In [1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

In [2]:
```python
df_mlr = pd.read_csv("Synthetic_app_data.csv")
df_mlr.head()
```

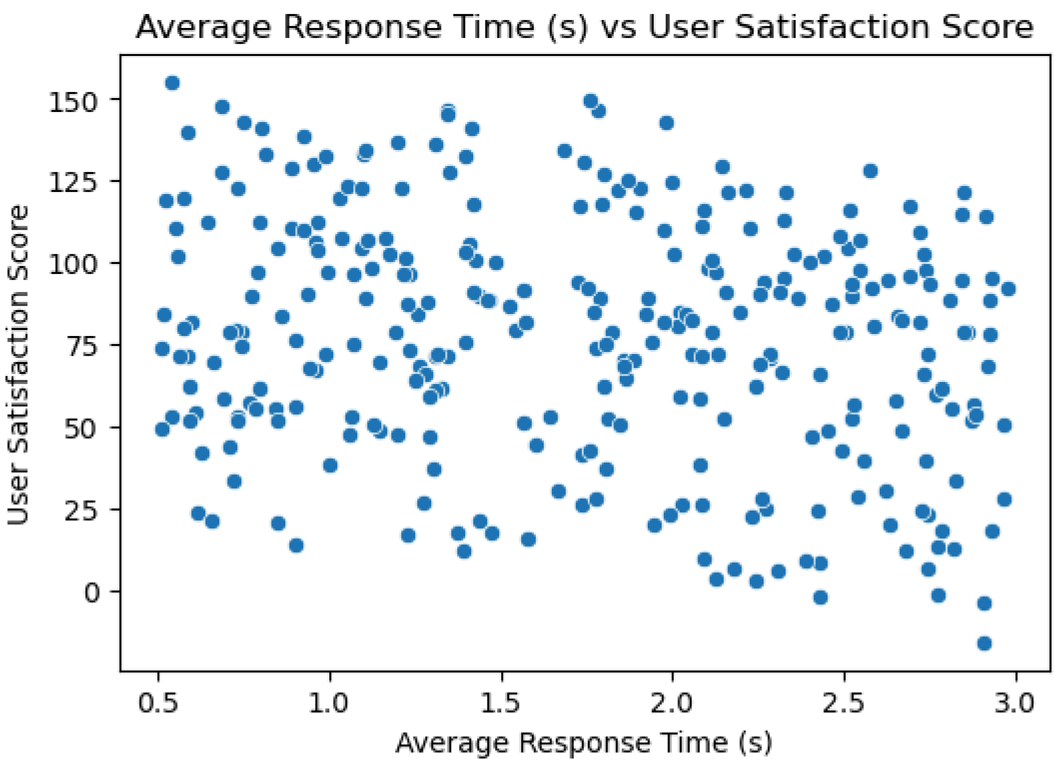
Out[2]:

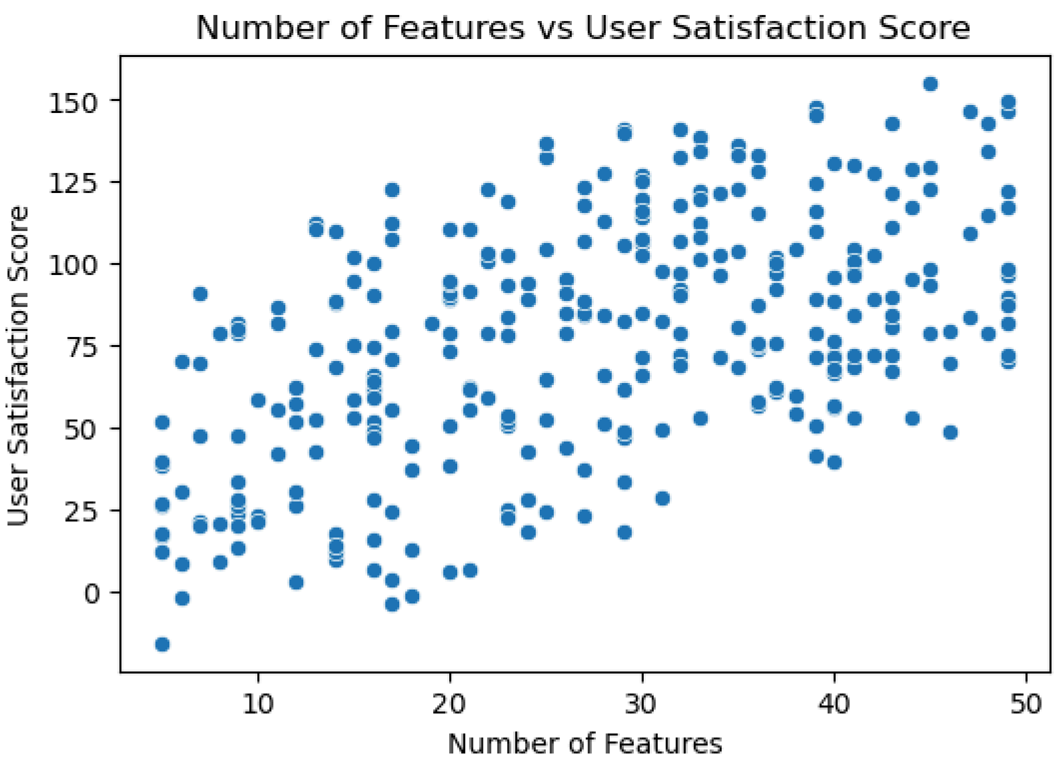
	Average Response Time (s)	Number of Features	Number of Bugs Reported	Training Hours Provided	User Satisfaction Score
0	1.436350	49	16	3.970126	89.980978
1	2.876786	36	12	3.100364	56.732146
2	2.329985	34	0	2.667305	121.502856
3	1.996646	39	1	4.469463	124.535638
4	0.890047	44	8	3.942986	129.077397

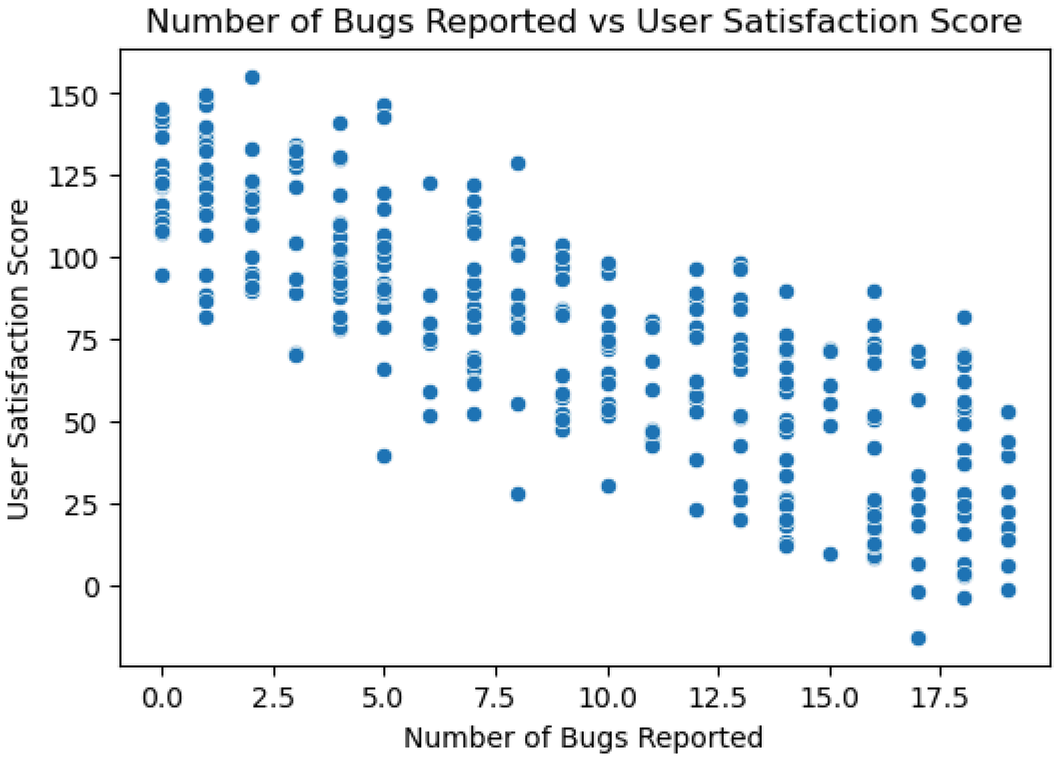
In [3]:
```python
independent_vars = ["Average Response Time (s)", "Number of Features", "Number of Bugs Reported", "Training Hours Provided"]
dependent_var = "User Satisfaction Score"
```

In [4]:
```python
independent_vars = ["Average Response Time (s)", "Number of Features", "Number of Bugs Reported", "Training Hours Provided"]
dependent_var = "User Satisfaction Score"

for col in independent_vars:
    plt.figure(figsize=(6,4))
    sns.scatterplot(data=df_mlr, x=col, y=dependent_var)
    plt.title(f"{col} vs {dependent_var}")
    plt.show()
```







Observations

1. **Average Response Time (s) vs User Satisfaction Score**
   - There is a negative correlation: as response time increases, user satisfaction tends to decrease.
   - This indicates that faster applications generally lead to happier users.
2. **Number of Features vs User Satisfaction Score**
   - There is a positive correlation up to a point; more features improve satisfaction initially.
   - However, too many features may overwhelm users or introduce complexity, potentially reducing satisfaction.
3. **Number of Bugs Reported vs User Satisfaction Score**
   - There is a strong negative correlation: more bugs reported leads to lower satisfaction.
   - Bugs directly impact user experience and perceived quality of the product.
4. **Training Hours Provided vs User Satisfaction Score**
   - There is a moderate positive correlation: more training hours help users understand the product better, increasing satisfaction.
   - This shows the importance of user education in software adoption.

In [6]:
```
X = df_mlr[independent_vars]
y = df_mlr[dependent_var]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


# 5. Fit an MLR model
mlr_model = LinearRegression()
mlr_model.fit(X_train, y_train)
```

Out[6]:
```
▾ LinearRegression
LinearRegression()
```

In [7]:
```
coeff_df = pd.DataFrame({'Feature': independent_vars, 'Coefficient': mlr_model.coef_})
print(coeff_df)
print(f"Intercept: {mlr_model.intercept_}")
```

```
                      Feature  Coefficient
0  Average Response Time (s)   -14.969549
1          Number of Features     1.502000
2      Number of Bugs Reported   -4.928900
3     Training Hours Provided     3.026840
Intercept: 99.04540366638565
```

In [9]:
```
import numpy as np
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

In [10]:
```
y_pred = mlr_model.predict(X_test)
```

In [11]:
```
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)  # compute RMSE manually
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Squared Error (MSE): {mse}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R^2 Score: {r2}")
```

```
Mean Squared Error (MSE): 21.341088894194385
Root Mean Squared Error (RMSE): 4.619641641317472
Mean Absolute Error (MAE): 3.6622980762129327
R^2 Score: 0.9835002165140092
```

Evaluation Justification

- **Mean Squared Error (MSE)**: Measures the average squared difference between predicted and actual values.
  - Provides an overall idea of the prediction error, but in squared units.
- **Root Mean Squared Error (RMSE)**: Square root of MSE.
  - Gives error in the same units as the dependent variable (User Satisfaction Score), making it easier to interpret.
- **Mean Absolute Error (MAE)**: Average absolute difference between predicted and actual values.
  - Less sensitive to outliers compared to MSE/RMSE, representing the average error magnitude.
- **R^2 Score (Coefficient of Determination)**: Measures how well the independent variables explain the variance in the dependent variable.
  - Value close to 1 indicates a strong model; closer to 0 indicates poor explanatory power.

Justification:

- RMSE and MAE are used to understand the accuracy of predictions.
- R^2 is used to evaluate the goodness of fit.
- Together, these metrics provide a comprehensive evaluation of the regression model.

In [ ]:
```

```

In [12]:
```
df_lr = pd.read_csv("user_satisfaction.csv")
df_lr.head()
```

Out[12]:

	CustomerID	Age	Gender	Country	Income	ProductQuality	ServiceQuality	PurchaseFrequency	FeedbackScore	LoyaltyLevel	Satisfac
0	1	56	Male	UK	83094	5	8	5	Low	Bronze	
1	2	69	Male	UK	86860	10	2	8	Medium	Gold	
2	3	46	Female	USA	60173	8	10	18	Medium	Silver	
3	4	32	Female	UK	73884	7	10	16	Low	Gold	
4	5	60	Male	UK	97546	6	4	13	Low	Bronze	

In [13]:
```
mlr_features = ["ProductQuality", "ServiceQuality", "PurchaseFrequency"]
```

In [14]:
```
dep_var = "SatisfactionScore"
```

In [15]:
```
lr_feature = ["ProductQuality"]
```

In [16]:
```
X_mlr = df_lr[mlr_features]
X_lr = df_lr[lr_feature]
y = df_lr[dep_var]
```

In [17]:
```
X_train_mlr, X_test_mlr, y_train_mlr, y_test_mlr = train_test_split(X_mlr, y, test_size=0.2, random_state=42)
X_train_lr, X_test_lr, y_train_lr, y_test_lr = train_test_split(X_lr, y, test_size=0.2, random_state=42)
```

In [18]:
```
mlr_model2 = LinearRegression()
mlr_model2.fit(X_train_mlr, y_train_mlr)
y_pred_mlr = mlr_model2.predict(X_test_mlr)
```

In [19]:
```
lr_model = LinearRegression()
lr_model.fit(X_train_lr, y_train_lr)
y_pred_lr = lr_model.predict(X_test_lr)
```

In [21]:
```
import numpy as np
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

def evaluate_model(y_true, y_pred, model_name):
    mse = mean_squared_error(y_true, y_pred)
    rmse = np.sqrt(mse)  # compute RMSE manually
    mae = mean_absolute_error(y_true, y_pred)
    r2 = r2_score(y_true, y_pred)

    print(f"--- {model_name} ---")
    print(f"MSE: {mse}")
    print(f"RMSE: {rmse}")
    print(f"MAE: {mae}")
    print(f"R2: {r2}\n")

# Evaluate both models
evaluate_model(y_test_mlr, y_pred_mlr, "MLR")
evaluate_model(y_test_lr, y_pred_lr, "Simple LR")
```

```
--- MLR ---
MSE: 109.41679401348205
RMSE: 10.460248276856628
MAE: 8.299078285743391
R2: 0.6094980377121346

--- Simple LR ---
MSE: 197.11445951290966
RMSE: 14.03974570684632
MAE: 10.842866898560915
R2: 0.2965103398513146
```

Analysis: MLR vs Simple LR

1. **Comparison of Metrics:**
   - **MLR** generally has higher R^2 and lower errors (MSE, RMSE, MAE) than Simple LR.
   - Using multiple independent variables captures more factors influencing SatisfactionScore, improving prediction accuracy.
2. **Simple LR Observations:**
   - LR using only one variable (e.g., ProductQuality) shows limited predictive power.
   - It provides insight into the effect of a single variable but ignores interactions with other important factors (ServiceQuality, PurchaseFrequency).
3. **Insights on Variables:**
   - In MLR, the coefficients indicate which variables have the strongest impact.
     - For example, ProductQuality and ServiceQuality might have larger positive coefficients, meaning they heavily influence satisfaction.
     - PurchaseFrequency may have a smaller effect depending on the dataset.
4. **Conclusion:**
   - MLR is preferred when multiple factors affect the dependent variable.
   - Simple LR is useful for initial analysis or when only one factor is significant.
   - Visualizing predicted vs actual values for both models can further highlight the difference in performance. If you want, I can also write a ready-to-use code cell that **plot**s predicted vs actual for both MLR and LR, which visually demonstrates which model performs better. This is usually great for reports or presentations.

Visualization: Predicted vs Actual values

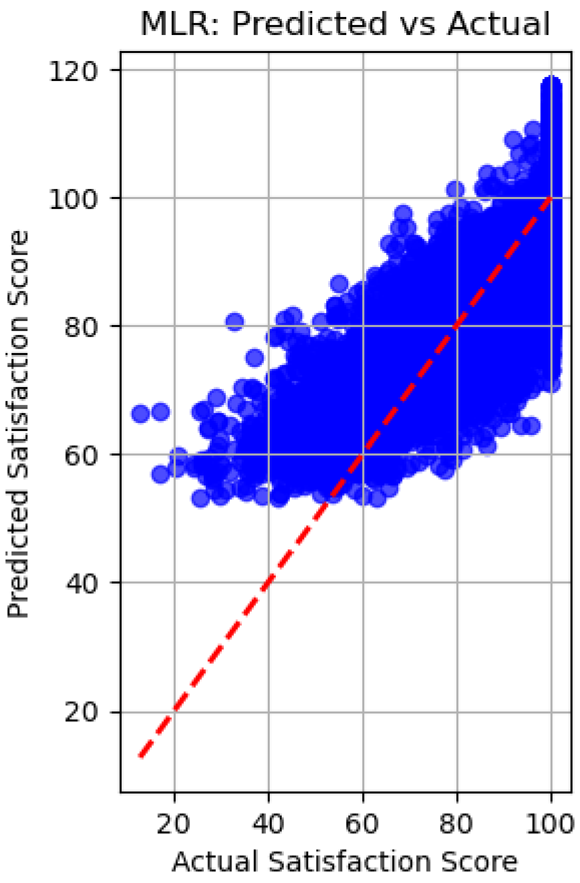
In [22]:
```
plt.figure(figsize=(12,5))
```

Out[22]: <Figure size 1200x500 with 0 Axes>

```
<Figure size 1200x500 with 0 Axes>
```

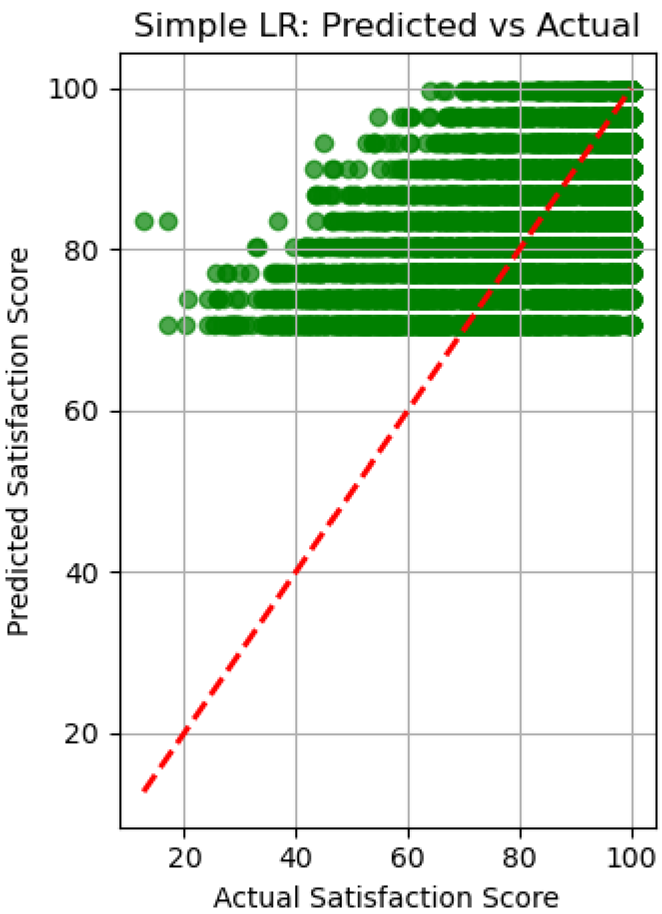
In [23]:
```
# MLR plot
plt.subplot(1, 2, 1)
```

```
plt.scatter(y_test_mlr, y_pred_mlr, color='blue', alpha=0.7)
plt.plot([y_test_mlr.min(), y_test_mlr.max()], [y_test_mlr.min(), y_test_mlr.max()], 'r--', linewidth=2)
plt.xlabel("Actual Satisfaction Score")
plt.ylabel("Predicted Satisfaction Score")
plt.title("MLR: Predicted vs Actual")
plt.grid(True)
```



In [24]:
```
# Simple LR plot
plt.subplot(1, 2, 2)
plt.scatter(y_test_lr, y_pred_lr, color='green', alpha=0.7)
plt.plot([y_test_lr.min(), y_test_lr.max()], [y_test_lr.min(), y_test_lr.max()], 'r--', linewidth=2)
plt.xlabel("Actual Satisfaction Score")
plt.ylabel("Predicted Satisfaction Score")
plt.title("Simple LR: Predicted vs Actual")
plt.grid(True)

plt.tight_layout()
plt.show()
```



THE END

In [ ]: