

# Rainbow Six: Siege Player Forecasting Models

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## OVERVIEW

Rainbow Six: Siege is a multiplayer, first-person shooter released in December 2015, which has grown to over 100,000 average monthly players at its peak. As a former player, I set out to determine when new or returning players might best jump back in. I forecasted the game's average monthly player count over the next year (August 2025 to July 2026) using several time series models, including exponential smoothing models (ESMs) and autoregressive integrated moving average (ARIMA) models. The ARIMA model proved the most accurate, achieving a mean absolute percentage error (MAPE) of 10.29%. According to its forecast, the best time to join is either now, when the player count is expected to reach an unusually high 73,000 average monthly players, or between December and March, when March could see nearly 110,000 players.

## METHODOLOGY

This section covers the data used, and models considered.

### *Data Used*

I retrieved data of the average monthly player count from [Steam Charts](#) and copied that information into a csv file. The dataset contained 116 observations from December 2015 to July 2025. The data was split into a train/validation/test split of approximately 80%/10%/10% (92/12/12 months) respectively. I used the Guerrero method to determine if a box-cox transformation for the response variable was needed which came out to be 0.38. Therefore, I explored square root transformations for ease of understanding. I considered how factors like COVID-19, new season updates, mid season updates, and free week/weekend launches influenced the outcome. Update information was sourced from Siege's [wiki page](#), and free weekend information came from [Steam DB](#). However, they were not included in modeling because early exploration of the data did not show these variables to be valuable. I estimated seasonality by using Season and Trend Loess (STL) decomposition.

### *Modeling*

Three sets of models were considered: (1) baseline models—mean, naive, seasonal naive, and random walk with drift; (2) ESMs; and (3) ARIMA models. I explored both stochastic ARIMA models (using seasonal and regular differencing) and deterministic ARIMA models (using Fourier terms to model seasonality). The best ESM and ARIMA models were selected based on the corrected Akaike Information Criterion (AICc) using the training data. These shortlisted models, along with the baseline models, were then forecast and evaluated against the validation dataset. Then, the model with the lowest MAPE on validation was evaluated against the test set.

## ANALYSIS and RESULTS

This section details how the set of candidate models performed on validation and test data, and the forecast for the next year.

## Validation and Testing

Table 1 shows the validation MAPE values for the models tested.

Table 1: MAPE values of the models when tested against the validation set

Model	MAPE
Random Walk w/ Drift (Baseline)	17.38%
Multiplicative Damped (ESM)	19.31%
<b>Stochastic ARIMA: (0,1,0)(0,1,1)[12]</b>	<b>17.32%</b>
Deterministic ARIMA: K = 2	18.18%

The stochastic ARIMA model (in bold) was the most accurate, slightly outperforming the baseline. This is the one I chose to evaluate on the final test set. The model had a final MAPE of 10.29%. Figure 1 shows the predicted values of the following year from the test set compared to their actual values.

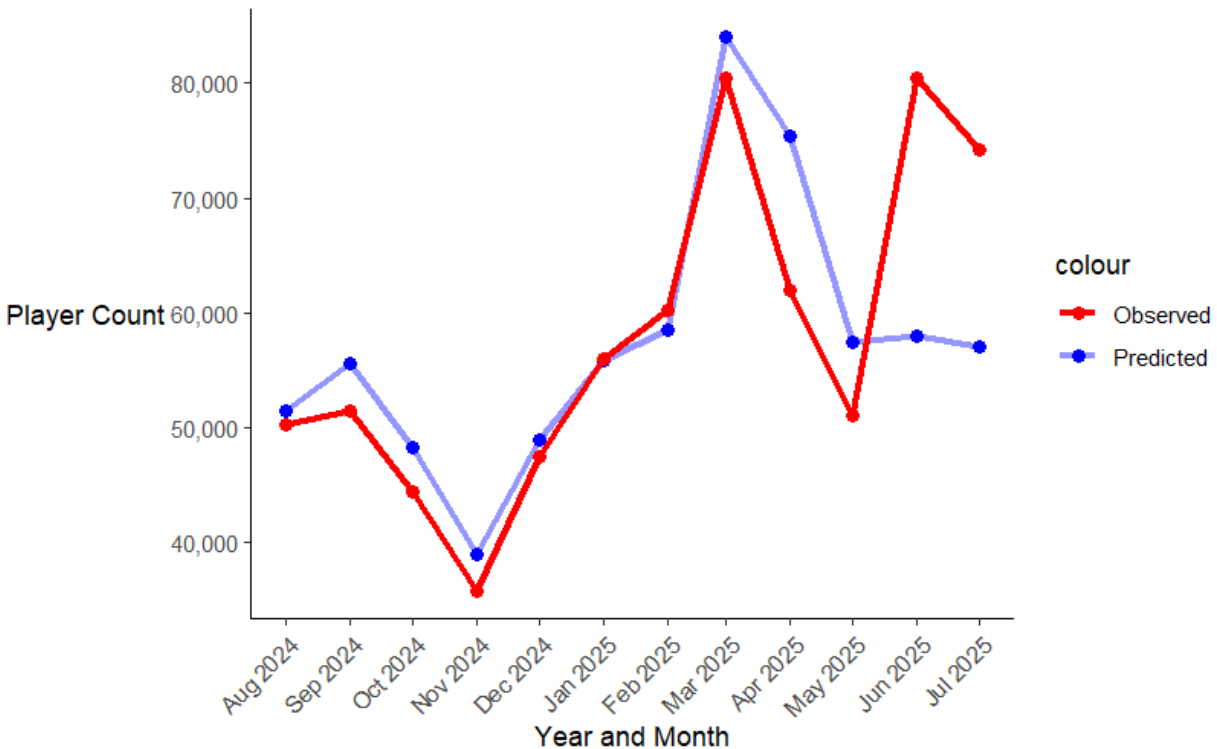


Figure 1: Predicted values from the ARIMA model against the observed values from the test set

The model was at its most accurate from August 2024 to March 2025. Then it experiences a noticeable difference in performance. It was the least effective at forecasting June and July. The drop in performance in the last two months was likely due to the launch of Siege X, a recent

update that brought several major changes. The biggest change was that Siege will now be a free-to-play game. Nevertheless, this spike in players still falls within the expected values of an 80% confidence interval (see Appendix).

## Forecasts

Figure 2 shows the forecasted values for the following year.

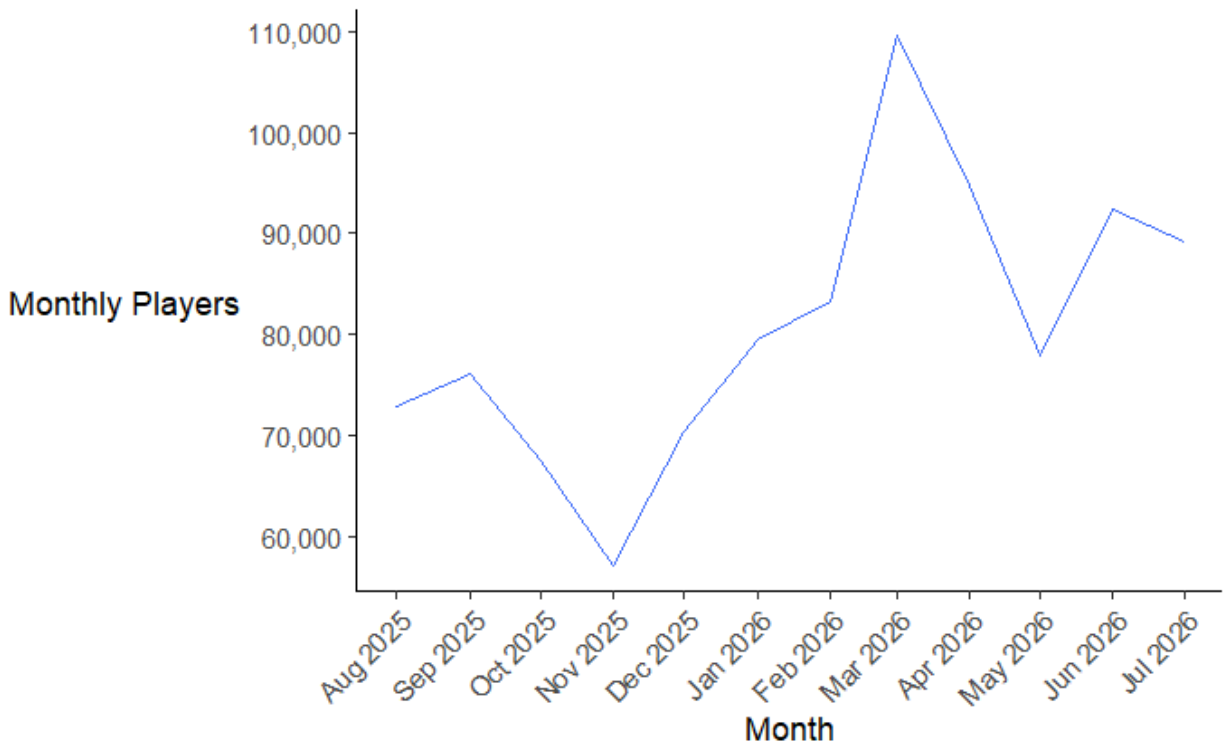


Figure 2: Forecasted monthly average player count of the next year

Based on the forecast, this upcoming March is expected to have nearly 110,000 average monthly players, which would be the highest average since April 2020. If Siege remains free-to-play and many of the new players continue playing and promote the game through word-of-mouth, the March forecast is plausible. However, if fewer players stay, actual numbers are more likely to fall toward the lower end of the 80% prediction interval (see Appendix).

## RECOMMENDATIONS

Based on the results, here are the best times to get back into the game:

- **New/returning players should start now:** The Siege X update in June has caused many new players to try out the game. This is a spike in players not normally seen in a year until March. If someone is new to the game, and intimidated by the learning curve, then now is the best time to learn with other new players.
- **Late winter/early spring:** Player counts typically decline throughout the year until December, then steadily increase, peaking in March. Returning players who come back

in December can take advantage of the growing community and, by March, will have gained enough experience to benefit from the influx of even newer players during the spring surge.

- **Seasonality:** the spring season in March seems to be the only season that has a notable spike, making the time series have a “yearly seasonality.” Other new seasonal updates do not seem to bring in more new players.

## CONCLUSION

If someone is a returning player, or brand new to the game, now is the best chance to get into the game while there are many other players learning along with you. This means that the learning curve will be less steep than usual. The player count will drop until December. At this time, these players will likely be playing with longtime veterans which makes it more difficult to get into. Then from December to March will have a consistent increase in player count, which should mean an easier time learning again.

## APPENDIX

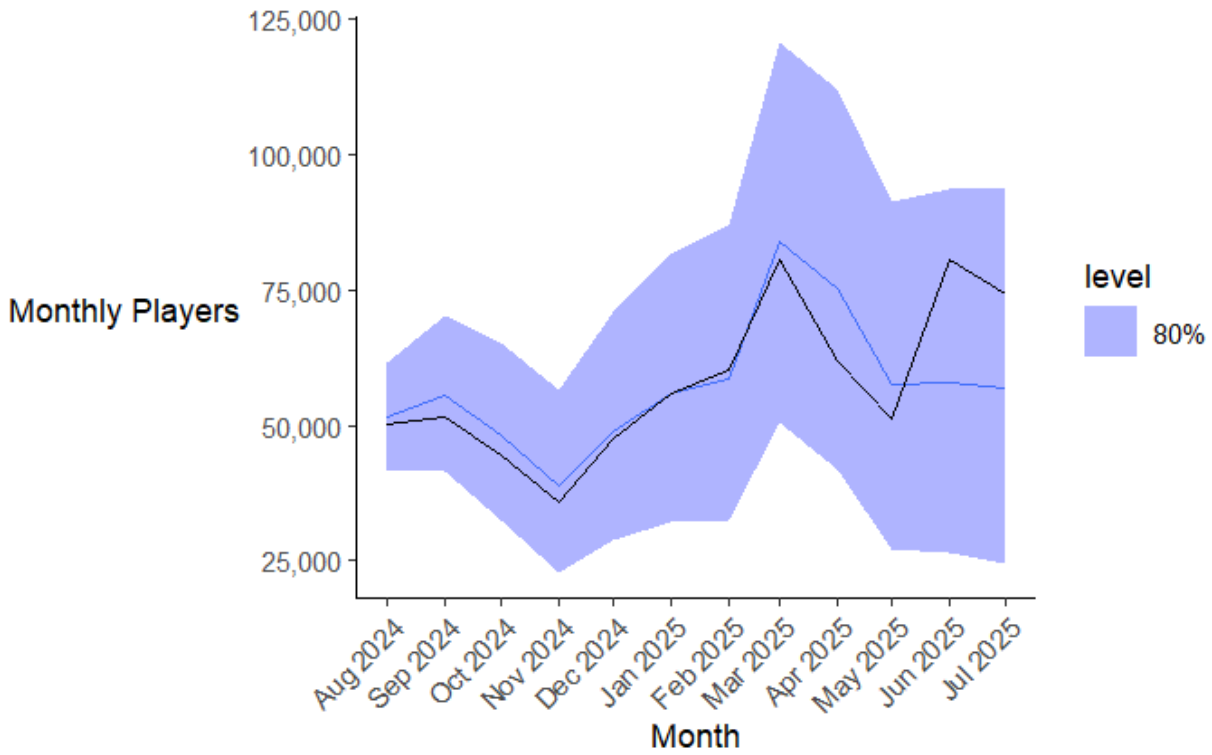


Figure 3: 80% prediction interval from the ARIMA model against the observed values from the test set

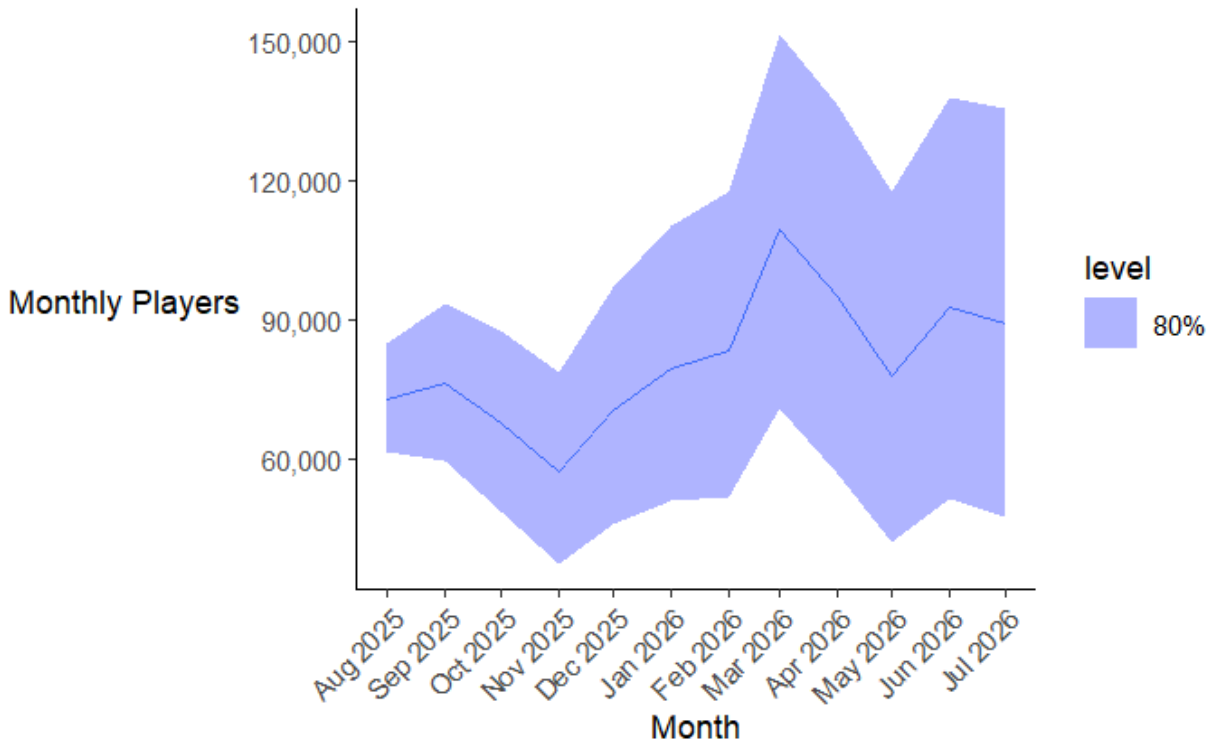


Figure 4: 80% prediction interval from the ARIMA model forecasting the next year