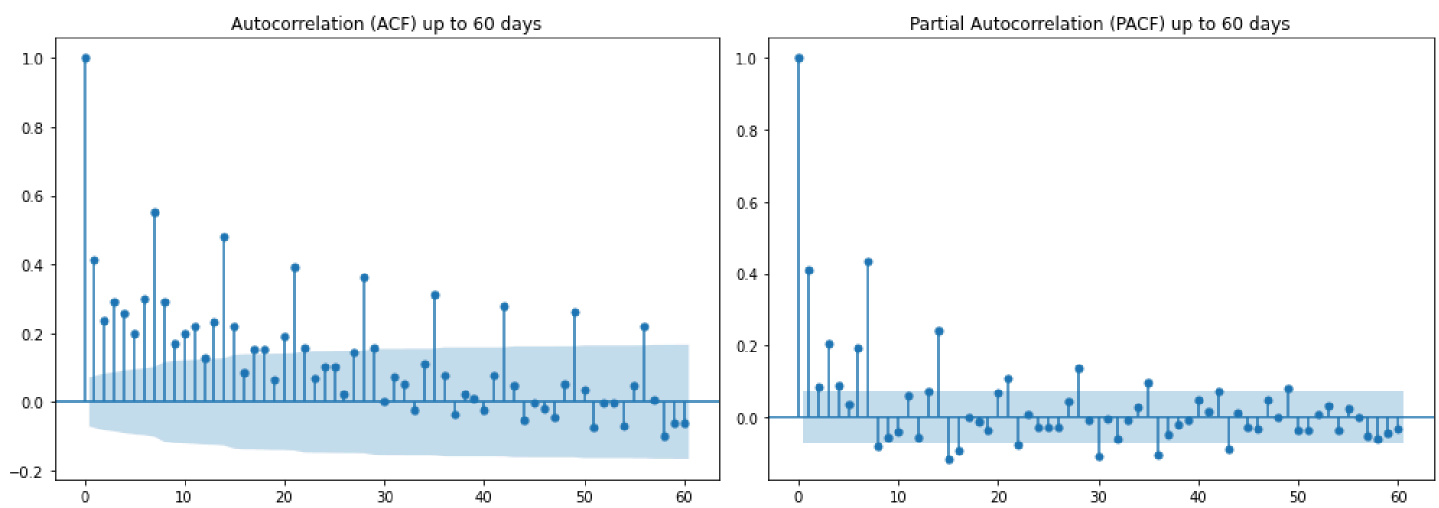
Seasonability

```
def decompose_absence(dfs, value_col='Total_Lost', samples='all', period=7):
    """
    Decompose a daily time series into trend, seasonality, and residuals.

    Parameters:
    -----------
    dfs : pandas.DataFrame
        Your daily dataframe (e.g. df_grouped)
        with a 'Date' column of type datetime64[ns].
    value_col : str
        The name of the column you want to decompose (default 'Total_Lost').
    samples : int or 'all'
        How many recent samples (days) to use for decomposition.
        If 'all', use the entire time series.
    period : int
        The seasonality period.
        For daily data with weekly seasonality, period=7.
        For monthly ~30, for yearly ~365, etc.
    """

    # Make a copy if you don't want to modify dfs in place
    df_copy = dfs.copy()

    # Ensure 'Date' is a DateTime index
    df_copy = df_copy.set_index('Date').sort_index()

    # Grab the series we want to decompose
    series = df_copy[value_col]

    # If we only want to decompose a portion of the data
    if samples != 'all':
        series = series.iloc[-samples:]  # last N samples

    # Perform seasonal decomposition
    result = seasonal_decompose(series, model='additive', period=period)

    # Extract the components
    observed = result.observed
    trend = result.trend
    seasonal = result.seasonal
    residual = result.resid

    # Plot the results
    fig, axs = plt.subplots(4, 1, figsize=(14, 10), sharex=True)
```

```
    axs[0].set_title(f'Observed  Total Lost', fontsize=14)
    axs[0].plot(observed, label='Observed')
    axs[0].grid(True)

    axs[1].set_title(f'Trend Total Lost', fontsize=14)
    axs[1].plot(trend, color='orange', label='Trend')
    axs[1].grid(True)

    axs[2].set_title(f'Seasonality Total Lost', fontsize=14)
    axs[2].plot(seasonal, color='green', label='Seasonality')
    axs[2].grid(True)

    axs[3].set_title(f'Residual Total Lost', fontsize=14)
    axs[3].plot(residual, color='red', label='Residual')
    axs[3].scatter(x=residual.index, y=residual, alpha=0.5, color='red')
    axs[3].grid(True)

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

Decompose weekly seasonality (period=7) & ACF & PACF Analysis

```
# 1) Decompose weekly seasonality (period=7)
decompose_absence(df_grouped, value_col='Total_Lost', samples='all', period=7)

# 2) Plot ACF and PACF side by side for up to 60 lags (about 2 months)
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 5))

plot_acf(df_grouped['Total_Lost'], lags=60, ax=ax1)
ax1.set_title('Autocorrelation (ACF) up to 60 days')

plot_pacf(df_grouped['Total_Lost'], lags=60, ax=ax2)
ax2.set_title('Partial Autocorrelation (PACF) up to 60 days')

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



1. Decomposition Analysis

Observed:

- Our **daily Total Losts series** shows considerable variation:
    - **Spikes:** Total Losts values occasionally spike between **80–100**.
    - **Baseline:** Fluctuates around **20–40** over extended periods.

📈 Trend:

- The **Trend line** gradually **rises and falls** over several months, suggesting:
    - **Long-term drift** possibly influenced by:
        - **Business cycles**
        - **Policy changes**
        - **Workforce dynamics**

🔄 Seasonality (Period = 7):

- The **green seasonality plot** forms a repeating wave **every 7 days**, indicating a **weekly pattern.**
- **Amplitude** ranges from roughly **+5 down to –15**, implying:
    - Certain **days of the week** consistently have **higher or lower** Total Losts rates.

📉 Residual:

- The **red scatter/line** represents what's left after removing **Trend** and **Seasonality**:
    - **Fluctuates** between **–40 and +40**, with some **extreme spikes.**
    - Indicates the presence of **additional drivers,** such as:
        - **Holidays**
        - **One-off events**
        - **Group-specific factors** that aren't captured by a simple weekly seasonality.

✅ Key Takeaway:

- We observe a clear **weekly seasonality (7-day cycle).**
- There's also a noticeable **long-term trend.**
- Our future models should account for both using:
    - **Seasonal terms**
    - **Dummy variables for the day of the week**
    - **Other time-based features**

📊 2. ACF & PACF Analysis

We plotted the **Autocorrelation Function (ACF)** and **Partial Autocorrelation Function (PACF)** for **lags = 60** (covering ~2 months).

🔗 ACF (Autocorrelation Function):

- **Lag 1:** A **large spike**, indicating that **today's Total Losts strongly correlate** with **yesterday's.**
- **Weekly Pattern:** Noticeable spikes at **lags 7, 14, 21**, etc., confirming the **weekly pattern.**
- **Monthly Effect?:** Smaller spikes around **30 days** may suggest a **monthly trend** (less pronounced but worth exploring).

🔗 PACF (Partial Autocorrelation Function):

- **Lag 1:** The **largest spike**, highlighting a **strong direct correlation** with the **previous day's Total Losts.**
- **Lag 7:** Another notable spike, showing a **weekly effect** beyond just the day-to-day correlation.
- **Higher Lags (14, 21, 28):** Smaller spikes, suggesting that once we account for **lag 1** and **lag 7**, additional multiples of 7 add **less explanatory power**.

📈 In General:

- If **ACF remains high** at lags like **14, 21, 28**, but **PACF is low**, it implies that these correlations are **indirectly explained** by **lag 1** or **lag 7**.
- Spikes around **30 days** hint at potential **monthly patterns**, although **weekly trends** often dominate in business contexts.

✅ Key Takeaway:

- The time series has a strong **autoregressive structure:**
  - Depends on **past values**, especially **1 day ago** and **7 days ago**.
- We can enhance model performance by introducing **lagged features** such as:
  - **Total Losts_{t-1}** (previous day)
  - **Total Losts_{t-7}** (previous week)
  - Potentially **Total Losts_{t-14}**, **Total Losts_{t-30}**, if data shows benefits.

💡 Final Thoughts

✅ Key Conclusions:

- **Lag Features Are Applicable:**
  ACF and PACF confirm that **past Total Losts values** help predict **future Total Losts.**
- **Critical Lags Identified:**
  - **Lag 1** (yesterday's Total Losts)
  - **Lag 7** (Total Losts from the same day last week)
  - Potentially **Lag 14** or **Lag 30**, depending on model performance.
- **Seasonality Confirmed:**
  Seasonal decomposition reaffirms a **weekly pattern.**

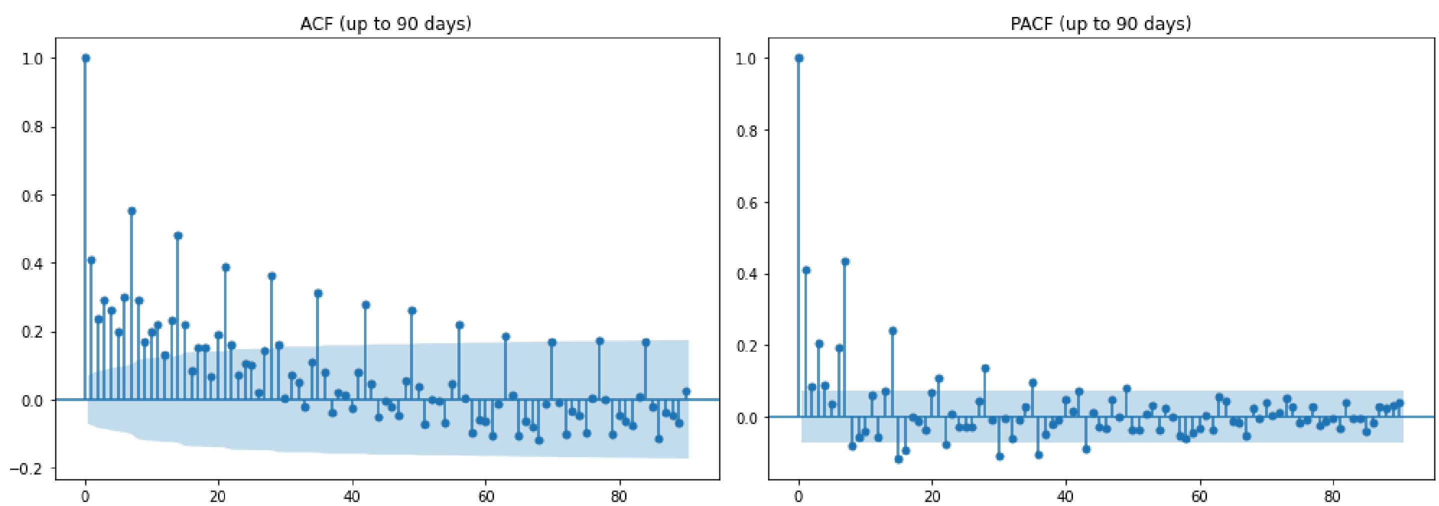
🔍 Next Steps for Modeling:

- Introduce **lag features**, particularly **day 1** and **day 7**.
- Consider adding:
  - **Explicit day-of-week features**
  - A **7-day seasonal term** for time-series models that support seasonality.

🚀 **In summary:**
Introducing these lag features can significantly **improve predictive accuracy**, ensuring the model captures both **short-term dependencies** and **long-term seasonal trends.**

Decomposemonthly seasonality (period=30) & ACF & PACF Analysis

```
# 1) Decompose monthly seasonality (period=30)
decompose_absence(dfs=df_grouped,  # or whatever your DataFrame is named
                  value_col='Total_Lost',
                  samples='all',
                  period=30)  # approximate 1-month cycle

# 2) Plot ACF and PACF side by side for up to 90 lags (~3 months)
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 5))

plot_acf(df_grouped['Total_Lost'], lags=90, ax=ax1)
ax1.set_title('ACF (up to 90 days)')

plot_pacf(df_grouped['Total_Lost'], lags=90, ax=ax2)
ax2.set_title('PACF (up to 90 days)')

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



📊 1. Decomposition Analysis (Period = 30)

🔍 Observed (Total Losts)

- The **daily Total Losts data** continues to show **significant variability:**
  - **Spikes** near **100** and periods closer to **0–20.**
- Compared to the **weekly decomposition:**

- The **overall shape remains the same** (as it's the same dataset).
- Now focusing on extracting a **30-day repeating cycle.**

📈 Trend

- The **orange trend line** reveals a **long-term, slowly varying pattern:**
  - **Rises** from near **0 to around 40.**
  - Gradually **declines** toward the end of the series.
- This suggests influences from:
  - **External factors** (e.g., policy changes, business trends).
  - **Seasonal workforce dynamics** or **general workforce behavior** over **months.**

🔄 Seasonality (Period ≈ 30 Days)

- The **green line** attempts to capture a **monthly pattern:**
  - A **wave repeats** approximately every **30 data points.**
  - **Amplitude** ranges from about **+5 down to −1 or −2**, indicating:
    - Certain **days of the month** systematically show **higher/lower Total Losts** rates.

🔍 **Comparison with Weekly Analysis:**

- The **weekly amplitude** was **larger** (±15).
- The **monthly amplitude** is **smaller** but **still visible.**

📉 Residual

- After removing the **30-day seasonality** and **trend**, the **residual (in red)** shows:
  - **Notable spikes** ranging from **−40 to +80.**
- This indicates that:
  - A simple **30-day cycle doesn't fully explain** daily fluctuations.
  - There are likely **other influences** such as:
    - **Weekly effects** (day-of-week patterns are strong).
    - **Holidays** and **random events.**

📊 2. ACF & PACF Analysis (Up to 90 Days)

🔗 ACF (Autocorrelation Function)

- **Lag 1:** A **large spike**, showing a **strong correlation** with **yesterday's Total Losts.**

- **Weekly Patterns:** Ongoing spikes at multiples of 7 (**lags 7, 14, 21, etc.**), confirming the **weekly cycle**.
- **Monthly Signals:** Moderate spikes near **30, 60, and 90 days** hint at **monthly correlations**, though **less pronounced** compared to weekly lags.

🔗 PACF (Partial Autocorrelation Function)

- **Lag 1:** The **dominant direct effect**, meaning most of the correlation is with the **previous day's Total Losts**.
- **Lag 7:** Shows significance, consistent with the **weekly pattern**.
- **Lag 30:** The **partial autocorrelation** is **smaller**, suggesting:
    - Once accounting for **shorter lags** (especially lag 1 and lag 7), the **monthly effect** adds **less direct explanatory power**.

💡 **Key Insight:**

- **ACF** shows evidence of a **monthly cycle**.
- **PACF** suggests this monthly effect might be **indirect**, influenced by **weekly patterns** or other variables.

✅ 3. Key Takeaways for Monthly Seasonality

📊 Insights:

- There **is** a **monthly signal**, but it's **weaker** compared to the **weekly effect**.
- **Residual noise** remains **substantial** after accounting for the 30-day cycle, indicating **stronger drivers** (like weekly patterns).

🔍 ACF vs. PACF:

- **Minor correlation spikes** near **30 days** in the ACF.
- **PACF** for those lags is **not as large**, implying the monthly pattern may be **partly indirect:**
    - **Monthly patterns** might result from **accumulated weekly effects** or **external variables.**

❓ Should We Use a Monthly Lag?

- **Yes**, we can consider including `Total Losts_{t-30}` as a feature.
- However, the data strongly suggests that:
    - **Weekly lags** (`t-7`) and **lag 1** are **more critical.**
- Given:
    - **12+ months of data**
    - **Business relevance** (e.g., payroll, scheduling, monthly reporting deadlines)

Adding a **monthly seasonal component** or **monthly lags** could help, but it's essential to **experiment** and assess if it **meaningfully improves model accuracy** compared to using only **weekly or daily lags.**

📊 4. Overall Conclusion

📈 Comparing Monthly vs. Weekly Decomposition:

- **Weekly patterns** and **short-term lags** (**1 day**, **7 days**) are **more dominant** in both:
  - **Seasonal decomposition**
  - **ACF/PACF analysis**
- **Monthly seasonality** exists but is **less pronounced.**
  - We may capture this with a **30-day lag.**

🚀 Modeling Plan:

- Start with **lagged features:**
  - `Total Losts_{t-1}`
  - `Total Losts_{t-7}`
  - Possibly `Absence_{t-14}`
- Test whether adding:
  - `Total Losts_{t-30}`
  - **Monthly dummies**
    Yields any **performance improvement.**

> 💡 **Final Thought:**
> While **weekly patterns** dominate, exploring **monthly lags** could uncover subtle trends, especially in business contexts where **monthly cycles matter.** Continuous **testing and validation** will determine their true **predictive value.** 🚀

```
#### Filter by Date & Select Columns

# df_grouped = df_grouped[df_grouped['Date']<='2025-01-01']

test_columns = ['Date',
 'Year',
 'Season',
 'Month',
 'WeekofYear',
 'DayofMonth',
 'DayofWeek',
```

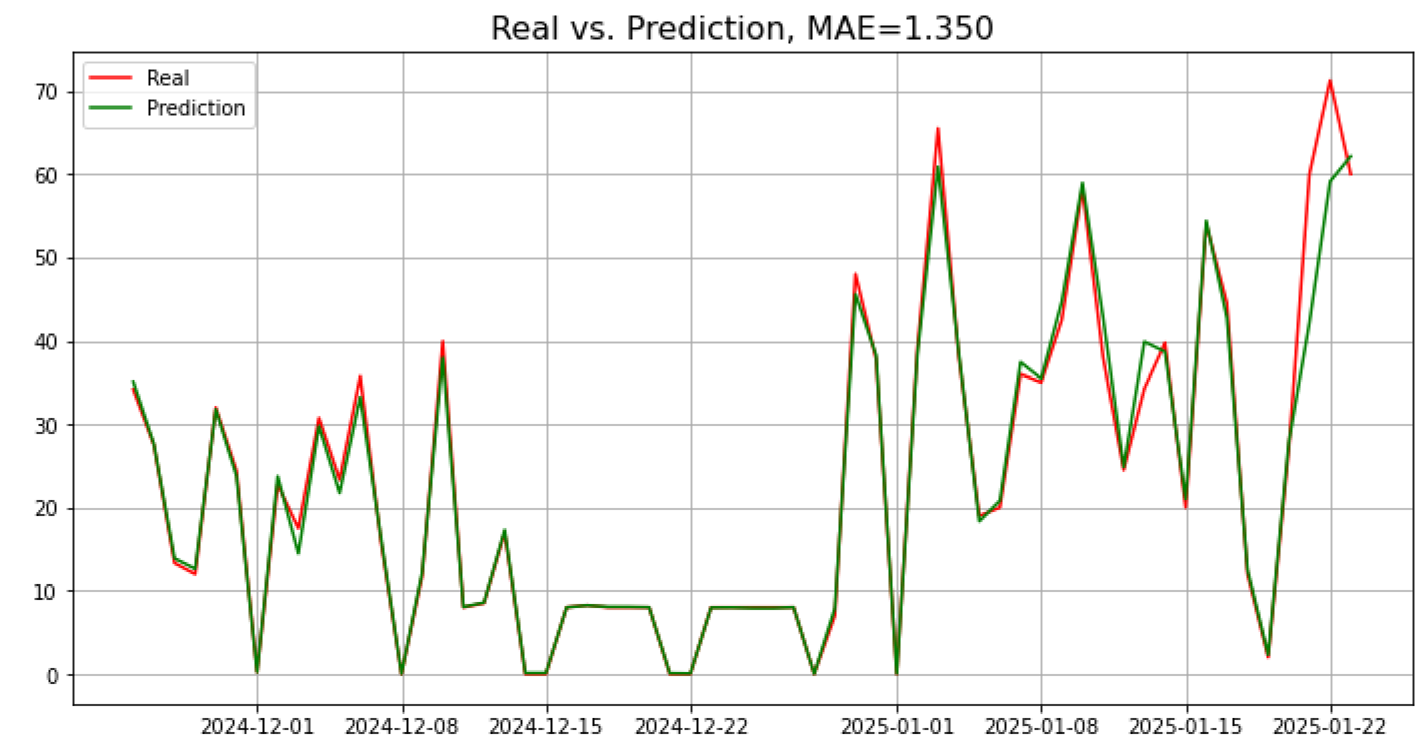
```python
 'Is_Holiday',
 'Is_Strike',
 'HC',
 'Scheduled',
 'Total_Lost',
 'Absence',
 'Early',
 'Late']
df_grouped_test = df_grouped[test_columns].copy()
df_grouped_test['Is_Holiday'] = df_grouped_test['Is_Holiday'].astype(int)

# 1) Convert to DateTime if it isn't already
df_grouped_test['Date'] = pd.to_datetime(df_grouped_test['Date'])

# 2) Set the index to the Date
df_grouped_test = df_grouped_test.set_index('Date')

# We'll overwrite them to be 100% sure they match the index
df_grouped_test['Year']       = df_grouped_test.index.year
df_grouped_test['Month']      = df_grouped_test.index.month
df_grouped_test['DayofMonth'] = df_grouped_test.index.day
df_grouped_test['DayofWeek']  = df_grouped_test.index.dayofweek  # Monday=0, Sunday=6
df_grouped_test['WeekofYear'] = df_grouped_test.index.isocalendar().week  # returns 1..53
```

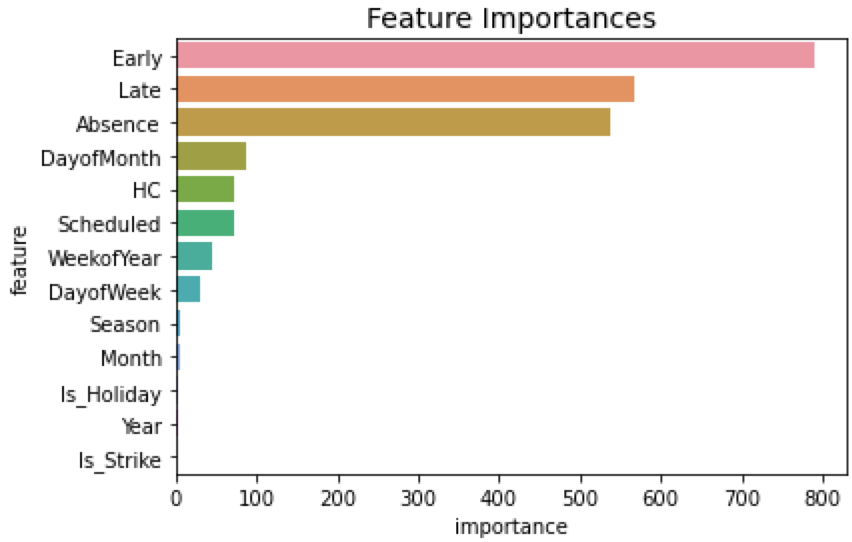
Scenario A: Modeling Without Lags

```python
def train_time_series(df, target='Total_Lost', horizon=30):
    """
    Trains an LGBMRegressor on time series data, splitting the last `horizon` rows as the test set.
    """
    # 1) Separate features and target
    X = df.drop(columns=[target])
    y = df[target]

    # 2) Split train/test by last 'horizon' rows
    X_train, X_test = X.iloc[:-horizon, :], X.iloc[-horizon:, :]
    y_train, y_test = y.iloc[:-horizon], y.iloc[-horizon:]

    # 3) Train LGBM with tuned hyperparameters and early stopping
    model = LGBMRegressor(
        random_state=42,
        learning_rate=0.05,
        n_estimators=1000,
        max_depth=7,
        num_leaves=31,
        verbose=-1  # Suppress LightGBM output
```

```
    )

    # Use early stopping
    model.fit(
        X_train, y_train,
        eval_set=[(X_test, y_test)],
        callbacks=[early_stopping(stopping_rounds=50, verbose=-1)]
    )

    # 4) Predict on test
    preds = model.predict(X_test)

    # 5) Calculate MAE
    mae = mean_absolute_error(y_test, preds)
    mse = mean_squared_error(y_test, preds)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_test, preds)

    # 6) Print evaluation metrics and averages
    print(f"R-squared (R2) score: {r2:.3f}")
    print(f"Mean Squared Error (MSE): {mse:.3f}")
    print(f"Mean Absolute Error (MAE): {mae:.3f}")
    print(f"Root Mean Squared Error (RMSE): {rmse:.3f}")
    print(f"Average of Actual Total_Lost: {y_test.mean():.3f}")
    print(f"Average of Predictions Total_Lost: {preds.mean():.3f}")

    # 7) Plot Real vs Prediction
    plt.figure(figsize=(12, 6))
    plt.plot(y_test.index, y_test.values, label='Real', color='red')
    plt.plot(y_test.index, preds, label='Prediction', color='green')
    plt.title(f"Real vs. Prediction, MAE={mae:.3f}", fontsize=16)
    plt.legend()
    plt.grid()
    plt.show()

    # 8) Feature importances
    feat_imp = pd.DataFrame({
        'feature': X_train.columns,
        'importance': model.feature_importances_
    }).sort_values(by='importance', ascending=False)

    plt.title("Feature Importances", fontsize=14)
    sns.barplot(x='importance', y='feature', data=feat_imp, orient='h')
    plt.show()

    return model, mae

# Run the model
model_no_lags, mae_no_lags = train_time_series(df=df_grouped_test, target='Total_Lost',
horizon=60)
print(f"MAE without lags = {mae_no_lags:.3f}")
```

```
Training until validation scores don't improve for 50 rounds

Early stopping, best iteration is:

[121]	valid_0's l2: 9.93353

R-squared (R2) score: 0.972

Mean Squared Error (MSE): 9.934

Mean Absolute Error (MAE): 1.350

Root Mean Squared Error (RMSE): 3.152

Average of Actual Total_Lost: 23.145

Average of Predictions Total_Lost: 22.748
```






```
MAE without lags = 1.350
```

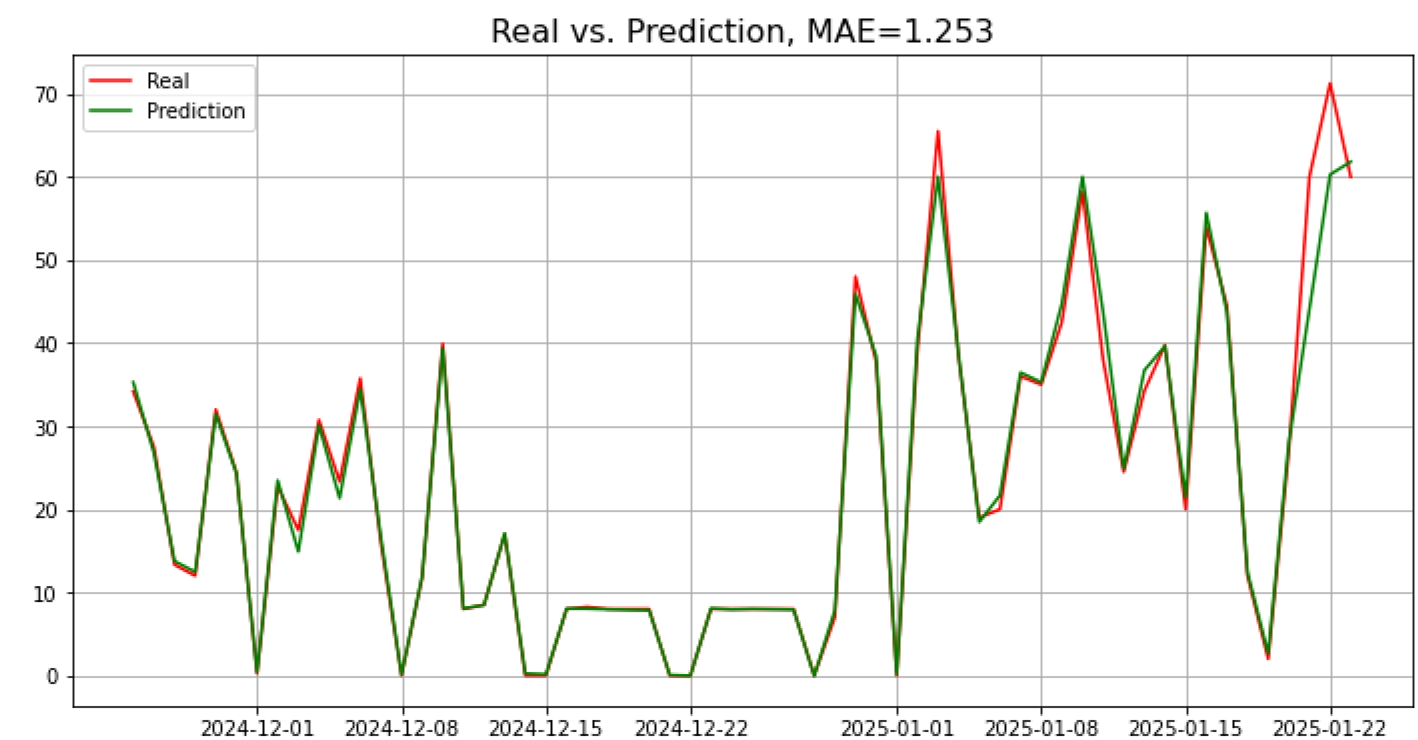
Scenario B: Create Lags & Model With Lags

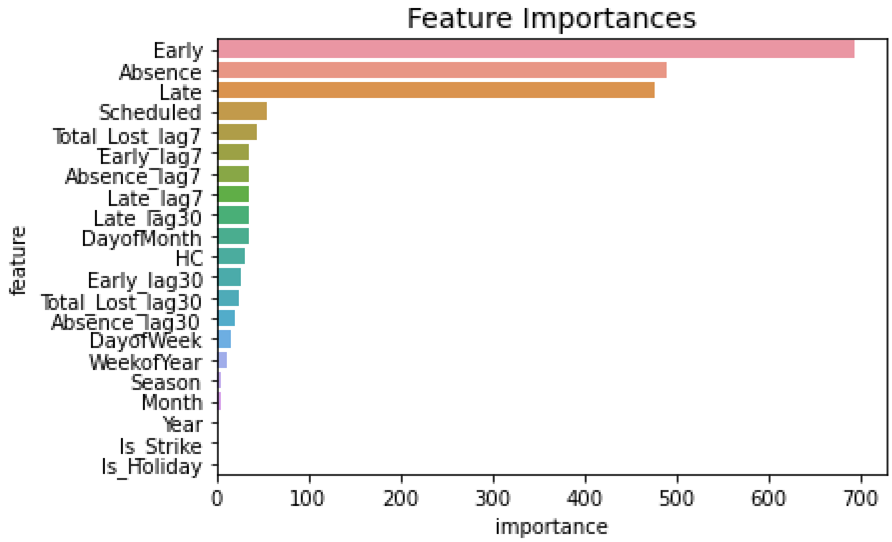
Now we'll add weekly (lag=7) and monthly (lag=30) lags for Absence, Early, and Late, just like you mentioned. Then we'll repeat the train/test approach.

```
df_with_lags = df_grouped_test.copy()

# Create weekly lag (7 days) and monthly lag (30 days) for Absence, Early, Late


df_with_lags['Total_Lost_lag7']  = df_with_lags['Total_Lost'].shift(7)
df_with_lags['Total_Lost_lag30'] = df_with_lags['Total_Lost'].shift(30)

df_with_lags['Absence_lag7']  = df_with_lags['Absence'].shift(7)
df_with_lags['Absence_lag30'] = df_with_lags['Absence'].shift(30)

df_with_lags['Early_lag7']    = df_with_lags['Early'].shift(7)
df_with_lags['Early_lag30']   = df_with_lags['Early'].shift(30)

df_with_lags['Late_lag7']     = df_with_lags['Late'].shift(7)
df_with_lags['Late_lag30']    = df_with_lags['Late'].shift(30)

# Drop rows that became NaN due to shifting (first 30 days)
df_with_lags.dropna(axis=0, how='any', inplace=True)

print("Shape after adding lags and dropping NaNs:", df_with_lags.shape)

# Re-run train_time_series
model_with_lags, mae_with_lags = train_time_series(df=df_with_lags,
                                                   target='Total_Lost',
                                                   horizon=60)
```

```python
print(f"MAE with lags = {mae_with_lags:.3f}")
```

```
Shape after adding lags and dropping NaNs: (724, 22)

Training until validation scores don't improve for 50 rounds

Early stopping, best iteration is:

[120]   valid_0's l2: 8.15827

R-squared (R2) score: 0.977

Mean Squared Error (MSE): 8.158

Mean Absolute Error (MAE): 1.253

Root Mean Squared Error (RMSE): 2.856

Average of Actual Total_Lost: 23.145

Average of Predictions Total_Lost: 22.887
```






```
MAE with lags = 1.253
```

📊 Model Performance and Readiness for Testing

✅ Key Observations

Based on the observed **Mean Absolute Error (MAE)** and **feature importance analysis**, it is evident that:

- **Introducing lagged columns** has significantly **improved the model's performance**, particularly in terms of:
  - **Feature relevance**
  - **Predictive power**

🔄 Why Lagged Features Matter:

- They provide **valuable context** by capturing **temporal patterns** and **trends.**
- This is essential for accurate **time series forecasting** as they:
  - Reflect **short-term dependencies** (e.g., yesterday's absence).
  - Capture **seasonal effects** (e.g., weekly or monthly cycles).

🚀 Readiness for Testing Phase

Given the **enhanced model performance** with the inclusion of lag features, we are now ready to proceed to the:

- **Testing Phase** for **Absence predictions.**
- Ensuring that the model delivers **robust** and **reliable results.**

⚠️ Important Note

- The model currently demonstrates a **very high R2 value** with **acceptable performance** because we **retained the following measures** in our dataset:
  - **Absence**
  - **Early**
  - **Late**
- These variables were included to **explore seasonality** during the **model development phase.**

❗ Impact of Removing Absence, Early, and Late:

- When these measures are **removed:**
  - The model's performance **declines significantly,** especially in:
    - **R2 score**
    - Other **evaluation metrics** (e.g., MAE, RMSE)
- This highlights the **critical role** these variables play in **capturing seasonality** and explaining **variations in absenteeism.**

⚙️ Approach for Model Experimentation

- For the **model experimentation process,** we will:
  - Use a **well-adjusted dataset** tailored for both **training** and **testing.**
  - Ensure that the dataset:
    - Maintains **relevant lagged features.**
    - Is structured to **balance performance** while minimizing dependence on unavailable future data.

💡 **Final Thought:**
The **lagged features** have proven to be **crucial** for capturing temporal dependencies. Moving forward, we will focus on **refining** the dataset and **evaluating** the model's robustness in different scenarios to ensure **consistent** and **accurate absenteeism predictions.** 🚀

```python
#############
df['Strike'] = df['c_name_y'].str.contains('Strike', na=False).astype(int)
df['Waha']=df['Location Type'].str.contains('WAHA', na=False).astype(int)
df['Is_Holiday'] = df['Is_Holiday'].astype(int)
df['Is_Strike'] = df['Is_Strike'].astype(int)
#######
def prepare_dataframe(df,  mu_name='All'):
    groupbycols = [
        'Date', 'Year', 'Season', 'Month', 'WeekofYear',
        'DayofMonth', 'DayofWeek', 'Is_Strike'
    ]
```

```python
    # Step 1: Filter the dataframe
    dfprep = df[df['Is_Actual'] == 'Actual']

    if  mu_name != 'All':
        dfprep = dfprep[(dfprep['MU_Name'] == mu_name)]

    # Step 2: Groupby and aggregate
    dfprep = dfprep.groupby(groupbycols, as_index=False).agg(
        Is_Holiday=('Is_Holiday', np.mean),  # Avg holiday % across countries
        HC=('CCMS_ID', 'size'),              # Headcount
        StrikeP=('Strike', np.mean),          # Strike participation %
        Waha=('Waha', np.mean),               # Waha employee %
        Scheduled=('Scheduled', np.sum),      # Scheduled hours sum
        Worked=('Worked', np.sum),            # Worked hours sum
        Overtime=('Overtime', np.sum),        # Overtime hours sum
        Training=('Training', np.sum),        # Training hours sum
        Vacation=('Vacation', np.sum),        # Vacation hours sum
        Sick=('Sick', np.sum),                # Sick hours sum
        Total_Lost=('Total_Lost', np.sum),    # Total lost = Absence + Early + Late
        Absence=('Absence', np.sum),          # Absence hours sum
        Early=('Early', np.sum),              # Early leaving hours sum
        Late=('Late', np.sum)                 # Late arrivals sum
    ).reset_index(drop=True)

    # Step 3: Define columns for rolling sums
    rolling_columns = ['Total_Lost', 'Absence', 'Early', 'Late','Scheduled', 'Worked',
'Training', 'Vacation', 'Sick']

    # Step 4: Define rolling windows
    rolling_windows = {
        '1W': 7,    # Last 1 week
        '1M': 30,   # Last 1 Month
    }

    # Step 5: Sort by date before rolling calculations
    dfprep = dfprep.sort_values(by=['Date'])

    # Step 6: Compute rolling sums with 1-week delay
    for window_label, window_size in rolling_windows.items():
        for col in rolling_columns:
            dfprep[f'{col}_RollingSum_{window_label}'] = (
                dfprep[col].shift(7)  # Shift by 7 days to delay calculation
                .rolling(window=window_size, min_periods=1)
                .sum()
                .reset_index(drop=True)
            )
    # Step 6: Compute rolling AVG with 1-week delay
    for window_label, window_size in rolling_windows.items():
        for col in rolling_columns:
            dfprep[f'{col}_RollingAVG_{window_label}'] = (
                dfprep[col].shift(7)  # Shift by 7 days to delay calculation
                .rolling(window=window_size, min_periods=1)
```

```python
                .mean()
                .reset_index(drop=True)
            )
    # Step 7: Convert 'Date' to datetime and set index
    dfprep['Date'] = pd.to_datetime(dfprep['Date'])
    dfprep = dfprep.set_index('Date')

    # Step 8: Overwrite columns based on index
    dfprep['Year'] = dfprep.index.year
    dfprep['Month'] = dfprep.index.month
    dfprep['DayofMonth'] = dfprep.index.day
    dfprep['DayofWeek'] = dfprep.index.dayofweek  # Monday=0, Sunday=6
    dfprep['WeekofYear'] = dfprep.index.isocalendar().week

    # Step 9: Create lagged features
    lag_days = [7,30]
    for lag in lag_days:
        for col in ['Scheduled', 'Worked','Total_Lost', 'Absence', 'Early', 'Late',
'Training', 'Vacation', 'Sick']:
            dfprep[f'{col}_lag{lag}'] = dfprep[col].shift(lag)

    # Step 10: Drop rows with NaN values introduced by shifting
    dfprep.dropna(axis=0, how='any', inplace=True)

    # Step 11: Drop unnecessary columns
    drop_cols = ['Absence', 'Early', 'Late', 'Worked', 'Training', 'Vacation',
'Sick','Overtime',]
    dfprep.drop(columns=drop_cols, inplace=True)

    dfprep['Month_sin'] = np.sin(2 * np.pi * dfprep['Month'] / 12)
    dfprep['Month_cos'] = np.cos(2 * np.pi * dfprep['Month'] / 12)
    dfprep['DayofWeek_sin'] = np.sin(2 * np.pi * dfprep['DayofWeek'] / 7)
    dfprep['DayofWeek_cos'] = np.cos(2 * np.pi * dfprep['DayofWeek'] / 7)
    dfprep['DayofMonth_sin'] = np.sin(2 * np.pi * dfprep['DayofMonth'] / 31)
    dfprep['DayofMonth_cos'] = np.cos(2 * np.pi * dfprep['DayofMonth'] / 31)


    return dfprep

# Example usage with default 'All' filters
processed_df = prepare_dataframe(df)
```

```python
# Re-run train_time_series
model_with_lags, mae_with_lags = train_time_series(df=processed_df,
                                                   target='Total_Lost',
                                                   horizon=14)

print(f"MAE with lags = {mae_with_lags:.3f}")
```

```
Training until validation scores don't improve for 50 rounds

Early stopping, best iteration is:

[56]	valid_0's l2: 242.982

R-squared (R2) score: 0.368

Mean Squared Error (MSE): 242.982

Mean Absolute Error (MAE): 13.931

Root Mean Squared Error (RMSE): 15.588

Average of Actual Total_Lost: 38.964

Average of Predictions Total_Lost: 36.791
```