Optimizing football squad selection: A multi-objective approach to transfer strategy under budget constraints

(DS Area Brown Bag Series)

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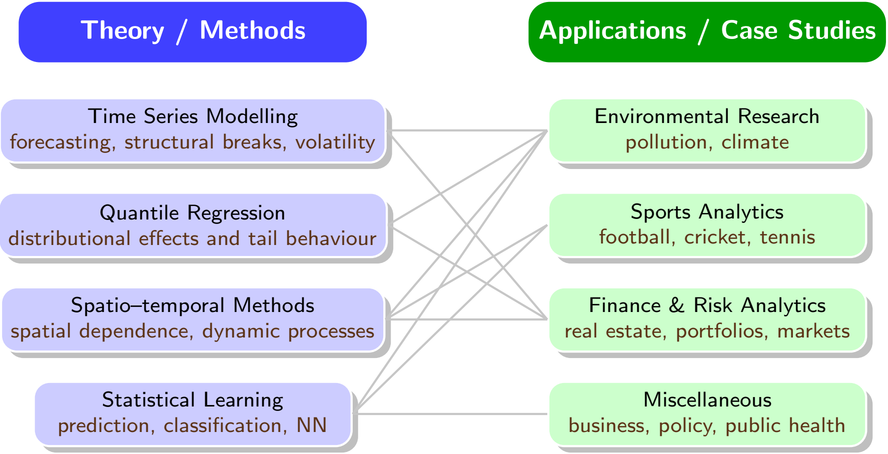
June 19, 2026

Research Overview



Outline of today's talk

1. Motivation
2. Methodology Overview
3. Modeling player ratings
4. Modeling transfer fees
5. Optimization Framework
6. Competitive bidding strategy
7. Concluding remarks

Collaborators

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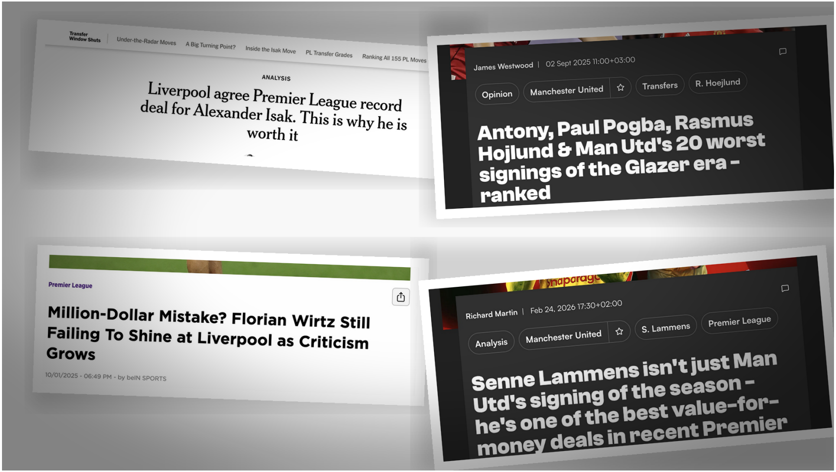
Outline

It’s always on the news



Introduction and motivation

- Football transfers are high-stakes, time-bound, and uncertain decisions: clubs buy and sell players to reshape squads.
- The transfer market is not only a pricing task; it is a decision problem:
  - predict future contribution (sporting value),
  - predict transfer fees (financial cost),
  - optimize squad composition under constraints.
- Player mobility is high across Europe: average tenure at a club is roughly 1.87–2.56 years.

Auctions, drafts, and transfers

Auctions

- Centralized bidding.
- Budget and time constraints.
- Requires dynamic valuation and strategy.

Drafts

- Sequential allocation
- Requires dynamic planning.
- Multi-stage decision structure.

Transfers (our focus)

- Decentralized negotiations and clauses.
- Multiple objectives: performance, cost, risk.
- Competition can arise simultaneously for the same target player.

What the literature has done

- **Player valuation and fee prediction:** regression, multilevel models, and ML using player traits and performance; some benchmark against crowd valuations. (Müller et al, 2017; Franceschi et al., 2024)
- **Economic view of fees:** bargaining and surplus-sharing perspectives that explain why observed fees may differ from productivity measures.(Carmichael et al., 1999; Campa, 2022)
- **Investment and uncertainty:** recent work frames transfers as risky projects with uncertain sporting and financial returns. (Tunaru et al., 2005; Follert & Gleißner, 2024)

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- **Investment and uncertainty:** recent work frames transfers as risky projects with uncertain sporting and financial returns. (Tunaru et al., 2005; Follert & Gleißner, 2024)
- **Research gap:** studies focus on valuation accuracy for individuals; fewer provide an integrated, constraint-aware decision model.

How this paper contributes

1. Two predictive models grounded in club/league structure
   - next-season rating forecast using linear mixed effects,
   - transfer fee forecast using linear mixed effects on log(fee).
2. A multi-objective optimization framework
   - jointly balances quality, expected cost, and risk,
   - chance constraint for budget feasibility,
   - operational constraints: squad size, positional composition, retention, profit, transfer-count.
3. Competitive layer (extension)
   - embeds optimal transfer decisions in an independent private-value bidding setting with reserve to reason about contested targets.

Outline

Workflow

- **Step 1: rating model.** Forecast $\hat{R}_{ic_0,s+1}$ for all candidate players (counterfactual rating at the focal club c_0).
- **Step 2: fee model.** Forecast $\widehat{Y}_{i,c \to c_0,s}$ for buying targets and the expected selling prices for current-squad players.
- **Step 3: optimization.** Choose $x_i \in \{0, 1\}$ (buy/sell decisions) to maximize quality while controlling expected cost and risk, subject to budget and squad constraints.
- **By-product:** Under optimal recommendations, analyze competitive bidding strategy

Key notations

- Teams $\mathcal{C}$, focal team $c_0 \in \mathcal{C}$; players indexed by $i \in [N]$.
- Decision variable $x_i \in \{0, 1\}$ indicates whether player i is selected in the proposed squad.
- Ratings: $R_{ics} \in \mathbb{R}$ for player i, club c, season s.
- Transfer fee for move $c \to c'$ after season s: $Y_{i,c \to c',s}$.
- Log-fee: $Z_{i,c \to c',s} = \log Y_{i,c \to c',s}$.

Dataset

- Extracted from `WhoScored` and `Transfermarkt`
- Data used span a decade: the seasons 2009/10 to 2019/20
- 20403 players from 500 clubs playing in the leagues of 17 different countries from four continents

Outline

Modeling player value via ratings

- Goal: forecast counterfactual rating if player i joins c_0 in season $s+1$.
- Linear mixed-effects structure:

$$R_{ics} = \mu_{ics} + u_{(c_{s-1} \to c_s)} + u^{\text{cur}}_{\ell(c_s)} + u^{\text{last}}_{\ell(c_{s-1})} + \varepsilon_{ics}.$$

- Fixed effects in μ_{ics} include: age (quadratic), anthropometrics, position, last-season rating, team context, position-group strength/depth, transfer history, same-team, same-nationality.
- Random effects: origin–destination corridor, current league, last league.

Out-of-sample rating prediction for the focal club

- For candidate player i at club c_0 in season $s+1$, form features $\boldsymbol{x}_{ic_0,s+1}$ using information at end of season s:

$$\hat{R}_{ic_0,s+1} = \boldsymbol{x}_{ic_0,s+1}^{\top}\hat{\boldsymbol{\beta}} + \hat{u}_{(c_s \to c_0)} + \hat{u}_{\ell(c_0)}^{\mathrm{cur}} + \hat{u}_{\ell(c_s)}^{\mathrm{last}}.$$

- If corridor $(c_s \to c_0)$ is unobserved, we shall set $\hat{u}_{(c_s \to c_0)} = 0$ (marginal forecast).
- These $\hat{R}_{ic_0,s+1}$ are the inputs for squad optimization.

Key insights

- **Age profile is nonlinear**: ratings exhibit diminishing returns, supporting a prime-age focus in transfer planning.
- **Strong persistence**: last season's rating is the dominant predictor.
- **Context matters**: higher team quality and positional strength are strongly associated with higher individual ratings, reinforcing the need for squad-level (not player-by-player) optimization.
- **Depth has benefits**: team depth is positively associated with ratings, motivating position-specific constraints in the optimizer.
- **Mobility penalty signal**: more prior transfers are associated with slightly lower subsequent ratings, suggesting adaptation/instability costs that the optimization can treat as an additional risk.

Results

Type of feature	Variable	Estimate	Standard error	t-score	p-value
General	Intercept	-2.828^{***}	0.140	-20.135	0.000
Player's information	Age (scaled)	0.570^{***}	0.038	15.127	0.000
	Age squared (scaled)	-0.106^{***}	0.007	-15.121	0.000
	Position (defender)	-0.009	0.009	-1.013	0.311
	Position (midfielder)	0.015	0.009	1.655	0.098
	Position (forward)	0.035^{***}	0.007	4.738	0.000
	Height	0.024	0.018	1.297	0.195
	Weight	0.002^{***}	0.000	7.753	0.000
	Last season's rating	0.303^{***}	0.005	65.004	0.000
	Number of times transferred	-0.004^{**}	0.001	-2.867	0.004
	If same team as last season	-0.003	0.003	-0.738	0.461
	Playing in the birth country	-0.007^{*}	0.003	-2.105	0.035
Team's information	Overall quality	0.257^{***}	0.021	12.151	0.000
	Quality in same position	0.723^{***}	0.011	67.059	0.000
	#players in same position	0.004^{***}	0.001	5.393	0.000

Outline

Transfer fee model I

- Transfer fees are strictly positive.
- Heavy right tail in empirical data.
- Linear structure becomes tractable on log scale.
- Define the key response variable as

$$Z_{i,c \to c',s} = \log Y_{i,c \to c',s}$$

Transfer fee model II

- Linear mixed effects with buyer/seller heterogeneity:

$$Z_{i,c \to c',s} = \nu_{i,c \to c',s} + b_{c'}^{\text{buy}} + b_{c}^{\text{sell}} + \epsilon_{i,c \to c',s}.$$

- $\nu_{i,c \to c',s}$ includes player characteristics, recent performance, career rating, and market/team context.
- Random intercepts capture systematic mark-ups and discounts by buying and selling clubs.
- A similar framework was adopted by McHale & Holmes (2023).

Transfer fee model: mean structure

Mean term $\nu_{i,c\to c',s}$ is additive in:

- **market trend:** t_s (captures inflation in fees),
- **biographical:** age (quadratic), height, weight, position,
- **quality:** career rating CR_{is} and most recent rating R_{ics},
- **recent performance:** matches, goals, assists, shots, passing accuracy, cards, clearances, interceptions,
- **market context:** club depth and club strength, purchasing and selling patterns of the buyer and the seller league.

Transfer fee model: buyer and seller heterogeneity

- Buyer and seller clubs exhibit persistent, unobserved effects:
  - some clubs systematically pay premiums,
  - some clubs systematically extract higher prices as sellers.
- We capture this via random intercepts:

$$b_{c'}^{\mathrm{buy}} \sim \mathcal{N}(0, \sigma_{\mathrm{buy}}^2), \qquad b_c^{\mathrm{sell}} \sim \mathcal{N}(0, \sigma_{\mathrm{sell}}^2), \qquad \epsilon_{i,c\to c',s} \sim \mathcal{N}(0, \tau^2).$$

- Interpretation:
  - $b_{c'}^{\mathrm{buy}} > 0$: buyer c' tends to overpay relative to observables,
  - $b_c^{\mathrm{sell}} > 0$: seller c tends to command higher fees.

Transfer fee prediction for planning

- For a prospective move $c \to c_0$, form the feature vector $\boldsymbol{w}_{i,c\to c_0,s}$.
- Predicted log-fee:

$$\widehat{Z}_{i,c\to c_0,s} = \boldsymbol{w}_{i,c\to c_0,s}^{\top}\hat{\boldsymbol{\theta}} + \hat{b}_{c_0}^{\text{buy}} + \hat{b}_{c}^{\text{sell}}.$$

- If buyer or seller has no support in training data, set the corresponding random effect to 0 (marginal forecast).
- To obtain a fee on the original scale:
  - baseline point forecast: $\widehat{Y}_{i,c\to c_0,s} = \exp(\widehat{Z}_{i,c\to c_0,s})$,
  - log-normal mean correction (if desired): $\widehat{\mathbb{E}}(Y) = \exp(\widehat{Z} + \frac{1}{2}\hat{\tau}^2)$.
- These predicted fees feed directly into the optimization.

Key insights

- **Market inflation is real**: positive time trend captures systematic fee growth over seasons, so planning needs an inflation adjustment.
- **Lifecycle pricing is concave**: age enters nonlinearly, implying peak pricing around prime years and depreciation thereafter.
- **Roles are different submarkets**: forwards (and to a lesser extent midfielders) command a premium.
- **Long-run quality anchors prices**: career rating is a strong driver of fees, while short-run performance signals refine pricing at the margin.
- **Context calibrates cross-league deals**: league-specific effects shift price levels materially, which is essential when comparing targets across leagues in the squad optimization.

Results I

Type of feature	Variable	Estimate	Standard error	t-score	p-value
General	Intercept	-17.552^{***}	2.156	-8.140	0.000
	Linear trend	0.064^{***}	0.012	5.340	0.000
Player's overall characteristics	Age (scaled)	2.361^{**}	0.743	3.178	0.002
	Age squared (scaled)	-0.668^{***}	0.150	-4.459	0.000
	Position (defender)	-0.323	0.198	-1.635	0.102
	Position (midfielder)	-0.143	0.197	-0.726	0.468
	Position (forward)	0.089	0.167	0.533	0.594
	Height	1.692^{**}	0.520	3.251	0.001
	Weight	0.001	0.004	0.181	0.857
	Career rating	1.601^{***}	0.129	12.392	0.000

Results II

Type of feature	Variable	Estimate	Standard error	t-score	p-value
Player's performance in last season	Rating	-0.373^{**}	0.136	−2.745	0.006
	Game-time	0.018^{***}	0.003	6.036	0.000
	Goals	0.399	0.342	1.166	0.244
	Goal contributions	0.270	0.266	1.015	0.310
	Penalty accuracy	−0.461	0.699	−0.659	0.510
	Shots	0.169^{***}	0.043	3.894	0.000
	Passing accuracy	0.023^{***}	0.005	4.216	0.000
	Cards	0.108	0.156	0.692	0.489
	Clearance	−0.006	0.020	−0.303	0.762
	Interception	−0.061	0.043	−1.401	0.161

Results III

Type of feature	Variable	Estimate	Standard error	t-score	p-value
Leagues and teams in last season	Median selling price (seller league)	0.169***	0.019	8.966	0.000
	Median buying price (buyer league)	0.056***	0.010	5.665	0.000
	#players in same position (seller)	−0.007	0.014	−0.522	0.602
	#players in same position (buyer)	−0.003	0.012	−0.219	0.827
	Quality in same position (seller)	−0.127	0.198	−0.644	0.520
	Quality in same position (buyer)	0.140	0.197	0.712	0.477
	Overall quality (seller)	0.748*	0.302	2.474	0.013
	Overall quality (buyer)	−0.184	0.198	−0.932	0.351

Outline

Optimization: objective and decision variables

- **Decision**: $x_i \in \{0,1\}$ selects the proposed squad from $\mathcal{P}$.
- **Inputs**: predicted rating R_i and predicted fee Y_i.
- Consider the following key terms:

$$\text{cost} = \sum_{i \in \mathcal{P} \setminus \mathcal{P}_{c_0}} x_i \, \mathbb{E}(Y_i) + \sum_{i \in \mathcal{P}_{c_0}} (1 - x_i) \big(\mathbb{E}(Y_i) - r_i \big),$$

$$\text{risk} = \sqrt{\sum_{i \in \mathcal{P} \setminus \mathcal{P}_{c_0}} x_i \, \mathrm{Var}\,(Y_i)}, \; \text{quality} = \sum_{i \in \mathcal{P}} x_i R_i.$$

- We focus on the objective

$$\mathcal{F} = -\big(\lambda_1 \, \text{cost} + \lambda_2 \, \text{risk}\big) + \lambda_3 \, \text{quality}.$$

Budget feasibility via chance constraint

- Total spend must stay within transfer budget $B_{\max}$ with high confidence:

$$\Pr\left(\sum_{i\in\mathcal{P}\setminus\mathcal{P}_{c_0}} x_i Y_i \leqslant B_{\max}\right) \geqslant 1-\alpha.$$

- Deterministic approximation used in the solver:

$$\mathbb{E}\left(\sum_{i\in\mathcal{P}\setminus\mathcal{P}_{c_0}} x_i Y_i\right) + z_\alpha \sqrt{\mathrm{Var}\left(\sum_{i\in\mathcal{P}\setminus\mathcal{P}_{c_0}} x_i Y_i\right)} \leqslant B_{\max}.$$

- Additional constraints: squad size, position minima/maxima, retention, profit, transfer-count, exposure constraints.

Constraints in practice

Squad and sporting constraints

- total squad size $\leqslant \overline{k_{\text{tot}}}$
- position-wise minimum
- maximum number of GK
- retain $\geqslant \underline{k_{\text{retain}}}$ current players
- average age does not increase
- average rating does not decrease

Financial and market constraints

- chance constraint on total spend
- max no of transfers $\leqslant \overline{k_{\text{transfer}}}$
- min profit from sales $\geqslant \underline{\text{profit}}$
- brand exposure constraints
- optional rules: must-buy / must-sell / no-sale list

Solving the constrained optimization

Fitness function:

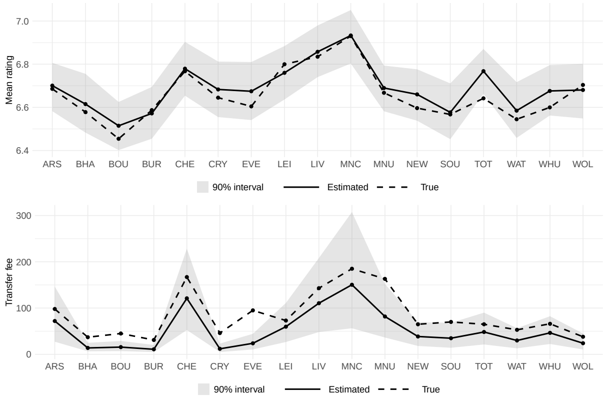
$$\mathcal{F}_\beta(x) = \Big[- \big(\lambda_1 \,\mathrm{cost} + \lambda_2 \,\mathrm{risk}\big) + \lambda_3 \,\mathrm{quality} \Big] - \beta \sum_{k=1}^{K} \mathsf{max}(0, \mathrm{Constraint}_k),$$

- We use a genetic-algorithm solver with a penalty formulation.
- K equals the number of constraints.
- $\beta \gg 0$ discourages infeasible solutions
- Outputs: the algorithm provides recommended squad, buy list, sell list, and implied cost/risk profile.

Key insights from the algorithm output

- Improved (but not significantly) predicted squad ratings for all but two clubs under consideration.
- Budget-respecting transfer portfolios.
- Identifies:
  - undervalued targets
  - overvalued sell candidates
- Demonstrates portfolio-level decision advantage.

Results: summary



Observed (dashed) versus estimated (solid) club-level means for player ratings (top) and average transfer fees (bottom), with shaded 90% uncertainty bands around the estimated means.

Results: high-valued transfers I

Comparison of recommended (according to our approach, after the 2018/19 season) and recorded transfers for players valued above €20 million who were actually sold.

Team	Player	Position	Expected Price	IQR	Actual Price	Rating
Panel A: Recommended and sold						
Chelsea	Eden Hazard	Forward	208	[58, 243]	121	7.68
Crystal Palace	Aaron Wan-Bissaka	Defender	24	[7, 28]	55	7.52
Leicester City	Harry Maguire	Defender	54	[15, 63]	87	7.08
Manchester City	Fabian Delph	Midfielder	29	[8, 34]	10	7.16
Manchester United	Romelu Lukaku	Forward	80	[22, 93]	74	7.29
Manchester United	Chris Smalling	Defender	31	[9, 36]	Loan	7.24
Southampton	Mario Lemina	Midfielder	32	[9, 38]	Loan	6.93
Tottenham Hotspur	Kieran Trippier	Defender	44	[12, 51]	22	7.04
West Ham United	Andy Carroll	Forward	26	[7, 30]	Free	6.69

Results: high-valued transfers II

Comparison of recommended (according to our approach) and recorded transfers for players valued above €20 million who were not sold in that year. The year in the parentheses indicates when the player was eventually transferred, 'Free': free agent.

Team	Player	Position	Expected Price	IQR	Actual Price	Rating
			Panel B: Recommended but not sold			
Liverpool	Sadio Mane	Forward	76	[21, 89]	32 (2022)	7.27
Liverpool	Andrew Robertson	Defender	28	[8, 32]	Free (2026)	7.02
Liverpool	Jordan Henderson	Midfielder	23	[7, 27]	14 (2023)	6.95
Manchester City	Bernardo Silva	Midfielder	59	[16, 69]	Free (2026)	6.79
Manchester City	Riyad Mahrez	Forward	53	[15, 61]	35 (2023)	7.28
Southampton	Pierre Emile Hojbjerg	Midfielder	27	[7, 31]	17 (2020)	6.61

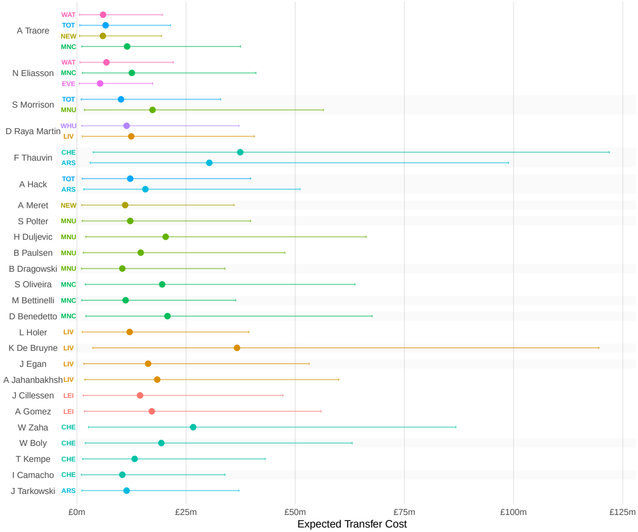
Results: high-valued transfers III

Comparison of expected and recorded transfer fees for players not recommended but sold in 2019. 'Free': free agent, 'Loan': loaned out.

Team	Player	Position	Expected Price	IQR	Actual Price	Rating
Panel C: Not recommended but sold						
Arsenal	Alex Iwobi	Midfielder	24	[7, 28]	30	6.88
Arsenal	Aaron Ramsey	Midfielder	20	[6, 24]	Free	7.27
Chelsea	David Luiz	Defender	43	[12, 50]	9	6.85
Liverpool	Daniel Sturridge	Forward	30	[8, 34]	Free	6.76
Manchester City	Danilo	Defender	74	[21, 86]	37	6.91
Manchester United	Alexis Sanchez	Forward	49	[14, 58]	Loan	7.55
Manchester United	Ander Herrera	Midfielder	35	[10, 40]	Free	6.60
Manchester United	Marouane Fellaini	Midfielder	28	[8, 33]	7	6.94
Newcastle United	Ayoze Perez	Forward	26	[7, 30]	33	6.74
Southampton	Charlie Austin	Forward	25	[7, 29]	4	6.53
Southampton	Matt Targett	Defender	24	[7, 28]	16	6.96
Tottenham Hotspur	Mousa Dembele	Midfielder	28	[8, 33]	5	6.90
West Ham United	Marko Arnautovic	Forward	32	[9, 37]	25	7.07

Outline

Players with (recommended) multiple bidders



Scope and motivation I

- In many transfers, multiple clubs target the same player, so the final fee reflects strategic competition, not just predicted market value.
- Clubs have asymmetric willingness-to-pay (financial strength, sporting objectives), motivating an asymmetric first-price auction framework.
- Sellers may reject the highest bid due to uncertainty and negotiation, so we model a random reserve price and allow a no-sale outcome.
- Football-specific frictions matter: inter-club relationships may affect deals, captured through a bid-dependent acceptance function.

Scope and motivation II

- Goal: translate **contested target** situations into an equilibrium-based tool for expected price, win probability, and negotiation dynamics.
- We take inspirations from the works of Lebrun (1999); Li & Perrigne (2003); Kotowski (2018).

Bidding setting for a contested target

- When multiple clubs target the same player, fees reflect strategic bidding and asymmetric budgets.
- Model the situation as an asymmetric first-price auction with independent private valuations:

$$\log S_c \sim \mathcal{N}(\mu_c, \sigma_c^2), \qquad c \in \mathcal{C}^i.$$

- Each club uses an increasing bid function $b = \kappa_c(s)$ (inverse $\psi_c = \kappa_c^{-1}$).
- Goal: characterize equilibrium bids and translate them into win probabilities and expected fees for planning.

Seller behaviour: random reserve and affinity

- Seller uncertainty is captured via a random reserve price:

$$\log \rho \sim \mathcal{N}(\mu_{c_0}, \sigma^2_{c_0}), \qquad H(b) = \Pr(\rho \leqslant b).$$

- Club-specific deal frictions are captured via bid-dependent acceptance $p_c(b) \in [0, 1]$.
- Buyout clause is modelled by truncation at υ_{thresh}:

$$\hat{H}(b) = \min\left\{\frac{H(b)}{H(\upsilon_{\text{thresh}})}, 1\right\}, \qquad \hat{p}_c(b) = \min\left\{\frac{p_c(b)}{p_c(\upsilon_{\text{thresh}})}, 1\right\}.$$

- This admits no-sale outcomes and captures rivalry/relationship effects.

Equilibrium characterization (main result)

- Probability that club c outbids rivals at bid b:

$$G_c(b) = \prod_{j \neq c} F_j(\psi_j(b)).$$

- Probability of a completed sale to club c at bid b:

$$q_c(b) = \hat{p}_c(b)\hat{H}(b)G_c(b).$$

- Expected utility for valuation s:

$$U_c(b; s) = (s - b)\, q_c(b).$$

- Bayes–Nash equilibrium yields an FOC and an ODE system for $\psi_c(b)$, enabling numerical solution of bidding strategies under asymmetry, random reserve, and affinity.

Theoretical results

Proposition 1

Suppose $p_c(\cdot)$ and $\psi_c(\cdot)$ are continuously differentiable function on $(0, \upsilon_{\text{thresh}}]$. Then, in an interior pure-strategy equilibrium under risk neutrality,

$$\frac{1}{s-b} = \frac{p_c'(b)}{p_c(b)} + \frac{h(b)}{H(b)} + \sum_{j \neq c} \frac{f_j(\psi_j(b))}{F_j(\psi_j(b))} \psi_j'(b).$$

Proposition 2

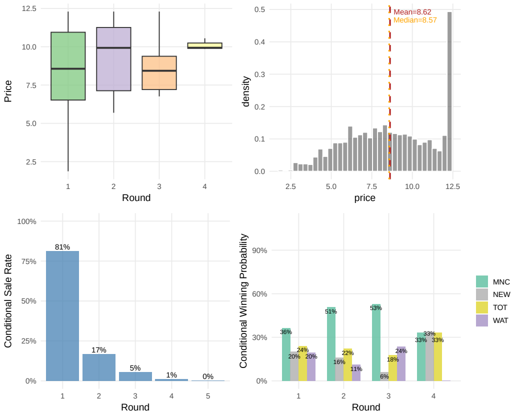
Suppose $p(\cdot)$ and $\psi_c(\cdot)$ are continuously differentiable in the interval $[b_{\min}, \upsilon_{\text{thresh}}]$ with $p(b), \psi_c(b) > 0$. Then, we get the following system of ODEs, for all c,

$$\psi_c'(b) = \frac{1}{(C-1)} \frac{F_c(\psi_c(b))}{f_c(\psi_c(b))} \left[\sum_{j \neq c} \left(\frac{1}{\psi_j(b) - b} - \frac{p_j'(b)}{p_j(b)} \right) \right. \\ \left. - (C-2) \left(\frac{1}{\psi_c(b) - b} - \frac{p_c'(b)}{p_c(b)} \right) - \frac{h(b)}{H(b)} \right].$$

Extension: Bidding in multiple rounds

- Negotiation is modeled as a multiple-round game with the possibility of no-sale.
- In each round, clubs bid, the seller observes the highest bid, then accepts or rejects.
- A rejection updates beliefs about the reserve price, so later rounds become more competitive.
- Buyers update participation by truncating to types that could bid above the last rejected maximum.
- Each round produces an updated equilibrium (solved numerically) with a small bid-gap for stability.

Case study of Adama Traore



(top-left) round-wise price distribution; (top-right) overall price distribution; (bottom-left) round-wise conditional sale rates; (bottom-right) round-wise win % for different teams

Outline

Key takeaways

- A transfer window can be planned as a multi-objective decision problem: quality, expected cost, and risk.
- Mixed-effects models give club- and league-aware forecasts for both ratings and fees.
- The optimization layer converts forecasts into actionable buy/sell recommendations under realistic constraints.
- Competitive pressure for contested targets can be incorporated to refine expected cost and success probability.

Future scope

- Add richer uncertainty: injuries, minutes forecasts, and scenario-based budget stress tests.
- Extend constraints: wages, amortization, registration rules, and multi-window planning.
- Improve price modeling with contract details and deal structure (add-ons, sell-on clauses).
- Calibrate the bidding layer using observed rival interest and seller affinity signals.
- Explore similar framework under the auction mechanism, and work with IPL data.

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Thank you for listening.

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Personal Webpage

Pre-print of the paper

TQRCG

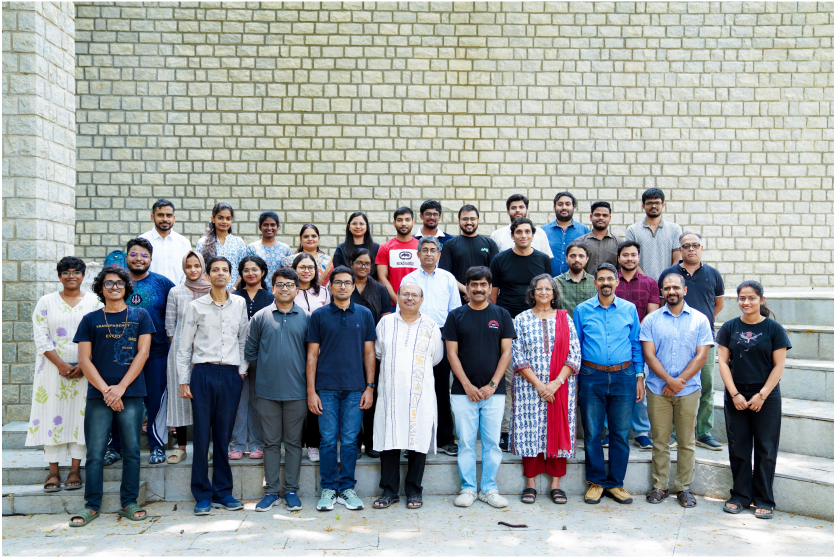
For people starting their research journey

What to know, do, and remember

From coursework to research thinking

Build habits early. Read deeply. Write regularly.

First question: can you identify everyone in this picture?



Understand the PhD Journey

A PhD is not just a longer degree

It is training in how to ask meaningful questions, evaluate evidence, and produce original knowledge.

First-year focus

- Learn the literature
- Explore possible questions
- Build methodological foundations

Do not rush

The goal is not a perfect topic immediately, but better research judgement.

Read, Organise, and Think

Read in layers

Keep a reading log

Identify gaps

- Do not try to understand every paper line by line at first.
- Track: question, data, method, contribution, limitation.
- Ask: what is known, what is missing, what can be improved?

Work Like a Researcher

Meetings

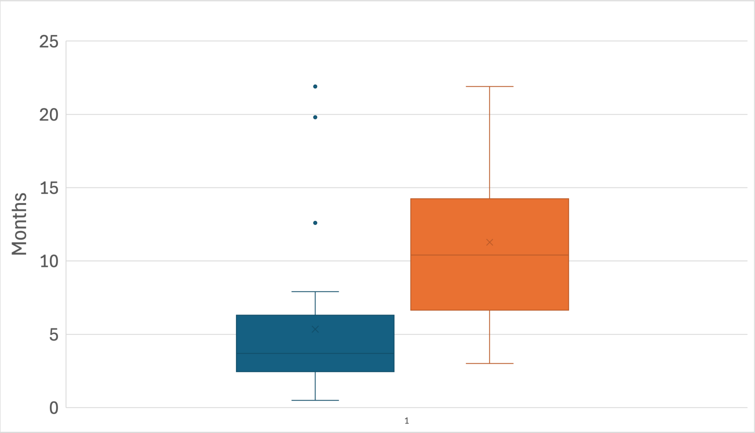
- Send short updates before meetings
- Bring specific questions
- Record action points after meetings

Research habits

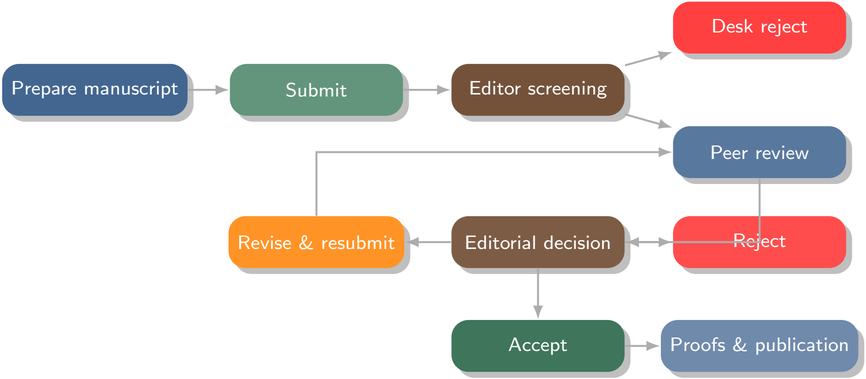
- Use reference managers
- Organise files clearly
- Back up work
- Learn Git / LaTeX early
- Maintain online presenece, Network well

Good systems reduce future stress.

Final question: can you identify what is represented here?



How a Paper Publication Works



Revision is normal. Rejection is common. Peer review improves the paper.

Write Early, Stay Ethical, Stay Well

Write

Start with notes, summaries, critiques, and proposal drafts.

Be ethical

Cite properly, use data responsibly, and be transparent.

Stay well

Progress is uneven. Seek help early and keep routines.

Final message

Enjoy the journey from consuming knowledge to producing knowledge.