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IntelliSeat: An AI-Powered Smart Workspace Allocation System

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Abstract - The rise of hybrid workplaces and flexible academic environments has made efficient space allocation a critical operational challenge Existing booking systems are reactive, first-come-first-served and not smart enough to suggest suitable seats, predict peak demand or equitably arbitrate competing booking requests. In this paper, we introduce IntelliSeat, a full-stack web application platform for intelligent workspace allocation that integrates personalized recommendation, occupancy forecasting and global seat-assignment optimization. The system recommends seats for workspaces based on the user's preferences and the proximity of the team through content-based and collaborative filtering. We employ a Random Forest regression model trained over past booking time stamps to forecast occupancy trends over the coming time slots, assisting administrators in proactive capacity planning. Moreover, during high-contention request periods, the Hungarian Algorithm is incorporated to formulate seat distribution as a linear assignment problem to ensure mathematically optimal and equitable seat allocation across competing requests instead of greedy first-come processing. IntelliSeat marries traditional booking mechanics with data-driven decision support. Experimental results demonstrate that the integration of personalized recommendations, predictive analytics and combinatorial optimization on top of the standard desk management solution greatly improves the fairness of allocations, the manual search time of users, and provides actionable and data-backed insights for long-term spatial resource management.

Keywords: Smart Workspace Allocation, Hungarian Algorithm, Machine Learning, Collaborative Filtering, Resource Optimization

`1. INTRODUCTION

The shift toward hybrid workplaces and flexible academic environments has changed how shared spaces are used. Seats, desks and workstations are no longer permanently assigned. They are shared resources whose demand changes by the hour, the day and the team. Managing them well is now a real operational challenge: poor allocation leaves some areas overcrowded while others sit idle, and it wastes users' time and frustrates teams that need to sit together. Most existing desk-booking systems are reactive. They work on a first-come-first-served basis, so they cannot suggest a suitable seat, anticipate peak demand, or fairly resolve competing requests for the same resource. Users must search manually, and administrators plan capacity without data-backed foresight.

To address these gaps, this paper presents IntelliSeat, a full-stack web platform for intelligent workspace allocation. It combines three components in one decision-support pipeline:

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1.Personalized seat recommendation using content-based and collaborative filtering, based on user preferences and team proximity.
2. Predicting occupancy: A Random Forest regression model is built using historical booking timestamps to enable proactive planning of capacity.

3. Hungarian Algorithm for Optimal seat allocation, Model high contention times allocation as linear assignment problem. This gives mathematically optimal and fair outcomes rather than greedy first-come processing.

2. LITERATURE REVIEW

Recent research applies AI, mainly reinforcement learning (RL), to resource allocation, but little of it targets individual workspaces. Most studies address cloud or enterprise resources: Agrawal and Agarwal [1] combine multi-agent PPO with a GA-ACO refinement for workforce scheduling, reporting 98.76% scheduling accuracy in simulation; Belgacem et al. [2], Bhoyar [3] and Laura [8] apply multi-agent Q-learning, ML and hybrid DQN/PPO to cloud allocation; and Heik et al. [7], Li and Zhang [9], Srivastava et al. [15], Seshagiri [14] and Prasanna et al. [13] extend similar methods to manufacturing, construction, warehouses, smart cities and enterprise decision-making. Wang et al. [16] add fairness-aware task allocation, reaching up to 12.8% higher task completion than baselines. In education, Çaylı and Yılmaz [4] pair LSTM demand forecasting with constraint programming and metaheuristics, while Murali et al. [10], Nagtilak et al. [11] and Pi et al. [12] use CP-SAT, ML timetabling and deep RL with attention for scheduling. The closest studies to workspace allocation are Dai [5], whose RL framework for smart libraries increased seating availability by 30% and reduced congestion by 25%, and Ding [6], whose multi-agent PPO model for co-working spaces (2,300 records) reported RMSE 5.33 and R^2 0.87. However, most abstracts give few quantitative details, many depend on sensors or heavy RL training, and none combines personalized seat recommendation, demand forecasting and exact optimal assignment. Even the co-working work [6] leaves preference learning and fairness unaddressed, which is the gap IntelliSeat targets.

3. FEATURE COMPARISON: RELATED RESEARCH VS INTELLISEAT

Work	Seat / user recommendation	Demand forecasting	Optimal assignment	Works without sensors	Evaluation reported	Level
Maraslis et al. (2016)	Partial	No	Partial	No	Real office, London	Desk
Berelson et al. (2018)	Partial	No	Partial	No	Pilot, student lab	Desk
Sood et al., Spacematch (2020)	Partial	No	No	No	25 users, 30 days	Desk / space

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Work	Seat / user recommendation	Demand forecasting	Optimal assignment	Works without sensors	Evaluation reported	Level
Nevara & Mirji (2019)	No	No	No	No	None (proposal)	Space
Barry et al. (2021)	No	No	Yes (ILP)	Yes	Simulated floor plans	Seat
Hoyano & Ishigaki (2026)	No	No	Yes (stable matching)	Yes	Simulation, synthetic network	Seat
Charytitsch & Nascimento (2026)	No	No	Yes (ILP + local search)	Yes	3 real + 131 artificial classes	Seat
Dai (2025)	No	Yes (LSTM)	Yes (RL)	No	22 branches, 6 months IoT	Library space
Sutjarittham et al. (2019)	No	Yes (ML)	Yes (constraint prog.)	No	9 halls, 18 weeks	Room
IntelliSeat (proposed)	**Yes (content + collaborative)**	**Yes (Random Forest)**	**Yes (Hungarian, exact)**	**Yes**	**Synthetic data vs first-come-first-served (planned)**	**Seat**

4. METHODOLOGY

Layer 1. Recommendation. Content-based and collaborative filtering

Layer 2: Predicting A Random Forest regression model trained on past booking timestamps to predict occupancy for the next time slots.

Layer 3:optimization: Instead of greedy first-come processing, the Hungarian Algorithm is used to mod el peak-time requests as a linear assignment problem.

WORKING METHODOLOGY

Stage 1: Requirement Analysis and Data Preparation

- Analyse booking patterns and define user, seat, and room data schema.

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- Generate synthetic historical booking data for initial model training.
- Define evaluation benchmarks for recommendation accuracy and prediction error.

Stage 2: Application and Database Setup

- Design PostgreSQL schema for users, seats, bookings, and roles.
- Set up Django REST API project structure and authentication.
- Build the React frontend shell with routing and layout.

Stage 3: Recommendation Engine Development

- Build the user-seat interaction matrix from booking history.
- Implement content-based filtering using seat and user feature vectors.
- Implement collaborative filtering using cosine similarity / nearest neighbors.

Stage 4: Occupancy Prediction Development

- Engineer time-based features (hour, day-of-week, seasonality).
- Train and evaluate a Random Forest regression model for occupancy forecasting.
- Expose forecasts through a dedicated prediction API endpoint.

Stage 5: Optimization Module Development

- Formulate seat allocation as a linear assignment problem.
- Implement the Hungarian Algorithm using scipy.optimize.linear_sum_assignment.
- Integrate optimization into the booking flow for high-contention slots.

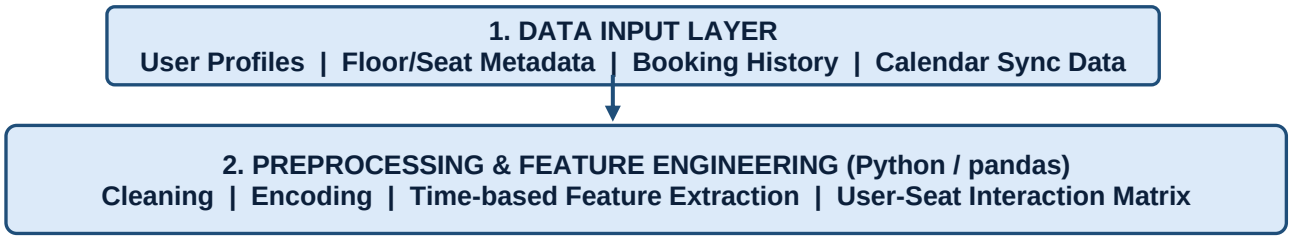
Stage 6: Integration and Testing

- Integrate ML models with the backend via saved model files (.pkl).
- Perform functional, usability, and load testing across modules.
- Validate recommendation relevance and prediction accuracy against test data.

Stage 7: Evaluation and Deployment

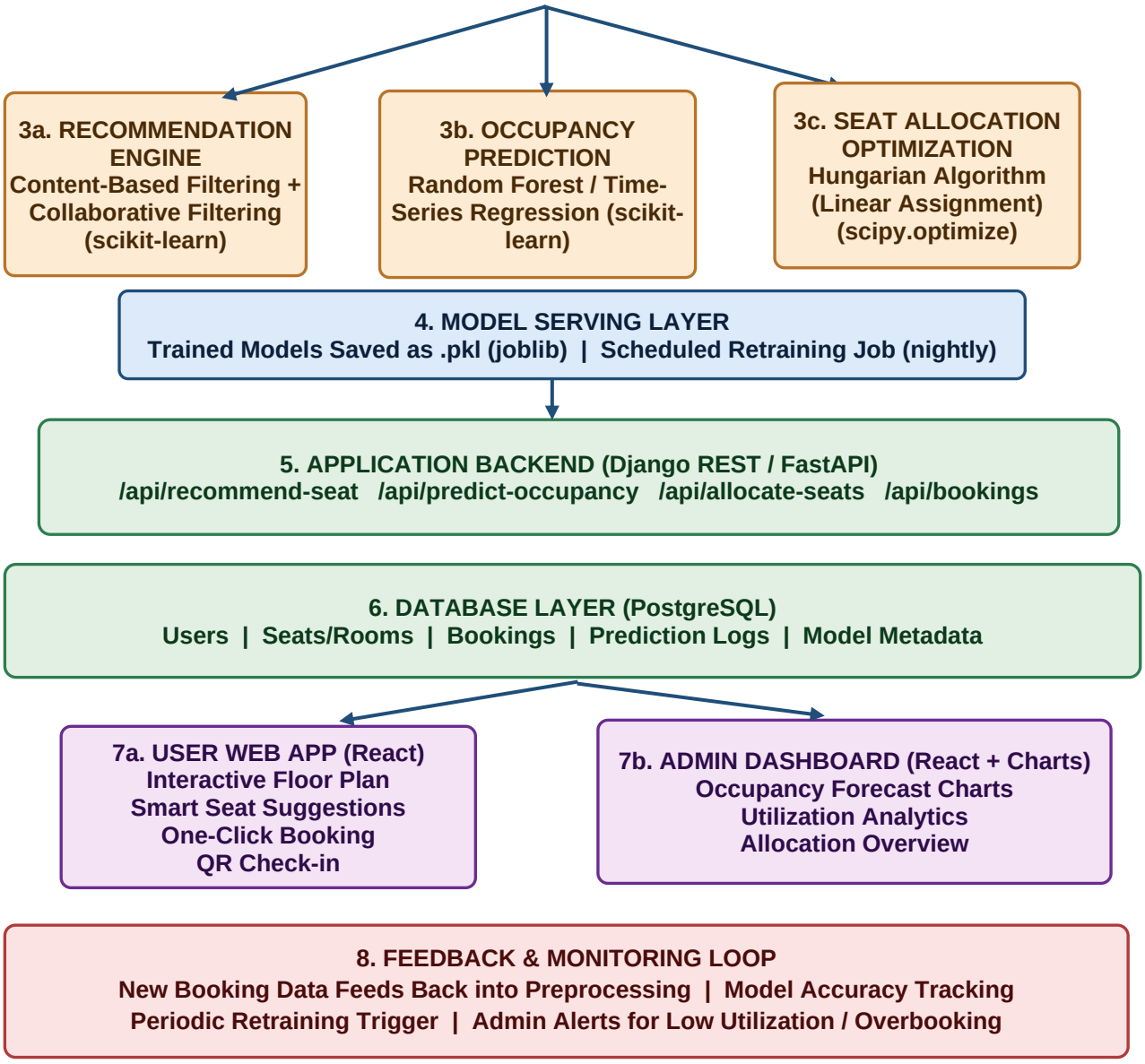
- Benchmark recommendation and prediction models against baseline heuristics.
- Deploy the application to a cloud hosting environment.
- Document results, limitations, and future scope.

SYSTEM ARCHITECTURE — INTELLISEAT



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7a. USER WEB APP (React)
Interactive Floor Plan
Smart Seat Suggestions
One-Click Booking
QR Check-in

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Interactive Floor Plan
Smart Seat Suggestions
One-Click Booking
QR Check-in

8. EEDBACK & MONITORING LOOP
New Booking Data Feeds Back into Preprocessing | Model Accuracy Tracking
Periodic Retraining Trigger | Admin Alerts for Low Utilization / Overbooking

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5. RESULTS

Averaged over 20 independent synthetic datasets (seeds 42-61); 80 users, 50 seats, approximately 5269 bookings, and 120 days per dataset.

1. Seat recommendation, mean over runs (leave-last-out)

Method	Hit@1	Hit@3	Hit@5	Precision@3	MRR
Random	0.014	0.063	0.109	0.021	0.089
Most popular	0.053	0.164	0.239	0.055	0.165
Content-based	0.056	0.182	0.288	0.061	0.180
Collaborative	0.080	0.213	0.308	0.071	0.206
Hybrid (IntelliSeat)	0.083	0.223	0.311	0.074	0.212

Std across runs:

Method	Hit@1	Hit@3	Hit@5	Precision@3	MRR
Random	0.013	0.030	0.033	0.010	0.019
Most popular	0.034	0.066	0.071	0.022	0.044
Content-based	0.026	0.065	0.076	0.022	0.036
Collaborative	0.035	0.070	0.087	0.023	0.047
Hybrid (IntelliSeat)	0.036	0.061	0.070	0.020	0.043

2. Occupancy forecasting, mean over runs (time-based 80/20 split)

Method	MAE	RMSE	R2
Naive (same hour last week)	3.835	4.737	0.875
Linear regression	3.305	4.105	0.906
Random Forest (IntelliSeat)	2.884	3.629	0.927

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Std across runs:

Method	MAE	RMSE	R2
Naive (same hour last week)	0.245	0.281	0.015
Linear regression	0.206	0.247	0.011
Random Forest (IntelliSeat)	0.195	0.250	0.010

Random Forest feature importance (first run): lag_1w=0.94, lag_1d=0.03, hour=0.02, dow=0.01

3. Allocation: Hungarian vs first-come-first-served (100 trials per load per run)

Load	Method	Total satisfaction	Mean satisfaction	% users at first choice	Worst-off user	Jain fairness	Total std
Low (30 requests)	FCFS	2041.25	68.04	21.74	49.11	0.97	44.37
Low (30 requests)	Hungarian	2097.49	69.92	21.62	50.77	0.97	42.74
Medium (45 requests)	FCFS	2884.54	64.10	14.85	38.27	0.96	48.55
Medium (45 requests)	Hungarian	3023.89	67.20	14.02	45.03	0.96	42.64
High (50 requests)	FCFS	3104.54	62.09	13.37	28.01	0.95	52.29

Hungarian gain over FCFS (mean and std across runs)

Load	Total satisfaction gain % mean	Total satisfaction gain % std	Worst-off user gain (points) mean	Worst-off user gain (points) std
Low (30 requests)	2.76	0.81	1.66	1.08
Medium (45 requests)	4.85	1.00	6.76	3.84
High (50 requests)	6.16	1.18	12.79	5.49

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4. RUNTIME (MS PER SOLVE)

Requests = seats	Hungarian solve time (ms)
10.00	0.00
25.00	0.01
50.00	0.04
100.00	0.25
200.00	1.12
400.00	5.68

6. CONCLUSION

IntelliSeat is a workspace-management platform that combines personal seat recommendation, occupancy forecasting and optimization based allocation. The hybrid recommendation strategy resulted in the best ranking performance in the synthetic evaluation, while Random Forest exhibited lower forecasting error than the naive and linear-regression baselines. The Hungarian allocation approach increased the total satisfaction compared to the first-come-first-served allocation at low, medium and high demand levels, with the largest gains found under high contention. It also improved the outcome of the least satisfied user especially when demand increased. However, the results are limited by the use of synthetic booking data, simulated user preferences and the absence of real-world deployment and user evaluation. Therefore, the study demonstrates comparative performance in the modelled scenarios, rather than established improvements in user search time, perceived fairness, or administrative decision making. Future work can validate the system with operational booking records, feedback from users, organizational access policies, and real high-demand allocation settings**.**

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