

Forecasting League of Legends Player Performance through In-Game Metrics and Key Statistics*

A Hybrid Model Predict the KDA for Bilibili Gaming (BLG) team players

Colin Sihan Yang

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This paper develops a hybrid model to forecast the 2024 performance of Bilibili Gaming (BLG) team players by analyzing team statistics from the League of Legends Pro League (LPL). The model focuses on predicting the Kill-Death-Assist ratio (KDA) for individual players across different games, leveraging both traditional in-game metrics such as gold difference, kills, assists, and vision score, and advanced variables like total creep score (total CS) to provide a comprehensive view of player performance. By integrating machine learning techniques with esports-specific insights, this model forecasting player KDAs, identifying performance trends, but also offers a clear assessment of individual contributions to the team. It highlights top-performing players while identifying those whose performance may negatively impact the team's success. The findings offer actionable insights, enabling the BLG organization to make informed decisions on player contracts.

```
cleaned_lol_data = read_parquet(here("data/02-analysis_data/cleaned_lol_data.parquet"))
```

1 Introduction

In recent years, esports has evolved into a global phenomenon, with professional gaming leagues such as the League of Legends Pro League (LPL) attracting millions of viewers and significant organizational investments. As the competitive landscape intensifies, teams and organizations

*Code and data are available at: https://github.com/hoodiexxx/lol_win_rate_prediction.

increasingly rely on data-driven approaches to gain a strategic edge. Among these, predictive analytics has emerged as a powerful tool to evaluate player performance, optimize team strategies, and make informed management decisions.

Bilibili Gaming (BLG), a prominent team in the LPL, faces the challenge of maintaining a competitive roster in the ever-changing meta of League of Legends. Accurate performance forecasting is critical for assessing individual player contributions, identifying areas for improvement, and making decisions about player contracts and roster changes.

This paper developing a hybrid model that leverages both traditional in-game metrics and advanced variables, such as total creep score (CS), to forecast player performance for BLG in the 2024 season. The model specifically focuses on predicting the Kill-Death-Assist ratio (KDA), a widely accepted indicator of individual performance, across various matches. Finally offers actionable insights into player roles and impacts, highlighting those who can consistently carry games and identifying players whose performance may not justify their perceived value.

The remainder of this paper is structured as follows: Section 2 provides an overview of the data.

the data gathering and analysis is done in R (R Core Team 2023) with the following packages: knitr (Xie 2014), tidyverse (Wickham et al. 2019), ggplot2 (Wickham 2016), dplyr (Wickham et al. 2023), arrow (Richardson et al. 2024), here (Müller 2020), and Rstan (Stan Development Team 2024)

1.1 Estimand

the estimand for this research paper is the predicted Kill-Death-Assist ratio (KDA) for the BLG team players. The prediction is based on quantifying various in-game factors, including total cs, gold earned, vision score, damage to champion, which are used as predictors.

2 Data

2.1 Measurement

The dataset we obtain from oracleselixir (n.d.) is accumulated from multiple league of legend esports league like LCS, LEC, LCK, LPL, and the rest of global pro LoL.

The dataset utilized in this study was compiled from multiple professional League of Legends (LoL) esports leagues, including the LCS (North America), LEC (Europe), LCK (South Korea), LPL (China), and other global professional leagues. The data aggregation spans from 2023-2024 (23-24 season) and encompasses a wide variety of matches played at different competitive levels. This diversity ensures a comprehensive representation of professional gameplay styles, strategies, and performances across regions.

Each data point corresponds to a single game of one player, identified by a unique gameid, teamid and playerid and includes contextual information such as the league, split (Spring, Summer, or playoffs), split (Winter, Spring, etc), and year. The dataset captures a rich array of in-game metrics and performance indicators for teams and individual players. Team-level data includes variables such as match result (win/loss), game duration (in minutes and seconds), and pivotal game objectives (e.g., First Blood, First Tower, Baron Nashor, and Dragon counts). These metrics are critical for understanding team performance and macro-level strategies.

Player-level statistics include detailed in-game actions such as kills, deaths, assists, gold earned, damage dealt, and wards placed or cleared. These variables allow for a granular examination of individual contributions to a team's success. Additionally, positional data (e.g., top lane, jungle, mid lane, ADC, and support) is included, enabling role-specific analyses. The dataset also tracks champion selections and bans, providing insights into meta trends and drafting strategies over time.

To ensure consistency, all metrics are measured using standardized definitions as provided by the data source, oracleselixir (n.d.). This source is widely regarded as reliable within the esports analytics community. The dataset is structured to facilitate longitudinal analyses, enabling researchers to explore trends and patterns across regions, seasons, and competitive tiers. Furthermore, derived metrics, such as the champion xp difference at 25 minutes (xpdiffat25), Gold Difference at 25 minutes (golddiffat25), and Damage Per Minute (dpm), are calculated to provide advanced insights into player and team efficiency.

These variables combined allow researchers to reliably analyze and predict the 23-24 season LPL BLG team's player performance.

However there are limitations in these measurements. The dataset combines data from multiple leagues (LCS, LEC, LCK, LPL, and others), each of which has distinct playstyles, metas, and competitive environments. These regional differences might introduce biases, as strategies or performance metrics effective in one league may not translate directly to another. For instance, the LCK may prioritize slower, macro-focused playstyles, whereas the LPL might exhibit faster, skirmish-heavy games. This variation could confound cross-regional comparisons unless properly controlled for (Tan 2020).

2.2 Raw Data

The raw data from oracleselixir@oracleselixir_oracles_nodate contains 52 columns, all the column headers are displayed below:

gameid	datacompleteness	url
league	year	split
playoffs	date	game
patch	participantid	side
position	playername	playerid
teamname	teamid	champion
ban1	ban2	ban3
ban4	ban5	pick1
pick2	pick3	pick4
pick5	gamelength	result
kills	deaths	assists
teamkills	teamdeaths	doublekills
triplekills	quadrakills	pentakills
firstblood	firstbloodkill	firstbloodassist
firstbloodvictim	team kpm	ckpm
firstdragon	dragons	opp_dragons
elementaldrakes	opp_elementaldrakes	infernals
mountains	clouds	oceans
chemtechs	hextechs	dragons (type unknown)
elders	opp_elders	firstherald
heralds	opp_heralds	void_grubs
opp_void_grubs	firstbaron	barons
opp_barons	firsttower	towers
opp_towers	firstmidtower	firsttothreetowers
turretplates	opp_turretplates	inhibitors
opp_inhibitors	damagetochampions	dpm
damageshare	damagetakenperminute	damagemitigatedperminute
wardsplaced	wpm	wardskilled
wcpm	controlwardsbought	visionscore
vspm	totalgold	earnedgold
earned gpm	earnedgoldshare	goldspent
gspd	gpr	total cs
minionkills	monsterkills	monsterkillsownjungle
monsterkillsenemyjungle	cspm	goldat10
xpat10	csat10	opp_goldat10
opp_xpat10	opp_csat10	golddiffat10
xpdiffat10	csdiffat10	killsat10
assistsat10	deathsat10	opp_killsat10
opp_assistsat10	opp_deathsat10	goldat15
xpat15	csat15	opp_goldat15
opp_xpat15	opp_csat15	golddiffat15
xpdiffat15	csdiffat15	killsat15
assistsat15	deathsat15	opp_killsat15
opp_assistsat15	opp_deathsat15	goldat20
xpat20	csat20	opp_goldat20
opp_xpat20	opp_csat20	golddiffat20
xpdiffat20	csdiffat20	killsat20
assistsat20	deathsat20	opp_killsat20
opp_assistsat20	opp_deathsat20	goldat25

These columns can be categorized into three types, elements of response variable, numeric predictors, and categorical predictors.

the elements of response variable are: - kills: The number of enemy champions defeated by the player. - deaths: The number of times the player was defeated by opponents. - assists: The number of assists a player contributes to a teammate’s kills.

These three attributes will later be combined to calculate the Kill-Death-Assist ratio (KDA), which serves as the response variable for the model in the cleaned data section Section 2.3.

example of Numeric Predictors are: - totalgold: Total gold earned by the player during the game. - total.cs: Total number of minions or monsters killed by the player. - visionscore: A composite measure of vision provided and vision denied. - damagetochampions: Total damage inflicted by the player on opponents. - golddiffat25: Gold advantage or deficit compared to the opposing player/team at the 25-minute mark.

example of categorical predictors are: - position: The player’s role in the game (e.g., top, jungle, mid, ADC, support). - league: The league where the match was played (e.g., LPL, LCK). - side: team or the blue side or the red side

2.3 Cleaned Data

The cleaned dataset used in this study focuses on matches from the League of Legends Pro League (LPL) involving Bilibili Gaming (BLG) during the 2024 season. To ensure the data aligns with the research objectives, the dataset was filtered to include only games played by BLG, with key variables retained for performance analysis. The cleaning process involved removing rows with missing values and selecting relevant columns, including contextual information such as game ID, league, year, split, and side, as well as in-game performance metrics like kills, deaths, assists, total gold, and vision score. A critical addition to the dataset was the calculation of the Kill-Death-Assist ratio (KDA), a widely used indicator of individual performance. The KDA was derived using the formula:

$$KDA = \frac{Kills + Assists}{Max(1, Deaths)} \quad (1)$$

ensuring robustness even when deaths were zero.

and we mutate the gamelength unit from second into minute.

The cleaned dataset was saved in Parquet formats to support flexibility in analysis and compatibility with various tools. This focused and structured dataset ensures reliability and completeness, providing a robust foundation for forecasting player performance, analyzing trends, and identifying key contributors to the analysis of BLG’s players performance.

The first 6 rows of the dataset are displayed in Table 1.

Table 1: Sample of cleaned league of legend esport data

side	position	playername	champion	kills	deaths	assists	visions	score	totalgold	total.cs	damagetochamps	K/D/A	kills	length	result
Blue	top	Bin	K'Sante	1	0	6	21	10913	251	10197	7.0	27.05000	1		
Blue	jng	Xun	Brand	8	0	8	34	12311	200	18832	16.0	27.05000	1		
Blue	mid	knight	LeBlanc	4	0	6	19	13156	247	26196	10.0	27.05000	1		
Blue	bot	Elk	Varus	1	2	8	34	11495	244	12877	4.5	27.05000	1		
Blue	sup	ON	Ashe	3	1	10	140	9104	43	10592	13.0	27.05000	1		
Red	top	Bin	Aatrox	0	2	2	35	11821	319	17950	1.0	30.56667	0		

2.4 DATA Exploration

2.4.1 Champion Pool for players

Table 2: the table that shows the champion pool for the BLG players

Table 2: Top 5 Most Played Champions by Player with Win Rate

Player Name	Champion	Position	Count	Win Rate
Bin	Renekton	top	18	0.7777778
Bin	Kennen	top	12	0.9166667
Bin	Gnar	top	11	0.7272727
Bin	K'Sante	top	11	0.5454545
Bin	Aatrox	top	10	0.7000000
Elk	Kai'Sa	bot	10	0.8000000
Elk	Kalista	bot	10	0.9000000
Elk	Lucian	bot	10	0.9000000
Elk	Ezreal	bot	9	0.7777778
Elk	Senna	bot	9	0.7777778
ON	Rell	sup	15	0.8000000
ON	Rakan	sup	13	0.6923077
ON	Nautilus	sup	11	0.7272727
ON	Alistar	sup	9	1.0000000
ON	Renata Glasc	sup	9	0.7777778
Wei	Sejuani	jng	6	0.8333333
Wei	Maokai	jng	5	1.0000000
Wei	Lillia	jng	4	1.0000000
Wei	Zyra	jng	4	0.7500000
Wei	Brand	jng	2	1.0000000

Player Name	Champion	Position	Count	Win Rate
Xun	Kindred	jng	12	0.8333333
Xun	Vi	jng	11	0.5454545
Xun	Xin Zhao	jng	8	0.8750000
Xun	Brand	jng	6	0.5000000
Xun	Lee Sin	jng	6	0.8333333
knight	Corki	mid	14	0.9285714
knight	Yone	mid	10	0.7000000
knight	Ahri	mid	8	0.8750000
knight	Karma	mid	7	0.8571429
knight	Neeko	mid	7	1.0000000
knight	Taliyah	mid	7	0.8571429
knight	Tristana	mid	7	0.5714286

The table Table 2 summarizes the top 5 most played champions for each Bilibili Gaming (BLG) player, including their positions, usage counts, and win rates. It highlights the players' preferences and effectiveness with specific champions, offering insights into individual strengths and team strategies.

- Bin (top lane) favors durable, aggressive champions like Renekton (18 games, 77.8% win rate) and Kennen (12 games, 91.7%). While most of his champions are highly effective, K'Sante has a lower win rate of 54.5%, suggesting Bin may not good at Tank champion.
- Elk (bot lane) excels on meta ADCs like Kai'Sa, Kalista, and Lucian, all boasting win rates of 80-90%, with consistent performance on utility champions like Senna and Ezreal (77.8%).
- ON (support) shines with engage-heavy champions such as Rell (80%) and Rakan (69.2%), but his Alistar stands out with a perfect 100% win rate, indicating strong synergy in specific scenarios. Wei (substitute jungle) shows exceptional results on niche picks like Maokai, Lillia, and Brand, each with 100% win rates, while his most-played Sejuani achieves 83.3%.
- Xun (main jungle) demonstrates a balanced pool with high win rates on Kindred (83.3%) and Xin Zhao (87.5%), though his performance on Vi (54.5%) is less consistent. Knight (mid lane) showcases versatility, excelling on Corki (92.9%) and Neeko (100%), but his Tristana struggles with a 57.1% win rate.

Wei's (Secondary jungle) limited champion pool suggests fewer games played, with Sejuani (6 games) and Maokai (5 games) leading the count. Wei appears to specialize in tanky jungle champions and niche picks like Zyra and Brand. it may shows BLG want wei play tank champion to protect other teammates.

Overall, most players exhibit strong performance with their preferred champions, though some picks, like K'Sante and Vi, show room for improvement. These insights can guide BLG's drafting strategies and optimize player-champion pairings for better outcomes in competitive play.

2.4.2 Players VisionScore

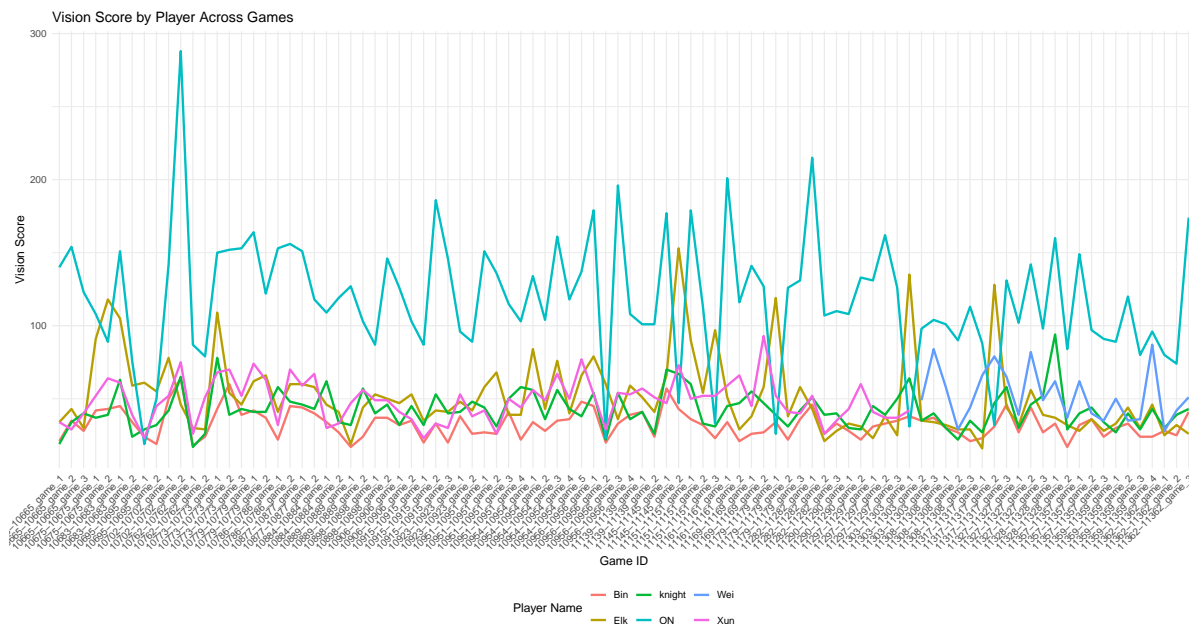


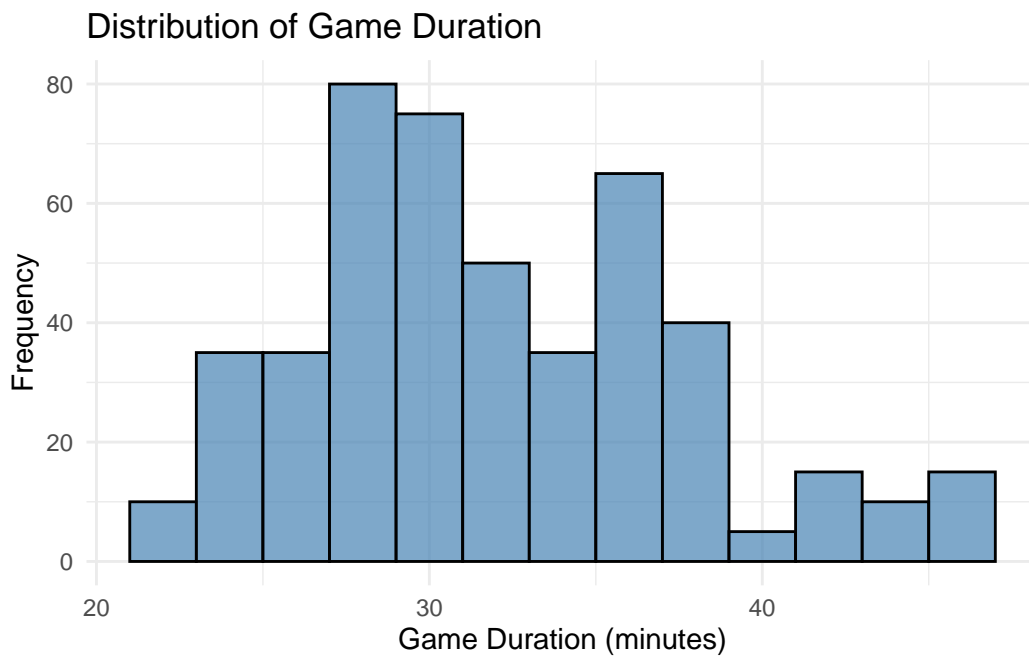
Figure 1: BLG players visionscore over game

The line chart Figure 1 visualizes the vision scores of individual players on the Bilibili Gaming (BLG) team across multiple games, offering insights into their vision control performance and consistency. Each line represents a player's cumulative vision score over the course of several matches, helping to compare and analyze their contributions to map awareness and team strategy.

Key observations highlight that ON, the team's support player, consistently records the highest vision scores across games. This is expected, as supports typically focus on warding and vision control, critical for map dominance. ELK, the ADC, also shows considerable vision score variability. Other roles, such as Bin (top lane), and Knight (mid lane), have lower and steadier vision scores, aligning with their roles' primary focus on laning and damage output rather than vision control.

2.4.3 Game duration

```
# Plotting a histogram for game duration in minutes
ggplot(cleaned_lol_data, aes(x = gamelength)) +
  geom_histogram(binwidth = 2, fill = "steelblue", color = "black", alpha = 0.7) +
  theme_minimal() +
  labs(
    title = "Distribution of Game Duration",
    x = "Game Duration (minutes)",
    y = "Frequency"
  )
)
```



2.4.4 players gold earned

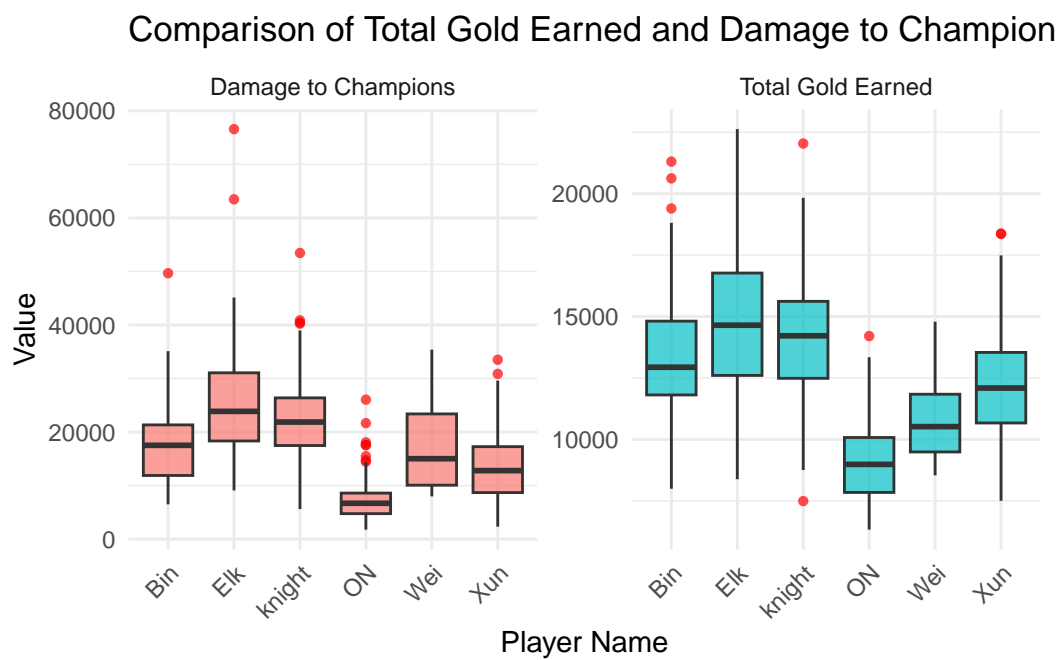
```
# Reshape the data for comparison
gold_damage_data <- cleaned_lol_data |>
  select(playername, totalgold, damagetochampions) |>
  pivot_longer(
    cols = c(totalgold, damagetochampions),
    names_to = "metric",
    values_to = "value"
  )
```

```

)

# Plot the boxplots for total gold and damage to champions
ggplot(gold_damage_data, aes(x = playername, y = value, fill = metric)) +
  geom_boxplot(outlier.color = "red", outlier.shape = 16, alpha = 0.7) +
  facet_wrap(~ metric, scales = "free_y", labeller = as_labeller(c(
    "totalgold" = "Total Gold Earned",
    "damagetochampions" = "Damage to Champions"
  ))) +
  theme_minimal() +
  labs(
    title = "Comparison of Total Gold Earned and Damage to Champions by Player",
    x = "Player Name",
    y = "Value"
  ) +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1),
    legend.position = "none"
  )

```



2.5 Outcome variables

Add graphs, tables and text. Use sub-sub-headings for each outcome variable or update the subheading to be singular.

Some of our data is of penguins (**?@fig-bills**), from Horst, Hill, and Gorman (2020).

Talk more about it.

And also planes (**?@fig-planes**). (You can change the height and width, but don't worry about doing that until you have finished every other aspect of the paper - Quarto will try to make it look nice and the defaults usually work well once you have enough text.)

Talk way more about it.

2.6 Predictor variables

Add graphs, tables and text.

Use sub-sub-headings for each outcome variable and feel free to combine a few into one if they go together naturally.

3 Model

The goal of our modelling strategy is twofold. Firstly,...

Here we briefly describe the Bayesian analysis model used to investigate... Background details and diagnostics are included in [Appendix B](#).

3.1 Model set-up

Define y_i as the number of seconds that the plane remained aloft. Then β_i is the wing width and γ_i is the wing length, both measured in millimeters.

$$y_i | \mu_i, \sigma \sim \text{Normal}(\mu_i, \sigma) \tag{2}$$

$$\mu_i = \alpha + \beta_i + \gamma_i \tag{3}$$

$$\alpha \sim \text{Normal}(0, 2.5) \tag{4}$$

$$\beta \sim \text{Normal}(0, 2.5) \tag{5}$$

$$\gamma \sim \text{Normal}(0, 2.5) \tag{6}$$

$$\sigma \sim \text{Exponential}(1) \tag{7}$$

We run the model in R (R Core Team 2023) using the `rstanarm` package of Brilleman et al. (2018). We use the default priors from `rstanarm`.

3.1.1 Model justification

We expect a positive relationship between the size of the wings and time spent aloft. In particular...

We can use maths by including latex between dollar signs, for instance θ .

4 Results

Our results are summarized in `?@tbl-modelresults`.

5 Discussion

5.1 First discussion point

If my paper were 10 pages, then should be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

5.2 Second discussion point

Please don't use these as sub-heading labels - change them to be what your point actually is.

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

A Additional data details

B Model details

B.1 Posterior predictive check

In `?@fig-ppcheckandposteriorvsprior-1` we implement a posterior predictive check. This shows...

In `?@fig-ppcheckandposteriorvsprior-2` we compare the posterior with the prior. This shows...

B.2 Diagnostics

`?@fig-stanareyouokay-1` is a trace plot. It shows... This suggests...

`?@fig-stanareyouokay-2` is a Rhat plot. It shows... This suggests...

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