2026 World Cup Prediction Game Week 1 Analysis

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June-July 2026

1 Points Table

Rank	Player	Points	Misclassification Rate
1	Kaleb	24	0.4167
2	Ritesh	23	0.4167
3	Octavio	22	0.3750
4	Smarak	21	0.3750
5	Mustafa	21	0.4583
6=	Shyam	20	0.4167
6=	Abhijeet	20	0.4167
8	Claude	20	0.4583
9	Brian	19	0.5000
10	Dylan	18	0.4167
11	Pratik	18	0.4583
12=	Luigi	18	0.5000
12=	Saathvik	18	0.5000
12=	Akshath	18	0.5000
15	Shankar	18	0.5417
16	Pankaj	17	0.4167
17	Pranav	17	0.4583
18	Josh	17	0.5000
19	Saujanya	16	0.4583
20	Amir	15	0.5000
21=	Praveen	15	0.5417
21=	Gemini	15	0.5417
23=	Nitish	14	0.5000
23=	Hari	14	0.5000
25=	Rohan	14	0.5417
25=	Anuroop	14	0.5417
25=	Joaquín	14	0.5417
28	Shreyas	14	0.5833
29	Adarsh	13	0.5417
30	Vatsin	13	0.6667

2 Rules Update

- If it's not clear what the misclassification rate (MCR) is, it is the percentage of games that were predicted incorrectly. It is a very simple loss function for a binary classifier. In math: for a game k, let $\hat{y}_k$ denote the predicted outcome and $\mathbf{y}_k$ denote the actual outcome. For n games, the misclassification rate is calculated as $\frac{1}{n}\sum_{k=1}^{n}\mathbb{I}(\hat{y}_k \neq \mathbf{y}_k)$.
- The main tiebreaker will be the MCR. So if two players have the same number of points, then the one with a lower MCR has a higher rank. If it so happens that players are still tied, then the next tiebreaker will be number of games that were predicted exactly right (for which they got three points). If there's still a tie, then they will be ranked based on the number of games for which the goal difference was predicted correctly.
- If the player with the lowest MCR is among the top three, the Paul Award will go to the one outside the top three with the lowest MCR, *a best of the rest, of sorts.*

3 Analytics

Average Points: 17.33
Standard Deviation: 3.08
Median: 17.5
Range: 13
Mean MCR: 0.4861

- The theoretical maximum at this stage is 72 points. Kaleb leads with 24, exactly a third of that number. Kudos!
- It is not meaningful to estimate any functional relationship between the points scored and misclassification rate because there's so much bunching, but the correlation appears to be negative (higher points $\implies$ lower MCR).
- The longest streak of correctly called results was 5. This streak was achieved by eight of you, bravo!
- *"One big mistake in these predictions was not giving atleast 1 goal to the team (whom you think might lose) regardless how bad they are. Just give them a goal" – Rohan LuckyPal.*
  In games that have at least one goal scored, only 6 out of 22 have seen the winning team keep a clean sheet. Valid reflection!
- *"I think draws are severely underpredicted in general" – (Dr.) Shreyas.*
  9 out of the 24 group stage matches have been draws. Our draw rate is just under 18 % (that is of the 720 = 24 * 30 predictions, 128 have been draws), less than half of the true draw rate. Spot on Shreyas!

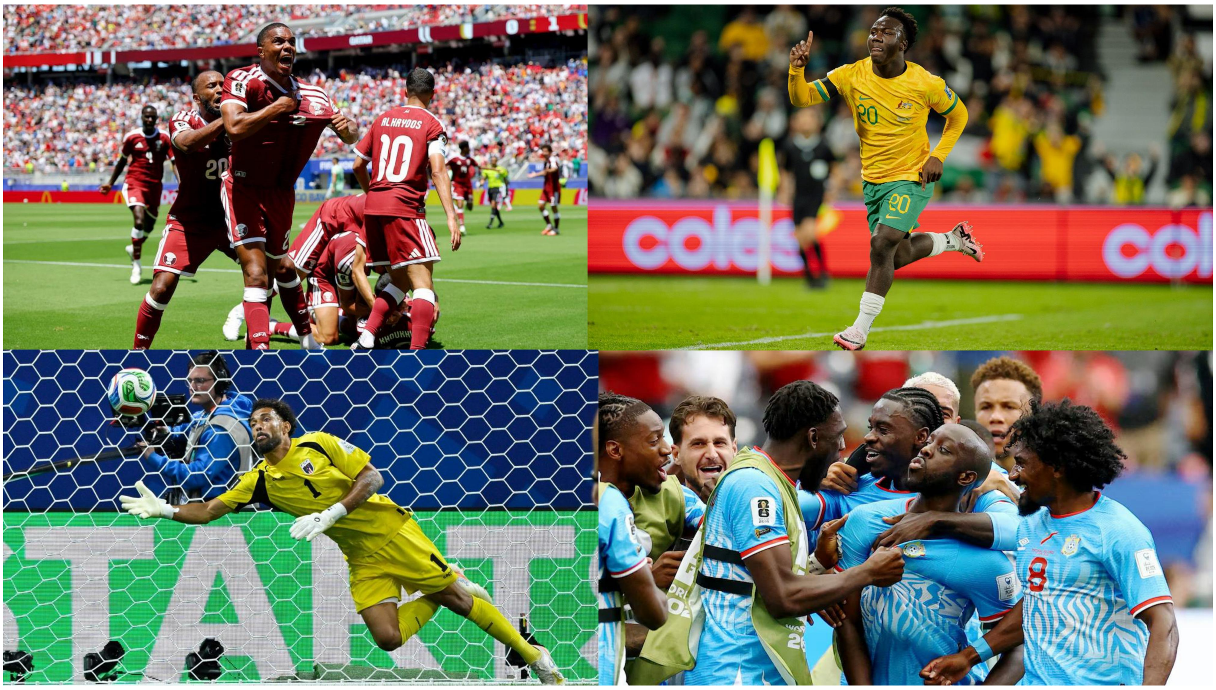


Figure 1: Upsets – the group was entirely or almost entirely wrong for these four games

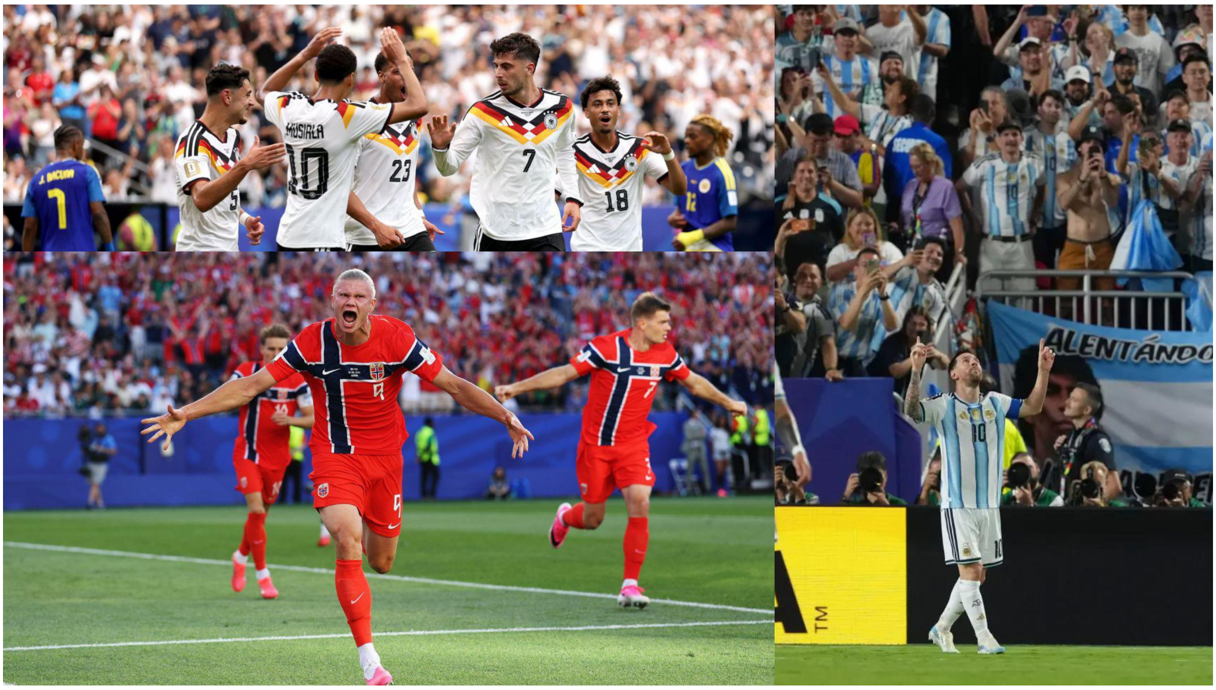


Figure 2: Prescient – everyone called these results correctly

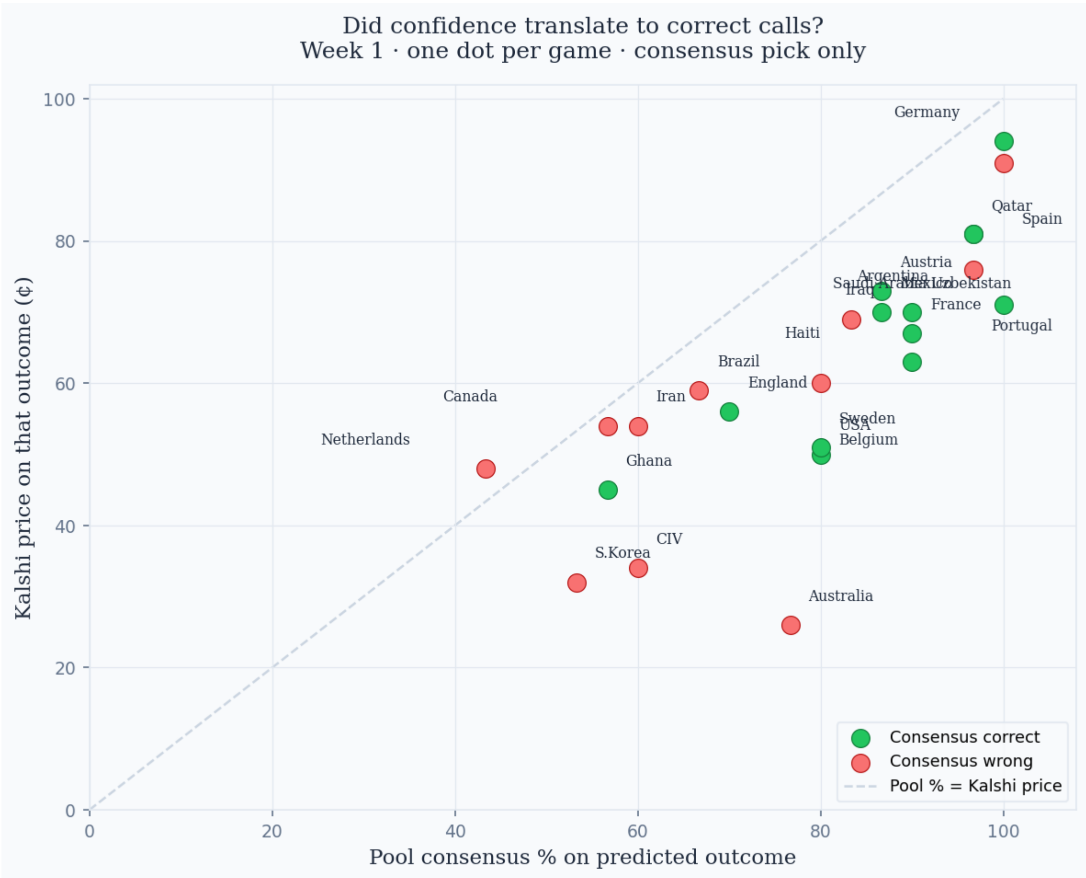
4 Trading Strategies

30 sets of predictions is actually quite a rich dataset. I am a finance PhD student after all, so naturally I was curious as to how best I could extract the signal from all of that data. You all paid a participation fee. Suppose I bought contracts worth $10 on Kalshi from that pool on each game. What would the return on that portfolio look like? Abstract away from fees and hold to maturity. The prices on Kalshi are as of 1pm ET 11 June, around when I closed the submission window. Consider the following strategies:

1. Naive consensus pick
    - For each game, buy contracts corresponding to the group's majority pick. So if above 50% of the group expects a win, I would YOLO $10 worth of contracts on that outcome. This strategy is naive because it does not capture the degree of confidence: a 16-14 split is treated the same as 30-0. In any case, **we would actually be down 21% on a strategy like this.** As a group, a majority rule like this would have predicted 12 results correctly, but the losses from the upsets are too big to overcome.
2. Divergence from Kalshi
    - Compare the group's implied probability to Kalshi's. If there's a divergence, buy. Treat the pool as a forecasting model and use Kalshi as the market to bet against when in disagreement. Such a strategy does much better, **we would be up 25 %**.
3. YOLO on consensus picks
    - Buy contracts on the six results where the group is most confident. Given there were a couple picks where we all collectively wrong, this naturally does poorly, and as expected, **we would be down 20%**.
4. BAV (Bet against Vatsin)
    - There was no way to know Vatsin would do poorly ex-ante, but this was a funny suggestion (sad guy got roasted by AI).

5. **Follow the contrarians selectively** — players like VATSIN who are systematically wrong are actually useful in reverse: if VATSIN picks X, consider the other side.

- Betting against Vatsin is the clear winner, delivering an outsized **return of 86% ($204)**.


Did confidence translate to correct calls?
Week 1 · one dot per game · consensus pick only
Kalshi price on that outcome (¢)
Pool consensus % on predicted outcome
0
20
40
60
80
100
Germany
Qatar
Spain
Austria
Argentina
France
Portugal
Haiti
Brazil
England
Canada
Iran
Netherlands
Sweden
USA
Belgium
Ghana
CIV
S.Korea
Australia
Consensus correct
Consensus wrong
Pool % = Kalshi price