Data Wrangling Report: Lifestyle Monitoring Dataset

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Github Link: https://github.com/SrijitK10/Data-Science

Overview

This report details the data wrangling process applied to a lifestyle monitoring dataset collected from wearable fitness trackers. The dataset contains activity records including step counts, heart rate measurements, sleep duration, and other health metrics. Several data quality issues were identified and addressed through a systematic wrangling process.

Dataset Description

The original dataset contained records for 100 users over 30 days with the following variables:

- **User_ID**: Unique identifier for each user
- **Date**: Record date
- **Step_Count**: Daily steps taken
- **Heart_Rate**: Average heart rate (bpm)
- **Sleep_Duration**: Sleep duration in hours
- **Calories_Burned**: Estimated calories burned
- **Activity_Level**: Activity categorization (Sedentary, Lightly Active, Active, Very Active)
- **Device_Type**: Brand/model of wearable device

Data Quality Issues Identified

1. **Missing values** in multiple columns:
   - Step_Count (0.1%)
   - Heart_Rate (0.16%)
   - Sleep_Duration (not shown in sample but handled)
   - Calories_Burned (0.16%)
   - Activity_Level (0.32%)
2. **Inconsistent device naming formats** (e.g., "FitBit", "fitbit", "FITBIT")
3. **Duplicate records** (180 records where User_ID and Date were duplicated)
4. **Outliers** in Heart_Rate (values exceeding physiological limits) and Step_Count
5. **Categorical variables** requiring conversion to numerical format for analysis

Data Wrangling Approach

1. Handling Missing Data

Various imputation strategies were implemented based on the nature of each variable:

- **Step_Count**: First filled with user-specific means to preserve individual patterns, then any remaining missing values with the global median
- **Sleep_Duration**: Filled with user-specific medians (preferred over mean to reduce impact of extreme values)
- **Heart_Rate**: Filled with user-specific medians
- **Calories_Burned**: Used a regression model based on Step_Count to predict missing values, leveraging the relationship between physical activity and calorie expenditure
- **Activity_Level**: Inferred from Step_Count values using the same threshold logic that generated the original data, with any remaining gaps filled by the mode

Justification: These strategies preserved individual user patterns where possible while ensuring complete data for analysis. The user-specific imputation maintains the characteristic patterns of individual users, which is important for accurate analysis.

2. Data Standardization

Device type names were standardized using a mapping dictionary:
FitBit', 'fitbit', 'FITBIT' → 'Fitbit'
'Apple Watch', 'apple watch', 'APPLE WATCH' → 'Apple Watch' etc.
Justification: Standardization improves consistency for filtering, aggregation, and analysis. Without this step, the same device would be treated as different categories, leading to fragmented analyses.

3. Removing Duplicates

Detected 180 duplicate records based on User_ID and Date. The first occurrence of each duplicate was kept, removing 90 records.Justification: Each user should have only one record per day. Keeping duplicates would bias analytical results toward users with duplicate entries.

4. Outlier Detection and Handling

Used the IQR method to identify outliers:

- For Heart_Rate: Values outside [36.0, 108.0] were flagged as outliers
- For Step_Count: Values outside [0, 17145.4] were flagged as outliers

Outliers were handled by capping at the calculated bounds rather than removal to preserve data points.Justification: Capping maintains the directionality of extreme values without allowing them to skew analyses. This approach retains all observations while minimizing the impact of physiologically implausible values.

5. Data Transformation

Transformed the categorical Activity_Level variable using:

1. **Label Encoding**: Created a numerical representation (Active → 0, Lightly Active → 1, etc.)
2. **One-Hot Encoding**: Created binary indicator variables for each category

Justification: Different machine learning algorithms have different requirements. Label encoding is compact but implies ordinal relationships, while one-hot encoding avoids this assumption but increases dimensionality.

6. Data Merging

Merged the activity dataset with demographic information (age, gender, BMI) using a left join on User_ID.Justification: Demographic attributes provide important context for health and fitness data analysis. The left join ensures all activity records were retained.

7. Feature Engineering

Created derivative metrics to enhance analysis capabilities:

- **Steps_Per_Calorie**: Measures efficiency of activity in generating calorie burn
- **Steps_Per_BMI**: Contextualizes step count relative to body mass
- **Sleep_Efficiency**: Relates sleep duration to energy expenditure

Justification: These derived features enable deeper insights into the relationships between activity patterns, physical characteristics, and health outcomes.

Final Dataset

The final cleaned dataset contains 3,000 records with 19 columns, including the original measurements, standardized categorical variables, encoded versions of categorical variables, and derived metrics. All missing values were resolved, outliers were addressed, and inconsistencies were standardized.This comprehensive data wrangling process has prepared the dataset for robust analysis, ensuring that insights derived from it will be based on clean, consistent, and properly formatted data.

In [8]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
```

In [12]:
```python
def load_data():
    print("Loading the lifestyle monitoring dataset...")
    df = pd.read_csv("data/lifestyle_monitoring.csv")
    print(f"Original dataset shape: {df.shape}")
    return df
```

In [13]:
```python
# Task 1: Handling Missing Data
def handle_missing_data(df):
    print("\n--- Task 1: Handling Missing Data ---")

    # Check for missing values
    missing_values = df.isnull().sum()
    missing_percentage = (missing_values / len(df) * 100).round(2)

    print("Missing values in each column:")
    for col in df.columns:
        if missing_values[col] > 0:
            print(f"{col}: {missing_values[col]} ({missing_percentage[col]}%)")

    # Strategy 1: Fill missing Step_Count with the user's mean
    print("\nFilling missing Step_Count with each user's mean...")
    df['Step_Count'] = df.groupby('User_ID')['Step_Count'].transform(lambda x: x.fillna(x.mean()))

    # Strategy 2: Fill remaining Step_Count with global median
    step_median = df['Step_Count'].median()
    df['Step_Count'] = df['Step_Count'].fillna(step_median)

    # Strategy 3: Fill missing Sleep_Duration with the user's median
    print("Filling missing Sleep_Duration with each user's median...")
    df['Sleep_Duration'] = df.groupby('User_ID')['Sleep_Duration'].transform(lambda x: x.fillna(x.median()))

    # Strategy 4: Fill remaining Sleep_Duration with global median
    sleep_median = df['Sleep_Duration'].median()
    df['Sleep_Duration'] = df['Sleep_Duration'].fillna(sleep_median)

    # Strategy 5: Fill missing Heart_Rate with the user's median
    print("Filling missing Heart_Rate with each user's median...")
    df['Heart_Rate'] = df.groupby('User_ID')['Heart_Rate'].transform(lambda x: x.fillna(x.median()))

    # Strategy 6: Fill remaining Heart_Rate with global median
    heart_rate_median = df['Heart_Rate'].median()
    df['Heart_Rate'] = df['Heart_Rate'].fillna(heart_rate_median)

    # Strategy 7: Fill missing Calories_Burned with a regression model based on Step_Count
    # First check if there are any missing values in Calories_Burned
    if df['Calories_Burned'].isnull().sum() > 0:
        print("Predicting missing Calories_Burned using regression on Step_Count...")

        # Create a simple linear regression using the available data
        from sklearn.linear_model import LinearRegression

        # Prepare data for modeling
        X_train = df.dropna(subset=['Calories_Burned'])[['Step_Count']].values
        y_train = df.dropna(subset=['Calories_Burned'])['Calories_Burned'].values

        # Train the model
        model = LinearRegression()
        model.fit(X_train, y_train)

        # Identify rows with missing Calories_Burned
        missing_calories_idx = df['Calories_Burned'].isnull()

        if missing_calories_idx.sum() > 0:
            # Predict missing values
            X_predict = df.loc[missing_calories_idx, ['Step_Count']].values
            df.loc[missing_calories_idx, 'Calories_Burned'] = model.predict(X_predict).round(0)

    # Strategy 8: Fill remaining Calories_Burned with global median
    calories_median = df['Calories_Burned'].median()
    df['Calories_Burned'] = df['Calories_Burned'].fillna(calories_median)

    # Strategy 9: Fill missing Activity_Level based on Step_Count
    if df['Activity_Level'].isnull().sum() > 0:
        print("Inferring missing Activity_Level based on Step_Count...")

        # Function to determine activity level from step count
        def infer_activity_level(step_count):
            if pd.isnull(step_count):
                return None
            elif step_count < 5000:
                return "Sedentary"
            elif step_count < 7500:
                return "Lightly Active"
            elif step_count < 10000:
                return "Active"
            else:
                return "Very Active"

        # Apply the function to rows with missing Activity_Level
        missing_activity_idx = df['Activity_Level'].isnull()
        df.loc[missing_activity_idx, 'Activity_Level'] = df.loc[missing_activity_idx, 'Step_Count'].apply(infer_activity_level)

    # Strategy 10: Fill any remaining missing Activity_Level with mode
    activity_mode = df['Activity_Level'].mode()[0]
    df['Activity_Level'] = df['Activity_Level'].fillna(activity_mode)

    # Check if any missing values remain
    missing_after = df.isnull().sum()
    print("\nMissing values after handling:")
    print(missing_after)

    return df
```

In [14]:
```
def standardize_device_types(df):
    print("\n--- Task 2: Data Cleaning & Standardization ---")

    # Check unique values in Device_Type before standardization
    print("Unique Device_Type values before standardization:")
    print(df['Device_Type'].unique())

    # Create a mapping dictionary for standardization
    device_mapping = {
        'FitBit': 'Fitbit', 'fitbit': 'Fitbit', 'FITBIT': 'Fitbit',
        'Apple Watch': 'Apple Watch', 'apple watch': 'Apple Watch', 'APPLE WATCH': 'Apple Watch',
        'Samsung': 'Samsung', 'samsung': 'Samsung', 'SAMSUNG': 'Samsung',
        'Garmin': 'Garmin', 'garmin': 'Garmin', 'GARMIN': 'Garmin'
    }

    # Apply the mapping to standardize device names
    df['Device_Type'] = df['Device_Type'].map(device_mapping)

    # Check unique values after standardization
    print("\nUnique Device_Type values after standardization:")
    print(df['Device_Type'].unique())

    return df

# Task 3: Removing Duplicates
def remove_duplicates(df):
    print("\n--- Task 3: Removing Duplicates ---")

    # Count initial records
    initial_count = len(df)
    print(f"Initial record count: {initial_count}")

    # Check for duplicates based on User_ID and Date
    duplicates = df.duplicated(subset=['User_ID', 'Date'], keep=False)
    duplicate_count = duplicates.sum()
    print(f"Found {duplicate_count} duplicate records based on User_ID and Date")

    if duplicate_count > 0:
        # Display some examples of duplicates
        print("\nSample duplicate records:")
        duplicate_sample = df[duplicates].head(6)
        print(duplicate_sample)

        # Remove duplicates, keeping the first occurrence
        df = df.drop_duplicates(subset=['User_ID', 'Date'], keep='first')

        # Count records after removing duplicates
        final_count = len(df)
        print(f"\nRemoved {initial_count - final_count} duplicate records")
        print(f"Record count after removing duplicates: {final_count}")

    return df
```

In [15]:
```
# Task 4: Outlier Detection
def handle_outliers(df):
    print("\n--- Task 4: Outlier Detection ---")

    # Check for Heart_Rate outliers using IQR method
    q1_hr = df['Heart_Rate'].quantile(0.25)
    q3_hr = df['Heart_Rate'].quantile(0.75)
    iqr_hr = q3_hr - q1_hr

    lower_bound_hr = q1_hr - (1.5 * iqr_hr)
    upper_bound_hr = q3_hr + (1.5 * iqr_hr)

    # Identify heart rate outliers
    hr_outliers = df[(df['Heart_Rate'] < lower_bound_hr) | (df['Heart_Rate'] > upper_bound_hr)]
    hr_outlier_count = len(hr_outliers)

    print(f"Heart Rate IQR: {iqr_hr}")
    print(f"Heart Rate bounds: [{lower_bound_hr}, {upper_bound_hr}]")
    print(f"Detected {hr_outlier_count} Heart_Rate outliers")

    if hr_outlier_count > 0:
        # Show some examples of heart rate outliers
        print("\nSample Heart_Rate outliers:")
        print(hr_outliers[['User_ID', 'Date', 'Heart_Rate']].head())

        # Strategy: Cap extreme heart rate values at upper/lower bounds
        print("\nCapping extreme Heart_Rate values...")
        df['Heart_Rate'] = df['Heart_Rate'].clip(lower=lower_bound_hr, upper=upper_bound_hr)

    # Check for Step_Count outliers using IQR method
    q1_steps = df['Step_Count'].quantile(0.25)
    q3_steps = df['Step_Count'].quantile(0.75)
    iqr_steps = q3_steps - q1_steps

    lower_bound_steps = q1_steps - (1.5 * iqr_steps)
    upper_bound_steps = q3_steps + (1.5 * iqr_steps)

    # Identify step count outliers
    steps_outliers = df[(df['Step_Count'] < lower_bound_steps) | (df['Step_Count'] > upper_bound_steps)]
    steps_outlier_count = len(steps_outliers)

    print(f"\nStep Count IQR: {iqr_steps}")
    print(f"Step Count bounds: [{lower_bound_steps}, {upper_bound_steps}]")
    print(f"Detected {steps_outlier_count} Step_Count outliers")

    if steps_outlier_count > 0:
        # Show some examples of step count outliers
        print("\nSample Step_Count outliers:")
        print(steps_outliers[['User_ID', 'Date', 'Step_Count']].head())

        # Strategy: Cap extreme step count values at upper/lower bounds
        print("\nCapping extreme Step_Count values...")
        df['Step_Count'] = df['Step_Count'].clip(lower=max(0, lower_bound_steps), upper=upper_bound_steps)

    # Verify outliers were handled
    hr_extreme_after = df[(df['Heart_Rate'] < lower_bound_hr) | (df['Heart_Rate'] > upper_bound_hr)]
    steps_extreme_after = df[(df['Step_Count'] < lower_bound_steps) | (df['Step_Count'] > upper_bound_steps)]
```

```python
    print(f"\nHeart_Rate values outside bounds after capping: {len(hr_extreme_after)}")
    print(f"Step_Count values outside bounds after capping: {len(steps_extreme_after)}")

    return df
```

In [16]:
```python
# Task 5: Data Transformation
def transform_categorical_data(df):
    print("\n--- Task 5: Data Transformation ---")

    # Display unique Activity_Level categories
    print("Unique Activity_Level categories:")
    print(df['Activity_Level'].unique())

    # Method 1: Label Encoding
    label_encoder = LabelEncoder()
    df['Activity_Level_Label'] = label_encoder.fit_transform(df['Activity_Level'])

    # Display mapping
    activity_mapping = dict(zip(label_encoder.classes_, label_encoder.transform(label_encoder.classes_)))
    print("\nLabel Encoding Mapping:")
    for activity, code in activity_mapping.items():
        print(f"{activity} -> {code}")

    # Method 2: One-Hot Encoding
    # Create dummy variables for Activity_Level
    activity_dummies = pd.get_dummies(df['Activity_Level'], prefix='Activity')

    # Join the dummy columns back to the main dataframe
    df = pd.concat([df, activity_dummies], axis=1)

    print("\nColumns after one-hot encoding:")
    print(df.columns.tolist())

    return df
```

In [17]:
```python
# Task 6: Data Merging
def merge_datasets(df):
    print("\n--- Task 6: Data Merging ---")

    # Load demographics dataset
    demographics = pd.read_csv("./data/user_demographics.csv")
    print(f"Demographics dataset shape: {demographics.shape}")
    print("\nSample of demographics data:")
    print(demographics.head())

    # Check for missing values in demographics dataset
    demo_missing = demographics.isnull().sum()
    if demo_missing.sum() > 0:
        print("\nMissing values in demographics dataset:")
        for col in demographics.columns:
            if demo_missing[col] > 0:
                print(f"{col}: {demo_missing[col]} missing values")

        # Fill missing Age with median
        demographics['Age'] = demographics['Age'].fillna(demographics['Age'].median())

        # Fill missing Gender with mode
        demographics['Gender'] = demographics['Gender'].fillna(demographics['Gender'].mode()[0])

        # Fill missing BMI with median
        demographics['BMI'] = demographics['BMI'].fillna(demographics['BMI'].median())

        print("\nMissing values after handling:")
        print(demographics.isnull().sum())

    # Merge with the main dataset on User_ID
    merged_df = pd.merge(df, demographics, on='User_ID', how='left')

    # Check for any users without demographic information
    missing_demographics = merged_df[merged_df['Age'].isna()]['User_ID'].nunique()
    print(f"\nUsers without demographic information: {missing_demographics}")

    # Check the merged dataset
    print(f"Merged dataset shape: {merged_df.shape}")
    print("\nSample of merged data:")
    print(merged_df.head())

    return merged_df
```

In [18]:
```python
def prepare_final_dataset(df):
    print("\n--- Task 7: Final Dataset Preparation ---")

    # Select relevant columns for the final dataset
    # Includes original columns plus the encoded activity levels but excludes the original Activity_Level
    final_columns = [col for col in df.columns if col != 'Activity_Level' or not col.startswith('Activity_')] + \
                    [col for col in df.columns if col.startswith('Activity_')]

    final_df = df.copy()

    # Additional preparation steps:
    # 1. Convert Step_Count to integer
    final_df['Step_Count'] = final_df['Step_Count'].astype(int)

    # 2. Round Sleep_Duration to one decimal place
    final_df['Sleep_Duration'] = final_df['Sleep_Duration'].round(1)

    # 3. Convert Heart_Rate to integer
    final_df['Heart_Rate'] = final_df['Heart_Rate'].astype(int)

    # 4. Convert Calories_Burned to integer
    final_df['Calories_Burned'] = final_df['Calories_Burned'].astype(int)

    # 5. Create derived features
    # Steps per Calorie
    final_df['Steps_Per_Calorie'] = (final_df['Step_Count'] / final_df['Calories_Burned']).round(3)

    # Steps per BMI unit (as a fitness efficiency metric)
    final_df['Steps_Per_BMI'] = (final_df['Step_Count'] / final_df['BMI']).round(1)

    # Sleep efficiency (sleep duration relative to calories burned)
    final_df['Sleep_Efficiency'] = (final_df['Sleep_Duration'] / (final_df['Calories_Burned'] / 1000)).round(2)
```

```python
    # Final dataset summary
    print("\nFinal dataset info:")
    print(final_df.info())

    print("\nFinal dataset descriptive statistics:")
    print(final_df.describe())

    # Save the final cleaned dataset
    final_df.to_csv("data/lifestyle_monitoring_cleaned.csv", index=False)
    print("\nFinal cleaned dataset saved to: data/lifestyle_monitoring_cleaned.csv")

    return final_df
```

In [19]:

```python
def main():
    # Load the data
    df = load_data()

    # Execute each task
    df = handle_missing_data(df)
    df = standardize_device_types(df)
    df = remove_duplicates(df)
    df = handle_outliers(df)
    df = transform_categorical_data(df)
    df = merge_datasets(df)
    final_df = prepare_final_dataset(df)

    print("\nData wrangling complete!")

if __name__ == "__main__":
    main()
```

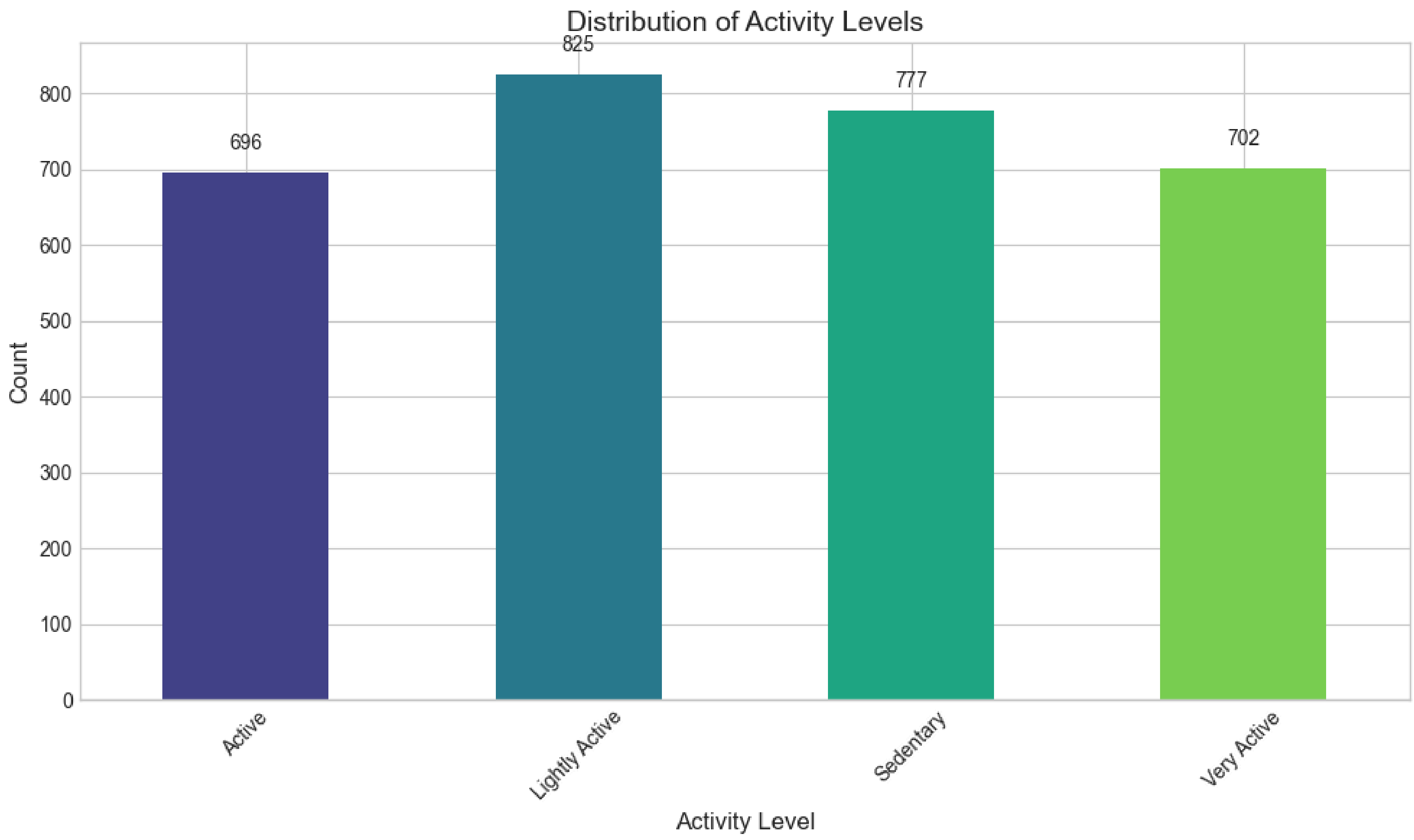
```
Loading the lifestyle monitoring dataset...
Original dataset shape: (3090, 8)

--- Task 1: Handling Missing Data ---
Missing values in each column:
Step_Count: 3 (0.1%)
Heart_Rate: 5 (0.16%)
Calories_Burned: 5 (0.16%)
Activity_Level: 10 (0.32%)

Filling missing Step_Count with each user's mean...
Filling missing Sleep_Duration with each user's median...
Filling missing Heart_Rate with each user's median...
Predicting missing Calories_Burned using regression on Step_Count...
Inferring missing Activity_Level based on Step_Count...

Missing values after handling:
User_ID           0
Date              0
Step_Count        0
Heart_Rate        0
Sleep_Duration    0
Calories_Burned   0
Activity_Level    0
Device_Type       0
dtype: int64

--- Task 2: Data Cleaning & Standardization ---
Unique Device_Type values before standardization:
['Apple Watch' 'fitbit' 'GARMIN' 'FitBit' 'FITBIT' 'APPLE WATCH' 'Garmin'
 'garmin' 'SAMSUNG' 'apple watch' 'Samsung' 'samsung']

Unique Device_Type values after standardization:
['Apple Watch' 'Fitbit' 'Garmin' 'Samsung']

--- Task 3: Removing Duplicates ---
Initial record count: 3090
Found 180 duplicate records based on User_ID and Date

Sample duplicate records:
     User_ID        Date  Step_Count  Heart_Rate  Sleep_Duration  \
74         3  2023-02-02     11695.0        64.0             5.9
154        6  2023-01-29      5737.0        89.0             7.2
178        6  2023-02-22      5003.0        85.0             6.7
316       11  2023-01-23      4279.0        46.0             7.5
333       12  2023-01-31      6523.0        77.0             6.7
347       12  2023-02-14      6857.0        55.0             7.0

     Calories_Burned  Activity_Level  Device_Type
74            2069.0     Very Active  Apple Watch
154           2115.0  Lightly Active       Fitbit
178           2297.0  Lightly Active       Fitbit
316           1902.0       Sedentary       Fitbit
333           2346.0  Lightly Active       Garmin
347           2263.0  Lightly Active       Garmin

Removed 90 duplicate records
Record count after removing duplicates: 3000

--- Task 4: Outlier Detection ---
Heart Rate IQR: 18.0
Heart Rate bounds: [36.0, 108.0]
Detected 8 Heart_Rate outliers

Sample Heart_Rate outliers:
     User_ID        Date  Heart_Rate
52         2  2023-01-27       119.0
489       17  2023-02-05       116.0
576       20  2023-01-15       109.0
630       22  2023-01-21       114.0
888       30  2023-01-22       110.0

Capping extreme Heart_Rate values...

Step Count IQR: 4884.25
Step Count bounds: [-2391.625, 17145.375]
Detected 1 Step_Count outliers

Sample Step_Count outliers:
      User_ID        Date  Step_Count
1563       53  2023-01-05     17292.0

Capping extreme Step_Count values...

Heart_Rate values outside bounds after capping: 0
Step_Count values outside bounds after capping: 0

--- Task 5: Data Transformation ---
Unique Activity_Level categories:
['Lightly Active' 'Sedentary' 'Active' 'Very Active']

Label Encoding Mapping:
Active -> 0
Lightly Active -> 1
Sedentary -> 2
Very Active -> 3

Columns after one-hot encoding:
['User_ID', 'Date', 'Step_Count', 'Heart_Rate', 'Sleep_Duration', 'Calories_Burned', 'Activity_Level', 'Device_Type', 'Activity_Level_Label', 'Activity_A
ctive', 'Activity_Lightly Active', 'Activity_Sedentary', 'Activity_Very Active']

--- Task 6: Data Merging ---
Demographics dataset shape: (100, 4)

Sample of demographics data:
   User_ID   Age      Gender   BMI
0        1  56.0        Male  27.3
1        2  38.0        Male  19.4
2        3  60.0      Female  23.2
3        4  56.0  Non-binary  25.2
4        5  62.0      Female  24.0
```

```
Missing values in demographics dataset:
Age: 2 missing values
Gender: 4 missing values
BMI: 4 missing values

Missing values after handling:
User_ID    0
Age        0
Gender     0
BMI        0
dtype: int64

Users without demographic information: 0
Merged dataset shape: (3000, 16)

Sample of merged data:
   User_ID        Date  Step_Count  Heart_Rate  Sleep_Duration  \
0        1  2023-01-21      5303.0        58.0             8.6
1        1  2023-01-22      4598.0        57.0             9.5
2        1  2023-01-23      4371.0        65.0             7.5
3        1  2023-01-24      5057.0        40.0             6.2
4        1  2023-01-25      3846.0        63.0             7.1

   Calories_Burned  Activity_Level  Device_Type  Activity_Level_Label  \
0           2305.0  Lightly Active  Apple Watch                     1
1           2154.0       Sedentary  Apple Watch                     2
2           1907.0       Sedentary  Apple Watch                     2
3           1888.0  Lightly Active  Apple Watch                     1
4           1718.0       Sedentary  Apple Watch                     2

   Activity_Active  Activity_Lightly Active  Activity_Sedentary  \
0            False                     True               False
1            False                    False                True
2            False                    False                True
3            False                     True               False
4            False                    False                True

   Activity_Very Active   Age Gender   BMI
0                 False  56.0   Male  27.3
1                 False  56.0   Male  27.3
2                 False  56.0   Male  27.3
3                 False  56.0   Male  27.3
4                 False  56.0   Male  27.3

--- Task 7: Final Dataset Preparation ---

Final dataset info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 19 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   User_ID                  3000 non-null   int64
 1   Date                     3000 non-null   object
 2   Step_Count               3000 non-null   int64
 3   Heart_Rate               3000 non-null   int64
 4   Sleep_Duration           3000 non-null   float64
 5   Calories_Burned          3000 non-null   int64
 6   Activity_Level           3000 non-null   object
 7   Device_Type              3000 non-null   object
 8   Activity_Level_Label     3000 non-null   int64
 9   Activity_Active          3000 non-null   bool
 10  Activity_Lightly Active  3000 non-null   bool
 11  Activity_Sedentary       3000 non-null   bool
 12  Activity_Very Active     3000 non-null   bool
 13  Age                      3000 non-null   float64
 14  Gender                   3000 non-null   object
 15  BMI                      3000 non-null   float64
 16  Steps_Per_Calorie        3000 non-null   float64
 17  Steps_Per_BMI            3000 non-null   float64
 18  Sleep_Efficiency         3000 non-null   float64
dtypes: bool(4), float64(6), int64(5), object(4)
memory usage: 363.4+ KB
None

Final dataset descriptive statistics:
           User_ID    Step_Count   Heart_Rate  Sleep_Duration  \
count  3000.000000   3000.000000  3000.000000     3000.000000
mean     50.500000   7521.030000    71.509333        7.033067
std      28.870882   3185.159093    12.964488        1.506454
min       1.000000    984.000000    40.000000        1.900000
25%      25.750000   4934.750000    63.000000        6.000000
50%      50.500000   7156.500000    71.000000        7.000000
75%      75.250000   9819.000000    81.000000        8.100000
max     100.000000  17145.000000   108.000000       12.300000

       Calories_Burned  Activity_Level_Label          Age          BMI  \
count      3000.000000           3000.000000  3000.000000  3000.000000
mean       2265.806333              1.495000    44.790000    26.076000
std         488.244283              1.087368    14.923811     4.486037
min        1211.000000              0.000000    19.000000    18.100000
25%        1859.750000              1.000000    34.000000    22.900000
50%        2244.000000              1.000000    43.000000    25.700000
75%        2637.000000              2.000000    56.000000    28.825000
max        3684.000000              3.000000    75.000000    35.000000

       Steps_Per_Calorie  Steps_Per_BMI  Sleep_Efficiency
count        3000.000000    3000.000000       3000.000000
mean            3.531860     296.922733          3.257433
std             1.808781     137.401516          1.019094
min             0.404000      38.300000          0.880000
25%             2.075000     188.075000          2.530000
50%             3.188500     271.350000          3.130000
75%             4.695000     390.025000          3.870000
max            13.415000     813.200000          8.090000

Final cleaned dataset saved to: data/lifestyle_monitoring_cleaned.csv

Data wrangling complete!
```

Data Visualization

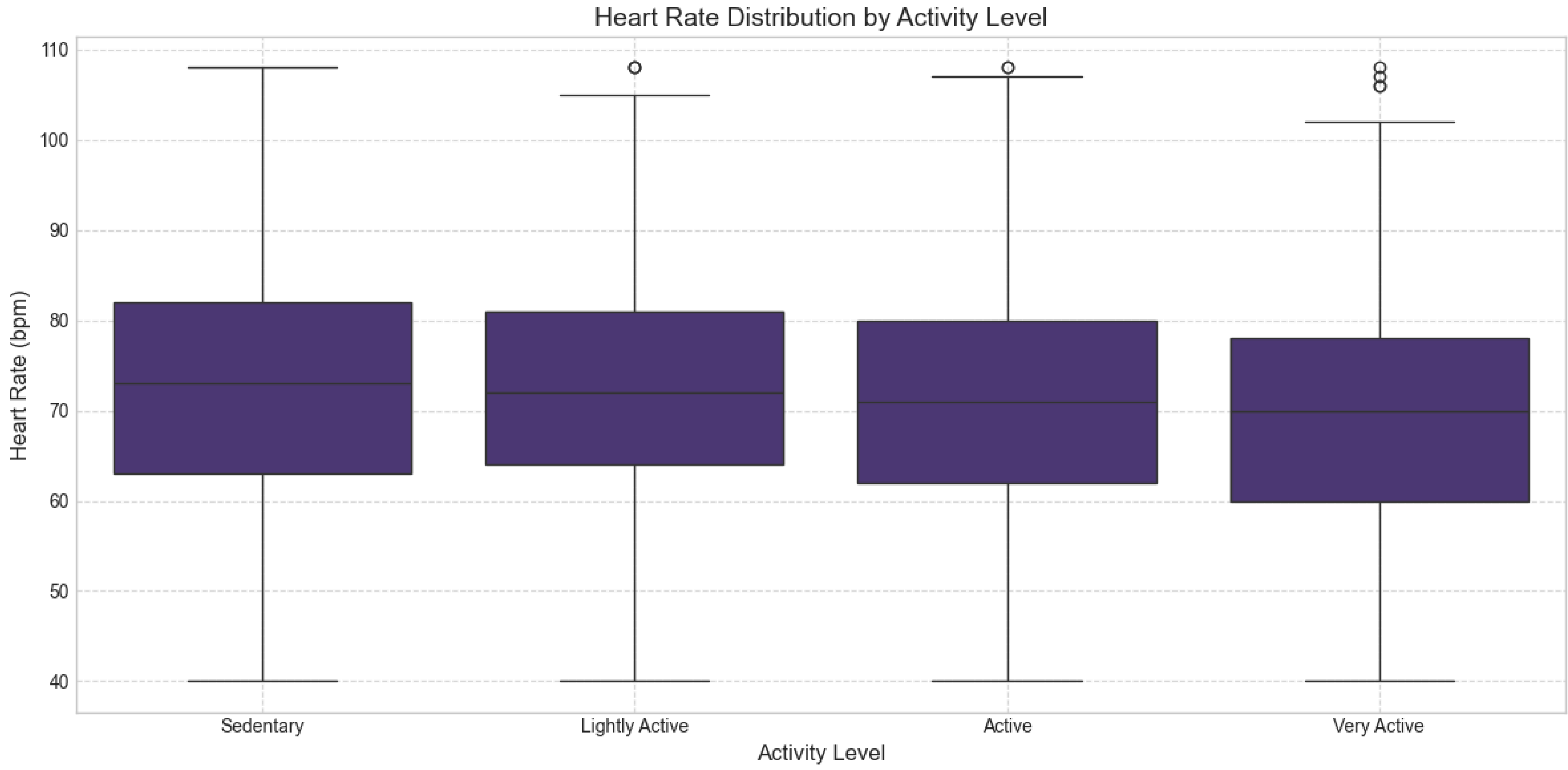
In [20]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# Set plot style
plt.style.use('seaborn-v0_8-whitegrid')
sns.set_palette("viridis")

# Load the cleaned dataset
cleaned_df = pd.read_csv("data/lifestyle_monitoring_cleaned.csv")

# Create a directory for visualizations
import os
if not os.path.exists('visualizations'):
    os.makedirs('visualizations')
```

In [21]:
```
# 1. Activity Level Distribution
plt.figure(figsize=(10, 6))
activity_counts = cleaned_df['Activity_Level'].value_counts().sort_index()
ax = activity_counts.plot(kind='bar', color=sns.color_palette("viridis", 4))
plt.title('Distribution of Activity Levels', fontsize=14)
plt.xlabel('Activity Level', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xticks(rotation=45)
for i, v in enumerate(activity_counts):
    ax.text(i, v + 30, str(v), ha='center', fontsize=10)
plt.tight_layout()
plt.show()
plt.savefig('visualizations/activity_distribution.png', dpi=300)
```



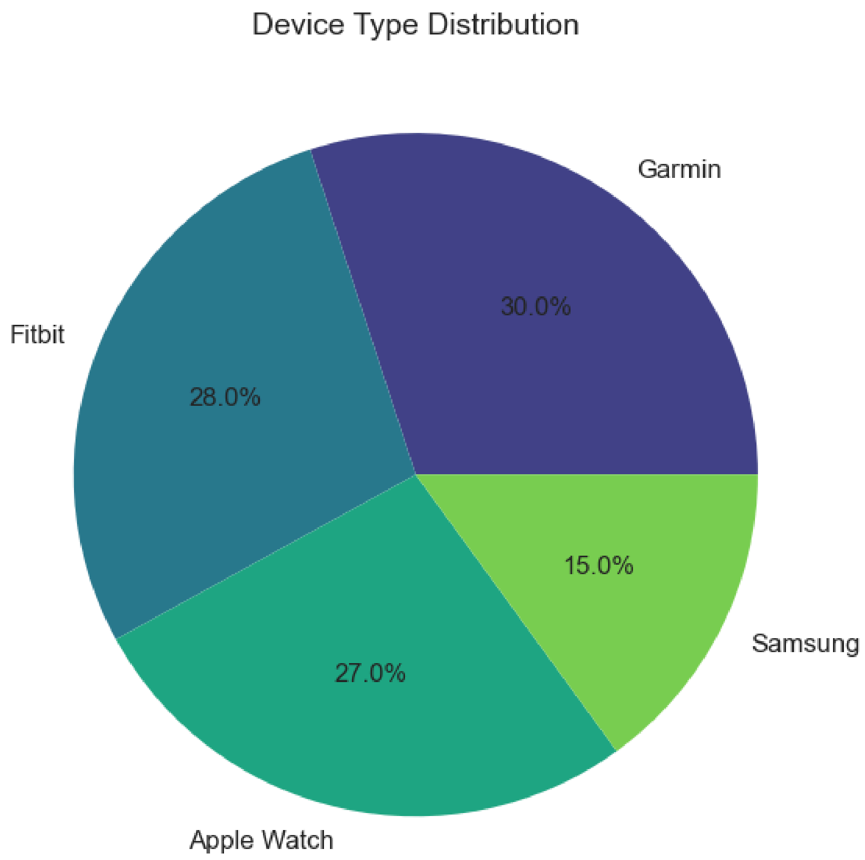

```
<Figure size 640x480 with 0 Axes>
```

In [22]:
```
# 2. Heart Rate by Activity Level
plt.figure(figsize=(12, 6))
sns.boxplot(x='Activity_Level', y='Heart_Rate', data=cleaned_df, order=['Sedentary', 'Lightly Active', 'Active', 'Very Active'])
plt.title('Heart Rate Distribution by Activity Level', fontsize=14)
plt.xlabel('Activity Level', fontsize=12)
plt.ylabel('Heart Rate (bpm)', fontsize=12)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
plt.savefig('visualizations/heart_rate_by_activity.png', dpi=300)
```



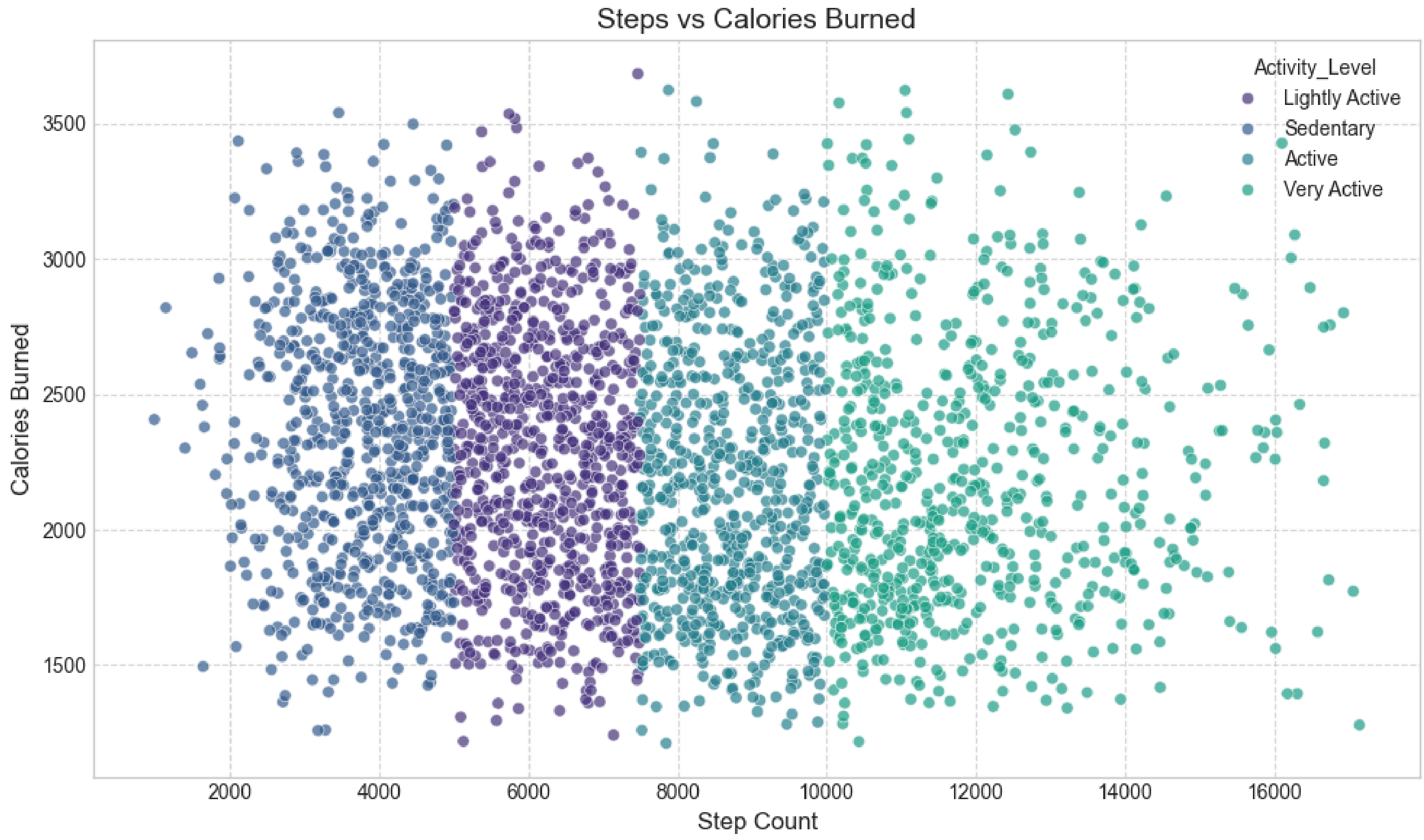

```
<Figure size 640x480 with 0 Axes>
```

In [23]:
```
# 3. Device Type Distribution
plt.figure(figsize=(10, 6))
device_counts = cleaned_df['Device_Type'].value_counts()
plt.pie(device_counts, labels=device_counts.index, autopct='%1.1f%%',
        textprops={'fontsize': 12}, colors=sns.color_palette("viridis", len(device_counts)))
plt.title('Device Type Distribution', fontsize=14)
plt.tight_layout()
plt.show()
plt.savefig('visualizations/device_distribution.png', dpi=300)
```



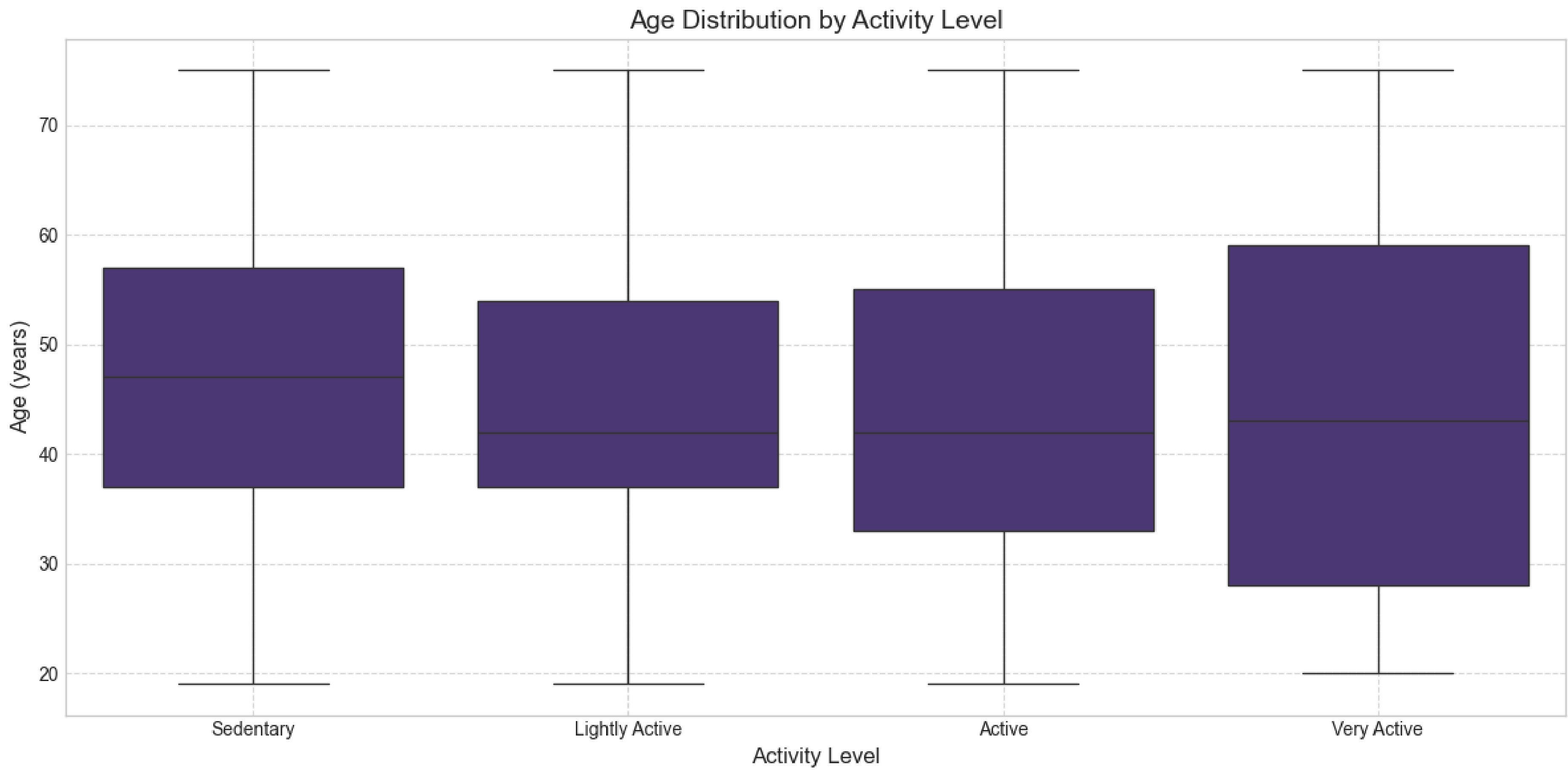

```
<Figure size 640x480 with 0 Axes>
```

In [24]:
```
# 4. Steps vs Calories Burned Scatter Plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Step_Count', y='Calories_Burned', hue='Activity_Level',
                data=cleaned_df, alpha=0.7)
plt.title('Steps vs Calories Burned', fontsize=14)
plt.xlabel('Step Count', fontsize=12)
plt.ylabel('Calories Burned', fontsize=12)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
plt.savefig('visualizations/steps_vs_calories.png', dpi=300)
```

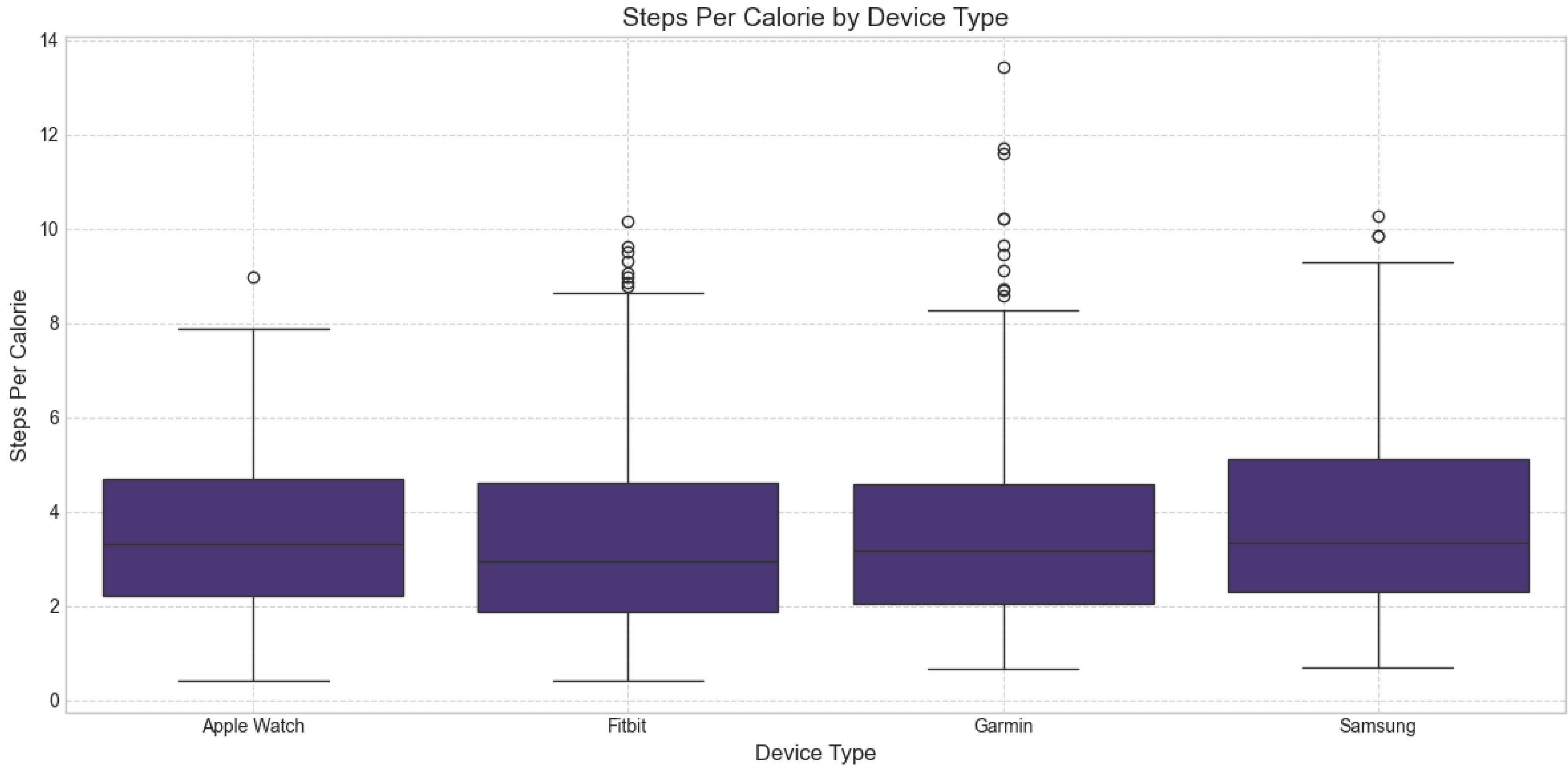



```
<Figure size 640x480 with 0 Axes>
```

In [25]:
```python
# 5. Age vs Activity Level
plt.figure(figsize=(12, 6))
sns.boxplot(x='Activity_Level', y='Age', data=cleaned_df, order=['Sedentary', 'Lightly Active', 'Active', 'Very Active'])
plt.title('Age Distribution by Activity Level', fontsize=14)
plt.xlabel('Activity Level', fontsize=12)
plt.ylabel('Age (years)', fontsize=12)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.savefig('visualizations/age_by_activity.png', dpi=300)
plt.show()
```



In [26]:
```python
# 6. Steps Per Calorie by Device Type
plt.figure(figsize=(12, 6))
sns.boxplot(x='Device_Type', y='Steps_Per_Calorie', data=cleaned_df)
plt.title('Steps Per Calorie by Device Type', fontsize=14)
plt.xlabel('Device Type', fontsize=12)
plt.ylabel('Steps Per Calorie', fontsize=12)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.savefig('visualizations/steps_per_calorie_by_device.png', dpi=300)
plt.show()
```



In [27]:
```python
# 7. Correlation Matrix
plt.figure(figsize=(12, 10))
# Select only numeric columns
numeric_df = cleaned_df.select_dtypes(include=[np.number])
# Calculate correlation matrix
corr = numeric_df.corr()
# Create heatmap
mask = np.triu(np.ones_like(corr, dtype=bool))
sns.heatmap(corr, mask=mask, annot=True, fmt=".2f", cmap='viridis',
            vmin=-1, vmax=1, square=True, linewidths=0.5)
plt.title('Correlation Matrix of Numeric Variables', fontsize=14)
plt.tight_layout()
plt.savefig('visualizations/correlation_matrix.png', dpi=300)
plt.show()
```