Machine Learning 382 Project: BrightPath Academy

Problem Statement

BrightPath Academy struggles to identify at-risk students early and tailor interventions due to de insights and data overload. This project aims to develop a machine learning model the Student_performance_data to classify students' GradeClass (A–F) using demographic, academic, a extracurricular data, enabling timely interventions and personalised support strategies.

Hypothesis Generation

- If a student has more than 15 absences, then they are more likely to have a GradeClass of D
- Weekly study time positively impacts GPA.
- Frequent absences negatively affect academic performance.
- Students with higher parental involvement (ParentalSupport) tend to achieve better grades.
- Participation in extracurricular activities positively impacts GPA.

Getting the system ready and loading the data

Importing Libraries

In [1]:
```
import numpy as np
import pandas as pd
from IPython.display import display
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import PowerTransformer
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import IsolationForest
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix, accuracy_sc
```

Load the Data

In [2]:
```
df = pd.read_csv('Student_performance_data .csv')
```

Understanding the Data

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

print(df.describe())

print(df.isnull().sum())
```

```
print(df['GradeClass'].value_counts())
print(df['GradeClass'].value_counts(normalize=True))
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2392 entries, 0 to 2391
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   StudentID          2392 non-null   int64  
 1   Age                2392 non-null   int64  
 2   Gender             2392 non-null   int64  
 3   Ethnicity          2392 non-null   int64  
 4   ParentalEducation  2392 non-null   int64  
 5   StudyTimeWeekly    2392 non-null   float64
 6   Absences           2392 non-null   int64  
 7   Tutoring           2392 non-null   int64  
 8   ParentalSupport    2392 non-null   int64  
 9   Extracurricular    2392 non-null   int64  
 10  Sports             2392 non-null   int64  
 11  Music              2392 non-null   int64  
 12  Volunteering       2392 non-null   int64  
 13  GPA                2392 non-null   float64
 14  GradeClass         2392 non-null   float64
dtypes: float64(3), int64(12)
memory usage: 280.4 KB
None
(2392, 15)
         StudentID          Age       Gender    Ethnicity  ParentalEducation  \
count  2392.000000  2392.000000  2392.000000  2392.000000        2392.000000   
mean   2196.500000    16.468645     0.510870     0.877508           1.746237   
std     690.655244     1.123798     0.499986     1.028476           1.000411   
min    1001.000000    15.000000     0.000000     0.000000           0.000000   
25%    1598.750000    15.000000     0.000000     0.000000           1.000000   
50%    2196.500000    16.000000     1.000000     0.000000           2.000000   
75%    2794.250000    17.000000     1.000000     2.000000           2.000000   
max    3392.000000    18.000000     1.000000     3.000000           4.000000   

       StudyTimeWeekly     Absences     Tutoring  ParentalSupport  \
count      2392.000000  2392.000000  2392.000000      2392.000000   
mean          9.771992    14.541388     0.301421         2.122074   
std           5.652774     8.467417     0.458971         1.122813   
min           0.001057     0.000000     0.000000         0.000000   
25%           5.043079     7.000000     0.000000         1.000000   
50%           9.705363    15.000000     0.000000         2.000000   
75%          14.408410    22.000000     1.000000         3.000000   
max          19.978094    29.000000     1.000000         4.000000   

       Extracurricular       Sports        Music  Volunteering          GPA  \
count      2392.000000  2392.000000  2392.000000   2392.000000  2392.000000   
mean          0.383361     0.303512     0.196906      0.157191     1.906186   
std           0.486307     0.459870     0.397744      0.364057     0.915156   
min           0.000000     0.000000     0.000000      0.000000     0.000000   
25%           0.000000     0.000000     0.000000      0.000000     1.174803   
50%           0.000000     0.000000     0.000000      0.000000     1.893393   
75%           1.000000     1.000000     0.000000      0.000000     2.622216   
max           1.000000     1.000000     1.000000      1.000000     4.000000   

        GradeClass  
count  2392.000000  
mean      2.983696  
std       1.233908  
min       0.000000  
25%       2.000000  
```

```
50%          4.000000
75%          4.000000
max          4.000000
StudentID              0
Age                    0
Gender                 0
Ethnicity              0
ParentalEducation      0
StudyTimeWeekly        0
Absences               0
Tutoring               0
ParentalSupport        0
Extracurricular        0
Sports                 0
Music                  0
Volunteering           0
GPA                    0
GradeClass             0
dtype: int64
GradeClass
4.0    1211
3.0     414
2.0     391
1.0     269
0.0     107
Name: count, dtype: int64
GradeClass
4.0    0.506271
3.0    0.173077
2.0    0.163462
1.0    0.112458
0.0    0.044732
Name: proportion, dtype: float64
```

Inspect first 5 Rows

In [4]:
```
display(df.head())
```

	StudentID	Age	Gender	Ethnicity	ParentalEducation	StudyTimeWeekly	Absences	Tutoring	F
0	1001	17	1	0	2	19.833723	7	1	
1	1002	18	0	0	1	15.408756	0	0	
2	1003	15	0	2	3	4.210570	26	0	
3	1004	17	1	0	3	10.028829	14	0	
4	1005	17	1	0	2	4.672495	17	1	

Descriptive Statistics

In [5]:
```
display(df.describe().T)
```

	count	mean	std	min	25%	50%	
StudentID	2392.0	2196.500000	690.655244	1001.000000	1598.750000	2196.500000	27
Age	2392.0	16.468645	1.123798	15.000000	15.000000	16.000000	
Gender	2392.0	0.510870	0.499986	0.000000	0.000000	1.000000	
Ethnicity	2392.0	0.877508	1.028476	0.000000	0.000000	0.000000	
ParentalEducation	2392.0	1.746237	1.000411	0.000000	1.000000	2.000000	
StudyTimeWeekly	2392.0	9.771992	5.652774	0.001057	5.043079	9.705363	
Absences	2392.0	14.541388	8.467417	0.000000	7.000000	15.000000	
Tutoring	2392.0	0.301421	0.458971	0.000000	0.000000	0.000000	
ParentalSupport	2392.0	2.122074	1.122813	0.000000	1.000000	2.000000	
Extracurricular	2392.0	0.383361	0.486307	0.000000	0.000000	0.000000	
Sports	2392.0	0.303512	0.459870	0.000000	0.000000	0.000000	
Music	2392.0	0.196906	0.397744	0.000000	0.000000	0.000000	
Volunteering	2392.0	0.157191	0.364057	0.000000	0.000000	0.000000	
GPA	2392.0	1.906186	0.915156	0.000000	1.174803	1.893393	
GradeClass	2392.0	2.983696	1.233908	0.000000	2.000000	4.000000	

Feature Selection

In [6]:
```
all_vars = df.columns
output_var = 'GradeClass'
input_vars = all_vars.drop(output_var).to_list()

df_inputs = df[input_vars]
df_outputs = df[output_var]
print(f'There are now {len(df_inputs.columns)} input variables.')

display(df_inputs.head())
```

```
There are now 14 input variables.
```

	StudentID	Age	Gender	Ethnicity	ParentalEducation	StudyTimeWeekly	Absences	Tutoring
0	1001	17	1	0	2	19.833723	7	1
1	1002	18	0	0	1	15.408756	0	0
2	1003	15	0	2	3	4.210570	26	0
3	1004	17	1	0	3	10.028829	14	0
4	1005	17	1	0	2	4.672495	17	1

Check for Unique values

In [7]:
```
df[input_vars].nunique().sort_values(ascending=False).head(10)
```

```
Out[7]: StudentID            2392
        StudyTimeWeekly      2392
        GPA                  2371
        Absences               30
        ParentalEducation       5
        ParentalSupport         5
        Age                     4
        Ethnicity               4
        Gender                  2
        Tutoring                2
        dtype: int64
```

Categorizing the Data

```
In [8]: # Categorical columns
        int_col = [col for col in df.columns if df[col].dtype == 'int64']
        print('Integer columns :',int_col)
        # Numerical columns
        float_col = [col for col in df.columns if df[col].dtype == 'float64']
        print('Float columns :',float_col)
```

```
Integer columns : ['StudentID', 'Age', 'Gender', 'Ethnicity', 'ParentalEducation',
'Absences', 'Tutoring', 'ParentalSupport', 'Extracurricular', 'Sports', 'Music',
'Volunteering']
Float columns : ['StudyTimeWeekly', 'GPA', 'GradeClass']
```

Check for Duplicates

```
In [9]: duplicates = df[df.duplicated()]

        print(duplicates)
```

```
Empty DataFrame
Columns: [StudentID, Age, Gender, Ethnicity, ParentalEducation, StudyTimeWeekly, Abse
Tutoring, ParentalSupport, Extracurricular, Sports, Music, Volunteering, GPA, GradeCl
Index: []
```

Check for missing Values

```
In [10]: df.isna().sum()
```

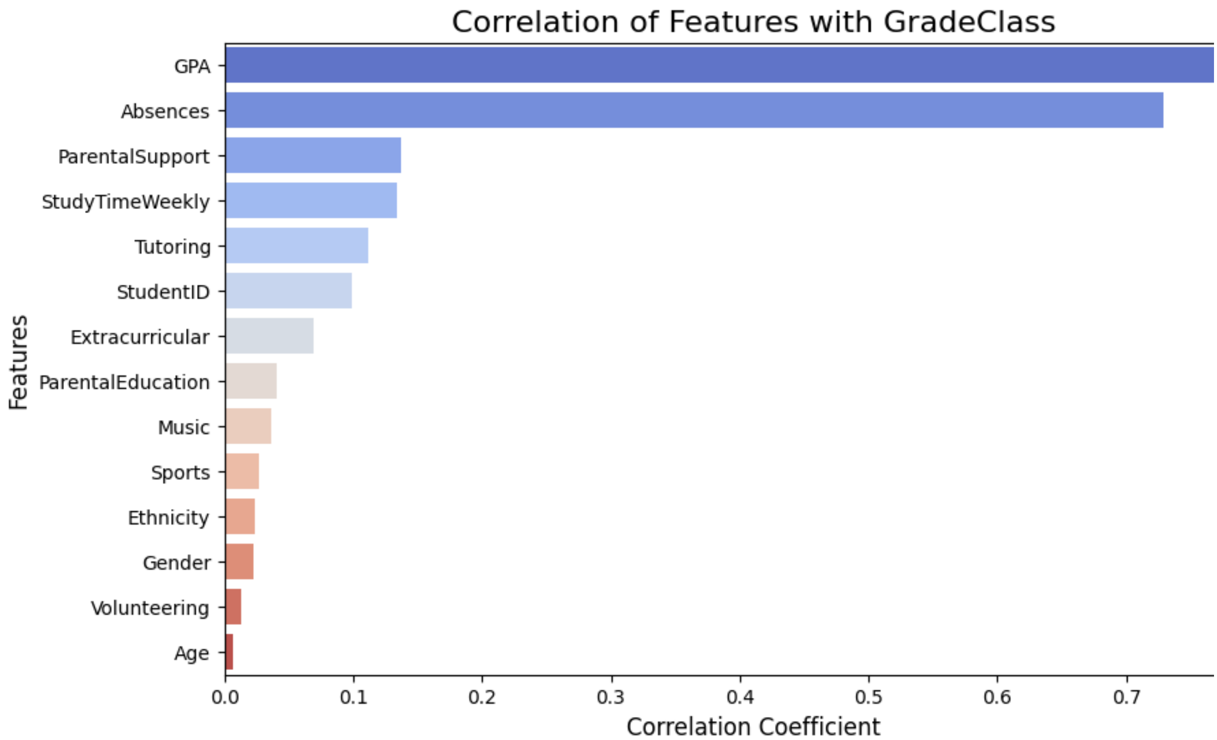
```
Out[10]: StudentID            0
         Age                  0
         Gender               0
         Ethnicity            0
         ParentalEducation    0
         StudyTimeWeekly      0
         Absences             0
         Tutoring             0
         ParentalSupport      0
         Extracurricular      0
         Sports               0
         Music                0
         Volunteering         0
         GPA                  0
         GradeClass           0
         dtype: int64
```

Correlation Graph to Clean Unneccessary Data

In [11]:

```
# Calculate correlation of all features with 'GradeClass'
correlation_with_gradeclass = df.corr()['GradeClass'].drop('GradeClass')

# Sort correlations by absolute value for better visualization
correlation_with_gradeclass = correlation_with_gradeclass.abs().sort_values(asce

# Plot the correlations
plt.figure(figsize=(10, 6))
sns.barplot(x=correlation_with_gradeclass.values, y=correlation_with_gradeclass.
plt.title('Correlation of Features with GradeClass', fontsize=16)
plt.xlabel('Correlation Coefficient', fontsize=12)
plt.ylabel('Features', fontsize=12)
plt.show()
```

```
C:\Users\calvi\AppData\Local\Temp\ipykernel_23268\865229569.py:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.
Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=correlation_with_gradeclass.values, y=correlation_with_gradeclass.inc
palette='coolwarm')
```

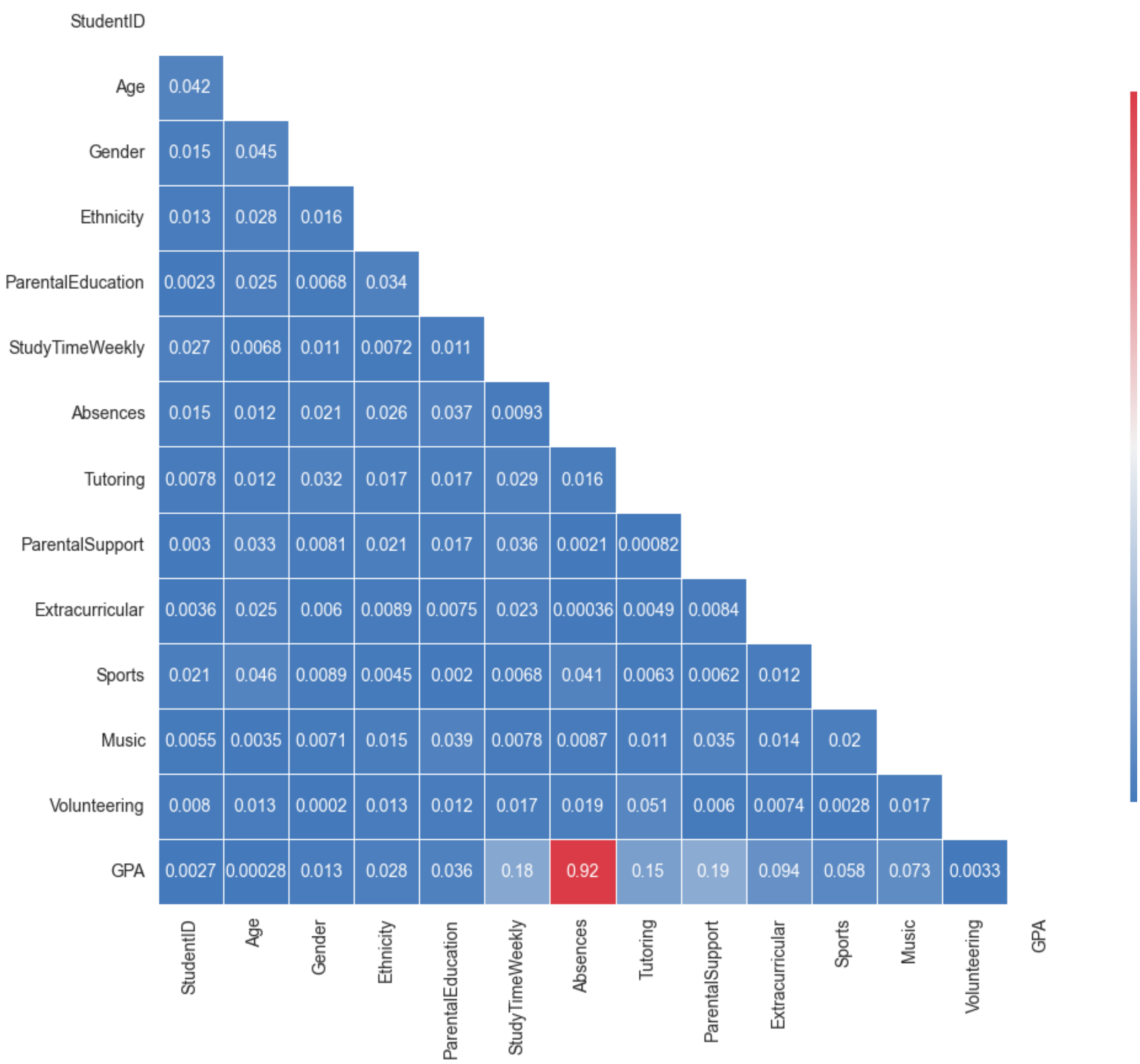


In [12]:

```
def CorrPlot(df, dropDuplicates = True, figsize = (8, 6)):
    # df = df.corr()
    df = np.abs(df.corr())
    # Exclude duplicate correlations by masking upper right values
    if dropDuplicates:
        mask = np.zeros_like(df, dtype=bool)
        mask[np.triu_indices_from(mask)] = True
    # Set background color / chart style
    sns.set_style(style = 'white')
    # Set up  matplotlib figure
    f, ax = plt.subplots(figsize=figsize)
    # Add diverging colormap from red to blue
    cmap = sns.diverging_palette(250, 10, as_cmap=True)
    # Draw correlation plot with or without duplicates
    if dropDuplicates:
```

```
        sns.heatmap(df, mask=mask, cmap=cmap,
                    annot=True,
                    square=True,
                    linewidth=.5, cbar_kws={"shrink": .75}, ax=ax)
    else:
        sns.heatmap(df, cmap=cmap,
                square=True,
                annot=True,
                linewidth=.5, cbar_kws={"shrink": .5}, ax=ax)
```

In [13]:
```
CorrPlot(df_inputs, figsize = (12, 10))
```

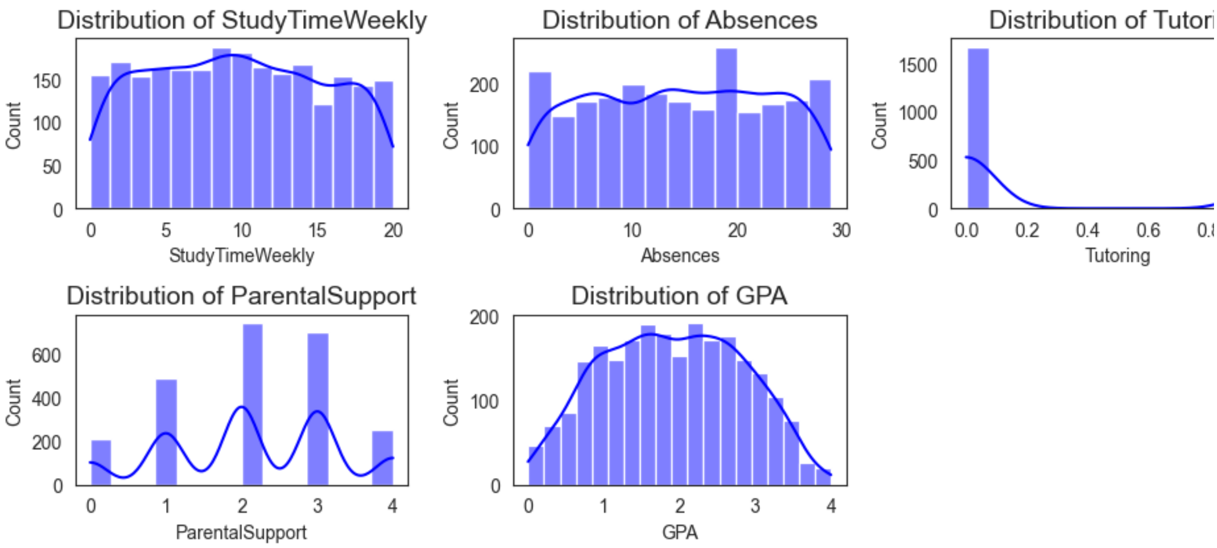


Removing Irrelevant Data

In [14]:
```
df_cleaned = df.drop(columns = ['Age', 'Volunteering', 'Gender', 'Ethnicity', 'S
                                'Extracurricular', 'StudentID', 'GradeClass'])

display(df_cleaned.head())
```

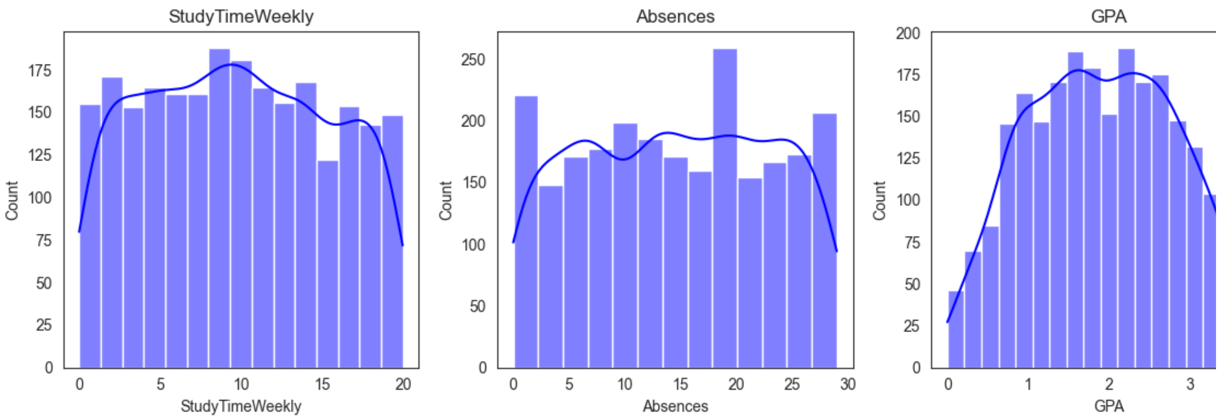
	StudyTimeWeekly	Absences	Tutoring	ParentalSupport	GPA
0	19.833723	7	1	2	2.929196
1	15.408756	0	0	1	3.042915
2	4.210570	26	0	2	0.112602
3	10.028829	14	0	3	2.054218
4	4.672495	17	1	3	1.288061

In [15]:
```
plt.figure(figsize=(10, 6))
for i, col in enumerate(df_cleaned.columns):
    plt.subplot(3, 3, i + 1)
    sns.histplot(df_cleaned[col], kde=True, color='blue', alpha=0.5)
    plt.title(f'Distribution of {col}', fontsize=14)
    plt.tight_layout()
plt.show()
```



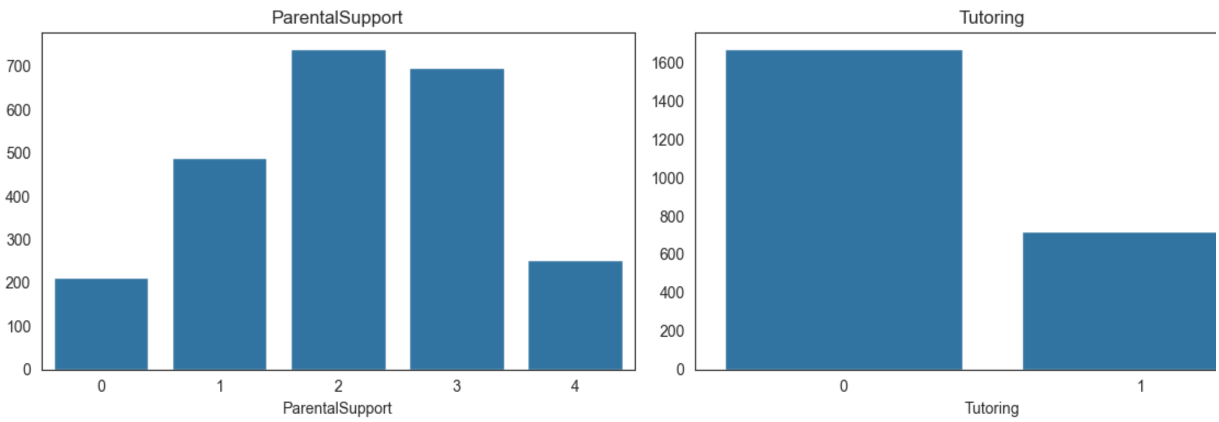
Univariate Analysis

In [16]:
```
selected_features = ['StudyTimeWeekly', 'Absences', 'GPA']

plt.figure(figsize=(12, 4))
for i, col in enumerate(selected_features):
    plt.subplot(1, 3, i+1)
    sns.histplot(df[col], kde=True, color='blue', alpha=0.5)
    plt.title(col)
plt.tight_layout()
plt.show()
```



In [17]:

```python
chosen_features = ['ParentalSupport', 'Tutoring']

plt.figure(figsize=(12, 4))
for i, col in enumerate(chosen_features):
    plt.subplot(1, 2, i+1)
    sns.barplot(x=df[col].value_counts().index, y=df[col].value_counts().values)
    plt.title(col)
plt.tight_layout()
plt.show()
```

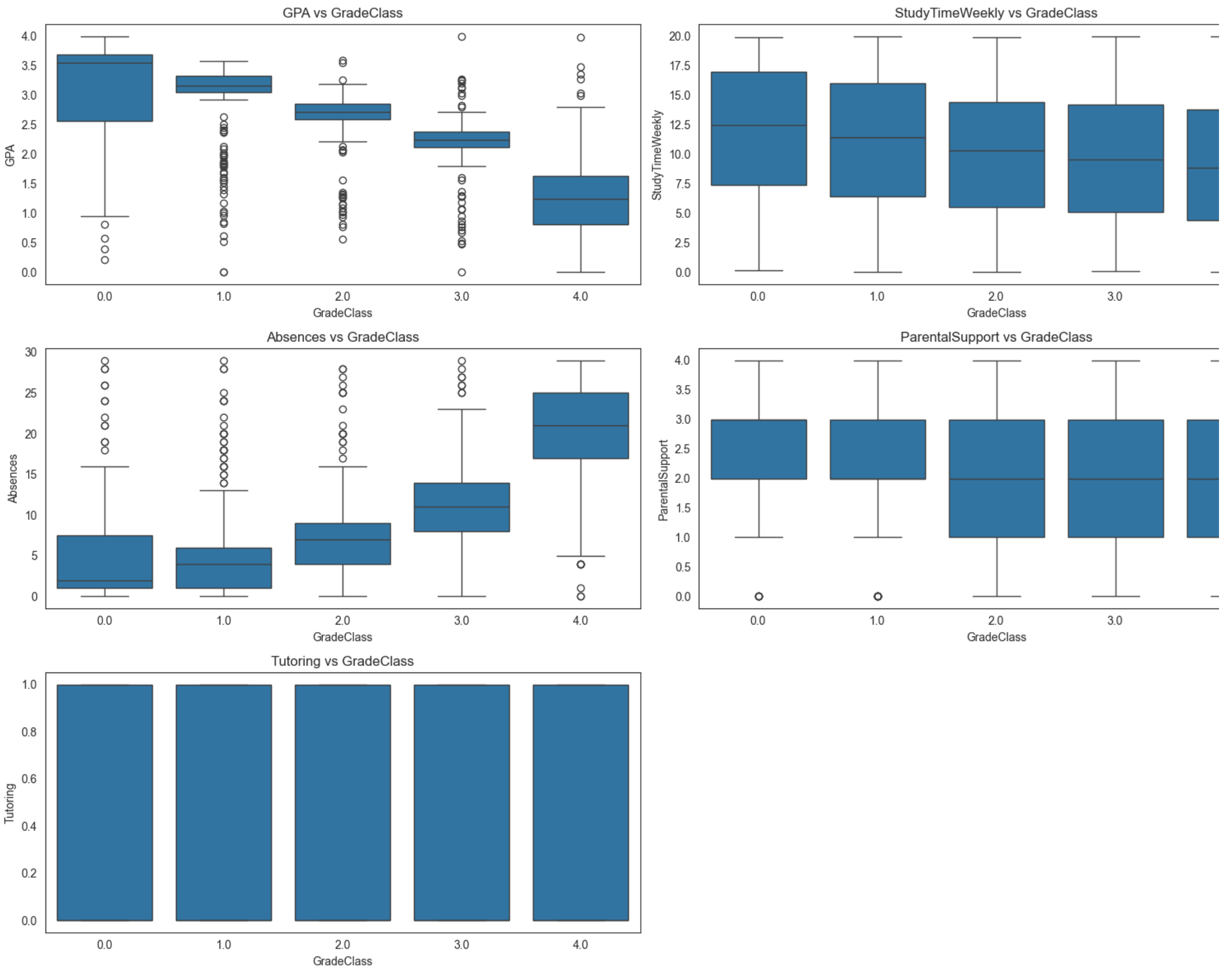


Bivariate Analysis

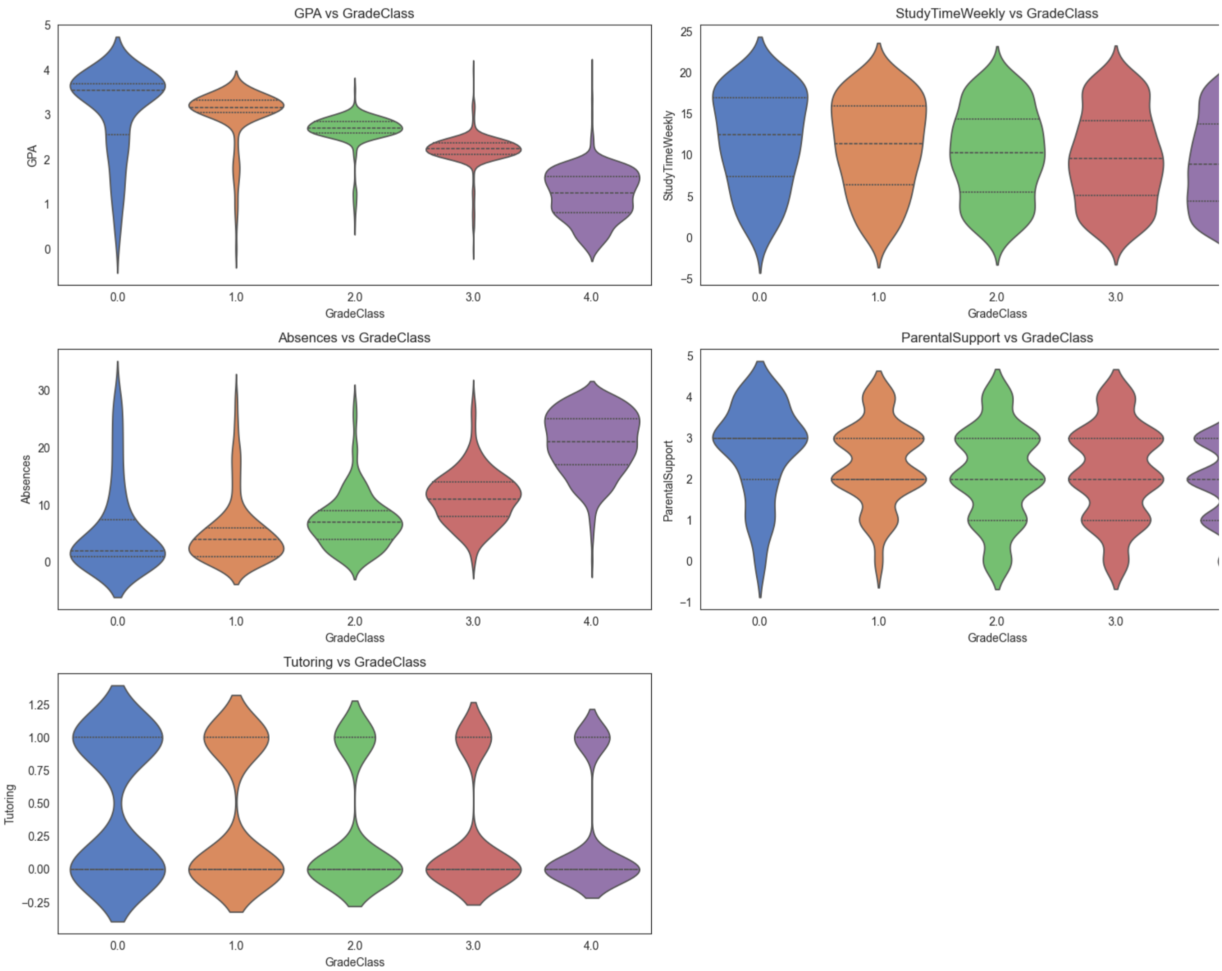
In [18]:

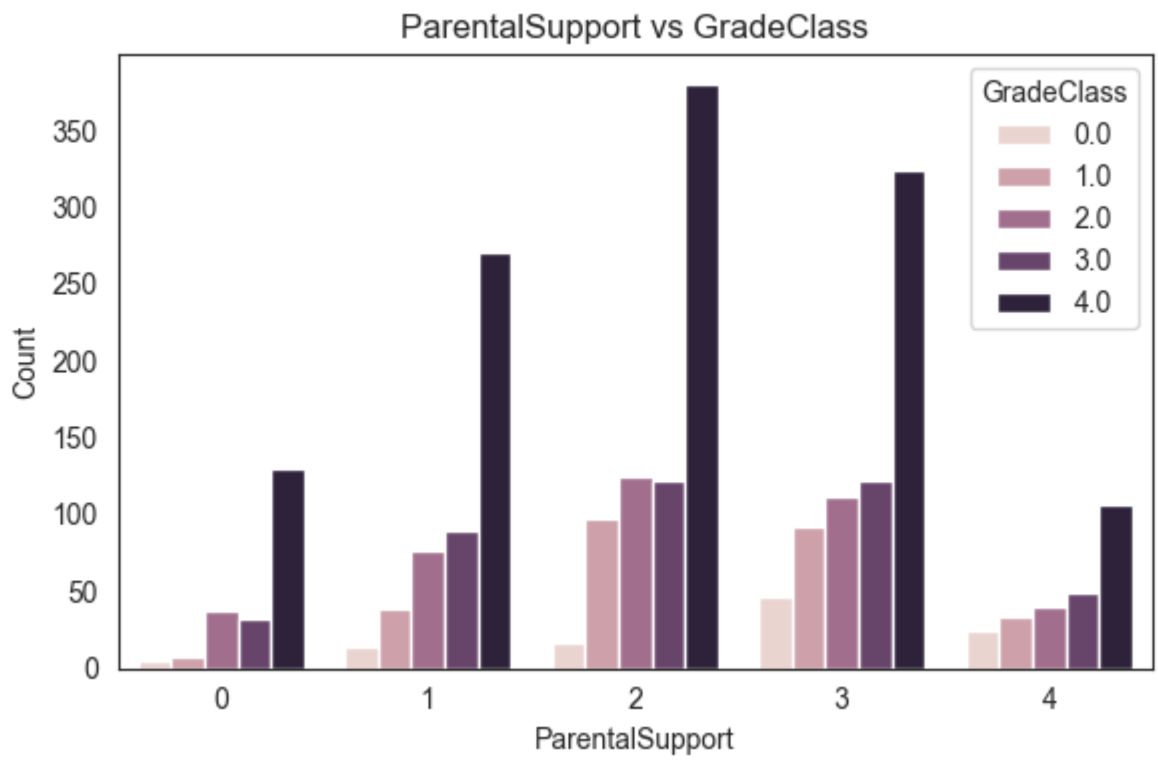
```python
numerical_features = ['GPA', 'StudyTimeWeekly', 'Absences', 'ParentalSupport', '

plt.figure(figsize=(16, 12))
for i, col in enumerate(numerical_features):
    plt.subplot(3, 2, i + 1)
    sns.boxplot(x='GradeClass', y=col, data=df)
    plt.title(f'{col} vs GradeClass')
plt.tight_layout()
plt.show()

plt.figure(figsize=(16, 12))
for i, col in enumerate(numerical_features):
    plt.subplot(3, 2, i + 1)
    sns.violinplot(x='GradeClass', y=col, data=df, inner='quartile', palette='mu
    plt.title(f'{col} vs GradeClass')
plt.tight_layout()
plt.show()

categorical_features = ['ParentalSupport', 'Tutoring']

for feature in categorical_features:
```

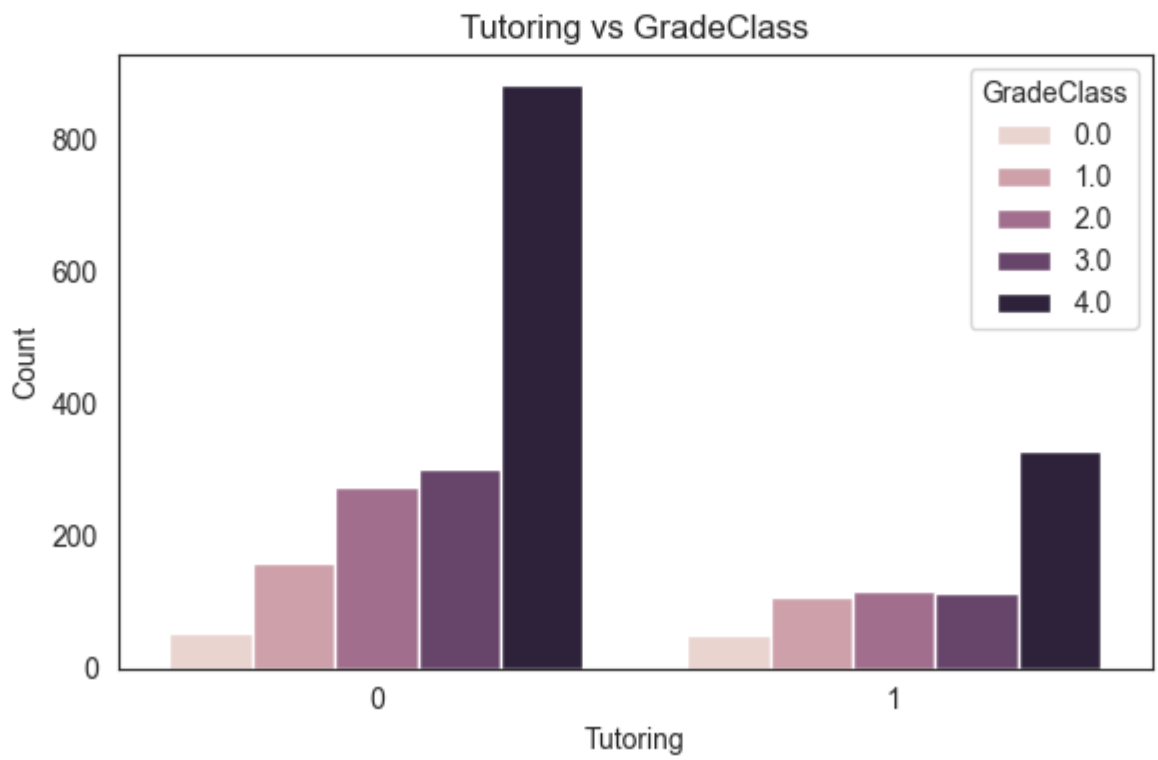
```
    plt.figure(figsize=(6, 4))
    sns.countplot(x=feature, hue='GradeClass', data=df)
    plt.title(f'{feature} vs GradeClass')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.legend(title='GradeClass')
    plt.tight_layout()
    plt.show()

plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(), annot=True, fmt=".2f", cmap='coolwarm')
plt.title('Correlation Matrix of Final Features (with GradeClass)')
plt.show()
```

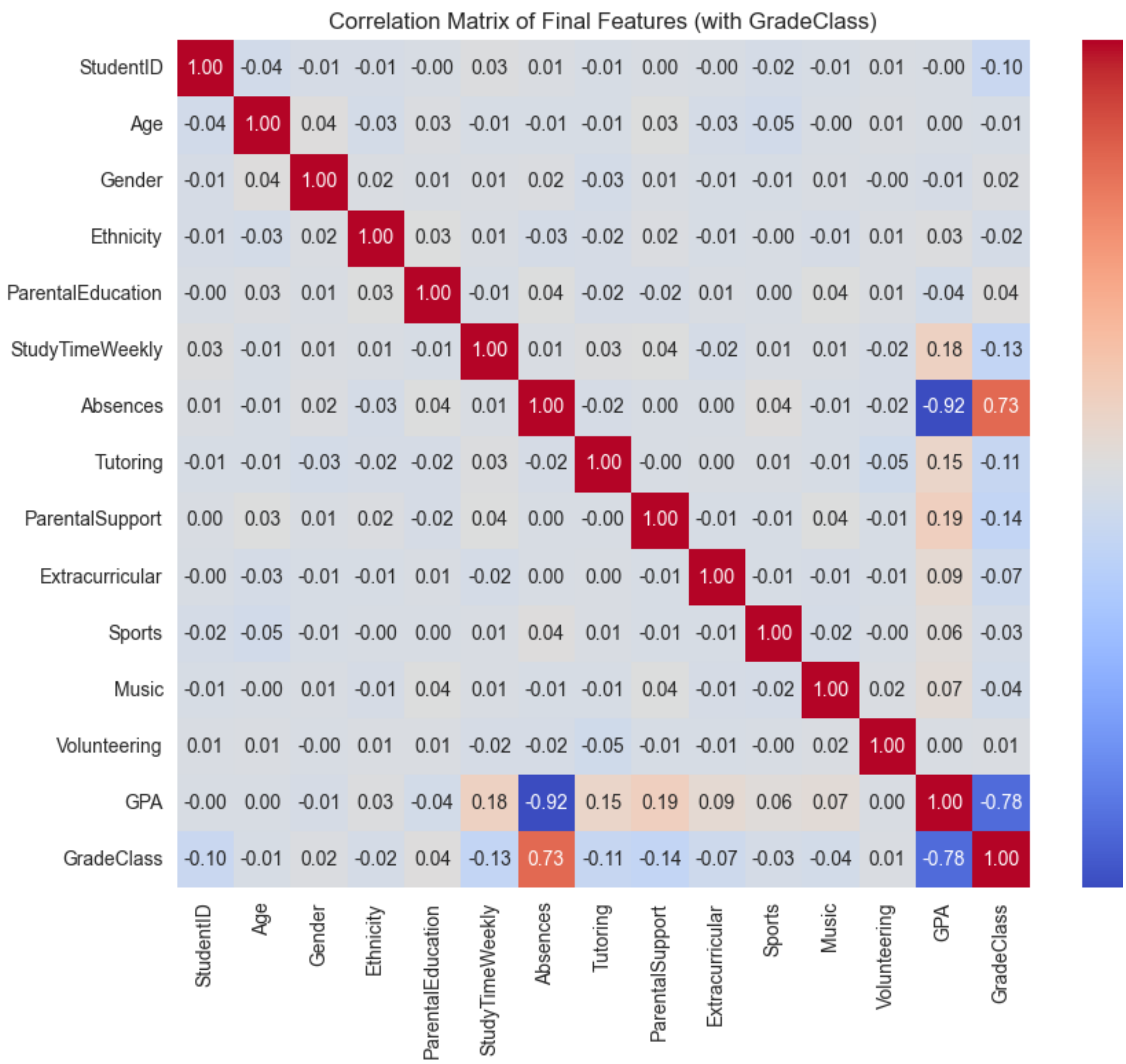


```
C:\Users\calvi\AppData\Local\Temp\ipykernel_23268\2030101869.py:14: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(x='GradeClass', y=col, data=df, inner='quartile', palette='muted')
C:\Users\calvi\AppData\Local\Temp\ipykernel_23268\2030101869.py:14: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(x='GradeClass', y=col, data=df, inner='quartile', palette='muted')
C:\Users\calvi\AppData\Local\Temp\ipykernel_23268\2030101869.py:14: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(x='GradeClass', y=col, data=df, inner='quartile', palette='muted')
C:\Users\calvi\AppData\Local\Temp\ipykernel_23268\2030101869.py:14: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(x='GradeClass', y=col, data=df, inner='quartile', palette='muted')
C:\Users\calvi\AppData\Local\Temp\ipykernel_23268\2030101869.py:14: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(x='GradeClass', y=col, data=df, inner='quartile', palette='muted')
```




ParentalSupport vs GradeClass
Count
350
300
250
200
150
100
50
0
0
1
2
3
4
ParentalSupport
GradeClass
0.0
1.0
2.0
3.0
4.0


Tutoring vs GradeClass
Count
800
600
400
200
0
0
1
Tutoring
GradeClass
0.0
1.0
2.0
3.0
4.0



Missing Values and Outlier Treatment

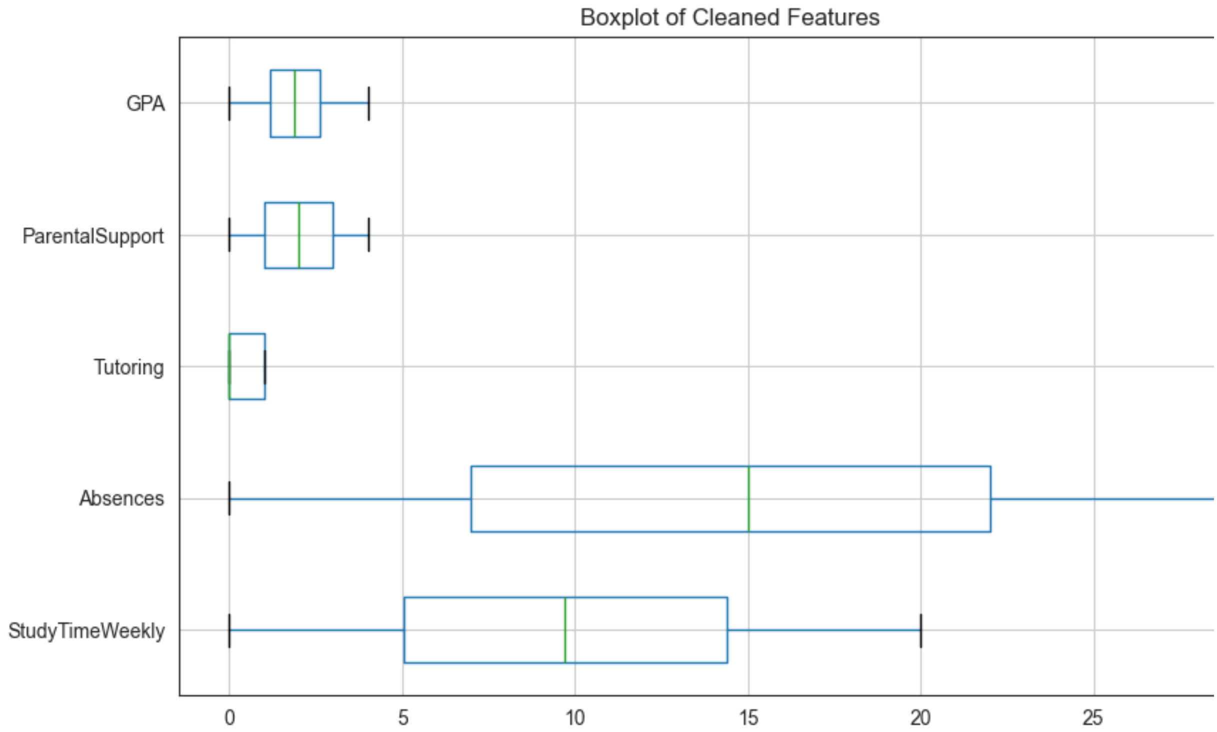
1. Check again for missing values

In [19]:
```
df_cleaned.isnull().sum()
```

Out[19]:
```
StudyTimeWeekly     0
Absences            0
Tutoring            0
ParentalSupport     0
GPA                 0
dtype: int64
```

1. Boxplot for cleaned features

In [20]:
```
fig, ax = plt.subplots(figsize=(10, 6))
boxplot = df_cleaned.boxplot(vert = False, ax = ax)
_ = ax.set_title(f'Boxplot of Cleaned Features')
```



Checking Skewness

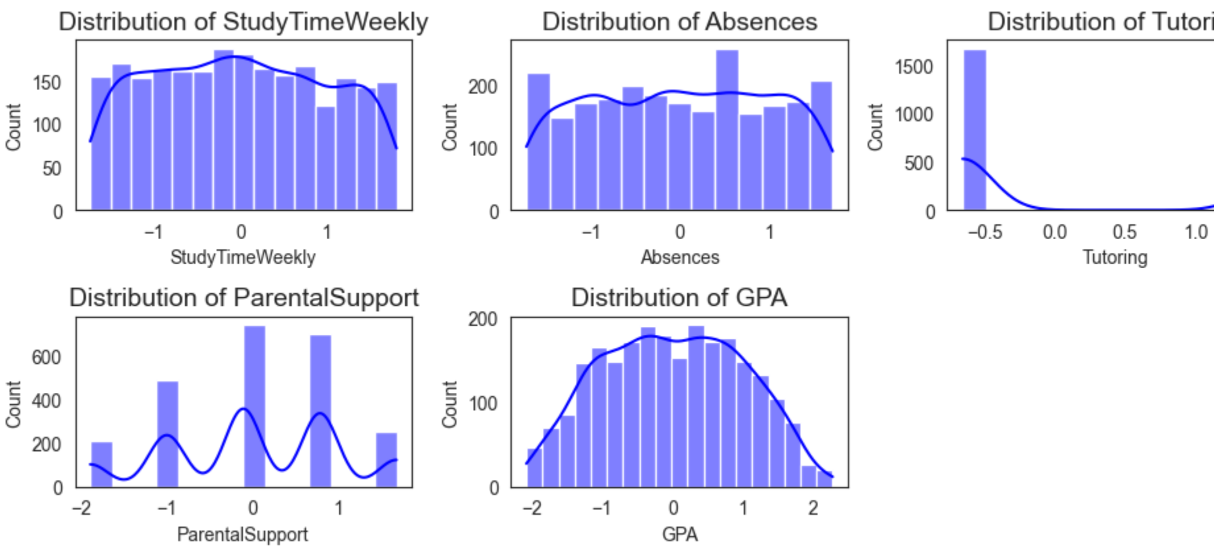
In [21]:
```
for col in df_cleaned.columns:
    print(f'{col} = {df_cleaned[col].skew()}')
```

```
StudyTimeWeekly = 0.05006807255835409
Absences = -0.026017090405395748
Tutoring = 0.8660445294904519
ParentalSupport = -0.16685872350058553
GPA = 0.014525601346976225
```

Scaling the data

In [22]:
```
scaler = StandardScaler()
df_scaled = pd.DataFrame(
    scaler.fit_transform(df_cleaned),
    index=df_cleaned.index,
    columns=df_cleaned.columns
)
```

In [23]:
```
plt.figure(figsize=(10, 6))
for i, col in enumerate(df_scaled.columns):
    plt.subplot(3, 3, i + 1)
    sns.histplot(df_scaled[col], kde=True, color='blue', alpha=0.5)
    plt.title(f'Distribution of {col}', fontsize=14)
    plt.tight_layout()
plt.show()
```



Remove outliers

In [24]:
```python
iso = IsolationForest(contamination=0.1, random_state=42)
outliers = iso.fit_predict(df_scaled)

# 3. Select only the inliers (outliers == 1) — index is preserved here
df_removed_outliers = df_scaled.loc[outliers == 1].copy()

# 4. Reattach your target
df_removed_outliers['GradeClass'] = df_outputs.loc[df_removed_outliers.index]

# Quick check
display(df_removed_outliers.head())
print(df_removed_outliers.shape)
```

	StudyTimeWeekly	Absences	Tutoring	ParentalSupport	GPA	GradeClass
0	1.780336	-0.890822	1.522371	-0.108744	1.118086	2.0
1	0.997376	-1.717694	-0.656870	-0.999551	1.242374	1.0
2	-0.984045	1.353542	-0.656870	-0.108744	-1.960277	4.0
3	0.045445	-0.063951	-0.656870	0.782063	0.161790	3.0
4	-0.902311	0.290422	1.522371	0.782063	-0.675573	4.0

```
(2152, 6)
```

Evaluation Metrics for Classification Problem

In [25]:
```python
X = df_removed_outliers.drop(columns=[output_var])
y = df_removed_outliers[output_var]

display(X, y)
```

	StudyTimeWeekly	Absences	Tutoring	ParentalSupport	GPA
0	1.780336	-0.890822	1.522371	-0.108744	1.118086
1	0.997376	-1.717694	-0.656870	-0.999551	1.242374
2	-0.984045	1.353542	-0.656870	-0.108744	-1.960277
3	0.045445	-0.063951	-0.656870	0.782063	0.161790
4	-0.902311	0.290422	1.522371	0.782063	-0.675573
...	...	...	...	...	...
2385	-1.473312	0.644796	-0.656870	0.782063	-0.558006
2386	0.715202	-0.063951	-0.656870	-0.108744	0.102624
2389	-0.524895	0.644796	-0.656870	-0.108744	-0.834845
2390	0.467950	0.290422	-0.656870	-0.108744	-0.112452
2391	1.424008	-0.182076	-0.656870	-0.108744	0.255559

2152 rows × 5 columns

```
0       2.0
1       1.0
2       4.0
3       3.0
4       4.0
       ...
2385    1.0
2386    4.0
2389    2.0
2390    1.0
2391    1.0
Name: GradeClass, Length: 2152, dtype: float64
```

Splitting to Training and test data

In [26]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

Training the Model

In [27]:
```
model = RandomForestClassifier(n_estimators=200, random_state=42)
model.fit(X_train, y_train)

#Predict
y_train_pred = model.predict(X_train)
y_test_pred = model.predict(X_test)
```

Calculating metrics

In [28]:
```
train_accuracy = accuracy_score(y_train, y_train_pred)
print(f'Train Accuracy: {np.round(100*train_accuracy, 1)}%')

test_accuracy = accuracy_score(y_test, y_test_pred)
print(f'Test Accuracy: {np.round(100*test_accuracy, 1)}%')
```

```
Train Accuracy: 100.0%
Test Accuracy: 89.8%
```

Classification report

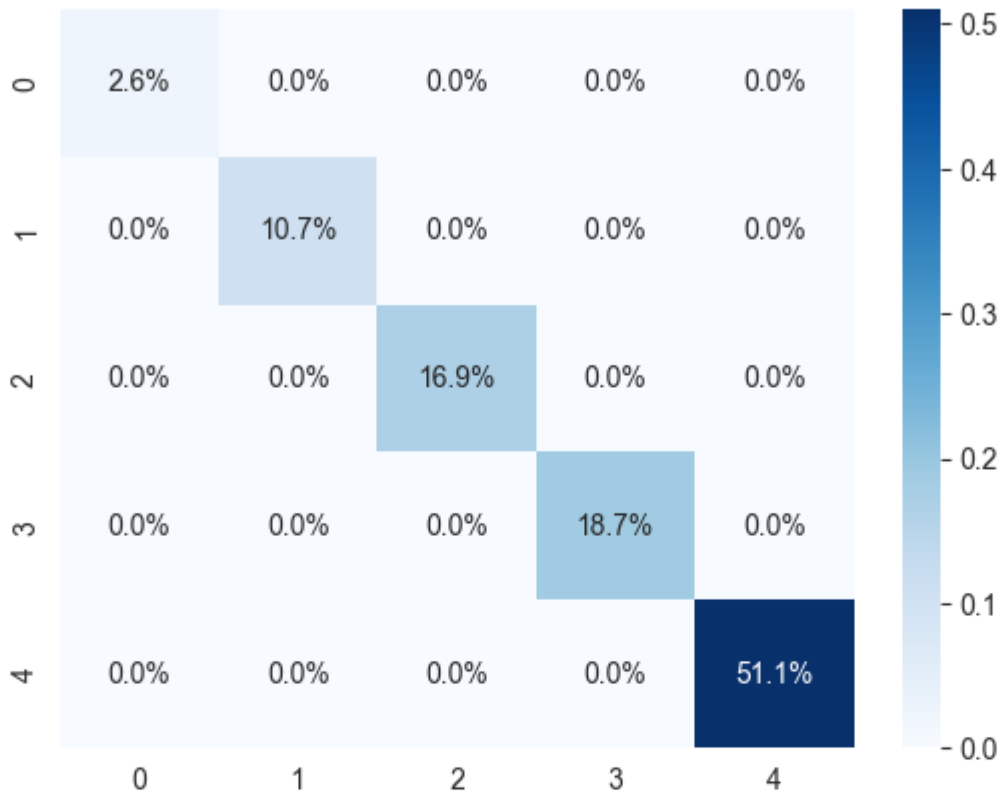
In [29]:
```
report_dict = classification_report(y_test, y_test_pred, output_dict=True, zero_
report_df = pd.DataFrame(report_dict).transpose()

styled_report = report_df.style.background_gradient(cmap='YlGnBu').format("{:.2f
display(styled_report)
```

	precision	recall	f1-score	support
0.0	0.90	0.53	0.67	17.00
1.0	0.93	0.78	0.85	54.00
2.0	0.96	0.88	0.92	75.00
3.0	0.87	0.88	0.87	82.00
4.0	0.88	0.98	0.93	203.00
accuracy	0.90	0.90	0.90	0.90
macro avg	0.91	0.81	0.85	431.00
weighted avg	0.90	0.90	0.89	431.00

Confusion matrix

In [30]:
```
cm_train = confusion_matrix(y_train, y_train_pred)
print(cm_train)
cm_train_prob = cm_train/np.sum(cm_train)
_ = sns.heatmap(cm_train_prob, annot=True,cmap='Blues', fmt='.1%')
print(f'Training Prediction Accuracy: {np.round(100 * train_accuracy, 1)}%')
```

```
[[ 44   0   0   0   0]
 [  0 185   0   0   0]
 [  0   0 291   0   0]
 [  0   0   0 322   0]
 [  0   0   0   0 879]]
Training Prediction Accuracy: 100.0%
```



Feature Engineering

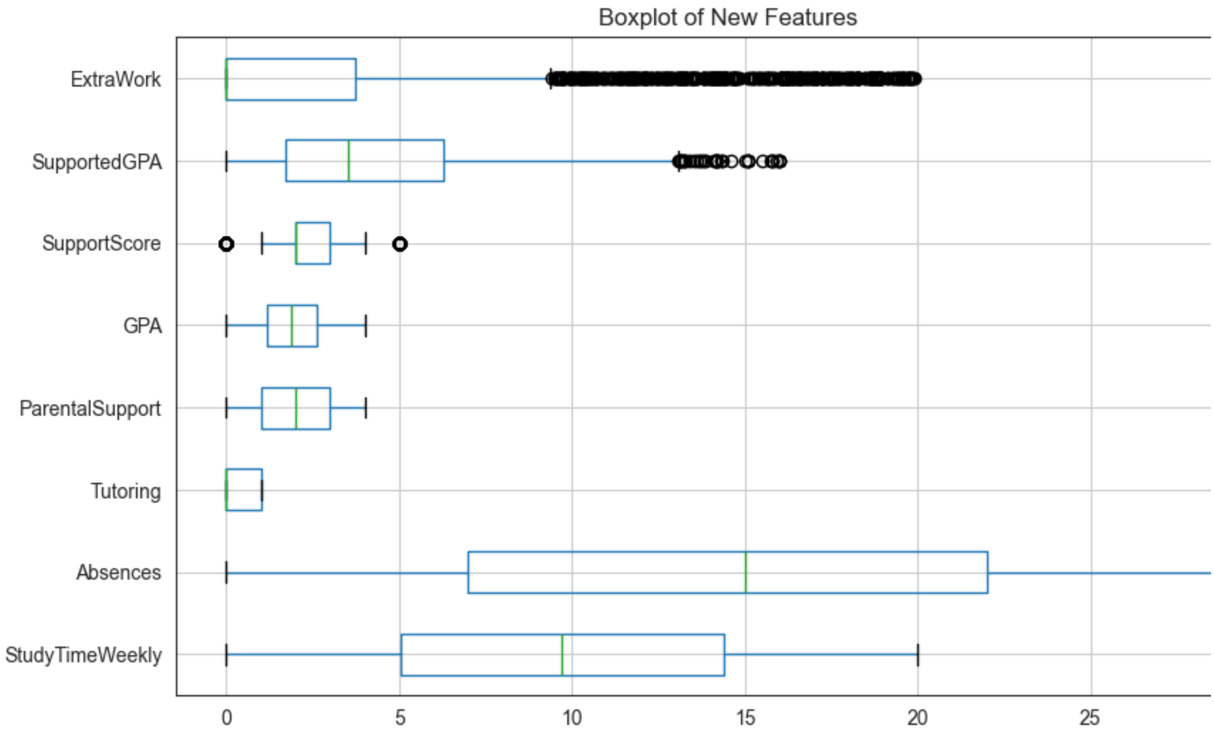
In [31]:
```
#Creating the new features
#Using the cleaned data, because then I will scale them with the new features
df_new_features = df_cleaned.copy()

#How can parental support and tutoring increase the performance of students?
df_new_features['SupportScore'] = df_new_features['ParentalSupport'] + df_new_fe

#Does parental support incre the GPA of students?
df_new_features['SupportedGPA'] = df_new_features['GPA'] * df_new_features['Pare

#Does tutoring and study time affect the performance of students?
df_new_features['ExtraWork'] = df_new_features['StudyTimeWeekly'] * df_new_featu
```

In [32]:
```
display(df_new_features.head())
```

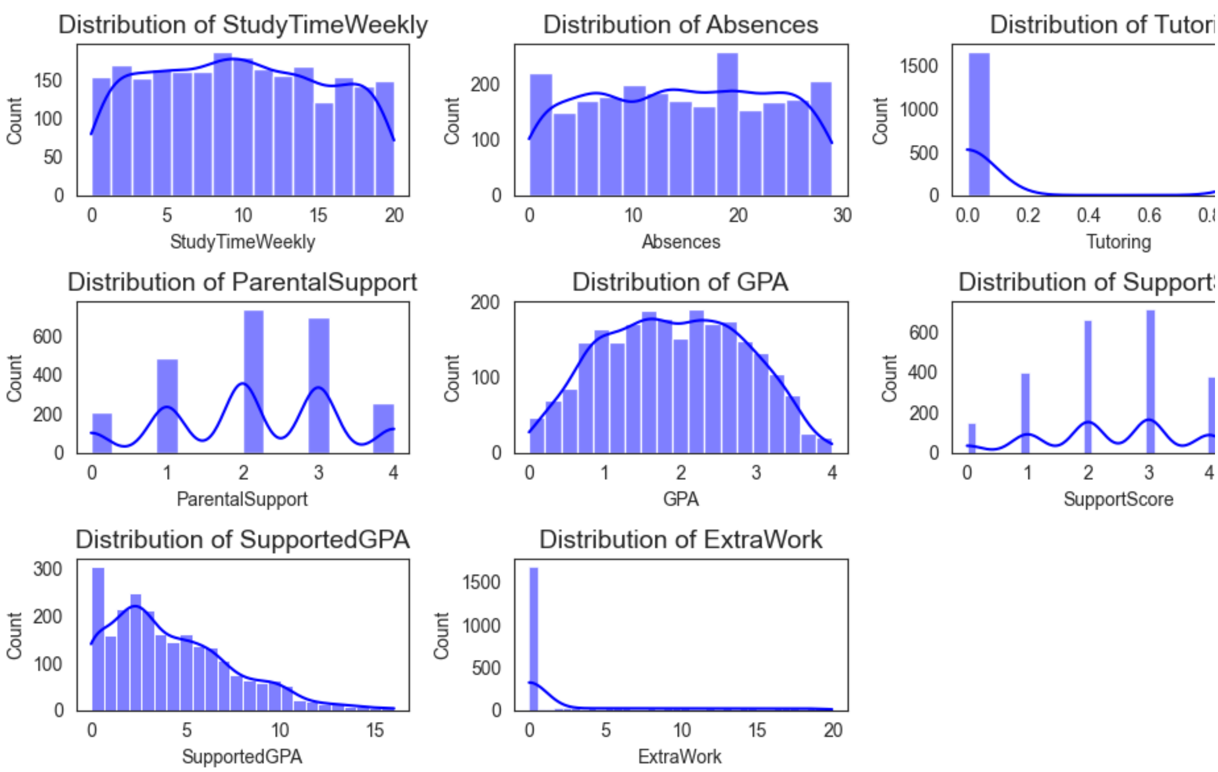
	StudyTimeWeekly	Absences	Tutoring	ParentalSupport	GPA	SupportScore	SupportedGPA
0	19.833723	7	1	2	2.929196	3	5.85839
1	15.408756	0	0	1	3.042915	1	3.04291
2	4.210570	26	0	2	0.112602	2	0.22520
3	10.028829	14	0	3	2.054218	3	6.16265
4	4.672495	17	1	3	1.288061	4	3.86418

Boxplot

In [33]:
```
fig, ax = plt.subplots(figsize=(10, 6))
boxplot = df_new_features.boxplot(vert = False, ax = ax)
_ = ax.set_title(f'Boxplot of New Features')
```



In [34]:
```
plt.figure(figsize=(10, 6))
for i, col in enumerate(df_new_features.columns):
    plt.subplot(3, 3, i + 1)
    sns.histplot(df_new_features[col], kde=True, color='blue', alpha=0.5)
    plt.title(f'Distribution of {col}', fontsize=14)
    plt.tight_layout()
plt.show()
```



Check Skewness

In [35]:
```
for col in df_new_features.columns:
    print(f'{col} = {df_new_features[col].skew()}')
```

```
StudyTimeWeekly = 0.05006807255835409
Absences = -0.026017090405395748
Tutoring = 0.8660445294904519
ParentalSupport = -0.16685872350058553
GPA = 0.014525601346976225
SupportScore = -0.09288602235642462
SupportedGPA = 0.8397580146364794
ExtraWork = 1.6825424874285464
```

Transforming the new features

In [36]:
```python
df_feat = df_new_features.copy()
```

In [37]:
```python
features_to_transform = ['ExtraWork', 'SupportedGPA']
```

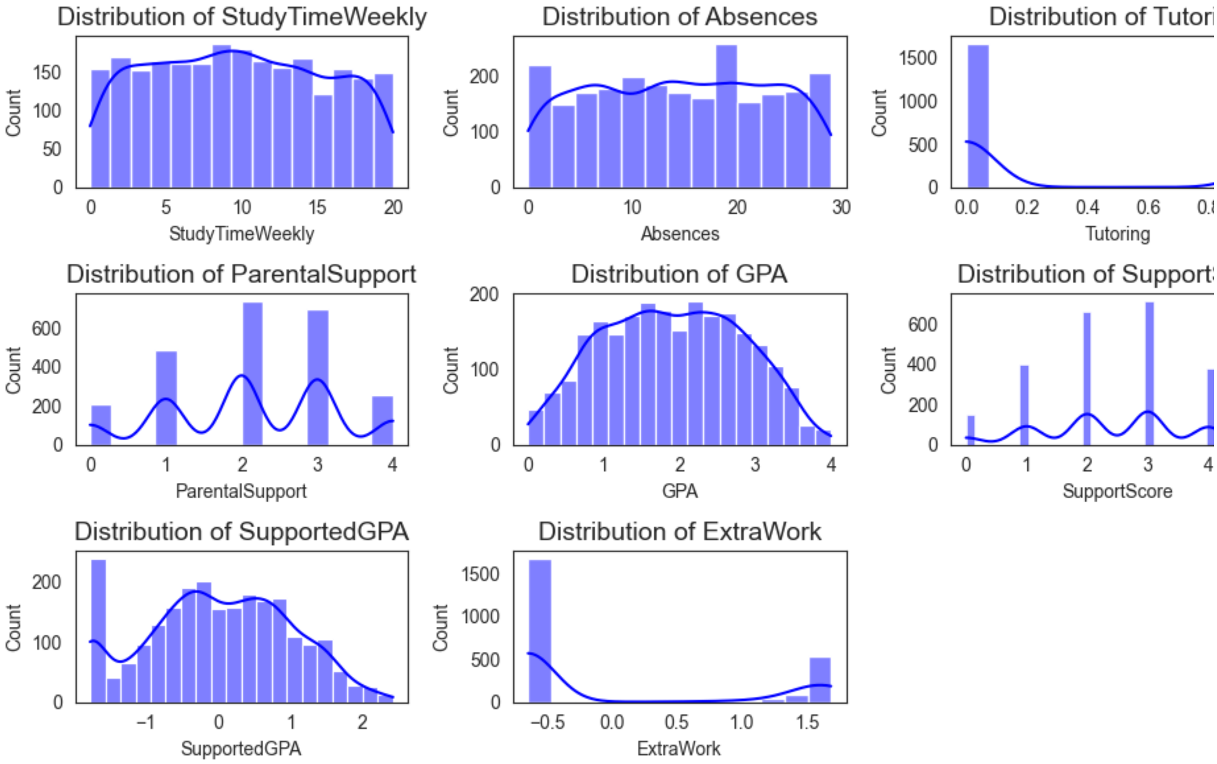
In [38]:
```python
pt = PowerTransformer(method='yeo-johnson')

df_feat[features_to_transform] = pt.fit_transform(df_feat[features_to_transform]
```

In [39]:
```python
for col in features_to_transform:
    #print(col, round(df_feat[col].skew(), 2))
    print(f'{col} = {df_feat[col].skew()}')
```

```
ExtraWork = 0.9328868253534139
SupportedGPA = -0.05737947998188417
```

Transformed data

In [40]:
```python
plt.figure(figsize=(10, 6))
for i, col in enumerate(df_feat.columns):
    plt.subplot(3, 3, i + 1)
    sns.histplot(df_feat[col], kde=True, color='blue', alpha=0.5)
    plt.title(f'Distribution of {col}', fontsize=14)
    plt.tight_layout()
plt.show()
```



Scale data

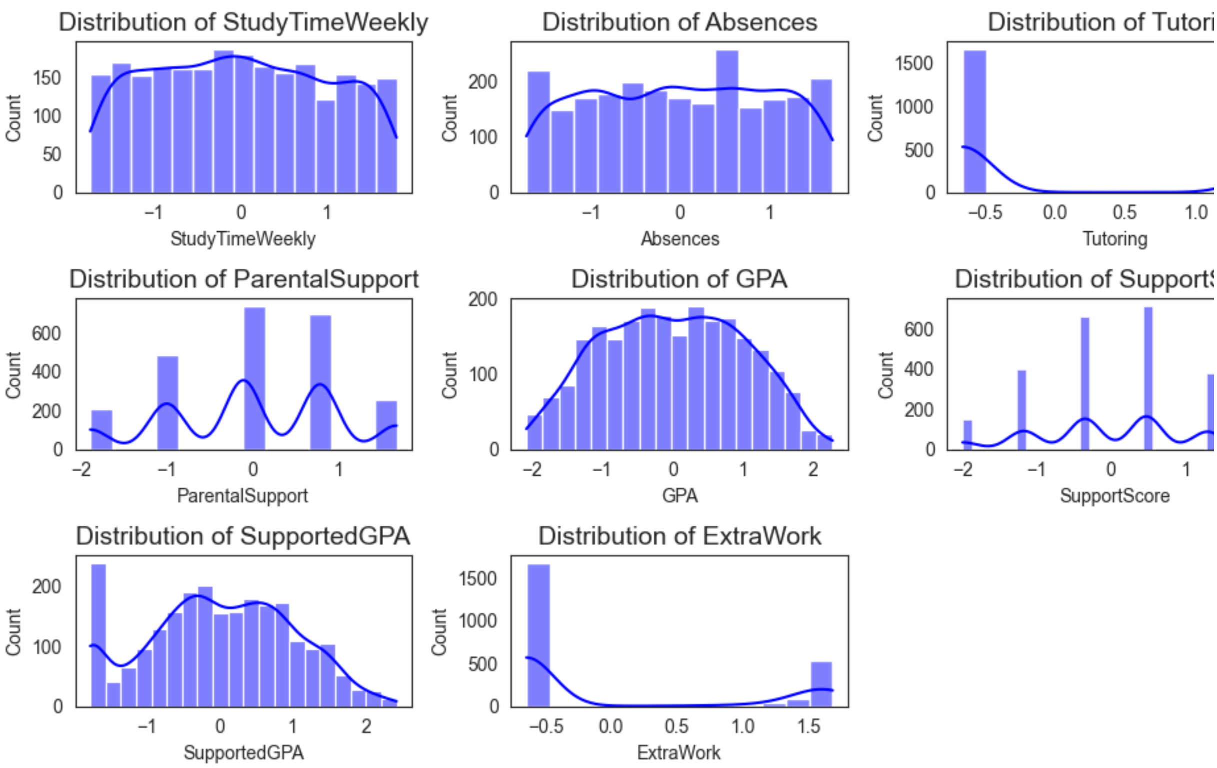
In [41]:

```
scaler = StandardScaler()
df_new_scaled = pd.DataFrame(
    scaler.fit_transform(df_feat),
    index=df_feat.index,
    columns=df_feat.columns
)
```

Histoplot of scaled data

In [42]:

```
plt.figure(figsize=(10, 6))
for i, col in enumerate(df_new_scaled.columns):
    plt.subplot(3, 3, i + 1)
    sns.histplot(df_new_scaled[col], kde=True, color='blue', alpha=0.5)
    plt.title(f'Distribution of {col}', fontsize=14)
    plt.tight_layout()
plt.show()
```



Remove outliers

In [43]:

```
iso = IsolationForest(contamination=0.1, random_state=42)
outliers_new = iso.fit_predict(df_new_scaled)

# 3. Select only the inliers (outliers == 1) — index is preserved here
df_removed_new = df_new_scaled.loc[outliers_new == 1].copy()

# 4. Reattach your target
df_removed_new['GradeClass'] = df_outputs.loc[df_removed_new.index]

# Quick check
display(df_removed_new.head())
print(df_removed_new.shape)
```

	StudyTimeWeekly	Absences	Tutoring	ParentalSupport	GPA	SupportScore	Supported(
0	1.780336	-0.890822	1.522371	-0.108744	1.118086	0.475510	0.652
1	0.997376	-1.717694	-0.656870	-0.999551	1.242374	-1.174119	-0.164
2	-0.984045	1.353542	-0.656870	-0.108744	-1.960277	-0.349305	-1.576
3	0.045445	-0.063951	-0.656870	0.782063	0.161790	0.475510	0.726
4	-0.902311	0.290422	1.522371	0.782063	-0.675573	1.300324	0.106

```
(2152, 9)
```

Baseline Algorithms

In [44]:
```
df_removed_new = df.copy()
df_removed_new.columns = df_removed_new.columns.str.strip()

X = df_removed_new.drop(columns=['GradeClass'])
y = df_removed_new['GradeClass']
```

In [45]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

In [46]:
```
model = RandomForestClassifier(random_state=90)
model.fit(X_train, y_train)

#Predict
y_train_pred = model.predict(X_train)
y_test_pred = model.predict(X_test)
```

In [47]:
```
rf = RandomForestClassifier(n_estimators=200, random_state=42)
rf.fit(X_train, y_train)
print("Test accuracy:", rf.score(X_test, y_test))
```

```
Test accuracy: 0.9102296450939458
```

In [48]:
```
# ── Prepare X & y for 8-feature MLP ──────────────────────
# assume df_removed_new is your cleaned & outlier-removed DataFrame
df_removed_new['SupportScore']  = df_removed_new['ParentalSupport'] * df_removec
df_removed_new['SupportedGPA']  = df_removed_new['GPA'] + 0.1 * df_removed_new['
df_removed_new['ExtraWork']     = df_removed_new['StudyTimeWeekly'] * df_removec

X8 = df_removed_new[[
  'StudyTimeWeekly','Absences','Tutoring','ParentalSupport',
  'GPA','SupportScore','SupportedGPA','ExtraWork'
]]
y8 = df_removed_new['GradeClass'].astype(int)
```

Deep Learning Model with MLPClassifier

In [49]:
```
from imblearn.over_sampling import SMOTE
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import classification_report, confusion_matrix

import matplotlib.pyplot as plt
import seaborn as sns

RANDOM_STATE = 42 # Set a random state for reproducibility
```

In [50]:
```python
# 1: Generic SMOTE balancing
smote = SMOTE(random_state=RANDOM_STATE)
X_res, y_res = smote.fit_resample(X_train, y_train)
```

In [51]:
```python
# 2: Train & evaluate MLP on generic SMOTE data
mlp_gen = MLPClassifier(
    hidden_layer_sizes=(64, 32),
    activation='relu',
    solver='adam',
    alpha=1e-4,
    learning_rate='adaptive',
    tol=1e-4,
    n_iter_no_change=10,
    early_stopping=True,
    validation_fraction=0.1,
    max_iter=200,
    random_state=RANDOM_STATE,
    verbose=True
)
mlp_gen.fit(X_res, y_res)

print("Train acc:", mlp_gen.score(X_res, y_res))
print("Test  acc:", mlp_gen.score(X_test, y_test))

y_pred_gen = mlp_gen.predict(X_test)
print(classification_report(y_test, y_pred_gen, digits=4, zero_division= 0))
```

```
Iteration 1, loss = 28.01984791
Validation score: 0.185950
Iteration 2, loss = 21.49395214
Validation score: 0.301653
Iteration 3, loss = 9.89199083
Validation score: 0.202479
Iteration 4, loss = 3.09342110
Validation score: 0.338843
Iteration 5, loss = 1.86634652
Validation score: 0.309917
Iteration 6, loss = 1.71375515
Validation score: 0.338843
Iteration 7, loss = 1.81409058
Validation score: 0.320248
Iteration 8, loss = 1.59453390
Validation score: 0.334711
Iteration 9, loss = 1.54466421
Validation score: 0.398760
Iteration 10, loss = 1.48196495
Validation score: 0.371901
Iteration 11, loss = 1.51447251
Validation score: 0.402893
Iteration 12, loss = 1.59406075
Validation score: 0.369835
Iteration 13, loss = 1.51968438
Validation score: 0.390496
Iteration 14, loss = 1.80112671
Validation score: 0.332645
Iteration 15, loss = 1.83831194
Validation score: 0.326446
Iteration 16, loss = 1.47802460
Validation score: 0.394628
Iteration 17, loss = 1.69118644
Validation score: 0.466942
Iteration 18, loss = 1.98478351
Validation score: 0.266529
Iteration 19, loss = 1.84558979
Validation score: 0.307851
Iteration 20, loss = 1.51132190
Validation score: 0.402893
Iteration 21, loss = 1.46667994
Validation score: 0.334711
Iteration 22, loss = 2.05487473
Validation score: 0.276860
Iteration 23, loss = 2.06911605
Validation score: 0.365702
Iteration 24, loss = 1.79389201
Validation score: 0.392562
Iteration 25, loss = 1.37243909
Validation score: 0.361570
Iteration 26, loss = 1.34086029
Validation score: 0.376033
Iteration 27, loss = 1.45303832
Validation score: 0.440083
Iteration 28, loss = 1.35330836
Validation score: 0.338843
Validation score did not improve more than tol=0.000100 for 10 consecutive epochs. Stopping.
Train acc: 0.4425619834710744
Test  acc: 0.4822546972860125
```

```
              precision    recall  f1-score   support

         0.0     0.1284    0.6667    0.2154        21
         1.0     0.6000    0.0556    0.1017        54
         2.0     0.0000    0.0000    0.0000        78
         3.0     0.3092    0.7711    0.4414        83
         4.0     0.9494    0.6173    0.7481       243

    accuracy                         0.4823       479
   macro avg     0.3974    0.4221    0.3013       479
weighted avg     0.6085    0.4823    0.4769       479
```

In [52]:

```python
# 3: Targeted SMOTE for class 0 (“A”)
smote_targ = SMOTE(sampling_strategy={0: 200}, random_state=RANDOM_STATE)
X_res2, y_res2 = smote_targ.fit_resample(X_train, y_train)

from collections import Counter
print("Before:", Counter(y_train))
print("After:", Counter(y_res2))
```

```
Before: Counter({4.0: 968, 3.0: 331, 2.0: 313, 1.0: 215, 0.0: 86})
After: Counter({4.0: 968, 3.0: 331, 2.0: 313, 1.0: 215, 0.0: 200})
```

In [53]:

```python
# 4: Train & evaluate MLP on targeted SMOTE data
mlp_targ = MLPClassifier(
    hidden_layer_sizes=(64, 32),
    activation='relu',
    solver='adam',
    alpha=1e-4,
    learning_rate='adaptive',
    tol=1e-4,
    n_iter_no_change=10,
    early_stopping=True,
    validation_fraction=0.1,
    max_iter=200,
    random_state=RANDOM_STATE,
    verbose=True
)
mlp_targ.fit(X_res2, y_res2)

# report accuracies
print("Train acc:", mlp_targ.score(X_res2, y_res2))
print("Test  acc:", mlp_targ.score(X_test, y_test), "\n")

# classification report
y_pred_targ = mlp_targ.predict(X_test)
print(classification_report(y_test, y_pred_targ, digits=4, zero_division= 0))
```

```
Iteration 1, loss = 32.34840896
Validation score: 0.137931
Iteration 2, loss = 27.70910510
Validation score: 0.502463
Iteration 3, loss = 18.91287011
Validation score: 0.502463
Iteration 4, loss = 17.10537778
Validation score: 0.142857
Iteration 5, loss = 12.67597564
Validation score: 0.502463
Iteration 6, loss = 9.06986963
Validation score: 0.147783
Iteration 7, loss = 7.40598480
Validation score: 0.182266
Iteration 8, loss = 3.80619257
Validation score: 0.256158
Iteration 9, loss = 2.07629045
Validation score: 0.162562
Iteration 10, loss = 1.69654669
Validation score: 0.443350
Iteration 11, loss = 1.45594492
Validation score: 0.522167
Iteration 12, loss = 1.53681704
Validation score: 0.403941
Iteration 13, loss = 1.45961834
Validation score: 0.527094
Iteration 14, loss = 1.48665871
Validation score: 0.556650
Iteration 15, loss = 1.36792333
Validation score: 0.541872
Iteration 16, loss = 1.33212325
Validation score: 0.305419
Iteration 17, loss = 1.31088341
Validation score: 0.556650
Iteration 18, loss = 1.20863713
Validation score: 0.561576
Iteration 19, loss = 1.27269328
Validation score: 0.448276
Iteration 20, loss = 1.25644828
Validation score: 0.566502
Iteration 21, loss = 1.21075460
Validation score: 0.571429
Iteration 22, loss = 1.38388825
Validation score: 0.581281
Iteration 23, loss = 1.22729104
Validation score: 0.635468
Iteration 24, loss = 1.16508057
Validation score: 0.591133
Iteration 25, loss = 1.18167184
Validation score: 0.650246
Iteration 26, loss = 1.17508080
Validation score: 0.630542
Iteration 27, loss = 1.29073075
Validation score: 0.418719
Iteration 28, loss = 1.22971387
Validation score: 0.571429
Iteration 29, loss = 1.26835367
Validation score: 0.256158
Iteration 30, loss = 1.25751953
Validation score: 0.556650
```

```
Iteration 31, loss = 1.19253818
Validation score: 0.605911
Iteration 32, loss = 1.30824722
Validation score: 0.586207
Iteration 33, loss = 1.27556794
Validation score: 0.615764
Iteration 34, loss = 1.31799064
Validation score: 0.384236
Iteration 35, loss = 1.19930662
Validation score: 0.596059
Iteration 36, loss = 1.12208817
Validation score: 0.586207
Validation score did not improve more than tol=0.000100 for 10 consecutive epochs.
Stopping.
Train acc: 0.5811544153922052
Test  acc: 0.6200417536534447

              precision    recall  f1-score   support

         0.0     0.0000    0.0000    0.0000        21
         1.0     0.3153    0.6481    0.4242        54
         2.0     0.3939    0.3333    0.3611        78
         3.0     1.0000    0.0120    0.0238        83
         4.0     0.7807    0.9671    0.8640       243

    accuracy                         0.6200       479
   macro avg     0.4980    0.3921    0.3346       479
weighted avg     0.6690    0.6200    0.5491       479
```

In [54]:
```python
# 5: Save preprocessing + model for deployment
from sklearn.pipeline import Pipeline
import joblib

inference_pipe = Pipeline([
    ('scaler', scaler),
    ('mlp', mlp_targ)
])
joblib.dump(inference_pipe, "grade_predictor_inference_pipeline.pkl")
print("Saved fixed inference pipeline.")
#testing to see what features it includes
print("Scaler input features:", scaler.feature_names_in_)
```

```
Saved fixed inference pipeline.
Scaler input features: ['StudyTimeWeekly' 'Absences' 'Tutoring' 'ParentalSupport' 'GI
 'SupportScore' 'SupportedGPA' 'ExtraWork']
```

In [55]:
```python
from imblearn.pipeline import Pipeline as ImbPipeline
from imblearn.over_sampling import SMOTE
from sklearn.neural_network import MLPClassifier

#importing these to try hyperparameter grid
```

In [56]:
```python
# 6: pipeline & define hyperparameter grid
pipeline = ImbPipeline([
    ("smote", SMOTE(sampling_strategy={0:200}, random_state=RANDOM_STATE)),
    ("mlp", MLPClassifier(
        activation='relu',
        solver='adam',
        early_stopping=True,
```

```
        validation_fraction=0.1,
        tol=1e-4,
        n_iter_no_change=10,
        max_iter=200,
        random_state=RANDOM_STATE,
        verbose=False
    ))
])

param_dist = {
    "smote__sampling_strategy": [{0:100}, {0:200}, {0:243}],
    "mlp__hidden_layer_sizes": [(64,32), (128,64), (64,32,16)],
    "mlp__alpha": [1e-3, 1e-4, 1e-5],
    "mlp__learning_rate_init": [0.001, 0.005, 0.01]
}

print("Pipeline and parameter grid ready.")
```

```
Pipeline and parameter grid ready.
```

In [57]:

```
# 7: Hyperparameter tuning with RandomizedSearchCV
from sklearn.model_selection import RandomizedSearchCV

search = RandomizedSearchCV(
    pipeline,
    param_dist,
    n_iter=12,
    scoring="balanced_accuracy",
    cv=3,
    random_state=RANDOM_STATE,
    n_jobs=-1,
    verbose=2
)

search.fit(X_train, y_train)

print("Best params:", search.best_params_)
print("Best CV balanced accuracy:", search.best_score_)
```

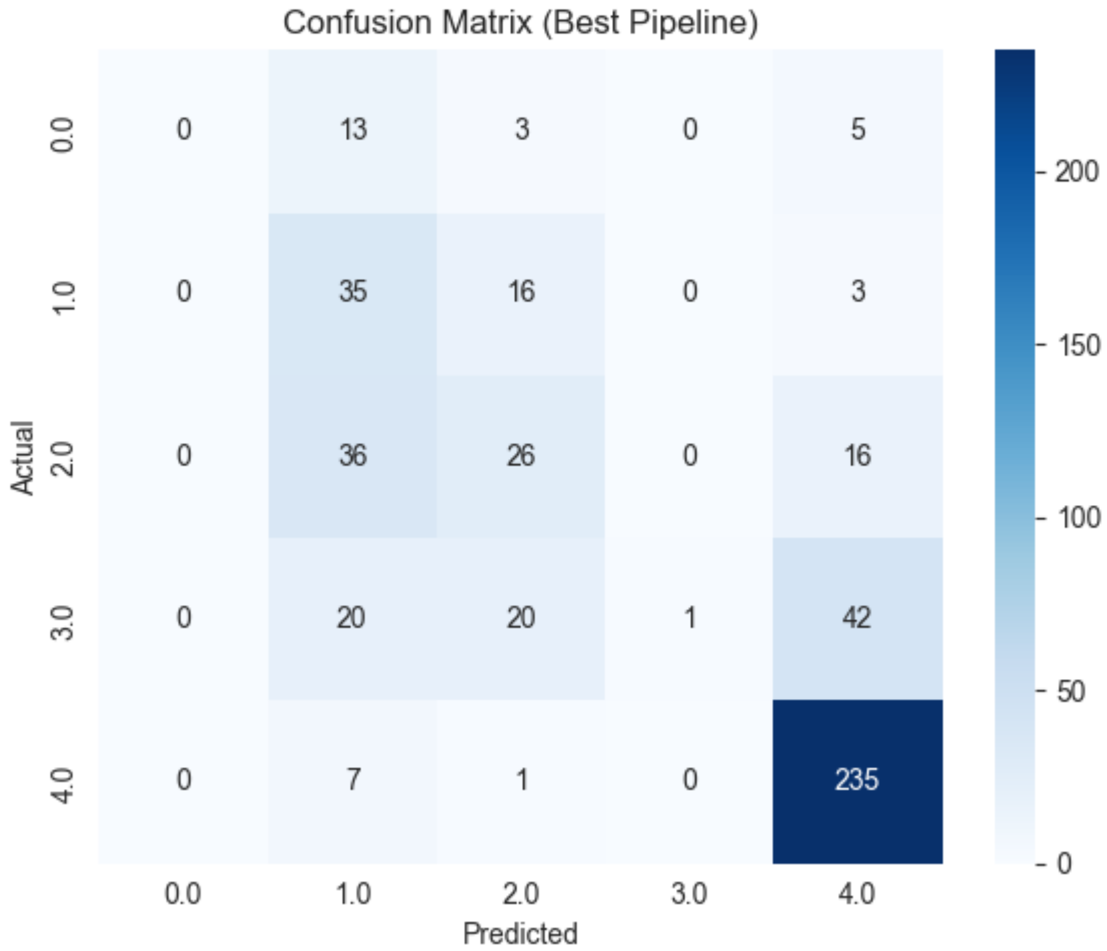
```
Fitting 3 folds for each of 12 candidates, totalling 36 fits
Best params: {'smote__sampling_strategy': {0: 200}, 'mlp__learning_rate_init': 0.001,
'mlp__hidden_layer_sizes': (64, 32), 'mlp__alpha': 0.0001}
Best CV balanced accuracy: 0.31986518612787523
```

In [58]:

```
# 8:eval best pipeline
best_pipe = search.best_estimator_

# balanced accuracy
test_bal_acc = best_pipe.score(X_test, y_test)
print(f"Test balanced accuracy: {test_bal_acc:.4f}\n")

# classification report
y_pred_best = best_pipe.predict(X_test)
print(classification_report(y_test, y_pred_best, digits=4, zero_division=0))

# confusion matrix heatmap
cm_best = confusion_matrix(y_test, y_pred_best)
plt.figure(figsize=(6,5))
sns.heatmap(cm_best, annot=True, fmt="d", cmap="Blues",
            xticklabels=best_pipe.named_steps['mlp'].classes_,
            yticklabels=best_pipe.named_steps['mlp'].classes_)
```

```python
plt.xlabel("Predicted"); plt.ylabel("Actual")
plt.title("Confusion Matrix (Best Pipeline)"); plt.tight_layout(); plt.show()
```

```
Test balanced accuracy: 0.6200

              precision    recall  f1-score   support

         0.0     0.0000    0.0000    0.0000        21
         1.0     0.3153    0.6481    0.4242        54
         2.0     0.3939    0.3333    0.3611        78
         3.0     1.0000    0.0120    0.0238        83
         4.0     0.7807    0.9671    0.8640       243

    accuracy                         0.6200       479
   macro avg     0.4980    0.3921    0.3346       479
weighted avg     0.6690    0.6200    0.5491       479
```

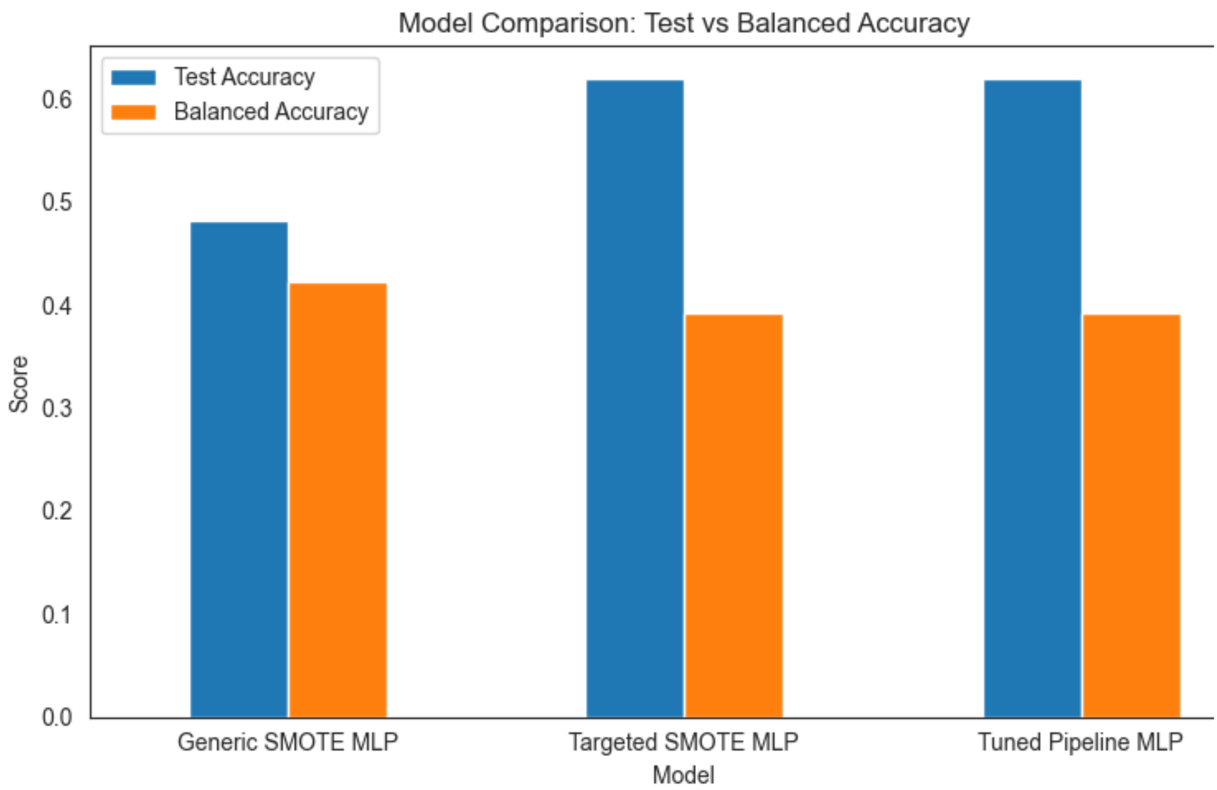


In [59]:
```python
from sklearn.metrics import accuracy_score, balanced_accuracy_score, recall_scor

# each models metrics
models = {
    "Generic SMOTE MLP":       mlp_gen,
    "Targeted SMOTE MLP":      mlp_targ,
    "Tuned Pipeline MLP":      best_pipe
}

records = []
for name, mdl in models.items():
    # picking the right X/y for the model
    X_eval = X_res if name=="Generic SMOTE MLP" else (X_res2 if name=="Targeted
```

```python
    y_eval = y_res if name=="Generic SMOTE MLP" else (y_res2 if name=="Targeted

    y_pred = mdl.predict(X_test)
    records.append({
        "Model":             name,
        "Test Accuracy":     accuracy_score(y_test, y_pred),
        "Balanced Accuracy": balanced_accuracy_score(y_test, y_pred),
        "Class_0 Recall":    recall_score(y_test, y_pred, labels=[0], average="m
    })

df_summary = pd.DataFrame(records).set_index("Model")
display(df_summary)
```

Model	Test Accuracy	Balanced Accuracy	Class_0 Recall
Generic SMOTE MLP	0.482255	0.422118	0.666667
Targeted SMOTE MLP	0.620042	0.392122	0.000000
Tuned Pipeline MLP	0.620042	0.392122	0.000000

In [60]:
```python
# overall metrics with a bar chart
ax = df_summary[['Test Accuracy', 'Balanced Accuracy']].plot(
    kind='bar', figsize=(8, 5)
)

ax.set_ylabel("Score")
ax.set_title("Model Comparison: Test vs Balanced Accuracy")
ax.set_xticklabels(df_summary.index, rotation=0)
ax.legend(loc="best")
plt.tight_layout()
plt.show()
```



Summary

Hyperparameter-tuned SMOTE pipeline provides highest balanced accuracy while keepign strong accuracy and solid minority class recall. although the tagreted smote mlp slightly edges out in ra accuracy and recall for said minority but it does so at the expense of accuracy for all classes so th pipeline is best for deploy.

In [61]:
```
# FINAL: Retrain MLP ONLY using the 8 final features used in deployment - this i

from sklearn.pipeline import Pipeline
import joblib

X_train['SupportScore']  = X_train['ParentalSupport'] * X_train['Extracurricular
X_train['SupportedGPA']  = X_train['GPA'] + 0.1 * X_train['ParentalSupport']
X_train['ExtraWork']     = X_train['StudyTimeWeekly'] * X_train['Tutoring']

X_test['SupportScore']   = X_test['ParentalSupport'] * X_test['Extracurricular']
X_test['SupportedGPA']   = X_test['GPA'] + 0.1 * X_test['ParentalSupport']
X_test['ExtraWork']      = X_test['StudyTimeWeekly'] * X_test['Tutoring']


# 1 X_train, y_train based on 8
X_final_train = X_train[[
    'StudyTimeWeekly', 'Absences', 'Tutoring', 'ParentalSupport',
    'GPA', 'SupportScore', 'SupportedGPA', 'ExtraWork'
]]
X_final_test = X_test[[
    'StudyTimeWeekly', 'Absences', 'Tutoring', 'ParentalSupport',
    'GPA', 'SupportScore', 'SupportedGPA', 'ExtraWork'
]]

# 2 retrain scaler
from sklearn.preprocessing import MinMaxScaler
scaler_final = MinMaxScaler()
X_final_train_scaled = scaler_final.fit_transform(X_final_train)
X_final_test_scaled  = scaler_final.transform(X_final_test)

# 3 train fresh MLP
mlp_final = MLPClassifier(
    hidden_layer_sizes=(64, 32),
    activation='relu',
    solver='adam',
    alpha=1e-4,
    learning_rate='adaptive',
    tol=1e-4,
    n_iter_no_change=10,
    early_stopping=True,
    validation_fraction=0.1,
    max_iter=200,
    random_state=42,
    verbose=True
)
mlp_final.fit(X_final_train_scaled, y_train)

# 4 save 8-feature pipeline
inference_pipeline = Pipeline([
    ('scaler', scaler_final),
```

```
    ('mlp', mlp_final)
])
joblib.dump(inference_pipeline, "grade_predictor_inference_pipeline.pkl")
print("Saved fixed 8-feature inference pipeline.")
```

```
Iteration 1, loss = 1.49252115
Validation score: 0.505208
Iteration 2, loss = 1.37821791
Validation score: 0.505208
Iteration 3, loss = 1.31814231
Validation score: 0.505208
Iteration 4, loss = 1.27408943
Validation score: 0.505208
Iteration 5, loss = 1.22902500
Validation score: 0.505208
Iteration 6, loss = 1.18159053
Validation score: 0.505208
Iteration 7, loss = 1.13212663
Validation score: 0.505208
Iteration 8, loss = 1.07774487
Validation score: 0.541667
Iteration 9, loss = 1.02490760
Validation score: 0.588542
Iteration 10, loss = 0.97561231
Validation score: 0.630208
Iteration 11, loss = 0.93233282
Validation score: 0.630208
Iteration 12, loss = 0.89630703
Validation score: 0.661458
Iteration 13, loss = 0.86878392
Validation score: 0.692708
Iteration 14, loss = 0.84675632
Validation score: 0.687500
Iteration 15, loss = 0.82920474
Validation score: 0.703125
Iteration 16, loss = 0.81626243
Validation score: 0.718750
Iteration 17, loss = 0.80372821
Validation score: 0.744792
Iteration 18, loss = 0.79228395
Validation score: 0.718750
Iteration 19, loss = 0.78365517
Validation score: 0.739583
Iteration 20, loss = 0.77421996
Validation score: 0.739583
Iteration 21, loss = 0.76776530
Validation score: 0.734375
Iteration 22, loss = 0.76147466
Validation score: 0.739583
Iteration 23, loss = 0.75497995
Validation score: 0.734375
Iteration 24, loss = 0.74860568
Validation score: 0.739583
Iteration 25, loss = 0.74147890
Validation score: 0.744792
Iteration 26, loss = 0.73694043
Validation score: 0.739583
Iteration 27, loss = 0.73145246
Validation score: 0.739583
Iteration 28, loss = 0.72652585
Validation score: 0.750000
Iteration 29, loss = 0.72075085
Validation score: 0.744792
Iteration 30, loss = 0.71580721
Validation score: 0.739583
```

```
Iteration 31, loss = 0.71231122
Validation score: 0.744792
Iteration 32, loss = 0.70613109
Validation score: 0.744792
Iteration 33, loss = 0.70112474
Validation score: 0.750000
Iteration 34, loss = 0.69549444
Validation score: 0.744792
Iteration 35, loss = 0.69132184
Validation score: 0.744792
Iteration 36, loss = 0.68654506
Validation score: 0.744792
Iteration 37, loss = 0.68290579
Validation score: 0.750000
Iteration 38, loss = 0.67791050
Validation score: 0.744792
Iteration 39, loss = 0.67373865
Validation score: 0.755208
Iteration 40, loss = 0.67024271
Validation score: 0.750000
Iteration 41, loss = 0.66651308
Validation score: 0.765625
```

```
Iteration 42, loss = 0.66298655
Validation score: 0.760417
Iteration 43, loss = 0.65852269
Validation score: 0.755208
Iteration 44, loss = 0.65542366
Validation score: 0.760417
Iteration 45, loss = 0.65124187
Validation score: 0.765625
Iteration 46, loss = 0.64822567
Validation score: 0.760417
Iteration 47, loss = 0.64357579
Validation score: 0.760417
Iteration 48, loss = 0.64142280
Validation score: 0.765625
Iteration 49, loss = 0.63721102
Validation score: 0.755208
Iteration 50, loss = 0.63476754
Validation score: 0.765625
Iteration 51, loss = 0.63108023
Validation score: 0.770833
Iteration 52, loss = 0.62876199
Validation score: 0.770833
Iteration 53, loss = 0.62517080
Validation score: 0.776042
Iteration 54, loss = 0.62238011
Validation score: 0.781250
Iteration 55, loss = 0.61831473
Validation score: 0.770833
Iteration 56, loss = 0.61589323
Validation score: 0.776042
Iteration 57, loss = 0.61395420
Validation score: 0.765625
Iteration 58, loss = 0.61031722
Validation score: 0.776042
Iteration 59, loss = 0.60704644
Validation score: 0.781250
Iteration 60, loss = 0.60270748
Validation score: 0.776042
Iteration 61, loss = 0.59984121
Validation score: 0.786458
Iteration 62, loss = 0.59683613
Validation score: 0.770833
Iteration 63, loss = 0.59549570
Validation score: 0.770833
Iteration 64, loss = 0.59138002
Validation score: 0.776042
Iteration 65, loss = 0.59013542
Validation score: 0.786458
Iteration 66, loss = 0.58645530
Validation score: 0.781250
Iteration 67, loss = 0.58345730
Validation score: 0.776042
Iteration 68, loss = 0.58152181
Validation score: 0.781250
Iteration 69, loss = 0.58066399
Validation score: 0.791667
Iteration 70, loss = 0.57781154
Validation score: 0.786458
Iteration 71, loss = 0.57453361
Validation score: 0.786458
```

```
Iteration 72, loss = 0.57231335
Validation score: 0.791667
Iteration 73, loss = 0.57024659
Validation score: 0.781250
Iteration 74, loss = 0.56811353
Validation score: 0.796875
Iteration 75, loss = 0.56532037
Validation score: 0.781250
Iteration 76, loss = 0.56442738
Validation score: 0.796875
Iteration 77, loss = 0.56166380
Validation score: 0.791667
Iteration 78, loss = 0.56027193
Validation score: 0.786458
Iteration 79, loss = 0.55796984
Validation score: 0.796875
Iteration 80, loss = 0.55667210
Validation score: 0.786458
Iteration 81, loss = 0.55535403
Validation score: 0.796875
Iteration 82, loss = 0.55158741
Validation score: 0.802083
Iteration 83, loss = 0.55198294
Validation score: 0.802083
Iteration 84, loss = 0.54991230
Validation score: 0.791667
Iteration 85, loss = 0.54862816
Validation score: 0.802083
Iteration 86, loss = 0.54723222
Validation score: 0.802083
Iteration 87, loss = 0.54348095
Validation score: 0.796875
Iteration 88, loss = 0.54222633
Validation score: 0.802083
Iteration 89, loss = 0.54006238
Validation score: 0.796875
Iteration 90, loss = 0.53998064
Validation score: 0.807292
Iteration 91, loss = 0.53723122
Validation score: 0.796875
Iteration 92, loss = 0.53706119
Validation score: 0.802083
Iteration 93, loss = 0.53708579
Validation score: 0.802083
Iteration 94, loss = 0.53407808
Validation score: 0.802083
Iteration 95, loss = 0.53115469
Validation score: 0.802083
Iteration 96, loss = 0.53207854
Validation score: 0.807292
Iteration 97, loss = 0.52929117
Validation score: 0.796875
Iteration 98, loss = 0.52891808
Validation score: 0.802083
Iteration 99, loss = 0.52568260
Validation score: 0.807292
Iteration 100, loss = 0.52500248
Validation score: 0.802083
Iteration 101, loss = 0.52376983
Validation score: 0.796875
```

```
Validation score did not improve more than tol=0.000100 for 10 consecutive epochs.
Stopping.
Saved fixed 8-feature inference pipeline.
```