

Problem D: Dynamic Sports Business Decision Model (WNBA)

Example Team: Indiana Fever (Indianapolis) — Team 2633018

REVISED MODEL DRAFT – August 7, 2026

Summary Sheet

Problem. A professional sports team must balance current profit, competitive quality, liquidity, and long-run franchise value while responding to injuries, macroeconomic stress, player-market constraints, and league expansion. We develop a state-based decision system for the Indiana Fever that links roster construction, ticket pricing, marketing investment, and financing choices over time.

Core modeling principle. A dynamic model requires both an evolving state and a policy mapping that state into actions. We use

$$X_t = (q_t, B_t, C_t, D_t, V_t, M_t, E_t, I_t), \quad u_t = (a_t, p_t, m_t, \Delta D_t) = \pi(X_t),$$

where q_t is normalized team quality, B_t is a bounded brand-demand stock, C_t is cash, D_t is debt, V_t is franchise value, M_t is macro stress, E_t is expansion status, and I_t collects player injury states. Decisions a_t, p_t, m_t , and ΔD_t determine roster actions, ticket prices, marketing investment, and debt changes.

Component	Revised treatment
Owner objective	Maximize discounted profit and terminal franchise value while penalizing liquidity distress, excessive leverage, and loss of competitive viability.
Roster policy	Binary constrained optimization under salary-cap, roster-size, mechanism, continuity, and optional depth constraints; value-per-dollar is only a heuristic or tie-breaker.
Demand/pricing	Normalize quality and brand before demand enters an exponential; calibrate baseline attendance to 16,560.23 and include the 2.08M market-size proxy.
Leverage	Borrow only to fund a positive-NPV approved investment or roster need; periodize interest consistently with the simulation calendar and deleverage under stress.
Injuries	Replace a one-period shock with Healthy/Limited/Out/Recovering states that affect availability, performance, ticket demand, and waiver/free-agent decisions.
Expansion	Model salary pressure, talent dilution/expansion-draft exposure, league-wide attention, and distance-based demand substitution.
Robustness	Monte Carlo uncertainty includes wins, attendance, injuries, sponsorship revenue, operating cost, and interest-rate shocks; report downside risk and CVaR, not bankruptcy rate alone.

Validation status. The previous numerical scenario outputs are not carried forward as validated results because the submitted tables contain internal inconsistencies: the injury scenario reports no quality decline or waiver activation, while deterministic and Monte Carlo baseline totals do not reconcile. The revised model below is complete at the mathematical and experimental-design level; scenario tables should be regenerated from the original workbook/code before final submission.

Key recommendation. Treat this model as a policy engine rather than a one-time forecast: ownership should preserve liquidity, acquire players for total expected value under league constraints, price games from a calibrated demand curve, and use debt only when the expected long-run return exceeds financing and distress costs.

1 Introduction and Problem Restatement

A professional sports franchise is simultaneously a competitive team and an entertainment business. Its decisions are interdependent: roster quality affects wins and star power; wins and popularity affect demand; demand determines ticket and sponsorship revenue; revenue changes cash; and cash, debt, and league rules constrain future decisions. The central challenge is therefore dynamic rather than static.

We model the Indiana Fever as an example WNBA franchise. The model addresses four management questions specified in the original submission: how leverage should change through time; how players should be acquired using draft, free agency, trades, and waivers; how the team should adapt to league expansion; and how ticket prices should respond to demand. It also explicitly models the response to a key-player injury.

The revision strengthens the original framework in five ways. First, it gives ownership one coherent intertemporal objective that includes both profit and franchise value. Second, it normalizes and bounds the demand system so that brand growth cannot mechanically force prices to the grid maximum. Third, it makes player selection a consistent constrained optimization. Fourth, it treats injuries and expansion as persistent states rather than one-period adjustments. Fifth, it builds validation and downside-risk tests into the simulation design.

2 Data Inputs and Provenance

The model preserves the data architecture described in the submitted paper: a league table, a teams table, raw player statistics, and a player-attribute table. All numerical inputs below are carried forward from the uploaded submission and should be rechecked against the original workbook before resubmission.

Input	Value / source role
Arena capacity	18,274 basketball seats
Average home attendance	16,560.23; primary baseline-demand calibration target
Home games	22
Market size	2,080,000 metro-population proxy; now enters the demand scale rather than being descriptive only
Season length	44 games
2025 salary cap	\$1,507,100
Roster size	11–12 players
Player performance	PTS, REB, AST, STL, BLK, TOV, and games played
Player attributes	Salary, position, age, and social-media followers

The source list is unchanged from the submitted paper: COMAP for the problem statement; Her Hoop Stats for salary-cap information; Across the Timeline for attendance; ESPN for team/player statistics; and the submitted team workbook for the merged player-level dataset. Because games missed include non-medical absences, we relabel the original injury-risk variable as an *availability-risk proxy* unless a verified injury dataset is added.

3 Assumptions

3.1 Business and finance

- Cash and debt are distinct state variables; accounting profit does not automatically imply liquidity.
- Borrowing is permitted only to finance an explicitly identified positive-NPV growth or roster investment, not merely because cash is already high.
- Interest rates rise with macro stress and leverage. Annual rates are converted to the simulation-period rate before interest expense is applied.
- Ownership maintains a minimum cash buffer and a target leverage ratio to limit distress risk.
- Franchise value is endogenous: sustained profit, brand growth, and competitive quality can increase value, while leverage risk reduces it.

3.2 Performance and demand

- Expected quality is built from player contribution adjusted for availability and roster-balance effects.
- Fan demand responds to normalized quality, bounded brand stock, market size, opponent/game effects, and ticket price.
- Social-media following is a popularity proxy, not a direct causal estimate of ticket purchases; it enters after a log transform and normalization.
- Attendance is capped by arena capacity and subject to stochastic game-level demand shocks.
- Marketing has diminishing marginal effects on brand rather than entering linearly without bound.

3.3 League mechanisms

- The roster must satisfy the league salary cap, payroll floor if included in the workbook, and 11–12 player size constraints.
- Draft, free agency, trades, and waivers are represented by eligibility and asset constraints, not only by labels.
- Expansion can alter both player-market supply and consumer demand. Expansion-draft protection and talent dilution are modeled separately from location overlap.

4 State, Decisions, and Ownership Objective

We use $t = 1, \dots, T$ decision periods. Because the submitted implementation divides a 44-game season into $T = 11$ blocks, we call these *four-game decision periods* rather than literal weeks unless an actual weekly schedule is supplied.

$$X_t = (q_t, B_t, C_t, D_t, V_t, M_t, E_t, I_t), \quad (1)$$

$$u_t = (a_t, p_t, m_t, \Delta D_t) = \pi(X_t). \quad (2)$$

The original paper states that the owner wants to maximize both profit and long-run franchise value. We therefore make that objective explicit:

$$J(\pi) = \mathbb{E} \left[\sum_{t=1}^T \delta^{t-1} (\Pi_t - \lambda_C L_C(C_t) - \lambda_D L_D(D_t/V_t) - \lambda_Q L_Q(q_t)) + \theta V_{T+1} \right]. \quad (3)$$

Here δ is the discount factor. L_C penalizes falling below the minimum cash buffer, L_D penalizes excessive leverage, and L_Q penalizes falling below a competitive-quality floor. This converts the model from several disconnected heuristics into one coherent owner-level decision problem.

5 Player Metrics and Roster Optimization

5.1 Player-level inputs

For each player i , the workbook provides salary c_i and the data needed to construct performance b_i , availability risk π_i , and popularity s_i :

$$b_i = \text{PTS}_i + 1.2 \text{REB}_i + 1.5 \text{AST}_i + 3(\text{STL}_i + \text{BLK}_i) - 2 \text{TOV}_i, \quad (4)$$

$$\pi_i = \frac{G_{\text{total}} - G_i}{G_{\text{total}}}, \quad G_{\text{total}} = 44, \quad (5)$$

$$s_i = \log(1 + \text{followers}_i). \quad (6)$$

To prevent units from dominating one another, roster-value components are standardized relative to the available player pool. Let $z_b(i)$ and $z_s(i)$ denote standardized performance and popularity:

$$v_i = w_b z_b(i) + w_s z_s(i) - w_r \pi_i - w_a \text{AgePenalty}_i. \quad (7)$$

The age term is optional and should be used only if age-related planning is supported by the data. The key revision is that salary is not inconsistently included in one objective and removed in another.

5.2 Constrained roster decision

Let $y_i \in \{0, 1\}$ indicate whether player i is selected, and let k_i denote transaction or asset cost for acquiring that player. The general-manager decision is

$$\max_y \sum_i y_i v_i - \lambda_K \sum_i y_i k_i \quad (8)$$

subject to

$$\sum_i y_i c_i \leq \text{Cap}_t, \quad 11 \leq \sum_i y_i \leq 12, \quad (9)$$

$$\sum_i y_i c_i \geq \text{PayrollFloor}_t \quad (\text{when applicable}). \quad (10)$$

Additional constraints encode league mechanisms. Draft candidates are limited by picks owned; trade candidates consume an asset budget and must satisfy the salary-matching rules represented in the implementation; waiver candidates enter only when eligible; free agents require cap space. Optional depth constraints can require minimum guard/wing/post coverage.

Implementation rule. If the code uses a fast greedy heuristic, value-per-dollar v_i/c_i may be used to rank candidates, but the mathematical objective remains total roster value. The final paper should state clearly whether the exact binary problem or the heuristic is used.

6 Dynamic Quality, Brand, and Demand System

Dynamic feedback system: actions alter future states

Performance and popularity create demand; demand creates cash; cash and financing constrain future roster and growth decisions.

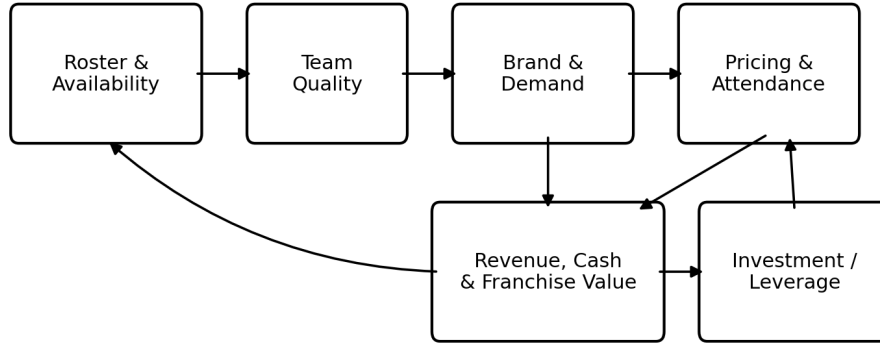


Figure 1: Revised feedback structure of the franchise decision system.

6.1 Team quality

$$Q_t = \sum_{i \in S_t} b_i a_{i,t} - \eta \text{Imbalance}(S_t), \quad (11)$$

where $a_{i,t} \in [0, 1]$ is the player availability/performance multiplier implied by the injury state. To keep demand

calibration stable, raw team quality is normalized relative to the candidate or league distribution:

$$q_t = \frac{Q_t - \mu_Q}{\sigma_Q}. \quad (12)$$

6.2 Bounded brand-demand stock

The submitted model lets brand accumulate and then places it inside an exponential attendance function. That structure can create runaway demand. We instead update a latent score and map it through a logistic function so brand remains bounded between zero and one:

$$H_{t+1} = \theta_0 + \theta_B B_t + \alpha W_t + \beta \bar{s}_t + \gamma \log\left(1 + \frac{m_t}{m_0}\right) + \chi_E E_t, \quad (13)$$

$$B_{t+1} = \frac{1}{1 + e^{-H_{t+1}}}. \quad (14)$$

W_t is the win-rate signal in the period and $\bar{s}_t$ is roster popularity adjusted for availability. Marketing therefore has diminishing returns, and a large B_t cannot explode attendance mechanically.

6.3 Attendance and ticket demand

Let N be the Fever market-size proxy and N_0 a reference market scale. For game g in period t , uncapped attendance is

$$A_{tg}^u(p) = A_0 \left(\frac{N}{N_0}\right)^\nu \exp(\xi B_t + \zeta q_t + \psi_g) \left(\frac{p}{p_0}\right)^{-\epsilon} \varepsilon_{tg}^A, \quad (15)$$

$$\text{Att}_{tg}(p) = \min\{\text{Cap}, A_{tg}^u(p)\}. \quad (16)$$

ψ_g can capture opponent/day effects if schedule data are available, and ε_{tg}^A is a mean-one stochastic demand shock. Baseline A_0 is calibrated so the reference state at price p_0 reproduces the historical average attendance target 16,560.23 rather than being chosen arbitrarily.

7 Revenue, Cash, Debt, and Franchise Value

7.1 Revenue and profit

$$R_t = \sum_{g \in G(t)} (p_{tg} + a) \text{Att}_{tg} + R_t^S, \quad (17)$$

$$R_t^S = \mu_B B_t \varepsilon_t^S, \quad (18)$$

$$\Pi_t = R_t - W_t - O_t - m_t - r_t^{(p)} D_t - K_t. \quad (19)$$

Here a is ancillary revenue per attendee, R_t^S is sponsorship/media revenue, W_t is payroll expense for the period, O_t is operating cost, K_t is transaction/acquisition cost, and $r_t^{(p)}$ is the periodized financing rate.

7.2 Financing cost and cash

$$r_t^{\text{annual}} = r_0 + r_M M_t + r_L (D_t/V_t), \quad (20)$$

$$r_t^{(p)} = (1 + r_t^{\text{annual}})^{\Delta\tau_t} - 1, \quad (21)$$

$$C_{t+1} = C_t + \Pi_t + \Delta D_t, \quad D_{t+1} = \max\{0, D_t + \Delta D_t\}. \quad (22)$$

$\Delta\tau_t$ is the fraction of a year represented by the decision period. This removes the unit inconsistency that arises when an annual 5% rate is charged once per simulation period as if every period were a full year.

7.3 Franchise value

Franchise value is no longer only a denominator in the interest-rate equation. We allow business and competitive performance to affect the terminal asset value:

$$\log V_{t+1} = \log V_t + \eta_{\Pi} \tilde{\Pi}_t + \eta_B (B_{t+1} - B_t) + \eta_Q (q_{t+1} - q_t) - \eta_D (D_t/V_t)^2. \quad (23)$$

$\tilde{\Pi}_t$ is profit scaled by a reference revenue or franchise-value level. Parameters η_{Π} , η_B , η_Q , and η_D should be treated as scenario/sensitivity parameters unless external valuation data are available for estimation.

8 Management Decision Policies

8.1 Ticket pricing

For each home game, management selects the feasible price that maximizes expected game-day contribution margin:

$$p_{tg}^* \in \arg \max_{p_{\min} \leq p \leq p_{\max}} \mathbb{E}[(p + a - c_v) \text{Att}_{tg}(p) \mid X_t]. \quad (24)$$

The grid search may still use \$5-\$250 in \$2 increments, but the model records how often the optimum hits either boundary. Frequent selection of \$249-\$250 is treated as a failed calibration signal rather than a substantive result.

8.2 Marketing and investment

Marketing is an investment decision with diminishing expected brand impact. Candidate investment levels are evaluated by their expected incremental contribution to future revenue and franchise value:

$$\text{NPV}_t(m) = \mathbb{E}_t \left[\sum_{h=0}^H \delta^h \Delta C F_{t+h}(m) + \theta \Delta V_{t+H+1}(m) \right] - m, \quad (25)$$

$$m_t^* = \arg \max_{0 \leq m \leq m_{\max}} \text{NPV}_t(m). \quad (26)$$

8.3 Leverage policy

Debt is used only when a positive-NPV approved investment or roster action cannot be financed from cash above the safety target. Define

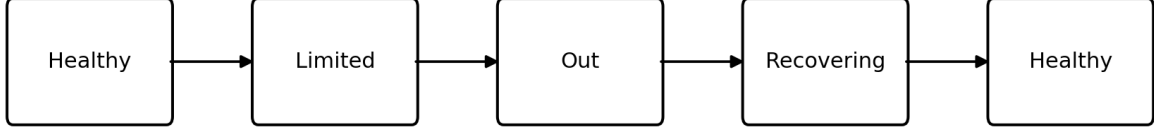
$$\text{FundingGap}_t = \max\{0, I_t^* - \max(C_t - C_{\text{target}}, 0)\}. \quad (27)$$

If $\text{NPV}(I_t^*) > 0$, macro stress is absent, and projected leverage remains below a maximum ratio, borrow up to the funding gap. If macro stress is active, cash falls below $C_{\min}$, or D_t/V_t exceeds its target, prioritize paydown. Otherwise hold debt constant. This gives borrowing an economic purpose and prevents the model from borrowing merely because liquidity is already strong.

9 Key-Player Injury Response

Injury-state process replaces a one-week mechanical shock

State-specific availability and performance multipliers feed directly into roster optimization, quality, pricing, and liquidity.



Example multipliers are parameters to calibrate, not medical probabilities.

Figure 2: Persistent injury-state process used in the revised simulation.

For a designated key player k , the state $I_{k,t}$ belongs to $\{\text{Healthy}, \text{Limited}, \text{Out}, \text{Recovering}\}$. A transition matrix P^I governs persistence and recovery. The exact probabilities must be calibrated or treated as scenario inputs.

$$a_{k,t} = m(I_{k,t}), \quad m(\text{Healthy}) = 1, \quad m(\text{Limited}) < 1, \quad m(\text{Out}) = 0, \quad m(\text{Recovering}) < 1. \quad (28)$$

When a player becomes Limited or Out, the model immediately recomputes team quality and ticket demand. If expected absence exceeds a roster threshold, waiver and free-agent candidates become eligible and the roster optimizer is rerun. The economic response is therefore explicit: injury state $\rightarrow$ availability $\rightarrow$ quality $\rightarrow$ pricing/attendance $\rightarrow$ revenue/cash $\rightarrow$ roster and financing response.

Validation requirement. In any injury scenario, the output must show a measurable decline in the injured player's contribution during the shock window. If the threshold is crossed, waiver/free-agent activation must be nonzero. A scenario that reports unchanged average quality and zero waiver activity fails this check.

10 Expansion and Location Effects

10.1 Player-market pressure and talent dilution

$$c_i^E = c_i(1 + \delta_c E_t). \quad (29)$$

Expansion can also expose roster depth through an expansion draft. Let $z_i^{\text{prot}} \in \{0, 1\}$ indicate protected players and L_t^E denote expected talent loss from unprotected players. The team-quality update becomes

$$Q_t^E = Q_t - \delta_Q L_t^E. \quad (30)$$

This separates salary inflation from actual talent dilution, which the original model combined only indirectly.

10.2 Demand substitution and league attention

$$\text{Overlap}(d) = e^{-d/\tau}, \quad (31)$$

$$H_{t+1} \leftarrow H_{t+1} + \delta_{\text{league}} E_t - \delta_{\text{sub}} \text{Overlap}(d) E_t. \quad (32)$$

The first term represents league-wide attention from expansion; the second represents local demand substitution. Distance d is the great-circle distance between Indianapolis and the expansion market. Because both effects are

uncertain, δ_{league} , δ_{sub} , and τ belong in the sensitivity analysis.

11 Simulation Implementation

The revised simulation preserves the original forward-simulation idea but changes the event order so shocks and decisions are internally consistent. For $t = 1, \dots, T$:

Step	Operation
1	Observe the current state and draw exogenous macro, demand, sponsor, cost, and injury shocks.
2	Update injury states and expansion constraints; construct the eligible player pool.
3	Solve or approximate the roster optimization under cap, size, mechanism, and depth constraints.
4	Compute raw and normalized team quality.
5	Choose marketing/investment, ticket prices, and any debt financing needed for approved investments.
6	Generate attendance, game outcomes, and sponsorship/media revenue.
7	Compute payroll, operating cost, interest, transaction cost, and profit.
8	Update cash, debt, brand stock, and franchise value.
9	Record all decisions, feasibility flags, and state variables for validation and later reporting.

Wins remain stochastic. A logistic transformation of normalized team quality can define game win probability, with realized wins sampled from a binomial distribution conditional on games played in the period. Unlike the submitted robustness check, stochasticity is not limited to wins.

12 Calibration and Internal Validation

12.1 Baseline attendance calibration

At a reference state (B_0, q_0) , reference price p_0 , and mean-one demand shock, choose A_0 so the model reproduces the Fever historical average home attendance of 16,560.23:

$$A_0 = \text{Att}_{\text{target}} \left(\frac{p_0}{p_{\text{ref}}} \right)^\epsilon \left(\frac{N_0}{N} \right)^\nu \exp(-\xi B_0 - \zeta q_0 - \psi_{\text{ref}}). \quad (33)$$

Rather than fixing $\epsilon = 1.2$ without validation, test an interpretable range (for example 1.1–2.0) and retain values that reproduce plausible price-attendance tradeoffs. ξ and ζ are calibrated or stress-tested after normalization so neither brand nor quality dominates the capacity constraint.

12.2 Required consistency checks

Check	Pass criterion
Cash identity	$C_{t+1} = C_t + \Pi_t + \Delta D_t$ exactly, up to numerical tolerance.
Debt bounds	Debt never becomes negative and never exceeds the chosen leverage ceiling.
Roster feasibility	Every selected roster satisfies cap/floor, roster size, and mechanism constraints.
Baseline demand	Average baseline attendance is close to 16,560.23 and is not at capacity in nearly every simulated game.
Price boundary	The optimal price does not repeatedly hit \$5 or \$250 unless a documented sellout/low-demand regime justifies it.
Injury response	Quality declines during the shock; waiver/FA eligibility activates when its threshold is crossed.
Macro response	Period financing cost increases under $M_t = 1$; leverage policy becomes weakly more conservative.
Expansion response	Salary pressure/talent-loss terms change only when $E_t = 1$.
Monte Carlo reconciliation	The deterministic baseline and Monte Carlo baseline mean are close when centered shocks and identical policies are used.

13 Scenario Design

We recommend at least five scenarios so each required mechanism is isolated before testing interactions.

Scenario	Primary change	Directional diagnostic
Baseline	$M_t = 0, E_t = 0$; no forced key-player injury	Calibrated attendance near the historical target; prices remain interior; cash and debt evolve under normal policy.
Macro stress	Higher financing rate and conservative debt policy	Higher interest cost; weakly lower borrowing; lower owner objective unless another effect offsets it.
Key-player injury	Persistent injury-state shock beginning in period 5	Lower quality during shock, lower willingness to pay/attendance, and possible waiver or FA activation.
Expansion	Salary inflation + talent dilution + league attention/substitution	Higher roster-cost pressure; demand effect depends on market overlap and league-attention parameters.
Combined stress	Macro stress + injury + expansion	Highest test of liquidity and downside resilience; useful for the cash-buffer recommendation.

A scenario is not considered successfully implemented merely because its label is active. The recorded state and policy outputs must confirm that its mechanism actually fired.

14 Results Reporting Architecture

Why the old totals are omitted. The submitted single-run and Monte Carlo outputs do not reconcile, and the injury scenario does not visibly trigger the intended mechanism. Carrying those values into a revised paper would create false precision. The table below is the exact structure to populate after rerunning the corrected model.

Scenario	Total profit	Final cash	Final debt	Avg price	Avg attendance	Avg quality	Waiver periods	Cash-breach prob.
Baseline	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN
Macro stress	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN
Key-player injury	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN
Expansion	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN
Combined stress	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN	RE-RUN

The final paper should replace raw dataframe screenshots with decision-oriented figures: (1) scenario profit and downside-risk comparison; (2) price versus attendance over time; (3) injury-state, team-quality, and roster-response trajectory; (4) cash and leverage paths; and (5) Monte Carlo profit distribution with the 5% tail highlighted.

15 Monte Carlo Robustness and Sensitivity Analysis

For each scenario, repeat the simulation for at least $N = 200$ trials with independent seeds. Draw uncertainty in more than weekly wins:

- game attendance/demand shock ε_{tg}^A ;
- key-player injury occurrence, severity, and recovery duration;
- sponsorship/media revenue shock ε_t^S ;
- operating-cost shock;
- macro interest-rate shock or stress duration;
- player performance around expected contribution; and
- optionally, salary inflation and expansion-demand parameters.

Report mean, standard deviation, median, 5th and 95th percentiles for profit and final cash. Risk should include

$$\Pr\left(\min_t C_t < C_{\min}\right), \quad \Pr(\Pi_{\text{season}} < 0), \quad \text{CVaR}_{5\%}(\Pi_{\text{season}}). \quad (34)$$

$\text{CVaR}_{5\%}$ is the mean outcome within the worst 5% of simulated season profits and is more informative than a bankruptcy indicator when every trial remains solvent. Perform one-at-a-time or global sensitivity analysis on $\epsilon, \xi, \zeta, r_M, \delta_c$, injury duration, and the brand/franchise-value weights. The most sensitive parameters identify where better real-world data would have the highest value.

16 Management Interpretation and Recommendations

The model is designed to recommend policies rather than a single point forecast. Conditional on validated calibration, the managerial interpretation is as follows:

- **Protect liquidity first.** Maintain a cash buffer large enough to survive combined demand, injury, and financing shocks without forcing distressed roster moves.
- **Use debt as project financing, not as a mechanical reward for strong cash.** Borrow only when the expected incremental value of an approved investment exceeds financing and risk costs.
- **Value roster flexibility.** A star can create both quality and demand, but injury-state persistence makes depth and waiver/free-agent access economically valuable.
- **Price to the state of demand.** Strong quality and brand justify higher prices only if the calibrated demand curve still predicts plausible attendance; hitting the price ceiling is a calibration warning.
- **Prepare for expansion before it arrives.** Protect high-value players, preserve cap flexibility, and distinguish league-wide demand growth from local market cannibalization.
- **Use Monte Carlo downside metrics to choose policy thresholds.** The cash target and leverage ceiling should be based on tail risk, not only average profit.

17 Strengths, Limitations, and Future Work

17.1 Strengths

- The system is genuinely dynamic: states evolve and policies map states to decisions each period.
- Business and basketball decisions are linked through explicit feedback loops.
- The revised owner objective aligns short-run profit, competitive viability, liquidity, leverage risk, and long-run franchise value.
- Roster, pricing, expansion, and injury mechanisms are represented explicitly rather than only discussed qualitatively.
- Validation criteria make it possible to detect inactive scenarios and unstable calibrations before interpreting results.

17.2 Limitations

- The player performance index is transparent but not a causal or possession-adjusted measure of player impact.
- Games missed measure overall unavailability rather than medical injury probability unless the dataset is enriched.
- Social-media followers are an imperfect popularity proxy and may be endogenous to team success.
- Ticket prices, sponsorship revenue, operating costs, and franchise-value parameters require stronger empirical calibration for real-world deployment.
- League salary rules, trade matching, contract guarantees, and expansion-draft rules are simplified unless encoded directly from the governing CBA.
- The revised numerical scenario results require the original workbook/code to be rerun; this draft intentionally does not invent replacement values.

17.3 Future work

With richer data, the model can estimate demand elasticities from game-level ticket prices and attendance; replace box-score scoring with possession-adjusted impact metrics; estimate injury transitions from historical availability; use opponent and schedule effects; calibrate sponsorship and franchise value to observed business data; and solve the full finite-horizon stochastic control problem rather than applying separate policies sequentially.

Letter to Owner and General Manager

To: Indiana Fever Ownership and General Manager
From: Team 2633018
Subject: Dynamic policy for roster, pricing, leverage, expansion, and injury response

Dear Owner and General Manager,

We developed a state-based decision system for managing the Indiana Fever as both a basketball team and a long-run business asset. Each decision period, the model observes competitive quality, brand demand, cash, debt, franchise value, economic conditions, expansion status, and player availability. It then updates roster actions, ticket prices, marketing investment, and financing decisions.

Our first recommendation is to protect liquidity. Debt should not increase simply because cash is strong; it should finance a specific roster or growth investment whose expected value exceeds its financing and distress costs. During macro stress or when cash approaches its safety threshold, the model shifts toward deleveraging and preserves flexibility.

Our second recommendation is to value players on total expected contribution under league constraints. The roster optimizer combines standardized on-court performance, popularity, and availability risk, then enforces the salary cap, roster size, and acquisition-mechanism rules. This makes depth particularly valuable when a key player becomes Limited or Out, because the model can immediately open waiver or free-agent alternatives and re-optimize.

Third, ticket prices should come from a calibrated demand curve. Quality and brand can move willingness to pay, but the model is anchored to historical Fever attendance and market size, so price increases are accepted only when predicted attendance remains plausible. A repeated recommendation at the maximum price is treated as a calibration failure rather than a business conclusion.

Finally, expansion requires two separate responses: protecting roster value from salary pressure and talent dilution, and adapting demand strategy to the balance between league-wide attention and local market substitution. We recommend preserving cap and cash flexibility before expansion so the team is not forced into expensive reactive moves.

The most important managerial output is therefore not one projected profit number. It is a set of contingent rules that explain what the team should do when the state changes, together with Monte Carlo downside metrics showing how much liquidity is needed when several shocks occur at once.

Sincerely,
Team 2633018

References

- [1] COMAP. (2026). *ICM Problem Statement (Sports Business)*. <https://www.comap.org/>
- [2] Her Hoop Stats. (2025). *Indiana Fever WNBA salary cap sheet*. <https://herhoopstats.com/salary-cap-sheet/wnba/team/2025/indiana-fever-11eaecc7-3565-c004-b611-2362f5011b0b/>
- [3] Across the Timeline. (2024). *WNBA attendance*. <https://www.acrossthetimeline.com/wnba/attendance.html>
- [4] Wikipedia contributors. (2025, December 4). *2025 Indiana Fever season*. https://en.wikipedia.org/wiki/2025_Indiana_Fever_season
- [5] ESPN. (2025). *Indiana Fever 2025 WNBA postseason statistics*. https://www.espn.com/wnba/team/stats/_/name/ind/indiana-fever

Source note. References above are carried forward from the uploaded submission. Verify dates, URLs, and the current COMAP AI-use/disclosure requirements before submitting a final competition paper.

Appendix A. Rerun Checklist for the Final Submission

Priority Required action before replacing this draft	
1	Run the corrected model from the original workbook/code and export period-level outputs for all five scenarios.

- 2 Verify the injury scenario reduces player contribution and team quality and activates waivers/free agency when the threshold is crossed.
 - 3 Recalibrate normalized demand so baseline attendance is near 16,560.23 and the price optimum is not pinned to \$250.
 - 4 Reconcile deterministic and Monte Carlo baseline results; confirm the same policies, parameters, and starting state are used.
 - 5 Convert annual interest rates to period rates and verify interest-expense units.
 - 6 Confirm every roster is feasible under cap, payroll floor if used, roster size, and mechanism constraints.
 - 7 Run at least 200 Monte Carlo trials per scenario with multi-source uncertainty and calculate cash-breach probability and CVaR.
 - 8 Replace the RE-RUN table with final results and add decision-oriented figures; move raw dataframes to an appendix.
 - 9 Update the Summary Sheet with 3–5 numerical findings only after all consistency checks pass.
 - 10 Verify every source and comply with current competition disclosure rules for computational and AI tools.
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