# Longitudinal Performance Analysis: A Comparative Study of Of Two Collegiate Basketball Athletes

An evidence-based examination of performance trends and the establishment of actionable monitoring thresholds.

# Project Objective: From Raw Data to Actionable Insight

The primary goal is to analyze and interpret the performance of collegiate athletes over a 12-month period. Based on the project brief, this involves:

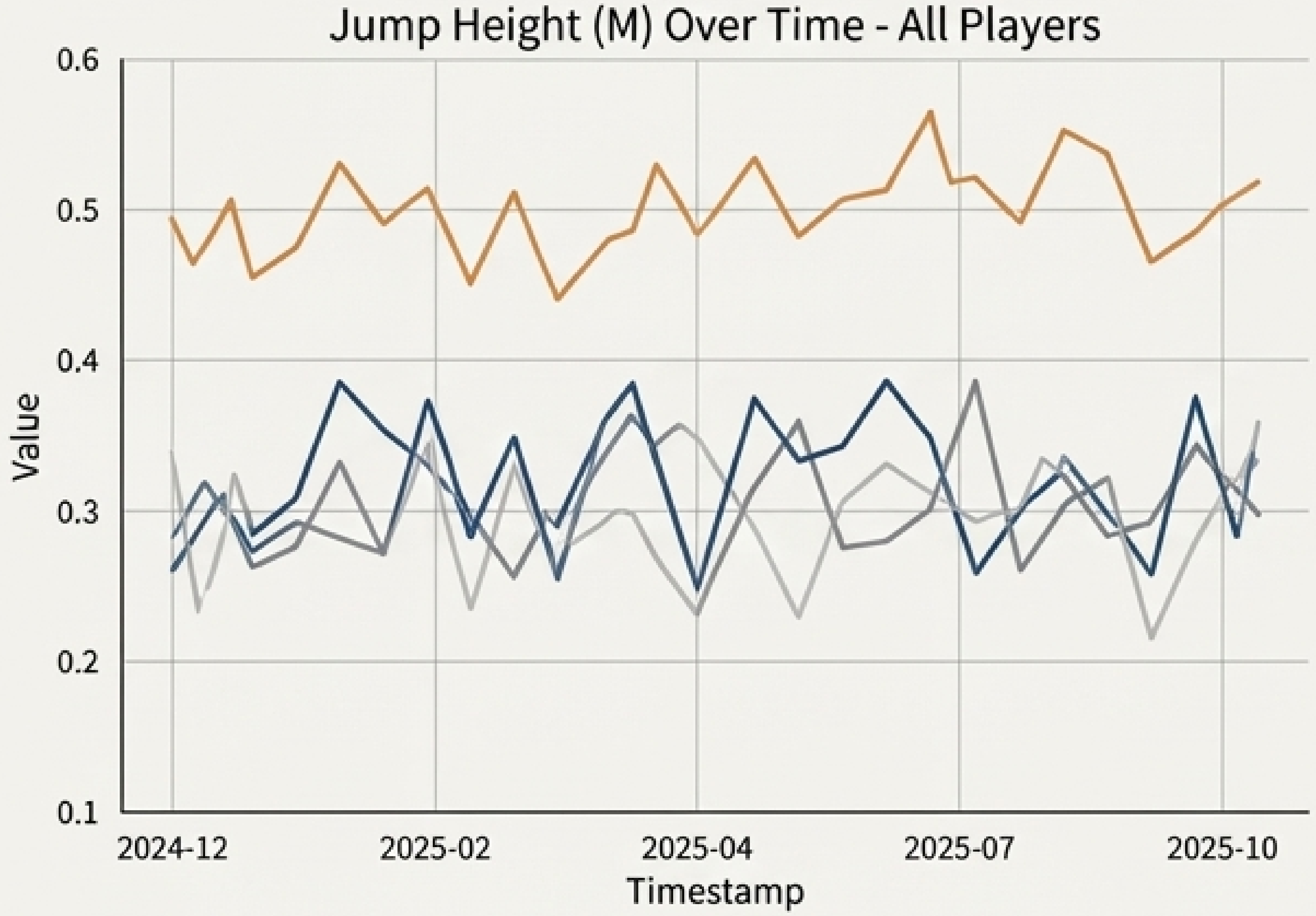
1. **Selecting two athletes** for an in-depth timeline analysis.
2. **Visualizing performance metrics** over time to identify trends and patterns.
3. **Calculating trend lines** (improvement, decline, or stability) for key metrics.
4. **Identifying peak and nadir** performance dates for each metric.
5. **Relating findings** to sport-specific demands and proposing data-driven performance thresholds."

Source Directive: 3.1 Individual Athlete Timeline

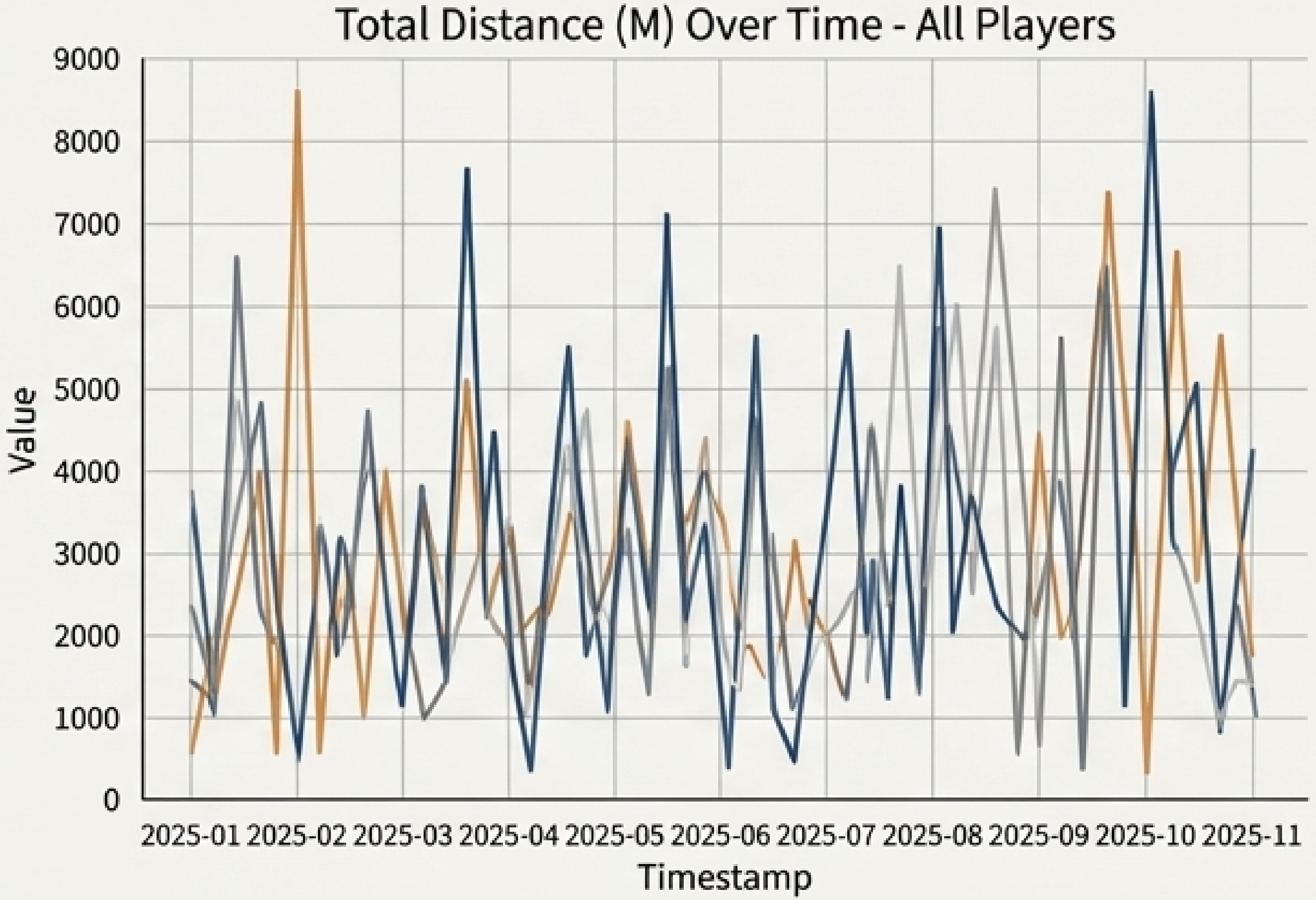
- Select 2 athletes from a team of your choice
- Create line plots showing their metric values over time
- Identify their best and worst performance dates
- Calculate if they show improvement or decline trend

# The Challenge: Discerning Signal from Noise in Multi-Athlete Data

A preliminary view of four players across key metrics reveals significant performance variability and overlapping data, making direct comparison difficult. To uncover meaningful trends, a focused individual analysis is necessary.




Jump height data shows clear stratification, with Player 995 consistently outperforming others.




Total distance covered exhibits high daily volatility for all athletes, with no immediately obvious trend.

# Case Study 1: Player 995, Men's Basketball

## A Profile of Improving Power and Explosiveness

**Player ID:**
995

**Sport:**
Men's Basketball

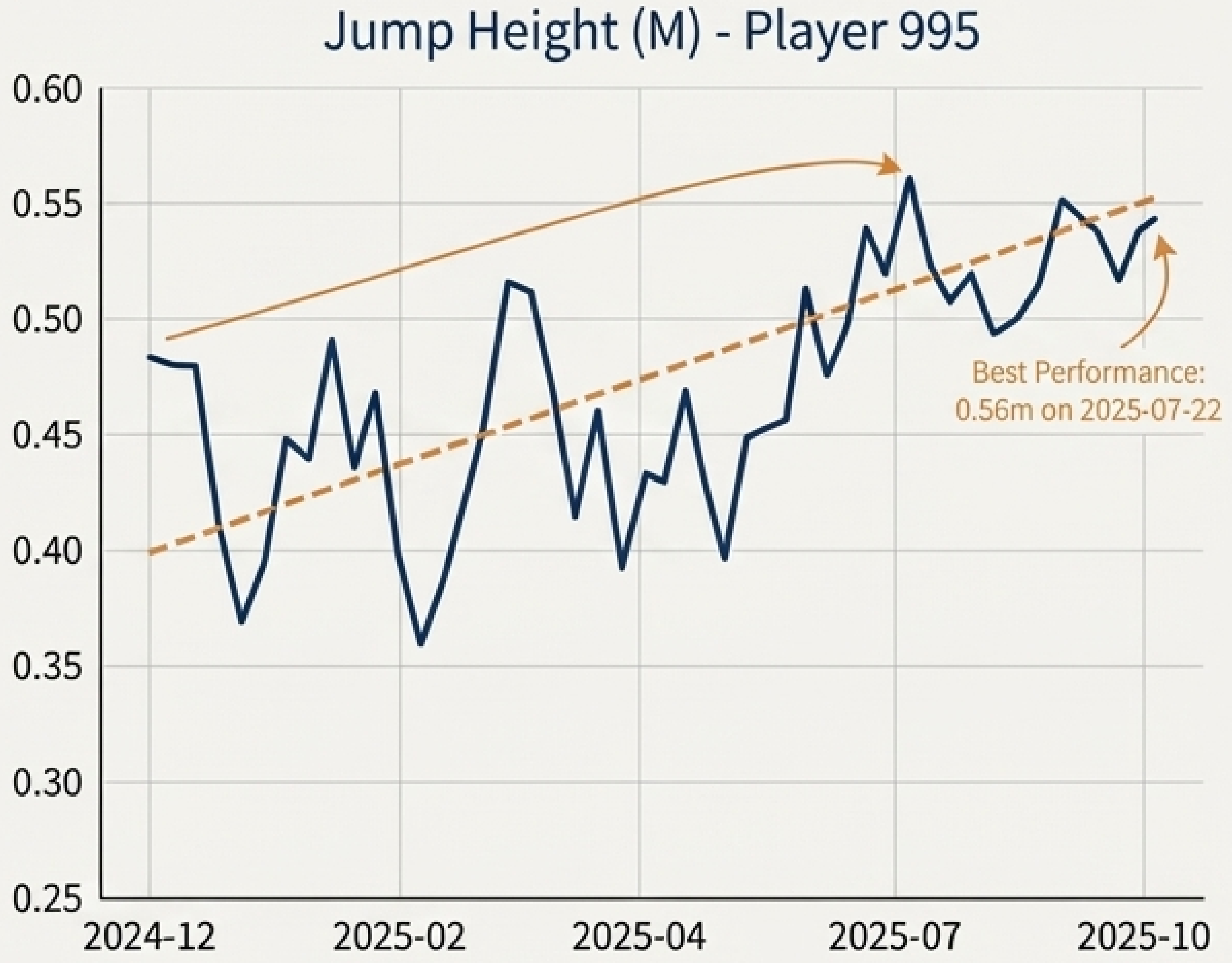
**Overall 12-Month Profile:**
This athlete demonstrates a clear pattern of improvement across all measured power, velocity, and reactive strength metrics. This is contrasted by a decline in total distance covered.

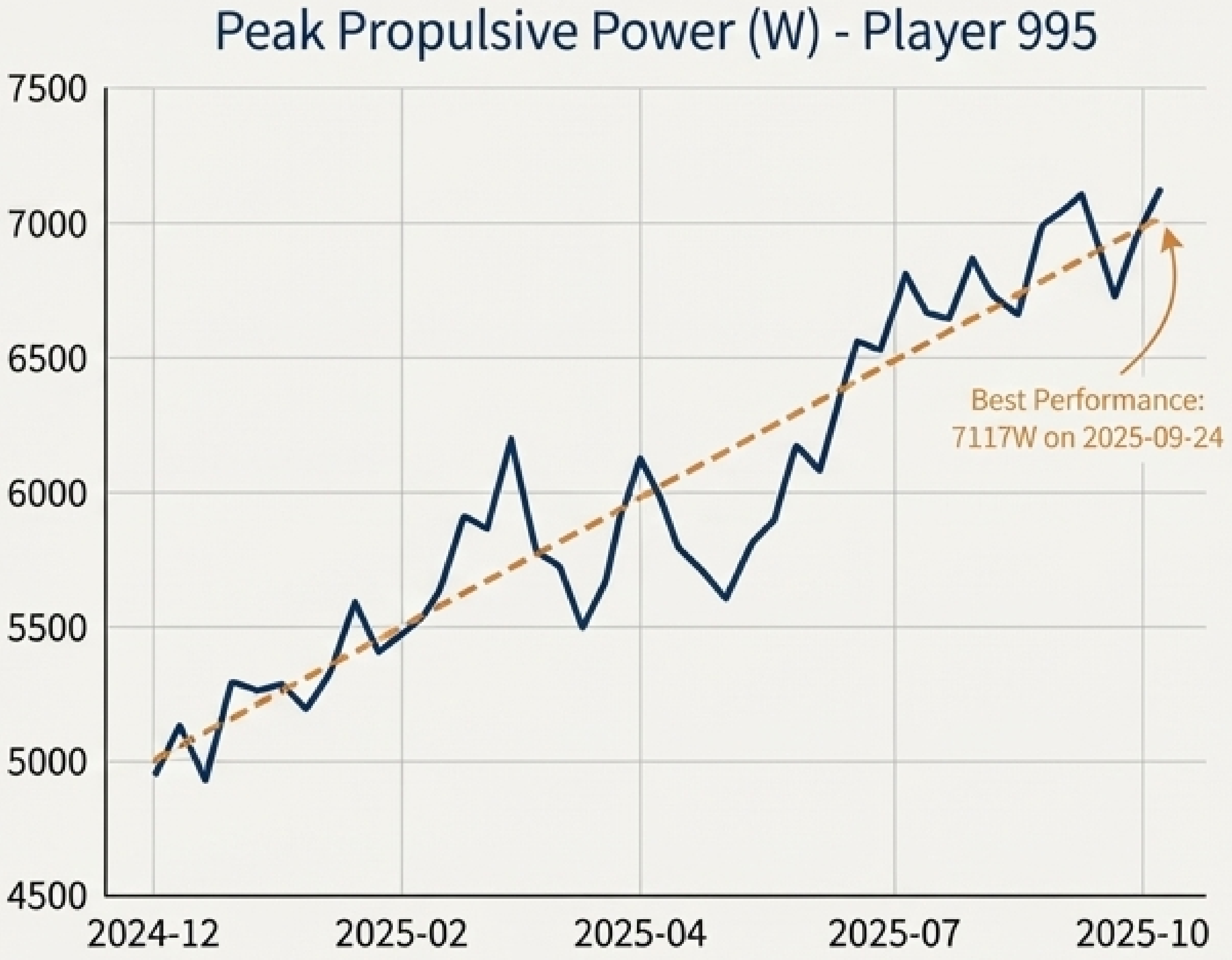
### 12-Month Performance Trend Summary

| Metric | Trend Direction | Significance (p-value) |
|---|---|---|
| Peak Propulsive Power | Improving (↑) | $p < 0.01$ |
| Jump Height | Improving (↑) | $p < 0.01$ |
| Peak Velocity | Improving (↑) | $p < 0.05$ |
| Mrsi | Improving (↑) | $p < 0.01$ |
| Speed_Max | Improving (↑) | $p < 0.01$ |
| Distance_Total | Declining (↓) | $p < 0.01$ |

# A Consistent Upward Trajectory in Key Explosive Metrics

Player 995's data shows significant, statistically robust improvement in metrics critical for basketball performance, such as vertical jump and power output. The period from June to September 2025 appears to be particularly strong.

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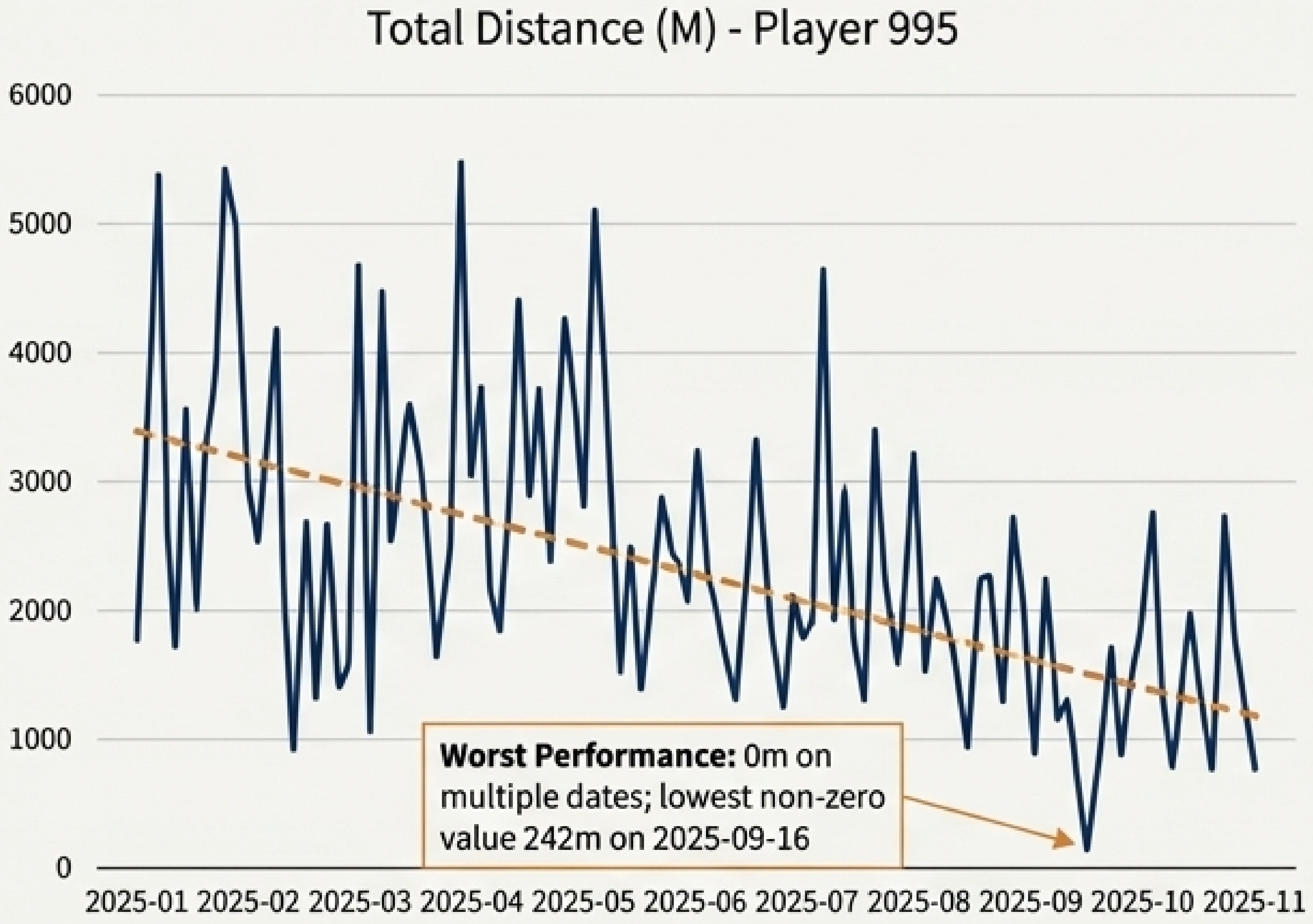
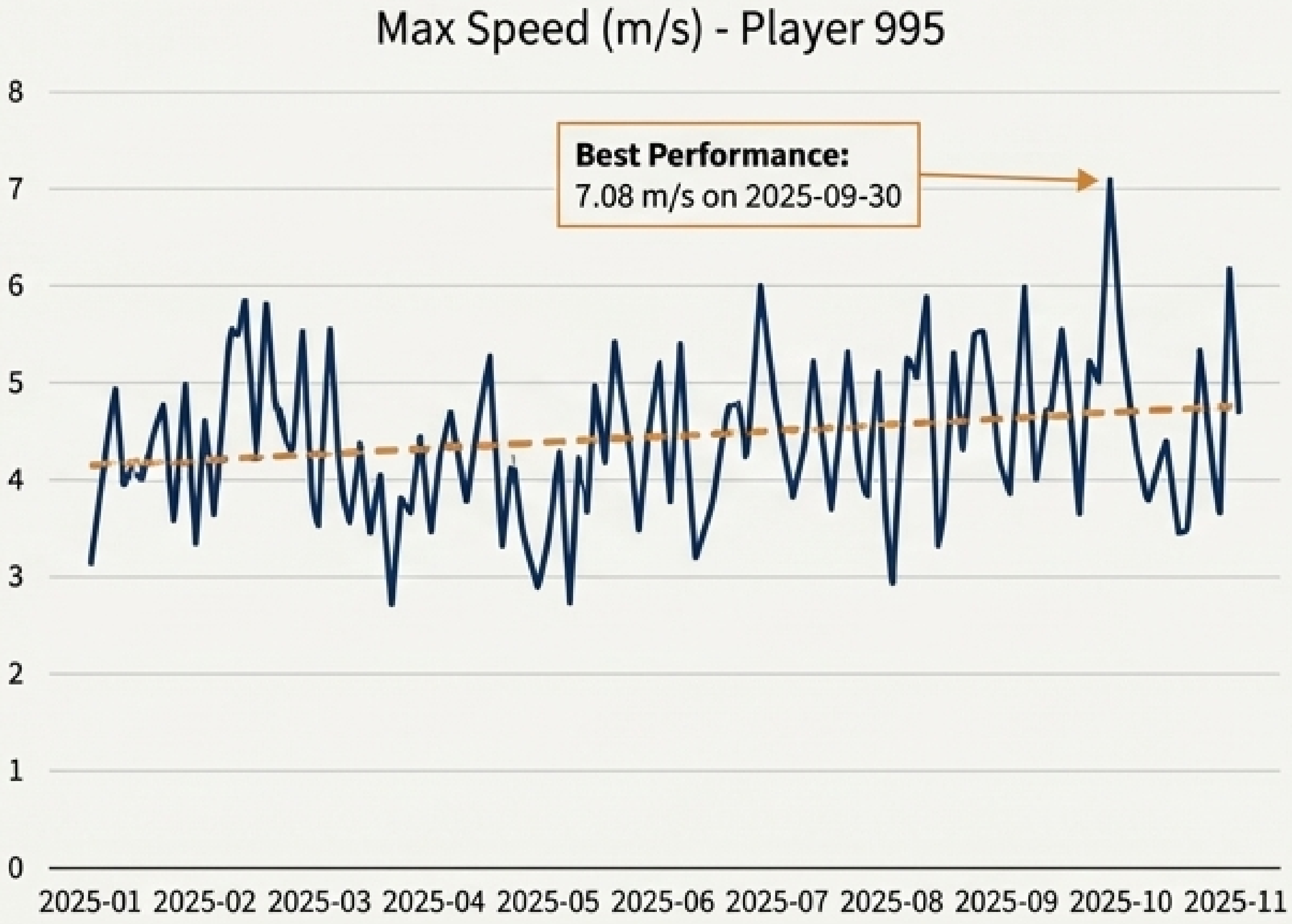
# A Potential Trade-Off: Declining Endurance Alongside Speed Gains

While max speed shows a slight upward trend, the total distance covered in sessions has trended downwards. This could indicate a shift in training focus towards shorter, more intense efforts, or a change in positional role demanding less overall volume.



# Case Study 2: Player 555, Women's Basketball

## A Profile of Performance Volatility and Emerging Gains

**Player ID:** 555
**Sport:** Women's Basketball

**Overall 12-Month Profile:** This athlete's performance is characterized by higher variability and sparser data points compared to Player 995. Despite this, positive trends are emerging in speed and reactive strength, while power output remains stable.

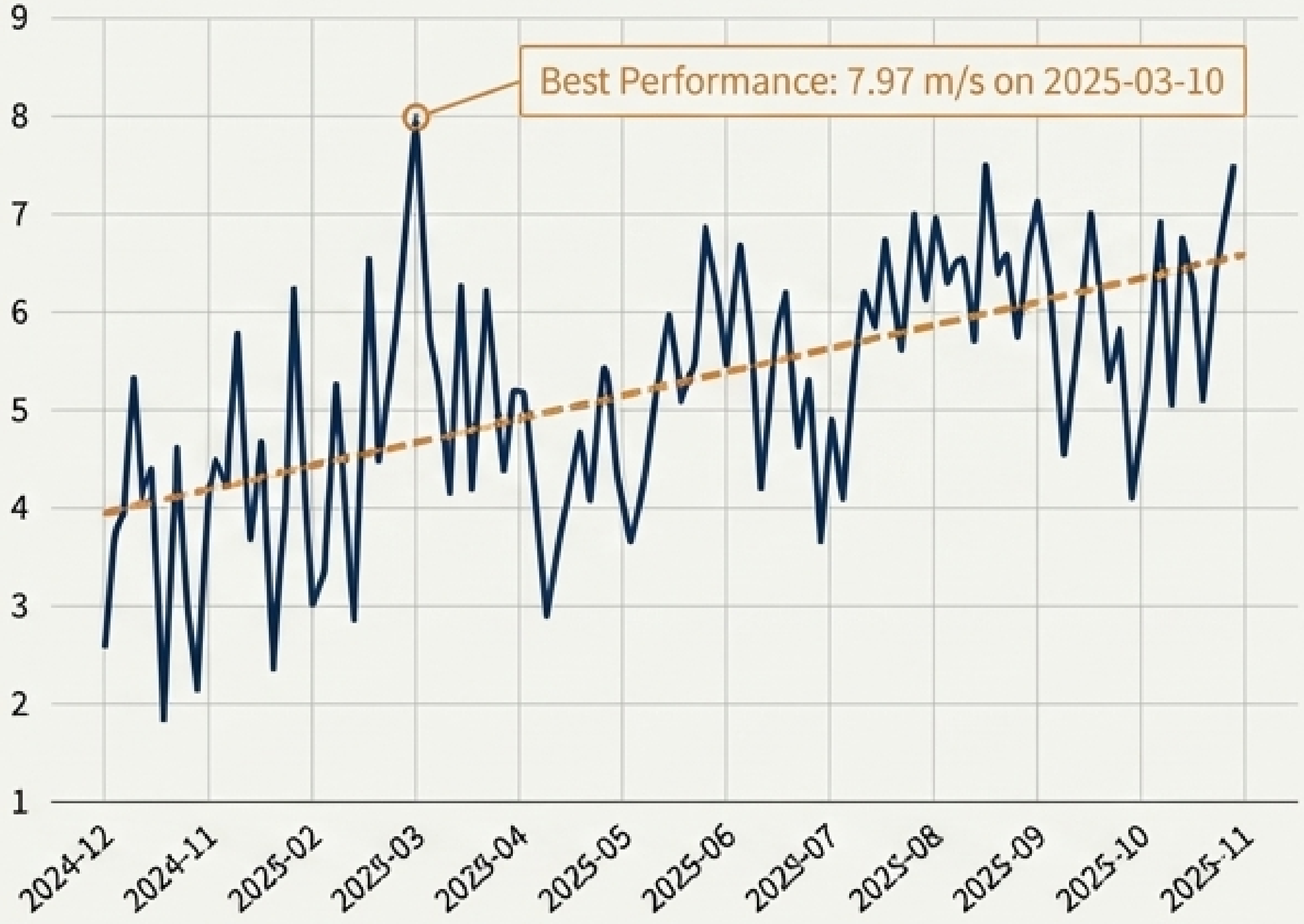
### 12-Month Performance Trend Summary

| Metric | Trend Direction | Significance (p-value) |
|---|---|---|
| Speed_Max | Improving (↑) | **$p < 0.01$** |
| Mrsi | Improving (↑) | **$p < 0.01$** |
| Peak Velocity | Improving (↑) | Not Statistically Significant |
| Jump Height | Improving (↑) | Not Statistically Significant |
| Peak Propulsive Power | Improving (↑) | Not Statistically Significant |
| Distance_Total | Declining (↓) | Not Statistically Significant |

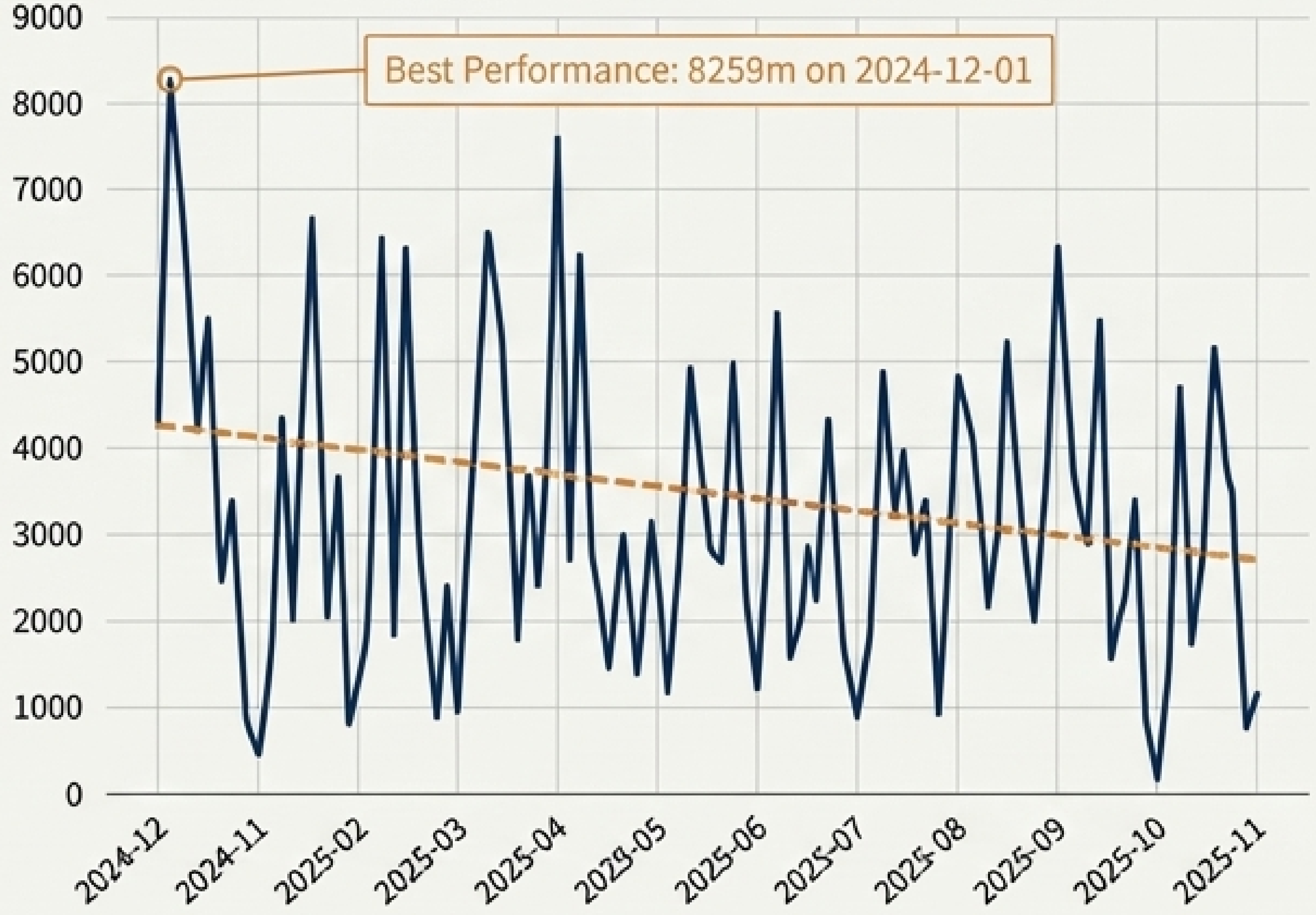
# Improving Top-End Speed Despite Declining Work Volume

Player 555’s most significant improvement is in maximum speed. Similar to Player 995, this is coupled with a decline in total distance, suggesting a potential focus on quality of movement over quantity.

Max Speed (m/s) - Player 555




Total Distance (M) - Player 555

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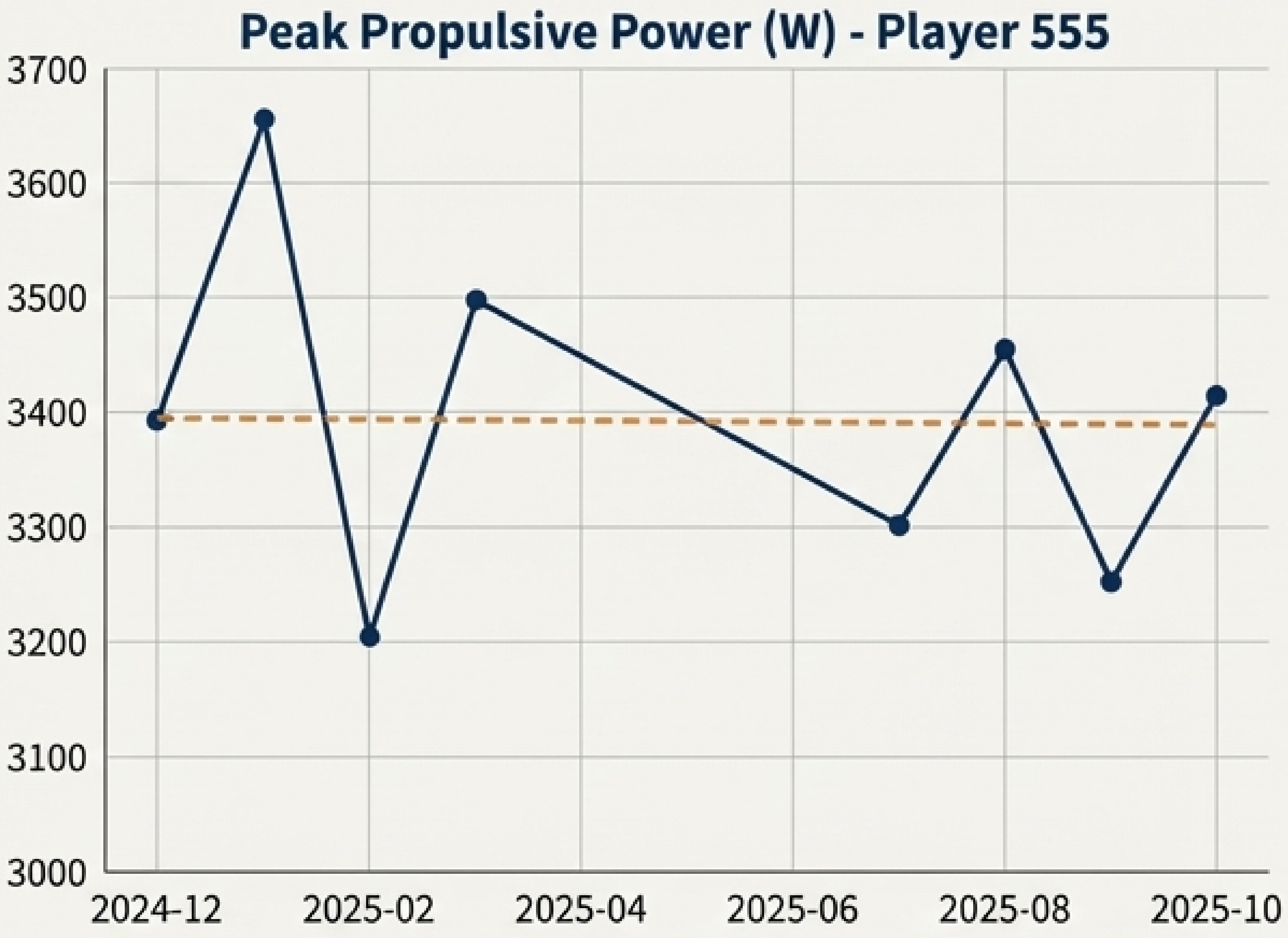
# Stable Power Output Characterized by High Performance Variability

Unlike the explosive metrics for Player 995, Player 555's jump height and power data show a flat overall trend with significant fluctuations between testing sessions. The gaps in data (e.g., between April and July 2025) make it more challenging to assess long-term progress.


The trend line is nearly flat, indicating stable but not improving average power output.

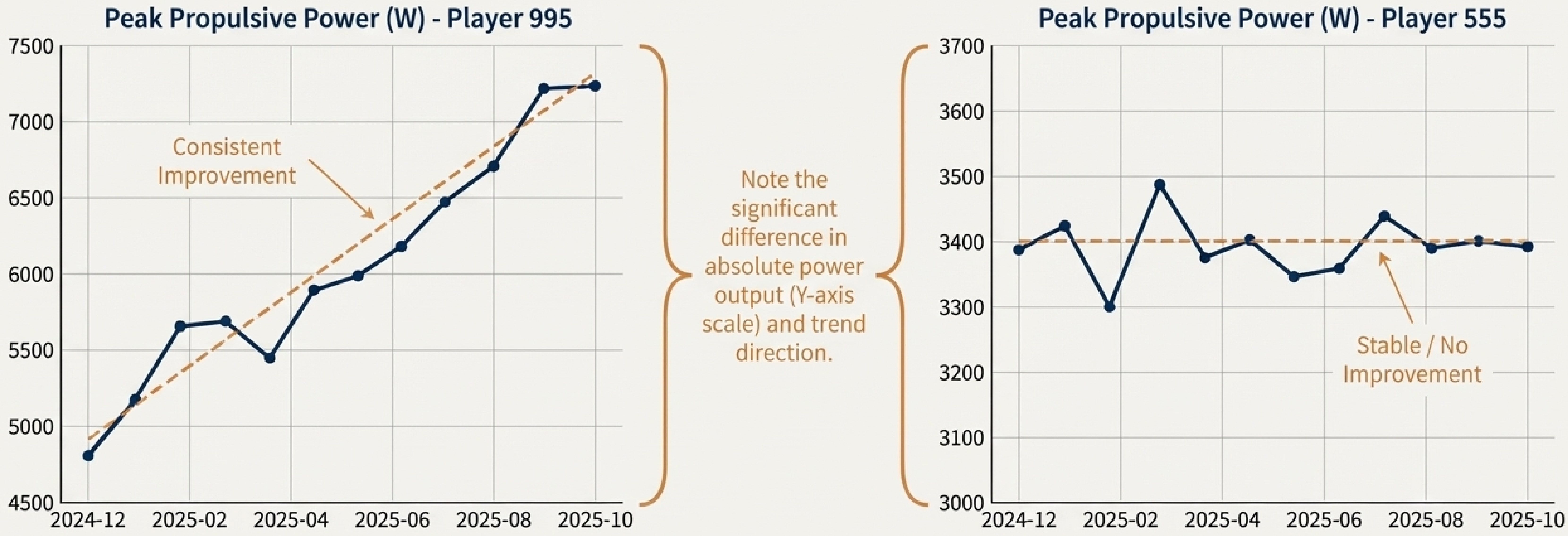
# Comparative Analysis: Two Distinct Performance Trajectories

Placing the two athletes' trend analyses side-by-side reveals fundamental differences in their physical development over the past year. Player **995** shows consistent, statistically significant improvement in power, while Player **555**'s profile is defined by speed gains amidst higher overall volatility.

| Performance Metric | Player 995 (Men's Basketball) | Player 555 (Women's Basketball) |
|---|---|---|
| **Primary Strength** | Power & Explosiveness (All metrics improving, $p<0.05$) | Max Speed (Improving, $p<0.01$) |
| **Endurance Profile** | Total Distance Declining ($p<0.01$) | Total Distance Declining (Not significant) |
| **Performance Consistency** | High consistency in upward trends | High variability session-to-session |
| **Data Density** | Frequent testing across metrics | Sparser data, especially for power metrics |

# Visualizing the Performance Gap: Power and Consistency

The difference in performance profiles is most apparent when visualizing their power output. Player 995 not only operates at a significantly higher absolute level—as expected in men's vs. women's basketball—but also demonstrates a much more consistent and positive trajectory.



# Interpretation: Connecting Trends to Sport-Specific Demands

The observed trends align with potential training and positional demands in basketball.

**Player 995:** The clear increase in power metrics concurrent with a decrease in total distance strongly suggests a training program focused on developing an explosive, anaerobic athlete, possibly for a role requiring short, powerful bursts (e.g., a center or power forward).

**Player 555:** The mix of improved speed, high variability, and stable power could reflect a different role (e.g., a guard), a period of rehabilitation from injury causing inconsistent training, or simply a different developmental stage.

*This analysis addresses the guiding questions from the project brief: "Do differences make sense given sport demands?" and "What might explain the differences or similarities?"*

# From Analysis to Action: Defining Data-Driven Performance Thresholds

Based on the analysis and literature best practices, the following thresholds can be implemnented to proactively monitor athlete readiness and development:

### 1. Readiness Alert (Decline from Baseline)

A >15% decline in Jump Height or Peak Propulsive Power from the athlete's 90-day rolling average triggers an immediate review with coaching and medical staff.

*Flags a significant, non-trivial drop in explosive capacity that may indicate fatigue or injury risk.*

### 2. Data Quality Alert (Testing Frequency)

If an athlete has not been tested on a key metric (e.g., Jump Height) in over 30 days, their profile is flagged.

*Ensures data is current for effective monitoring, preventing data gaps like those seen with Player 555.*

### 3. Negative Trend Alert (Deviation from Norms)

Three consecutive data points below the 25th percentile of an athlete's 12-month historical data for a given metric.

*Differentiates a sustained negative trend from normal day-to-day performance fluctuations.*

# Appendix A: Methodology for Trend Analysis

A simple linear regression was performed on the time-series data for each metric to determine the overall trend (improving, declining, or stable) over the last 12 months. The slope of the regression line indicates the direction of the trend.

```python
# calculate_trend_per_metric
trend_results = []
for metric in metrics_player:
    metric_df = player_df[player_df['metric'] == metric]
    if len(metric_df) > 2:  # minimum_data_check
        # Convert timestamps to ordinal for regression
        x = metric_df['timestamp'].map(pd.Timestamp.toordinal)
        y = metric_df['value']

        # Perform linear regression
        slope, intercept, r_value, p_value, std_err = linregress(x, y)
        trend = 'improving' if slope > 0 else 'declining' if slope < 0 else 'stable'

        # Append results
        trend_results.append({
            'metric': metric,
            'trend': trend,
            'p_value': p_value
        })
```

Python script using `scipy.stats.linregress` to calculate slope and p-value for each metric.

# Appendix B: Methodology for Identifying Key Performance Dates

To identify the best and worst performance dates for annotation, the data was grouped by metric, and the timestamps corresponding to the maximum (.idxmax()) and minimum (.idxmin()) values were extracted.

```
# Group by metric to find best and worst performance dates
best_dates = (
    player_df.loc[player_df.groupby('metric')['value'].idxmax()]
    [['metric', 'value', 'timestamp']]
    .rename(columns={'value': 'best_value', 'timestamp': 'best_date'})
)

worst_dates = (
    player_df.loc[player_df.groupby('metric')['value'].idxmin()]
    [['metric', 'value', 'timestamp']]
    .rename(columns={'value': 'worst_value', 'timestamp': 'worst_date'})
)

# Merge best and worst into one summary
performance_summary = pd.merge(best_dates, worst_dates, on='metric')
```

Python script using `pandas` to group data by metric and locate the index of the maximum and minimum values.