In [32]:

```python
# Print the feature importances
feature_importances = pd.DataFrame(
    {"Feature": feature_names, "Importance": normalized_coefficients}
)

# feature_importances.sort_values('Importance',ascending=False)

print(feature_importances.sort_values("Importance", ascending=False).to_string())
```

```
                 Feature  Importance
2             Sex_female    0.174236
15         Lunch_reduced    0.127047
17   Test_Prep_completed    0.122090
18        Test_Prep_none    0.068282
16        Lunch_standard    0.063324
5       Ethnicity_group B   0.060824
7       Ethnicity_group D   0.055430
6       Ethnicity_group C   0.052470
10   PLE_bachelor degree    0.050083
14  PLE_some high school    0.044833
4       Ethnicity_group A   0.040436
13      PLE_some college    0.027630
9   PLE_associate degree    0.024452
12     PLE_master degree    0.022992
11       PLE_high school    0.020380
8       Ethnicity_group E   0.018788
3               Sex_male    0.016136
1          Writing_Score    0.007369
0          Reading_Score    0.003197
```

In [39]:

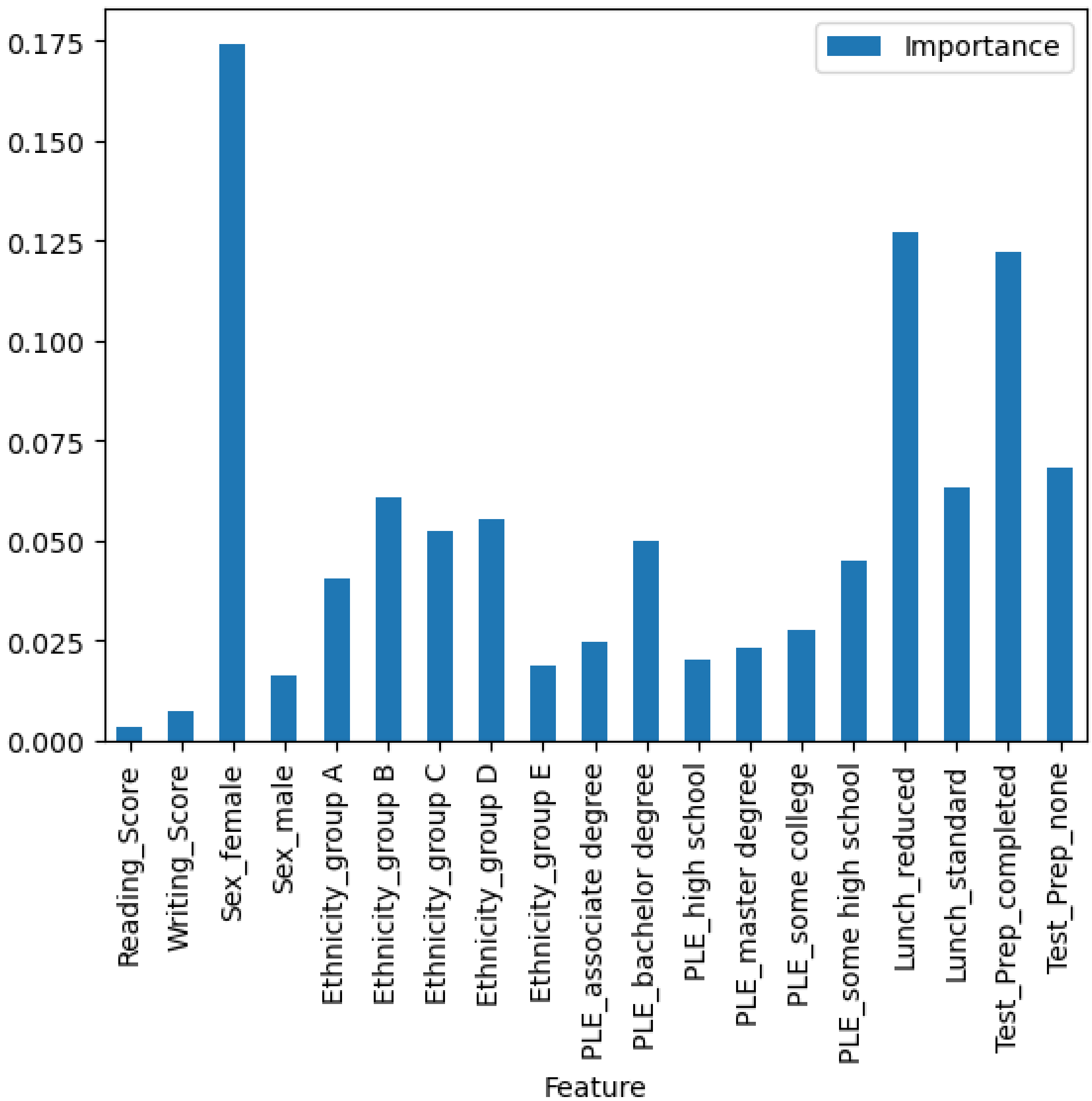
```
import matplotlib.pyplot as plt
```

In [44]:

```
feature_importances.plot(x="Feature", y="Importance", kind="bar")
```

Out[44]:

```
<Axes: xlabel='Feature'>
```



These feature importances indicate the relative importance of each feature in predicting math achievement in the model. The features are ranked in descending order of their importance, with the most important feature listed first.

According to the feature importances, the top 3 features that have the most impact on the target variable are:

- Sex_female: This feature has the highest importance with a value of 0.174236.
- Lunch_reduced: This feature has an importance of 0.127047.
- Test_Prep_completed: This feature has an importance of 0.122090.
- Other features such as ethnicity, parental level of education, and individual test scores also contribute to predicting the target variable, but to a lesser extent.