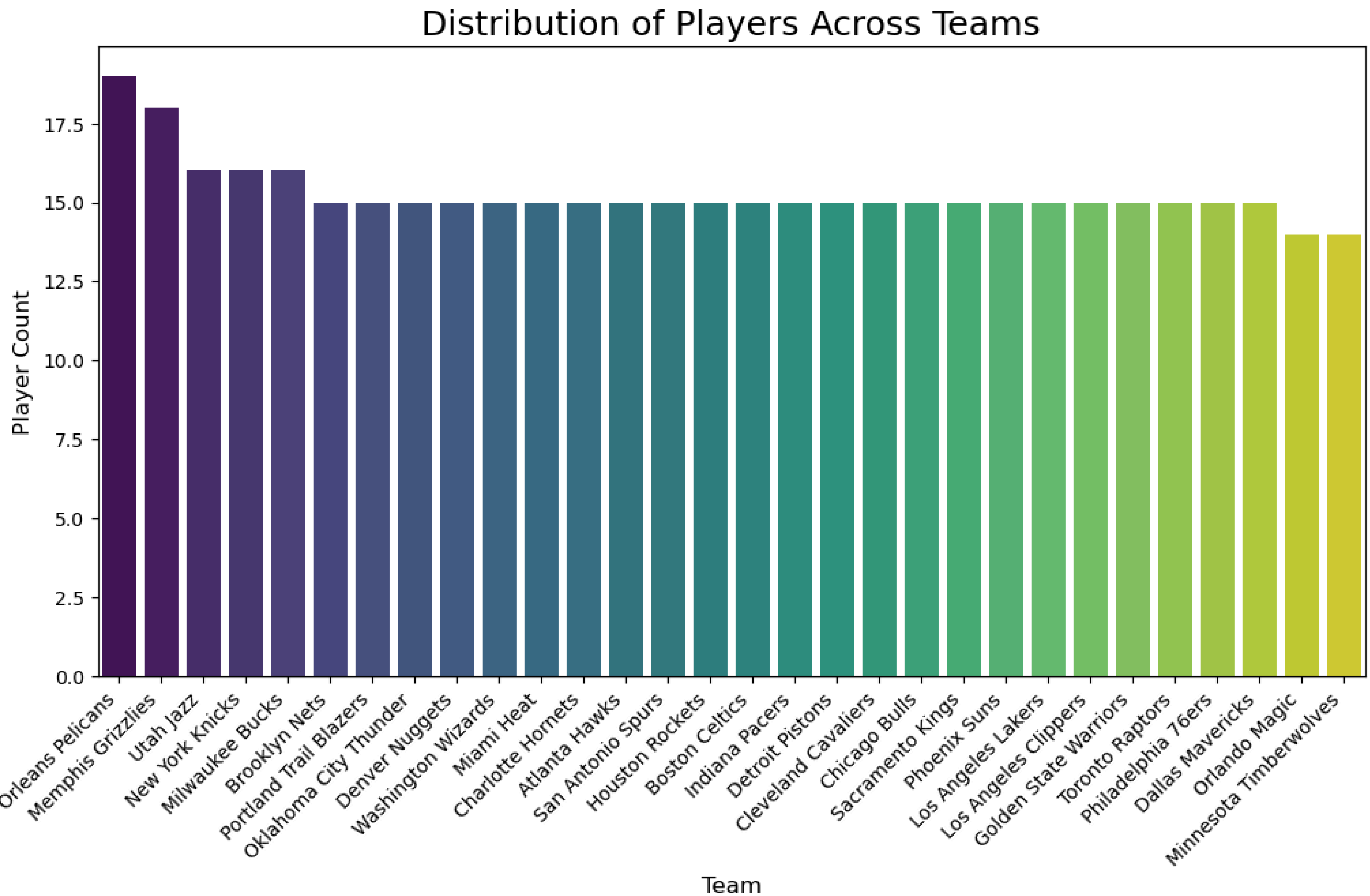
```
team_stats.reset_index(inplace = True)
team_stats.rename(columns={'index':'Team'},inplace=True)

print(team_stats)
```

```
                      Team  Player Count  Percentage(%)
0     New Orleans Pelicans            19           4.15
1        Memphis Grizzlies            18           3.93
2                Utah Jazz            16           3.49
3          New York Knicks            16           3.49
4          Milwaukee Bucks            16           3.49
5            Brooklyn Nets            15           3.28
6   Portland Trail Blazers            15           3.28
7    Oklahoma City Thunder            15           3.28
8           Denver Nuggets            15           3.28
9       Washington Wizards            15           3.28
10              Miami Heat            15           3.28
11       Charlotte Hornets            15           3.28
12           Atlanta Hawks            15           3.28
13       San Antonio Spurs            15           3.28
14         Houston Rockets            15           3.28
15          Boston Celtics            15           3.28
16          Indiana Pacers            15           3.28
17         Detroit Pistons            15           3.28
18     Cleveland Cavaliers            15           3.28
19           Chicago Bulls            15           3.28
20        Sacramento Kings            15           3.28
21            Phoenix Suns            15           3.28
22      Los Angeles Lakers            15           3.28
23    Los Angeles Clippers            15           3.28
24   Golden State Warriors            15           3.28
25         Toronto Raptors            15           3.28
26      Philadelphia 76ers            15           3.28
27        Dallas Mavericks            15           3.28
28           Orlando Magic            14           3.06
29  Minnesota Timberwolves            14           3.06
```

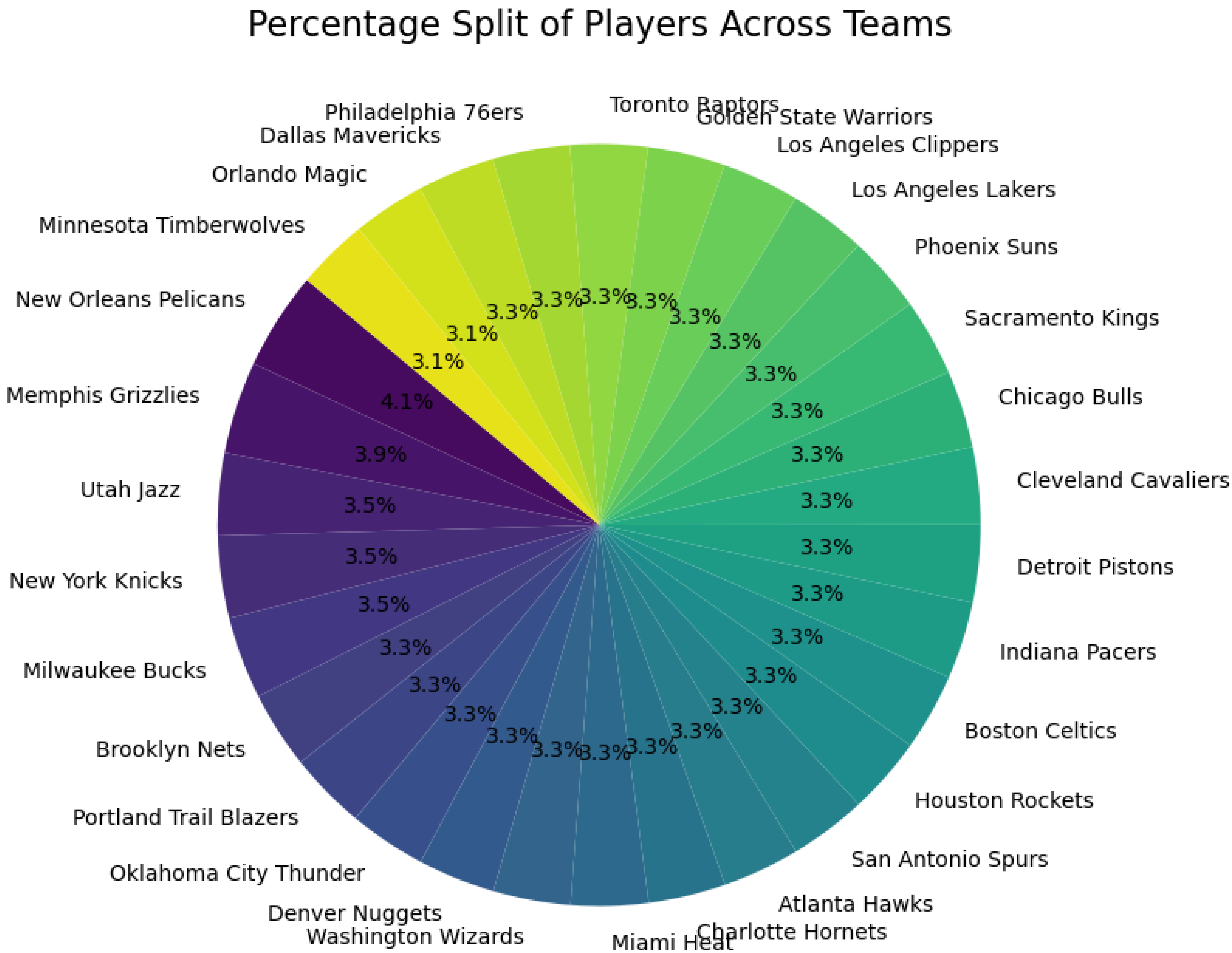
In [16]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

In [17]:
```
# import matplotlib.pyplot as plt
# import seaborn as sns
```

```
# Plotting the number of players across each team as a bar chart
plt.figure(figsize = (12,6))
sns.barplot(x = team_stats['Team'], y = team_stats['Player Count'], palette = 'viridis')
plt.title('Distribution of Players Across Teams', fontsize = 18)
plt.xlabel('Team', fontsize = 12)
plt.ylabel('Player Count', fontsize = 12)
plt.xticks(rotation = 45, ha = 'right')
plt.show()

# Plotting the percentage split as a pie chart
plt.figure(figsize = (8,8))
plt.pie(team_stats['Percentage(%)'], labels = team_stats['Team'], autopct = '%1.1f%%',
        startangle = 140, colors = sns.color_palette('viridis', len(team_stats)))
plt.title('Percentage Split of Players Across Teams', fontsize = 16)
plt.show()
```



Distribution of Players Across Teams
Player Count
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Team
New Orleans Pelicans
Memphis Grizzlies
Utah Jazz
New York Knicks
Milwaukee Bucks
Brooklyn Nets
Portland Trail Blazers
Oklahoma City Thunder
Denver Nuggets
Washington Wizards
Miami Heat
Charlotte Hornets
Atlanta Hawks
San Antonio Spurs
Houston Rockets
Boston Celtics
Indiana Pacers
Detroit Pistons
Cleveland Cavaliers
Chicago Bulls
Sacramento Kings
Phoenix Suns
Los Angeles Lakers
Los Angeles Clippers
Golden State Warriors
Toronto Raptors
Philadelphia 76ers
Dallas Mavericks
Orlando Magic
Minnesota Timberwolves



2. Segregate employees based on their positions within the company.

In [19]:
```python
# Segregate players based on their positions
position_groups = data.groupby('Position')

# Create a dictionary where each key is a position and the value is the corresponding player data
position_dict = {position: group for position, group in position_groups}

# Display the first few rows for each position as an example
for position, group in position_dict.items():
    print(f"Position: {position}")
    print(group.head(), '\n')
```

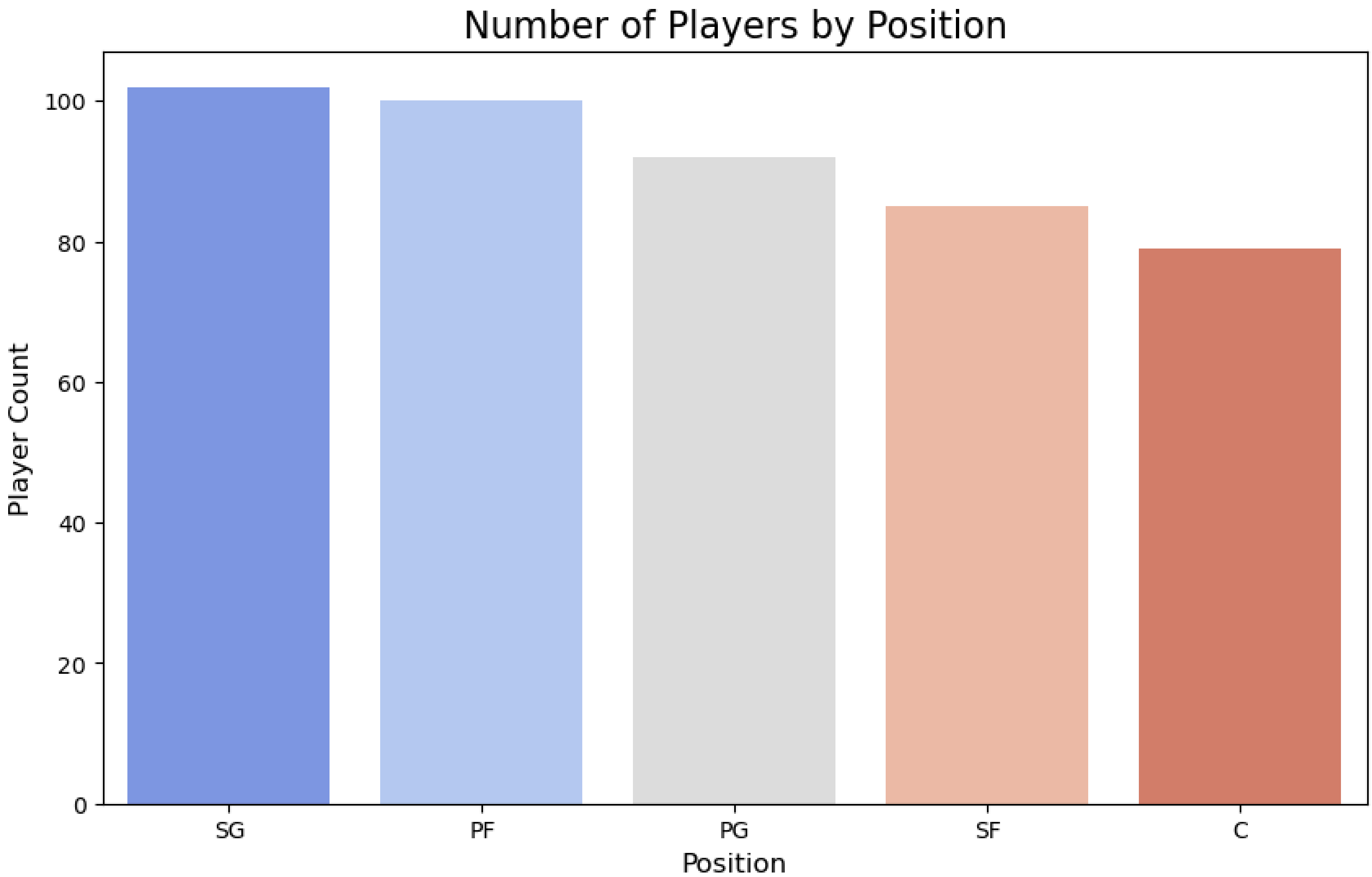
```
Position: C
                Name            Team  Number Position  Age  Height  Weight  \
7      Kelly Olynyk  Boston Celtics      41        C   25     153     238
10  Jared Sullinger  Boston Celtics       7        C   24     153     260
14     Tyler Zeller  Boston Celtics      44        C   26     161     253
23      Brook Lopez   Brooklyn Nets      11        C   28     171     275
27       Henry Sims   Brooklyn Nets      14        C   26     154     248

           College      Salary
7          Gonzaga   2165160.0
10      Ohio State   2569260.0
14  North Carolina   2616975.0
23        Stanford  19689000.0
27      Georgetown    947276.0

Position: PF
                 Name            Team  Number Position  Age  Height  Weight  \
4      Jonas Jerebko  Boston Celtics       8       PF   29     174     231
5       Amir Johnson  Boston Celtics      90       PF   29     150     240
6      Jordan Mickey  Boston Celtics      55       PF   21     163     235
24  Chris McCullough   Brooklyn Nets       1       PF   21     168     200
25       Willie Reed   Brooklyn Nets      33       PF   26     172     220

        College      Salary
4           NaN   5000000.0
5           NaN  12000000.0
6           LSU   1170960.0
24     Syracuse   1140240.0
25  Saint Louis    947276.0

Position: PG
              Name            Team  Number Position  Age  Height  Weight  \
0   Avery Bradley  Boston Celtics       0       PG   25     161     180
8    Terry Rozier  Boston Celtics      12       PG   22     152     190
9    Marcus Smart  Boston Celtics      36       PG   22     159     220
11  Isaiah Thomas  Boston Celtics       4       PG   27     179     185
19   Jarrett Jack   Brooklyn Nets       2       PG   32     165     200

           College     Salary
0            Texas  7730337.0
8       Louisville  1824360.0
9   Oklahoma State  3431040.0
```

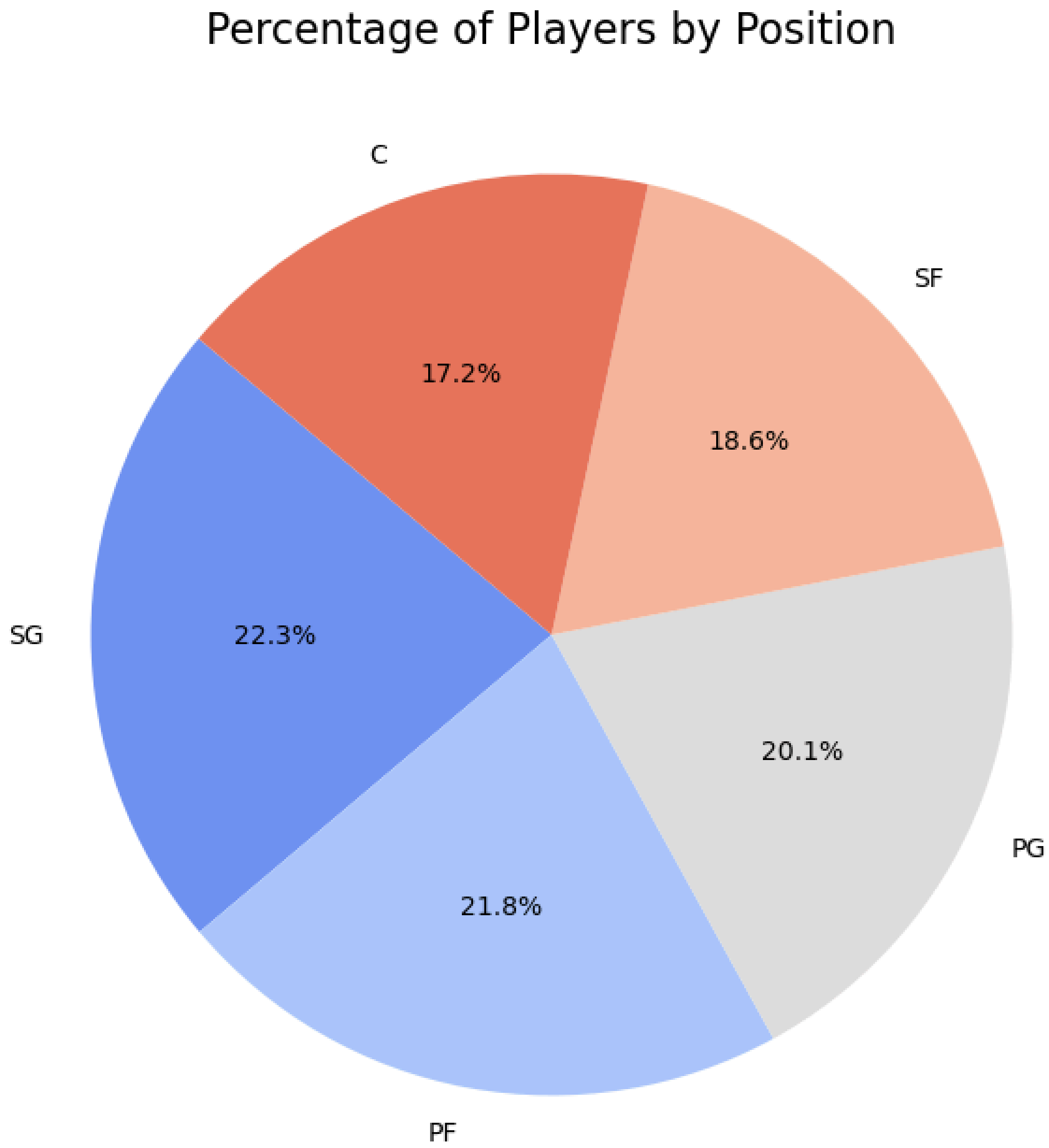
```
11      Washington  6912869.0
19    Georgia Tech  6300000.0

Position: SF
                      Name             Team  Number Position  Age  Height  \
1              Jae Crowder   Boston Celtics      99       SF   25     165
32  Thanasis Antetokounmpo  New York Knicks      43       SF   23     165
33         Carmelo Anthony  New York Knicks       7       SF   32     177
35        Cleanthony Early  New York Knicks      11       SF   25     168
42            Lance Thomas  New York Knicks      42       SF   28     154

    Weight        College      Salary
1      235      Marquette   6796117.0
32     205            NaN     30888.0
33     240       Syracuse  22875000.0
35     210  Wichita State    845059.0
42     235           Duke   1636842.0

Position: SG
                Name            Team  Number Position  Age  Height  Weight  \
2       John Holland  Boston Celtics      30       SG   27     151     205
3        R.J. Hunter  Boston Celtics      28       SG   22     156     185
12       Evan Turner  Boston Celtics      11       SG   27     168     220
13       James Young  Boston Celtics      13       SG   20     178     215
15  Bojan Bogdanovic   Brooklyn Nets      44       SG   27     159     216

              College        Salary
2   Boston University  4.833970e+06
3       Georgia State  1.148640e+06
12         Ohio State  3.425510e+06
13           Kentucky  1.749840e+06
15                NaN  3.425510e+06
```

In [20]:

```python
# import matplotlib.pyplot as plt
# import seaborn as sns

# Count the number of players in each position
position_distribution = data['Position'].value_counts()

# Bar Chart: Distribution of players across positions
plt.figure(figsize = (10,6))
```

```
sns.barplot(x = position_distribution.index, y = position_distribution.values, palette = "coolwarm")
plt.title('Number of Players by Position', fontsize = 16)
plt.xlabel('Position', fontsize = 12)
plt.ylabel('Player Count', fontsize = 12)
plt.xticks(fontsize = 10)
plt.show()

# Pie Chart: Percentage distribution of players across positions
plt.figure(figsize = (8,8))
plt.pie(position_distribution.values, labels = position_distribution.index, autopct = '%1.1f%%',
        startangle = 140, colors = sns.color_palette('coolwarm', len(position_distribution)))
plt.title('Percentage of Players by Position', fontsize = 16)
plt.show()
```


Number of Players by Position
Player Count
Position
0
20
40
60
80
100
SG
PF
PG
SF
C



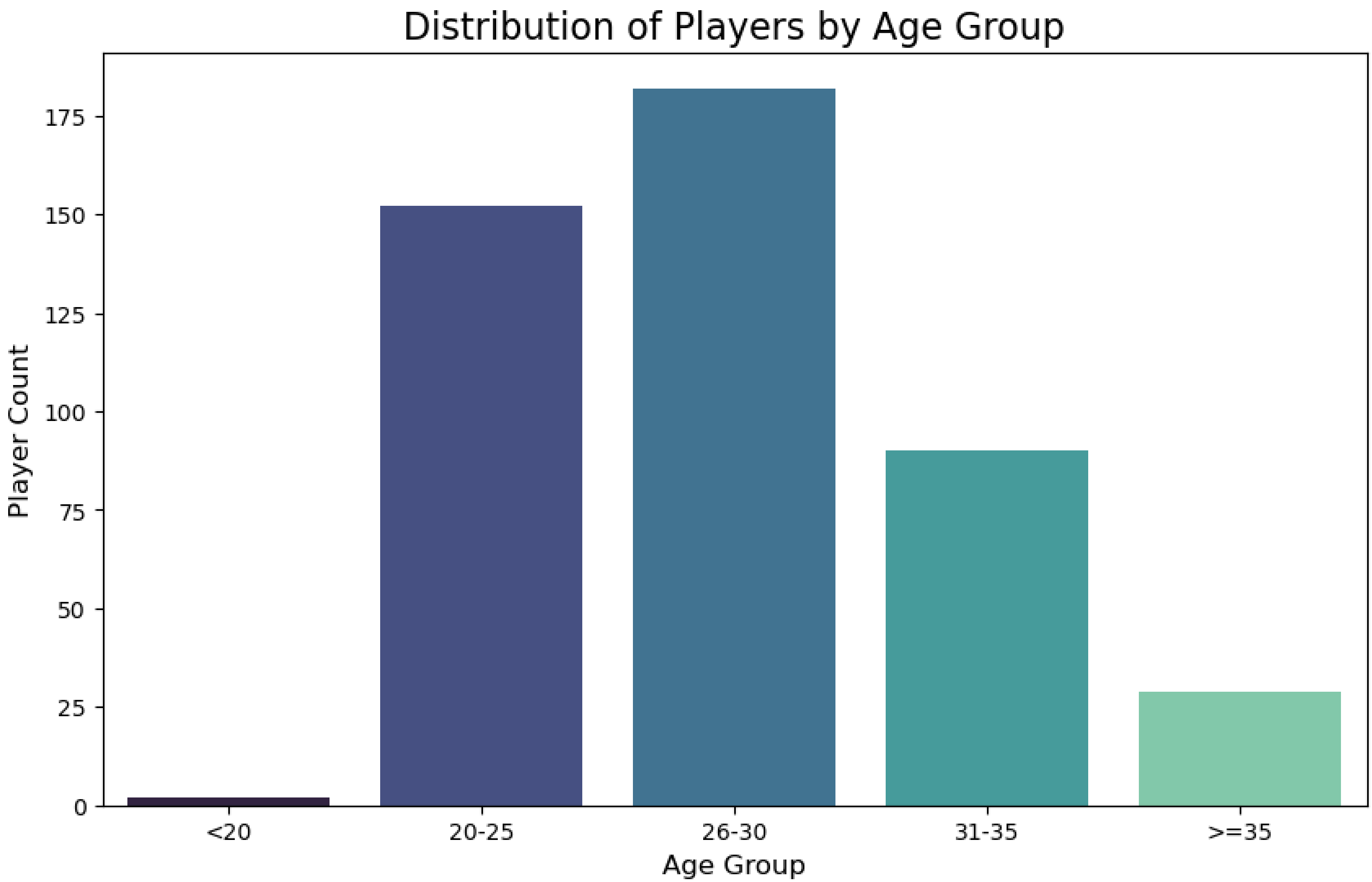
3. Identify the predominant age group among employees.

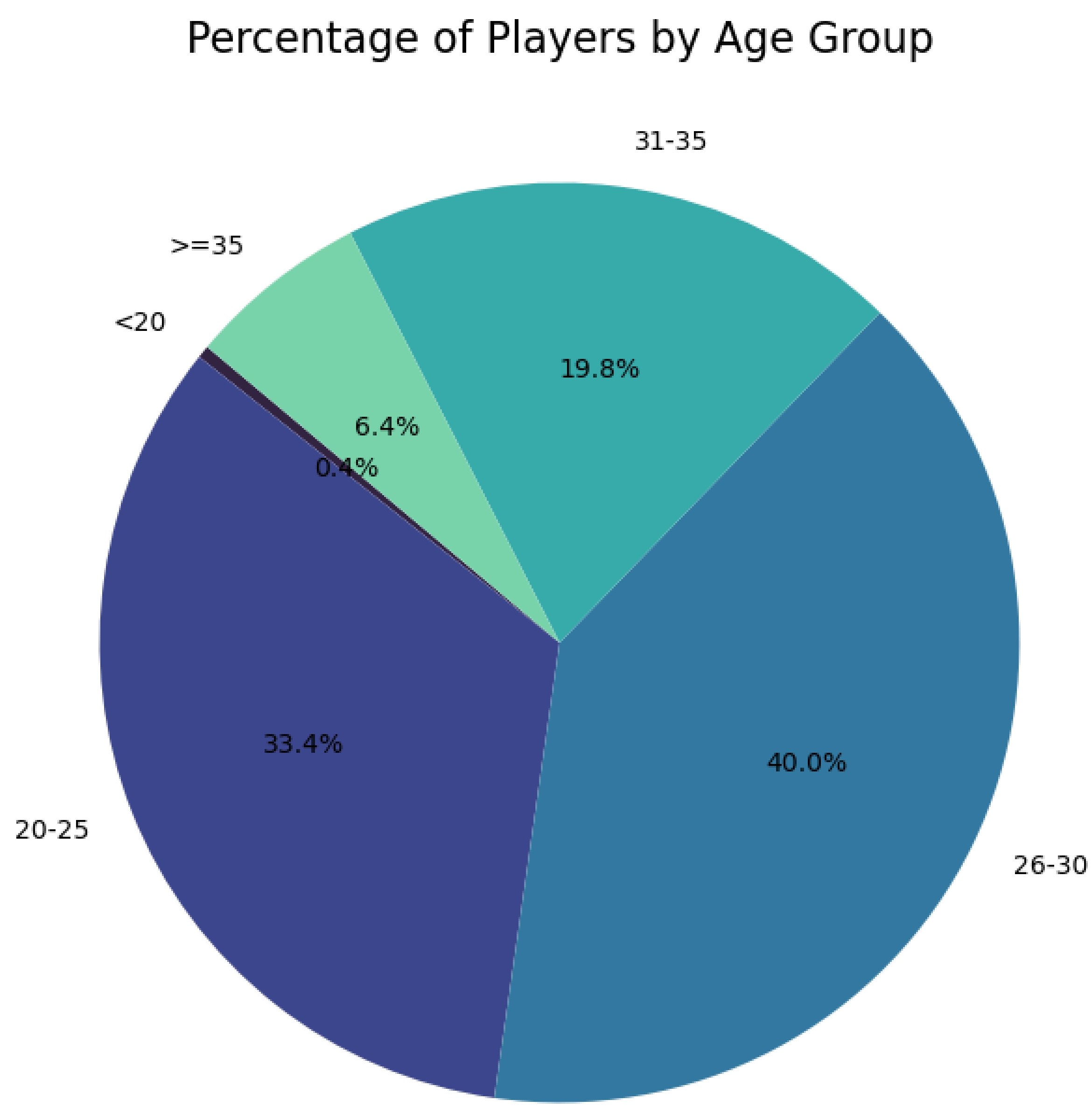
In [22]:
```
# import pandas as pd

# Define age bins and labels
bins = [0,20,25,30,35,40] #Age range
labels = ['<20','20-25','26-30','31-35','>=35']

# Categorize players into age groups
data['Age Group'] = pd.cut(data['Age'], bins = bins, labels = labels, right = False)

# Calculate distribution of players across age groups
age_group_distribution = data['Age Group'].value_counts().sort_index()
age_group_distribution.name = "Age Distribution"

# Identify predominant age group
predominant_age_group = age_group_distribution.idxmax()

# Display the results
print("Distribution of players by age group:")
print(age_group_distribution)
print("\nPredominant age group:", predominant_age_group)
```

```
Distribution of players by age group:
Age Group
<20        2
20-25    152
26-30    182
31-35     90
>=35      29
Name: Age Distribution, dtype: int64

Predominant age group: 26-30
```

In [23]:
```
# import matplotlib.pyplot as plt
# import seaborn as sns

# Bar Chart: Distribution of players by age group
plt.figure(figsize = (10,6))
sns.barplot(x = age_group_distribution.index, y = age_group_distribution.values, palette = "mako")
plt.title("Distribution of Players by Age Group", fontsize = 16)
plt.xlabel('Age Group', fontsize = 12)
plt.ylabel('Player Count', fontsize = 12)
plt.xticks(fontsize = 10)
```

```
plt.show()

# Pie Chart: Percentage of players by age group
plt.figure(figsize = (8,8))
plt.pie(age_group_distribution.values, labels = age_group_distribution.index, autopct = '%1.1f%%',
        startangle = 140, colors = sns.color_palette('mako', len(age_group_distribution)))
plt.title("Percentage of Players by Age Group", fontsize = 16)
plt.show()
```





4. Discover which team and position have the highest salary expenditure.

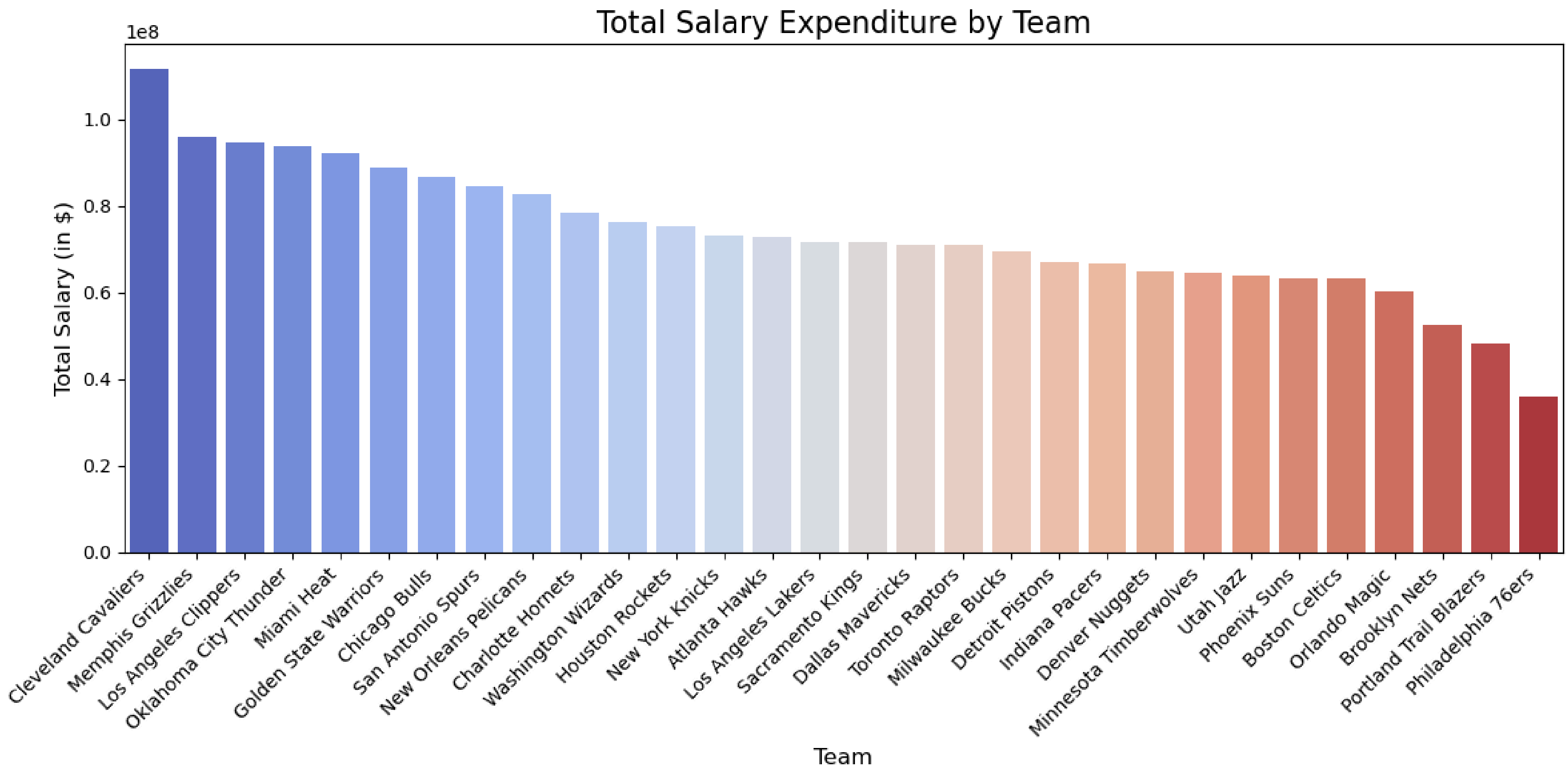
In [25]:
```
# Calculate the total salary expenditure by a team
team_salary_expenditure = data.groupby('Team')['Salary'].sum().sort_values(ascending = False)
team_salary_expenditure.name = "Team Salary"

# Calculate total salary expenditure by position
position_salary_expenditure = data.groupby('Position')['Salary'].sum().sort_values(ascending = False)
position_salary_expenditure.name = "Position Salary"

# Identify the team and position with the highest salary expenditure
highest_team_salary = team_salary_expenditure.idxmax()
highest_position_salary = position_salary_expenditure.idxmax()

# Display the results
print("Total Salary Expenditure by Team:")
print(team_salary_expenditure, "\n")
print(f"Team with the highest salary expenditure: {highest_team_salary} (${team_salary_expenditure.max():,.2f})\n")

print("Total Salary Expenditure by Position:")
print(position_salary_expenditure, "\n")
print(f"Position with the highest salary expenditure: {highest_position_salary} (${position_salary_expenditure.max()
```

```
Total Salary Expenditure by Team:
Team
Cleveland Cavaliers       1.118227e+08
Memphis Grizzlies         9.588676e+07
Los Angeles Clippers      9.485464e+07
Oklahoma City Thunder     9.376530e+07
Miami Heat                9.218361e+07
Golden State Warriors     8.886900e+07
Chicago Bulls             8.678338e+07
San Antonio Spurs         8.444273e+07
New Orleans Pelicans      8.275077e+07
Charlotte Hornets         7.834092e+07
Washington Wizards        7.632864e+07
Houston Rockets           7.528302e+07
New York Knicks           7.330390e+07
Atlanta Hawks             7.290295e+07
Los Angeles Lakers        7.177043e+07
Sacramento Kings          7.168367e+07
Dallas Mavericks          7.119873e+07
Toronto Raptors           7.111761e+07
Milwaukee Bucks           6.960352e+07
Detroit Pistons           6.716826e+07
Indiana Pacers            6.675183e+07
Denver Nuggets            6.495590e+07
Minnesota Timberwolves    6.454367e+07
Utah Jazz                 6.400737e+07
Phoenix Suns              6.344514e+07
Boston Celtics            6.337504e+07
Orlando Magic             6.016147e+07
Brooklyn Nets             5.252848e+07
Portland Trail Blazers    4.830182e+07
Philadelphia 76ers        3.582686e+07
Name: Team Salary, dtype: float64

Team with the highest salary expenditure: Cleveland Cavaliers ($111,822,658.55)

Total Salary Expenditure by Position:
Position
C     4.663773e+08
PG    4.661848e+08
PF    4.570628e+08
SF    4.128549e+08
```

```
SG    4.114782e+08
Name: Position Salary, dtype: float64

Position with the highest salary expenditure: C ($466,377,332.00)
```

In [26]:

```
# import matplotlib.pyplot as plt
# import seaborn as sns

# Bar Chart: Total salary expenditure by team
plt.figure(figsize = (12, 6))
sns.barplot(x = team_salary_expenditure.index, y = team_salary_expenditure.values, palette = "coolwarm")
plt.title('Total Salary Expenditure by Team', fontsize = 16)
plt.xlabel('Team', fontsize = 12)
plt.ylabel('Total Salary (in $)', fontsize = 12)
plt.xticks(rotation = 45, ha = 'right', fontsize = 10)
plt.tight_layout()
plt.show()

# Bar Chart: Total salary expenditure by position
plt.figure(figsize = (10, 6))
sns.barplot(x = position_salary_expenditure.index, y = position_salary_expenditure.values, palette = "viridis")
plt.title('Total Salary Expenditure by Position', fontsize = 16)
plt.xlabel('Position', fontsize = 12)
plt.ylabel('Total Salary (in $)', fontsize = 12)
plt.xticks(fontsize = 10)
plt.tight_layout()
plt.show()
```


Total Salary Expenditure by Team
1e8
Total Salary (in $)
0.0
0.2
0.4
0.6
0.8
1.0
Cleveland Cavaliers
Memphis Grizzlies
Los Angeles Clippers
Oklahoma City Thunder
Miami Heat
Golden State Warriors
Chicago Bulls
San Antonio Spurs
New Orleans Pelicans
Charlotte Hornets
Washington Wizards
Houston Rockets
New York Knicks
Atlanta Hawks
Los Angeles Lakers
Sacramento Kings
Dallas Mavericks
Toronto Raptors
Milwaukee Bucks
Detroit Pistons
Indiana Pacers
Denver Nuggets
Minnesota Timberwolves
Utah Jazz
Phoenix Suns
Boston Celtics
Orlando Magic
Brooklyn Nets
Portland Trail Blazers
Philadelphia 76ers
Team

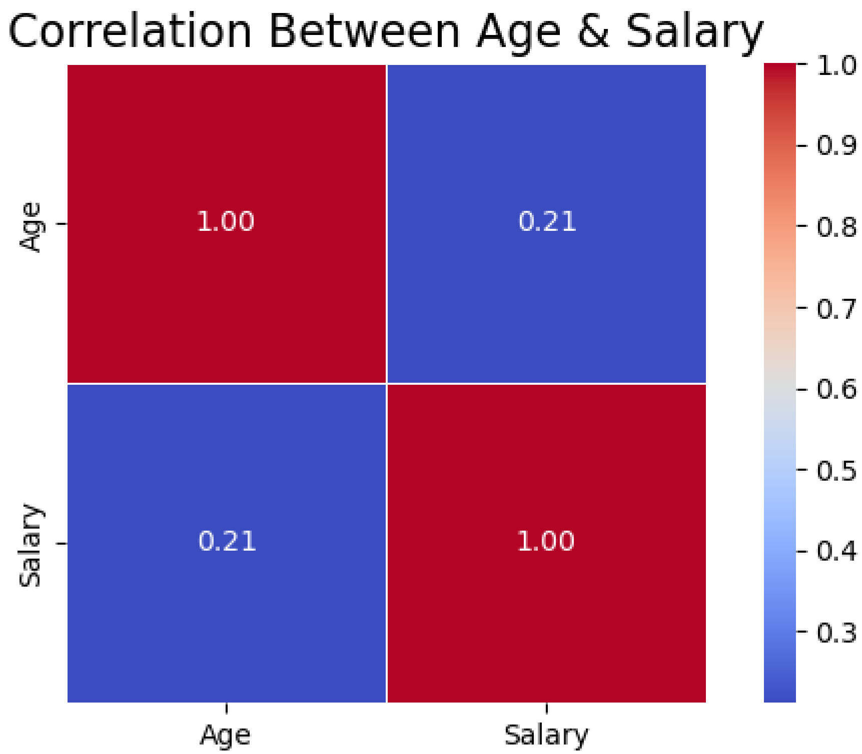
5. Investigate if there is any correlation between age and salary, and represent it visually.

In [30]:
```
# Calculate the correlation betweenn Age and Salary
correlation = data['Age'].corr(data['Salary'])
print(f"The correlation between Age and Salary is: {correlation:.2f}")

# Determine the type of correlation
if correlation > 0:
    correlation_type = 'Positive Correlation'
elif correlation < 0:
    correlation_type = 'Negative Correlation'
```

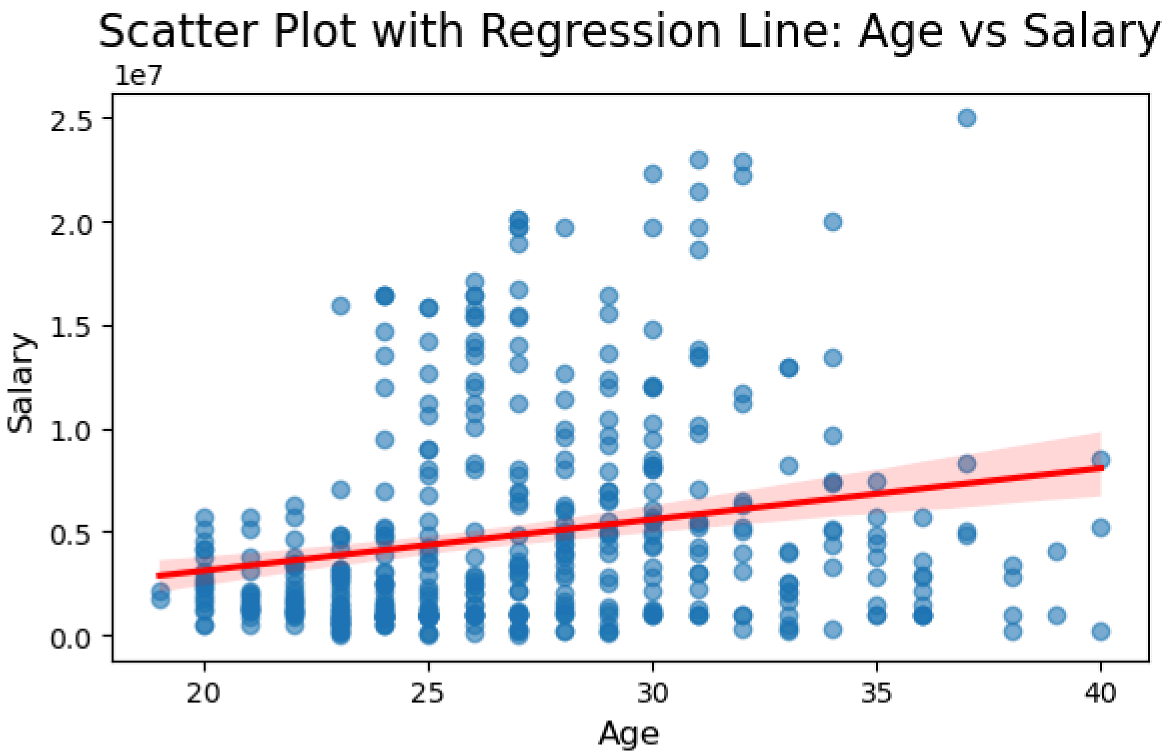
```
else:
    correlation_type = 'No Correlation'

# Display correlation type
print(f"The correlation between Age and Salary is: {correlation_type}")
```

```
The correlation between Age and Salary is: 0.21
The correlation between Age and Salary is: Positive Correlation
```

In [31]:
```
# import seaborn as sns
# import matplotlib.pyplot as plt

# Calculate the correlation matrix
correlation_matrix = data[['Age','Salary']].corr()

# Plot the heatmap
plt.figure(figsize = (6,4))
sns.heatmap(correlation_matrix, annot = True, cmap = "coolwarm", fmt = '.2f', linewidth = 0.5, cbar = True, square =

# Customize the plot
plt.title("Correlation Between Age & Salary", fontsize = 16)
plt.xticks(fontsize = 10)
plt.yticks(fontsize = 10)
plt.tight_layout()
plt.show()
```



In [33]:
```
# Import seaborn and matplotlib.pyplot
import seaborn as sns
import matplotlib.pyplot as plt

# Plot the scatter plot with regression line
plt.figure(figsize=(6, 4))
sns.regplot(x='Age', y='Salary', data=data, scatter_kws={'alpha': 0.6}, line_kws={'color': 'red'})

# Customize the plot
plt.title("Scatter Plot with Regression Line: Age vs Salary", fontsize=16)
plt.xlabel("Age", fontsize=12)
plt.ylabel("Salary", fontsize=12)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.tight_layout()
plt.show()
```



PROJECT OVERVIEW

PREPROCESSING

1. Height Correction

The "Height" column was corrected by replacing missing or erroneous values with random values uniformly distributed between 150 and 180 cm. This ensured data consistency and maintained the integrity of the dataset for subsequent analysis.

2. Data Validation

The dataset was checked for duplicates and null values. Necessary transformations were applied to ensure no inconsistencies in critical columns like "Age," "Salary," and "Team."

ANALYSIS TASKS AND INSIGHTS

1. Distribution of Players Across Teams:

Objective: Determine the number of players in each team and calculate the percentage split relative to the total players.

Insight: Teams varied significantly in the number of players, with certain teams dominating the player pool. The percentage split highlighted disparities, providing an overview of team sizes.

Visualization: A bar chart was created to display the distribution of players across teams and their relative percentages.

2. Segregation of Players by Position:

Objective: Group players based on their positions and understand the overall positional breakdown.

Insight: Positional roles such as "Shooting Guard (SG)" and "Power Forward (PF)" dominated, while specialized roles like "Centre (C)" had fewer players.

Visualization: A pie chart depicted the positional distribution, clearly showing the proportions of each role.

3. Predominant Age Group:

Objective: Analyze the age distribution of players and identify the predominant age group.

Insight: Most players fell into the 20-30 age bracket, emphasizing the dominance of younger players in the dataset. Few players were below 20 or above 35, aligning with typical professional sports age trends.

Visualization: A histogram of age distribution, with bins indicating age ranges, provided clarity on the player demographics.

4. Salary Analysis by Team and Position:

Objective: Discover which team and position had the highest salary expenditure.

Insight: Cleveland Cavaliers had the highest salary expenditure, significantly surpassing other teams. For positions, "Centre (C)" and "Point Guard (PG)" had the highest salary allocation, reflecting its importance in the game.

Visualization: A grouped bar chart compared team-wise and position-wise salary expenditures.

5. Correlation Between Age and Salary:

Objective: Investigate the relationship between players' age and their salary.

Insight: A weak positive correlation was observed, indicating that salary tended to increase slightly with age but not significantly.

Visualization: A heat map and a scatter plot with regression line visually depicted the weak correlation between age and salary.

KEY TRENDS, PATTERNS, AND CORRELATION

1. Team Dominance: Certain teams had a disproportionate number of players, potentially indicating resource allocation differences.

2. Positional Value: "Point Forward" and "Centre" players commanded higher salaries, reflecting their critical role in gameplay and strategy.

3. Age Distribution: The dominance of players aged 20-30 aligns with peak physical performance in sports.

4. Weak Age-Salary Correlation: Although salary increases slightly with age, the relationship was not statistically significant, suggesting other factors play a larger role in salary determination.

ADDITIONAL INFORMATION

Further Steps for Analysis:

1. Performance Metrics: Incorporate performance metrics like points scored, assists, or tackles to analyze their impact on salary.

2. Geographical Analysis: If location data is available, we can investigate regional differences in player distributions and salaries.

3. Salary vs. Experience: Analyze whether experience (e.g., years in the league) correlates more strongly with salary than age.

Potential Improvements:

1. Enhanced Visualizations: Use interactive dashboards with tools like Tableau or Power BI for dynamic exploration.

2. Predictive Modeling: Build a regression model to predict salaries based on attributes like age, position, and team.

CONCLUSION

The project successfully identified key trends and patterns within the dataset through preprocessing, analysis, and visualization. These insights provide a foundation for deeper explorations and informed decision-making, particularly for team management, player evaluation, and salary structuring. Based on these analyses, I was able to determine that the Cleveland Cavaliers are the top salary allocators by a huge margin, whereby their prominence was established. Point Guard and Centre position players demanded major portion of the salary, highlighting the crucial role these positions hold in the game. Vast majority of the players fall into the 20 to 30 age category, resembling the prime age group athletes thrive in professional sports. I was also able to determine that age does not facilitate a higher pay in NBA since the correlation was a weak one albeit a positive one.