Modeling the Likelihood of Kabaddi Adoption Across Countries

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Abstract

Kabaddi's adoption varies across countries due to differences in culture, economics, media infrastructure, and institutional support. This document presents a structured framework to estimate the likelihood that Kabaddi will succeed in a new market. The approach treats adoption as a latent variable—something we can't observe directly at first but can infer from features and later, from actual outcomes. The model uses pre-entry country-level features, post-entry adoption metrics, Bayesian updating, and time-series/stochastic modeling to provide a dynamic, interpretable probability of success. This framework is designed for strategic decision-making, risk management, and phased investment planning.

1 Introduction

Kabaddi has achieved strong popularity in some countries but struggled to form a base in others. Investors, league operators, and sports federations need a systematic way to estimate the likelihood of success before entering a market and to adapt strategies after launch.

This model approaches the problem by defining a latent adoption variable that represents whether Kabaddi will establish a sustainable fan base, league infrastructure, and commercial ecosystem in a country. The model then updates this probability over time as new evidence becomes available.

2 Defining Adoption Success

We define success as a binary outcome for clarity and interpretability:

$$A_c = \begin{cases} 1, & \text{if Kabaddi achieves sustained adoption (league formation,fan engagement, sponsors)} \\ 0, & \text{otherwise} \end{cases}$$

In other words, a country is "successful" if the sport can establish itself beyond a trial phase and maintain steady growth in participation, audience, and revenue.

The probability that a country C will be successful before launch is denoted:

$$P(A_c = 1 \mid X_c)$$

where X_c is the set of pre-entry features describing the country.

3 Pre-Entry Features and Modeling

Before launching Kabaddi in a new market, no direct data from that country exists. To make an informed estimate, we rely on indicators that act as proxies for potential adoption.

3.1 Feature Categories

We organize features into five main categories:

A. **Cultural Compatibility (C_c)**
Factors indicating whether the population is likely to enjoy Kabaddi:

- Popularity of contact or combat sports
- Presence of wrestling or similar indigenous games
- Youth participation in team sports
- South Asian diaspora population (early adopter fan base)

B. **Economic Capacity (E_c)**
The ability of the market to support a professional sport financially:

- GDP per capita
- Entertainment expenditure per capita
- Ticket affordability index
- Corporate sponsorship capacity

C. **Media and Digital Readiness (M_c)**
How easily the sport can reach fans through media:

- OTT platform penetration
- Smartphone and broadband access
- Social media engagement with comparable sports
- Local sports broadcasting infrastructure

D. **Institutional Support (I_c)**
Government and organizational factors that influence adoption:

- Public investment in sports
- Availability of indoor/outdoor arenas
- School and federation-level sports programs
- Regulatory and policy environment

E. **Demographic & Social Indicators (D_c)**
Population characteristics and local communities that affect adoption:

- Population density and urbanization
- Youth population percentage
- Presence of community sports clubs or leagues
- Expatriate communities, especially South Asian populations

3.2 Pre-Entry Logistic Model

We relate these features to adoption probability using a logistic regression:

$$P(A_c = 1 \mid X_c) = \sigma(\beta^\top X_c + u_{\text{region}} + \epsilon_c), \quad \epsilon_c \sim \mathcal{N}(0, \sigma^2)$$

where $\sigma(z) = \frac{1}{1+e^{-z}}$.

- β captures the contribution of each feature
- u_{region} models unobserved regional effects
- ϵ_c accounts for noise specific to the country

Bayesian priors on β can be introduced using historical data from other countries where Kabaddi has been launched, improving the estimates especially when data is scarce.

4 Hierarchical Bayesian Modeling

Countries are not independent. Neighboring countries or markets with similar culture/media infrastructure share characteristics. We model this as a hierarchical Bayesian structure:

$$\beta_c \sim \mathcal{N}(\mu_\beta, \Sigma_\beta)$$

where:

- β_c = country-specific sensitivity of features
- μ_β = average effect of features across all countries
- Σ_β = covariance that captures feature interactions and variability

This structure:

- Shares information between countries to reduce overfitting.
- Accounts for uncertainty in countries with little historical data.
- Provides interpretable posterior distributions indicating feature importance.

This modelling allows countries with limited data to benefit from patterns observed in more mature markets without forcing identical behavior. It also helps distinguish structural similarities from genuine country-specific deviations in adoption dynamics.

5 Post-Entry Adaptive Learning

Once Kabaddi is launched, real adoption metrics become available and the model updates dynamically.

5.1 Latent Adoption Dynamics

Let $Z_{c,t}$ represent the latent adoption strength at time t:

$$Z_{c,t} = \phi Z_{c,t-1} + \gamma^\top W_{c,t} + \epsilon_{c,t}, \quad \epsilon_{c,t} \sim \mathcal{N}(0, \sigma_\epsilon^2)$$

where:

- ϕ captures momentum (adoption persistence)
- $W_{c,t}$ = vector of observed signals (attendance, TV/OTT viewership, social engagement, merchandise sales, player-fan interactions)
- $\epsilon_{c,t}$ = stochastic shock (e.g., sudden media attention)

Observed metrics are noisy measurements:

$$Y_{c,t}^{(k)} = \lambda_k Z_{c,t} + \nu_{c,t}^{(k)}, \quad \nu_{c,t}^{(k)} \sim \mathcal{N}(0, \sigma_k^2)$$

5.2 Time-Series and State-Space Modeling

- Use Kalman or particle filters to separate long-term adoption trends from short-term fluctuations
- Detect structural changes: saturation, sudden growth, or decline
- Forecast adoption momentum for operational decisions
- Model stochastic evolution of adoption explicitly, accounting for randomness in behavior

5.3 Bayesian Updating

As new data arrives, update beliefs:

$$P(Z_{c,t} \mid D_{c,1:t}) \propto P(Y_{c,t} \mid Z_{c,t}) \cdot P(Z_{c,t} \mid Z_{c,t-1})$$

The updated probability of sustained adoption:

$$P(A_c = 1 \mid D_{c,1:t}) = \sigma(Z_{c,t})$$

This allows investors and operators to continuously monitor success and adjust marketing spend, infrastructure, and operational focus dynamically.

6 Methodology Workflow

1. Feature engineering: C_c, E_c, M_c, I_c, D_c
2. Pre-entry logistic/Bayesian estimation of $P(A_c = 1)$
3. Hierarchical Bayesian pooling for cross-country information
4. Post-entry stochastic tracking of $Z_{c,t}$

5. Sequential Bayesian updating with time-series filters
6. Decision support: entry planning, marketing allocation, phased investment

7 Decision Relevance

- Provides a quantitative, interpretable probability of adoption
- Early detection of weak markets reduces risk
- Estimates ROI for promotions and marketing campaigns
- Supports adaptive strategy based on real-time data and stochastic evolution

8 Conclusion

By treating Kabaddi adoption as a latent variable that evolves over time, this framework combines pre-entry features, hierarchical Bayesian modeling, and post-entry stochastic dynamics. It is transparent, interpretable, and actionable, allowing strategic decisions that balance risk and opportunity in new markets.