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Data-Informed UI Decision Cards for Emergency Department Renovation: Linking Patient-Flow Simulation to Configurable Spatial Scenarios

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Abstract. *Emergency department renovation requires designers to connect operational indicators with spatial planning choices through a clear visual interface. This study developed and analytically demonstrated a data-informed UI decision-card prototype linking patient-flow analysis to configurable wayfinding, nurse-station, and staff-support scenarios. The analysis used public CSV files from the 2024 Synthetic Dataset of Emergency Healthcare Services, with the California Emergency Department Volume and Capacity dataset providing facility-level context. Dataset-derived variables included waiting time, queue count, resource utilization, length of stay (LOS), and satisfaction; wayfinding friction, walking load, visibility, collaboration, station count, and respite-room count were prespecified scenario inputs. Composite indices represented ED pressure and operational staff-support review. The outpatient analysis set contained 236 records. Mean total waiting time was 36.42 minutes, mean LOS was 50.79 minutes, mean simulated satisfaction was 82.84%, and mean ED Pressure Index was 0.298. Gradient boosting achieved a mean five-fold RMSE of 4.119 and an R^2 of 0.944 on the synthetic data; its output served as a secondary-priority cue for congestion and provider-load cards. CheckPatientType had the highest mean wait, and Triage the highest mean provider utilization. Under the prespecified scenario inputs and base-case weights, Scenario C received the highest support score (66.95) and highest collaboration risk. Evidence labels indicate whether each card is based on dataset variables, model outputs, or configured scenario inputs, making the basis of each renovation trade-off explicit.*

Keywords: *emergency department; healthcare UI/UX; data visualization; spatial decision support; patient flow*

INTRODUCTION

Emergency departments are spatially dense, information-rich, and operationally volatile settings. Their renovation problems cannot be solved by aesthetic wayfinding alone or by an operations dashboard alone. Clinicians must maintain situation awareness while patients move through registration, triage, diagnostic work, medical-record review, and discharge pathways. ED crowding has been modeled as an interaction of input, throughput, and output pressures, and the throughput component is especially relevant to interior planning because it connects patient queues, provider workload, and local circulation constraints (Asplin et al., 2003; Hoot & Aronsky, 2008; Morley et al., 2018). Recent patient-flow reviews also emphasize that ED flow problems are system-level phenomena rather than isolated departmental issues (Samadbeik et al., 2024).

Graphic design and UI/UX research can contribute by converting operational indicators into legible planning prompts (Chen & Li, 2025). The practical question is not whether a dashboard can display waiting time, but whether a visual system can help a renovation team inspect where congestion, provider pressure, route complexity, visibility needs, collaboration risks, and staff-support concerns converge. The proposed interface connects simulation outputs

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with design reasoning while keeping evidence labels and trade-offs visible (Jin, 2025b; Liu et al., 2025).

The interface distinguishes dataset-derived quantities from configured spatial assumptions. Waiting time, queue count, provider utilization, LOS, and simulated satisfaction come from the CSV files. The ED Pressure Index and Operational Staff-Support Review Index are author-defined composites calculated from those variables. Wayfinding friction, walking load, visibility coverage, collaboration continuity, nurse-station count, and respite-room count are prespecified scenario inputs rather than observations from an ED layout. Figure 1 summarizes the relationship among these evidence classes, the predictive cue, and the UI decision-card layer.

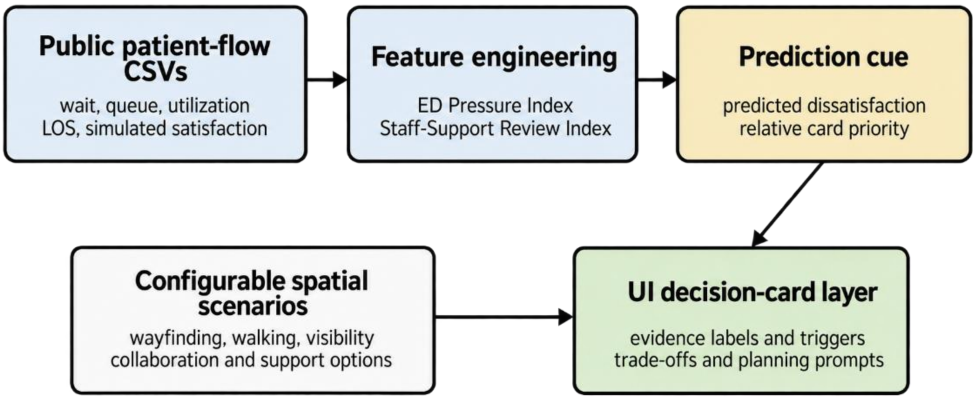

Figure 1. Evidence flow from simulation-derived indicators and model cues to configurable scenario decision cards.

The primary contribution is a UI decision-card layer that makes five design-relevant signals legible: congestion, provider load, wayfinding review, staff-support review, and nurse-station trade-offs (Zhou et al., 2025). Supporting analyses build pressure features from public simulation CSVs, test whether those features predict simulated satisfaction within the same data source, and compare three prespecified spatial scenarios. A model-derived dissatisfaction ranking supplies a secondary visual-priority cue for congestion and provider-load cards, while the spatial prompts remain controlled by visible scenario inputs and weights (Zhang & Zhang, 2025b).

The research question is: how can patient-flow indicators be translated into UI decision cards that keep simulation-derived operational evidence distinguishable from configurable spatial assumptions? Three sub-questions guided the analysis. The first asked which operational stages and hours produced the strongest pressure signals. The second asked whether engineered patient-flow features carried enough internal outcome signal to support card prioritization. The third asked how prespecified spatial scenarios compare under different design-priority weights.

LITERATURE REVIEW

ED patient flow is a classic case for systems modeling because waiting and crowding emerge from interactions among arrival demand, service processes, staffing, and discharge constraints. Discrete-event simulation has long been used in healthcare clinics to test throughput alternatives before implementation (Jun et al., 1999). In ED research, simulation and forecasting approaches have been used to predict crowding states and examine operational changes such as staffing, process redesign, and queue management (Hoot et al., 2008; Wiler et al., 2011). Crowding has also been associated with patient satisfaction (Pines et al., 2008). The value of these models for design is that they expose pressure patterns, not that they directly produce floor plans. A design interface must therefore separate operational evidence from spatial assumptions.

Healthcare dashboards provide one precedent for this translation. Yoo et al. (2018) developed a real-time autonomous ED dashboard using principles of visibility at a glance, low workflow interruption, and privacy protection. Their dashboard included a geographical layout, patient-level alerts, and real-time summary data, showing that ED users require spatially legible displays rather than isolated metrics. Situation awareness theory likewise emphasizes perception, comprehension, and projection of system states (Endsley, 1995). Information visualization research argues that displays should expose task-relevant structure rather than merely list values (Card et al., 1999; Munzner, 2014; Shneiderman, 1996).

Wayfinding research adds a second foundation. Healthcare buildings are often difficult to navigate because patients, visitors, and staff must move through unfamiliar, high-stress, and restricted zones. Wayfinding design has been described as a relationship among environmental layout, signage, cognitive mapping, and user goals (Arthur & Passini, 1992; Passini, 1996; Qi et al., 2022). Devlin (2014) argues that wayfinding has a pivotal role in healthcare facilities because navigation failure affects patients, visitors, and staff. Interior features and signage clarity also influence wayfinding performance and stress in healthcare environments (Qi et al., 2022). For the present study, wayfinding is modeled as a design-scenario risk because the patient-flow dataset includes no physical route observations.

Nurse-station configuration is a third foundation. Centralized stations can support team communication and shared awareness, but they can also concentrate traffic and increase walking. Decentralized stations can place staff closer to patients and improve local visibility, but excessive decentralization may reduce team communication, peer support, and informal coordination. Studies comparing centralized and decentralized station designs have shown that the issue is a trade-off among communication, technology use, work activity, space use, and perceived work environment rather than a universal preference for one layout (Gurascio-Howard & Malloch, 2007; Zborowsky et al., 2010). Therefore, the interface designed in this study reports decentralization benefit together with collaboration risk.

Staff respite planning is a fourth foundation. Evidence-based healthcare design has linked restorative environmental features to stress, satisfaction, and care quality (Pati et al., 2008; Ulrich, 1984; Ulrich et al., 2008). Pati et al. (2008) examined relationships between exterior views and nurse stress, while Nejati, Shepley, and Rodiek (2016) reviewed design and policy interventions that promote restorative breaks. Nejati, Shepley, Rodiek, Lee, et al. (2016) further found that break areas are more likely to be used when they are near nurses' work areas, private from patients and families, and supportive of both privacy and socialization. These findings support a staff-support review prompt, but patient-flow data alone cannot establish the number, location, or size of respite rooms.

Several general design principles shaped the interface. Usability engineering emphasizes that systems must support users' tasks and constraints rather than display information for its own sake (Nielsen, 1994). Norman's (2013) account of signifiers, feedback, and conceptual models is relevant because renovation stakeholders need to understand what a card is asking them to do. The proposed cards therefore report a trigger, an interpretation, and a design action (Li et al., 2025). This structure follows the information-seeking mantra of overview first, zoom and filter, and details on demand (Shneiderman, 1996).

The literature supports an interface-centered design contribution: patient-flow analytics can supply operational triggers, while visual hierarchy and evidence-labeled scenario cards can make assumptions and trade-offs inspectable (Jin, 2025b; Li et al., 2025; Zhang & Zhang, 2025b). The present prototype applies this separation to congestion, provider load, wayfinding review, staff support, predictive priority, and nurse-station configurations.

METHODS

The study used the public CSV files from the Synthetic Dataset of Emergency Healthcare Services released by Ferreira (2024). The dataset documentation describes a Simio-generated emergency-healthcare workflow and includes files for patient-type checking, information filling, triage, blood-pressure checking, medical-record pathways, and outpatient outcomes. The variables used here include patient ID, patient type, arrival and exit timestamps, waiting time, resource used, utilization percentage, queue counts, queue difference, LOS, LOS without queues, satisfaction percentage, and new-patient status. The dataset contains no real patient information and no hospital floor-plan geometry.

The semicolon-delimited CSV files were parsed after converting comma-based decimal values. Table 1 reports the file-level record counts, analytical roles, and fields used. The outpatient department file served as the principal patient-level analysis set because it contains LOS and simulated satisfaction outcomes. To place the simulation results in a broader planning context, the study also used the California Emergency Department Volume and Capacity dataset for 2021–2023 from the Department of Health Care Access and Information, Healthcare Analytics Branch (HCAI, 2025). The facility-level file was not merged with the patient-level simulation records; it was used only to show how ED burden can be expressed through annual encounters, treatment stations, and visits per station.

Table 1. Dataset files, record counts, analytical roles, and fields used in the experiments.

File	Records	Analytical role	Fields used
CheckPatientType.csv	242	Entry/process typing and ticket-machine queue baseline	Patient ID, patient type, waiting time, queue counts
Triage.csv	112	Clinical triage and relative provider-load signal	Triage wait, utilization %, queue counts
Fill_Information.csv	14	New-patient administrative demand	Waiting time, queue counts
CheckBloodPressure.csv	112	Diagnostic sub-process demand	Waiting time, queue counts
MedicalRecord1.csv	84	Type-1 medical-record pathway	Waiting time, utilization %, queue counts
MedicalRecord2.csv	28	Type-2 medical-record pathway	Waiting time, utilization %, queue counts
MedicalRecord3.csv	10	Type-3 medical-record pathway	Waiting time, utilization %, queue counts
MedicalRecord4.csv	117	Type-4 medical-record pathway	Waiting time, utilization %, queue counts
OutPatientDepartment.csv	236	LOS and simulated satisfaction outcomes	LOS, LOS without queues, satisfaction %, new patient

The patient-level ED Pressure Index was computed from four normalized components: total waiting time, mean queue count before processing, mean provider utilization, and LOS. Min–max normalization was applied within the 236-record outpatient analysis set. The formula was ED Pressure Index = 0.35 × normalized total waiting time + 0.25 × normalized mean queue count + 0.25 × normalized mean utilization + 0.15 × normalized LOS. The weights were prespecified for interface prioritization and were not learned from the data. Waiting received the largest weight as the most direct patient-facing flow signal; queue count and utilization represented demand and resource load, while LOS received a smaller weight to limit overlap with waiting-related delay. The index is an interface prioritization measure rather than a validated clinical crowding scale.

The Operational Staff-Support Review Index was computed as 0.35 × normalized provider utilization + 0.25 × normalized hourly process duration + 0.25 × normalized queue pressure + 0.15 × hourly type-4 pathway ratio. Patient type 4 was retained as a pathway-mix indicator and was not treated as clinical acuity. Low (<0.33), Medium (0.33–0.66), and High (>0.66) were prespecified display bands used only to set review priority; they did not determine a required number or size of staff-support rooms. Table 2 distinguishes dataset variables, derived measures, model cues, external context, and scenario inputs.

Table 2. Evidence classes, variables, engineered measures, and scenario rules used in the study.

Construct	Evidence class	Source or input	Formula/rule
Waiting pressure	Simulation-derived	Stage waiting times	Sum of available process-stage waiting times by patient
Queue pressure	Simulation-derived	Queue counts	Mean pre-processing queue count across observed stages
Provider load	Simulation-derived	Utilization %	Mean utilization in triage and medical-record stages
LOS pressure	Simulation-derived	Outpatient LOS	Recorded length of stay (min)
ED Pressure Index	Author-defined composite	Wait, queue, utilization, LOS	0.35 wait + 0.25 queue + 0.25 utilization + 0.15 LOS
Staff-Support Review Index	Author-defined composite	Utilization, duration, queue, type-4 share	0.35 utilization + 0.25 duration + 0.25 queue + 0.15 type-4 pathway ratio
Predicted dissatisfaction	Model-derived cue	Out-of-fold satisfaction model	100 − predicted satisfaction; percentile-based card priority
External ED burden	Facility-level context	Annual encounters and stations	ED encounters divided by treatment stations
Spatial criteria	Scenario assumption	Author-defined values	Wayfinding, walking, visibility, collaboration, stations, support spaces

Three spatial scenarios were specified before scoring. Scenario A retained one centralized nurse station and an existing shared break area, with no added support room. Scenario B added one dedicated staff-support room to a hybrid station model, and Scenario C paired decentralized stations with three distributed support rooms. Nurse-station count, added support rooms, wayfinding friction, walking load, visibility coverage, and collaboration continuity were configured scenario inputs. Table 3 reports these inputs.

Table 3. Prespecified spatial scenario inputs used by the interface.

Scenario	Spatial strategy	Stations	Added support rooms	Wayfinding	Walking	Visibility	Collaboration
A	Centralized station + existing shared break area	1	0	0.80	1.00	0.55	0.95
B	Hybrid station + one dedicated support room	2	1	0.58	0.72	0.74	0.82
C	Decentralized stations + three distributed support rooms	4	3	0.45	0.55	0.90	0.62

The base-case support score was computed as 100 × [0.30 × (1 − wayfinding friction) + 0.25 × (1 − walking load) + 0.20 × visibility coverage + 0.15 × staff-support provision + 0.10 × collaboration continuity]. Staff-support provision used a three-level scenario scale (0.00 for no added room, 0.50 for one dedicated room, and 1.00 for a distributed option); it was not calculated as a linear function of room count. Collaboration risk was calculated as 1 − collaboration continuity. The base weights emphasize navigation, with wayfinding and walking together accounting for 55% of the score. Because the weights are normative, the same scenario inputs were also evaluated under equal weights and a collaboration-priority profile. A 200,000-draw Dirichlet(1,1,1,1,1) sensitivity analysis with random seed 20260723 sampled additional nonnegative weight combinations summing to one while holding all scenario inputs fixed.

Data integration used patient ID as the join key. Waiting and queue variables were aggregated across process stages, provider utilization across triage and medical-record stages, and LOS and simulated satisfaction from the outpatient file. All 236 outcome records had at least one provider-utilization observation after aggregation. A median imputer was nevertheless retained inside each cross-validation pipeline as a safeguard; it was fitted on the training fold and applied to the held-out fold. LOS and satisfaction were not imputed.

The evaluation followed four sequential tests. The descriptive test identified stage-level pressure and patient-type differences. The temporal test aggregated ED Pressure and Staff-Support Review indices by arrival hour. The predictive test compared models for simulated satisfaction and mapped the selected output to card priority. The scenario test compared the three spatial strategies under the base case, alternative weight profiles, and Monte Carlo weight sensitivity.

The predictive task estimated simulated Satisfaction % from patient type, type-4 pathway flag, arrival hour, total waiting time, queue pressure, utilization, LOS, new-patient flag, and process-stage count. Five models were compared with 5-fold cross-validation: dummy mean, ridge regression, elastic net, random forest, and gradient boosting. Records were assigned to shuffled folds with random seed 42. The dummy model used the training-fold mean; ridge used $\alpha = 1.0$; elastic net used $\alpha = 0.10$, l1 ratio = 0.50, and 100,000 maximum iterations; random forest used 100 trees; and gradient boosting used 100 regression trees, learning rate 0.10, and maximum depth 3.

Randomized estimators also used seed 42, with unlisted settings left at their scikit-learn defaults. RMSE, MAE, and R^2 were calculated in each held-out fold and then averaged; RMSE SD is the population standard deviation across folds. To connect the selected model to the visual interface, out-of-fold predicted satisfaction was clipped to the 0–100 display range before predicted dissatisfaction (100 − predicted satisfaction) was converted to a sample-relative percentile. Records above the 75th percentile received high visual priority, those above the 25th through the 75th percentile received standard priority, and those at or below the 25th percentile reduced priority. Model metrics used the unclipped predictions. The underlying wait, queue, utilization, and LOS values remained visible, and the cue did not alter the wayfinding, nurse-station, or staff-support scenario scores.

RESULTS

Across the 236 outpatient outcome records, mean total waiting time was 36.42 minutes, mean LOS was 50.79 minutes, mean simulated satisfaction was 82.84%, mean ED Pressure Index was 0.298, and mean Operational Staff-Support Review Index was 0.353. The correlation between ED Pressure Index and simulated satisfaction was −0.647 within the analysis set.

Table 4. Stage-level waiting, queue, utilization, and recorded-duration descriptives.

Process stage	Rows	Mean wait	Median wait	Mean queue	Mean util.	Mean duration
CheckPatientType	242	26.23	25.50	11.02	—	26.23
Fill_Information	14	5.58	5.00	0.00	—	5.58
Triage	112	10.54	2.61	1.76	10.18	10.53
CheckBloodPressure	112	0.82	0.82	0.00	—	0.82
MedicalRecord1	84	0.25	0.25	0.00	1.18	0.25
MedicalRecord2	28	0.25	0.25	0.00	2.59	0.25
MedicalRecord3	10	2.77	2.86	0.00	3.26	2.77
MedicalRecord4	117	7.42	1.99	0.97	6.74	7.42

Stage-level results are reported in Table 4 and visualized in Figure 2. CheckPatientType had the highest mean waiting time and largest mean queue before processing, identifying it as the strongest entry-stage operational signal in the simulation. Because the data contain no floor-plan or route observations, the corresponding card prompts review of the entry sequence rather than locating a physical bottleneck. Among stages with utilization values, Triage had the highest recorded mean utilization and supplied the strongest relative provider-load signal; the value was not interpreted as high utilization in absolute terms. MedicalRecord4 represents the type-4 pathway but was not treated as clinical acuity.

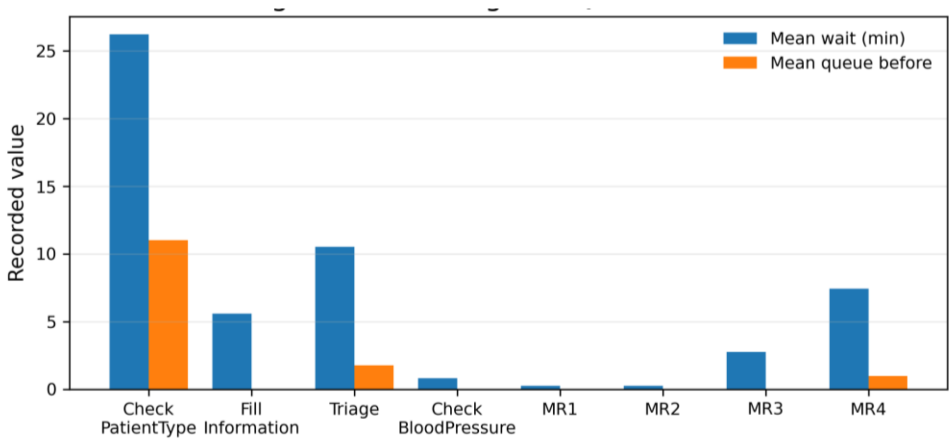

Figure 2. Stage-level waiting and queue pressure comparison.

Patient-type results in Table 5 show how the pressure index differentiates simulated pathway groups. Type 4 formed the largest subgroup and had the highest mean pressure value. Type 2 had the lowest simulated satisfaction, indicating that the outcome was not explained by pressure alone and helping to account for the stronger performance of non-linear models. Hourly results are presented in Table 6 and Figure 3. The highest absolute pressure occurred at 5:00, but that hour contained only four outcome records. For the interface, the planning peak was defined as the highest-pressure hour with at least 10 outcome records. Under that rule, 10:00 produced the strongest planning condition, with mean ED Pressure Index 0.435 and mean Operational Staff-Support Review Index 0.450.

Table 5. Patient-type summary for the outpatient analysis set.

Patient type	Patients	Type-4 pathway flag	Mean wait	Mean LOS	Mean simulated satisfaction	Mean pressure
1	83	0.00	39.54	56.21	89.46	0.268
2	27	0.00	36.62	51.62	52.78	0.311
3	9	0.00	28.85	39.47	86.11	0.238
4	117	1.00	34.75	47.62	84.83	0.321

Table 6. Hourly ED Pressure Index and Operational Staff-Support Review Index results.

Hour	Patients	Mean wait	Mean queue	Mean util.	Mean LOS	ED pressure	Staff-support review
5	4	87.34	3.25	9.12	103.35	0.546	0.519
6	31	44.71	3.37	9.25	58.88	0.365	0.430
7	36	30.08	4.34	7.65	44.40	0.290	0.359
8	29	31.27	4.14	6.21	45.47	0.266	0.310
9	43	42.86	9.26	4.84	57.18	0.377	0.409
10	28	62.08	7.70	4.94	76.55	0.435	0.450
11	15	43.29	4.39	5.19	57.25	0.303	0.369
12	21	20.99	2.07	5.24	35.73	0.171	0.256
13	17	8.00	0.21	5.34	23.03	0.086	0.174
14	12	5.30	0.04	5.03	18.96	0.064	0.164

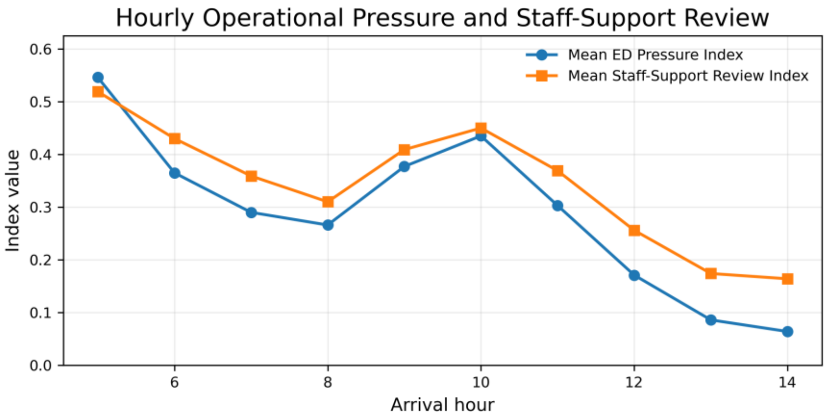

Figure 3. Hourly operational pressure and staff-support review indices.

Table 7 provides facility-level capacity context from the HCAI data. All-visit records increased from 8,819,742 ED encounters in 2021 to 10,788,583 in 2023, and median visits per station also increased. These annual facility records were analyzed separately from the patient-level simulation.

Table 7. External Emergency Department Volume and Capacity context, all ED visits only.

Year	Facilities	ED encounters	ED stations	Median visits/station	Mean visits/station	MH HPSA	PC HPSA
2021	247	8,819,742	6,859	1273.83	1373.99	99	78
2022	258	10,375,703	7,420	1386.73	1512.02	101	81
2023	252	10,788,583	7,328	1504.99	1570.40	104	76

The internal model comparison is reported in Table 8 and Figure 4. Gradient boosting had the lowest mean held-out-fold error, with RMSE 4.119, MAE 1.860, and R^2 0.944; random forest also performed well, while the dummy mean baseline had RMSE 18.965. Within the synthetic dataset, the engineered features therefore captured substantially more variation in simulated satisfaction than the constant baseline. Figure 5 shows the negative relationship between ED Pressure Index and simulated satisfaction. The selected model supplied only the secondary priority cue described in the Methods and did not score spatial layouts.

Table 8. Five-fold cross-validation comparison for satisfaction prediction.

Model	CV RMSE	CV MAE	CV R^2	RMSE SD
Gradient boosting	4.119	1.860	0.944	1.273
Random forest	5.741	2.802	0.898	1.695
Ridge regression	8.562	6.972	0.787	0.492
Elastic Net	10.631	8.497	0.674	1.427
Dummy mean	18.965	16.967	−0.035	1.201

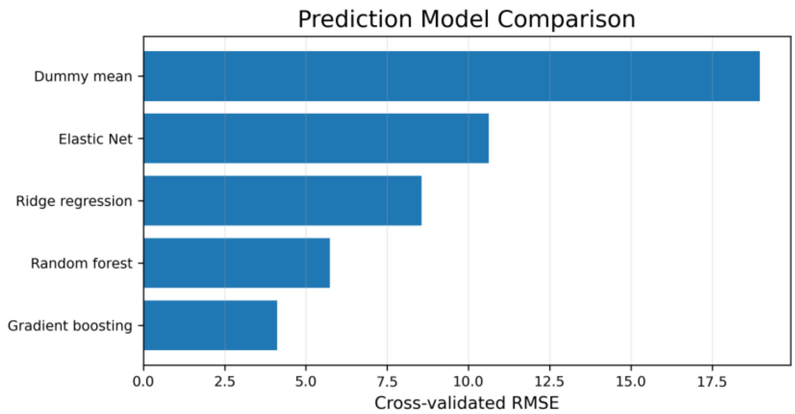

Figure 4. Internal five-fold cross-validation RMSE for the satisfaction models

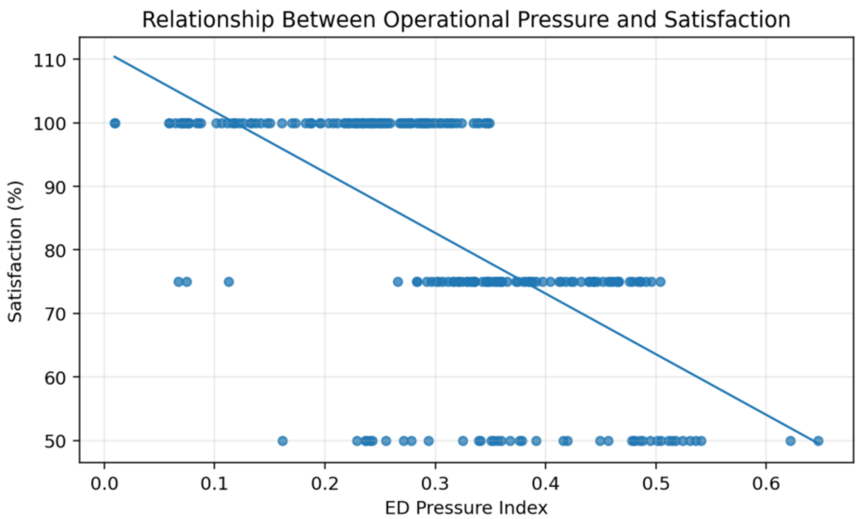

Figure 5. Relationship between ED Pressure Index and simulated satisfaction.

Scenario scoring produced a conditional trade-off. Table 9 and Figure 6 show base-case scores of 26.50 for Scenario A, 50.10 for Scenario B, and 66.95 for Scenario C. Scenario C received the highest model score because it was assigned lower wayfinding friction and walking load and higher visibility and staff-support provision. Its collaboration risk was also the highest at 0.38. The interface therefore displays the base-case ranking together with the configured inputs and the coordination trade-off.

Table 9. Base-case scenario scores and interface outputs under prespecified inputs and weights.

Scenario	Stations	Support spaces	Wayfinding	Walking	Visibility	Collab. risk	Support provision	Score	Interface output
A	1	0	0.80	1.00	0.55	0.05	0.00	26.50	Lowest base-case score
B	2	1	0.58	0.72	0.74	0.18	0.50	50.10	Middle score; stronger collaboration
C	4	3	0.45	0.55	0.90	0.38	1.00	66.95	Highest base-case score + warning

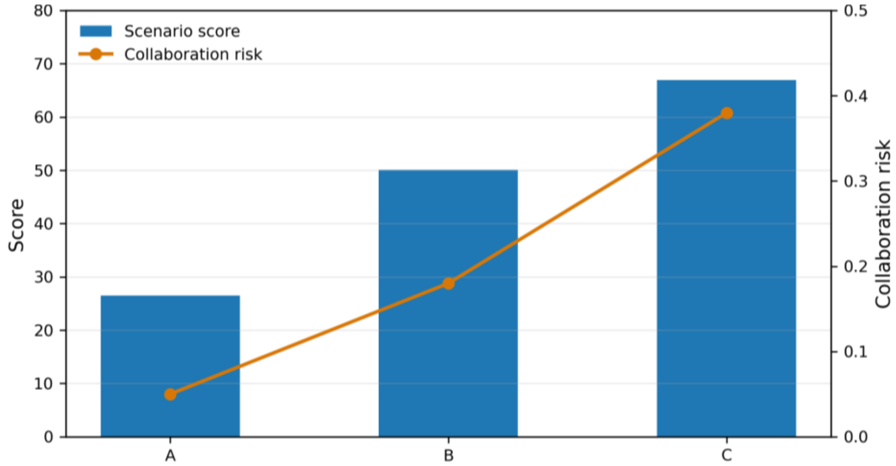

Figure 6. Base-case scenario scores calculated from prespecified inputs and weights, shown with collaboration risk.

The UI decision-card layer is summarized in Table 10 and shown in Figure 7. The patient-congestion and provider-load cards use simulation-derived triggers. The predicted-dissatisfaction ranking assigned 59 records to reduced priority, 118 to standard priority, and 59 to high priority; the high-priority quartile controlled the prominence of those two cards. The wayfinding card pairs the 10:00 operational peak with a scenario-based route review. The staff-support card uses the Medium review band to prompt comparison of proximity, privacy, access, and distribution options. The station card displays the base-case score alongside collaboration risk and weight provenance.

Table 11 evaluates the same scenario inputs under three weight profiles. Scenario C ranked first under the base-case and equal-weight profiles, whereas Scenario B ranked first when collaboration continuity received 55% of the total weight. Across 200,000 uniformly sampled simplex weight combinations, Scenarios A, B, and C ranked first in 0.97%, 4.22%, and 94.81% of draws, respectively. The sensitivity analysis shows that the base-case ranking is stable across most weights but changes when collaboration becomes the dominant priority.

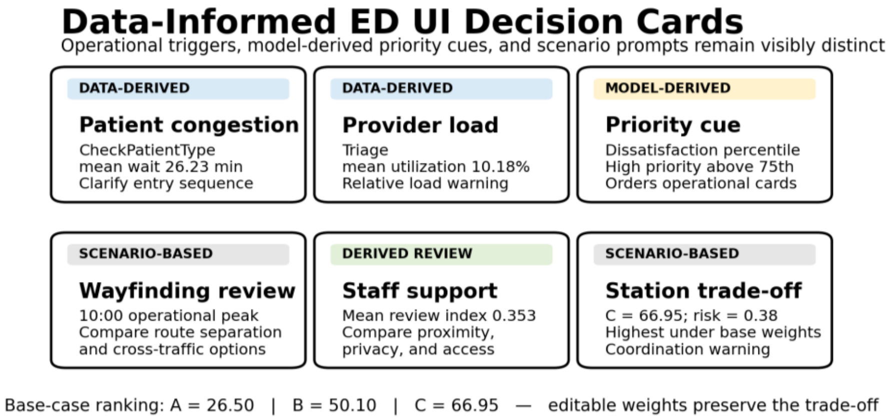

Figure 7. Decision-card prototype separating data-derived triggers, model-derived priority cues, and scenario-based prompts.

Table 10. Evidence basis and interface logic for the UI decision cards.

UI decision card	Evidence basis	Trigger or prompt	Interface response
Patient congestion	Simulation-derived	CheckPatientType mean wait 26.23 min	Flag entry-stage queue and prompt review of first-step communication
Provider load	Simulation-derived	Triage mean utilization 10.18%	Show relative provider-load warning with the recorded value
Model priority cue	Model-derived	Dissatisfaction above 75th percentile	Assign high prominence to congestion and provider-load cards
Wayfinding review	Operational trigger + scenario prompt	Planning peak 10:00; index 0.435	Compare route separation and cross-traffic options; no inferred route problem
Staff-support review	Author-defined composite	Mean review index 0.353 (Medium)	Compare proximity, privacy, access, and distribution; no room-count prescription
Nurse-station trade-off	Scenario inputs and weights	C = 66.95; collaboration risk 0.38	Display base-case ranking, coordination warning, and editable weights

Table 11. Weight sensitivity of scenario rankings with scenario inputs held fixed.

Weight profile	Wayfinding	Walking	Visibility	Staff support	Collaboration	A	B	C	Highest
Base case	0.30	0.25	0.20	0.15	0.10	26.50	50.10	66.95	C
Equal	0.20	0.20	0.20	0.20	0.20	34.00	55.20	70.40	C
Collaboration priority	0.15	0.10	0.10	0.10	0.55	60.75	66.60	65.85	B

DISCUSSION

The primary design contribution is the decision-card layer that keeps operational triggers, model-derived priority cues, and spatial scenario assumptions visible within the same interface.

The operational layer identifies pressure patterns; the model layer supplies a secondary ordering cue; and the scenario layer presents configurable trade-offs. Evidence labels and visible weights allow each card to show how its trigger or recommendation was produced (Jin, 2025b; Li et al., 2025). The strongest simulation-derived signals appeared at CheckPatientType for waiting and queueing and at Triage for relative provider utilization. In the cards, those findings prompt review of entry communication, queue visibility, and clinical workflow rather than specifying where walls, signs, or workstations should be placed. This translation is consistent with evidence-based design because the simulation-derived operational pressure remains traceable to its source variables (Jin, 2025a; Ulrich et al., 2008).

Simulated satisfaction showed substantial predictive consistency with the engineered operational features. The gradient-boosting output was translated into high, standard, and reduced visual-priority tiers for the congestion and provider-load cards, while the source indicators remained visible (Chen & Xu, 2026; Zhou et al., 2025). Because the outcome is discrete and simulated, the tiers are used for relative ordering within this analysis.

Scenario C scored highest under the base-case profile because its assigned inputs represented lower wayfinding friction and walking load, higher visibility, and greater staff-support provision. The weight analysis clarifies the trade-off: Scenario C remained first under equal weights, but Scenario B became first under the collaboration-priority profile. The interface therefore pairs the score with a coordination warning and retains editable weights rather than presenting decentralization as a universal recommendation. The California data add a facility-level view of ED burden through capacity indicators such as visits per station. A future planning interface could place these indicators beside local flow signals while preserving their different levels of analysis.

The Operational Staff-Support Review Index similarly serves as a prompt rather than a spatial prescription. Its Medium band activates a card asking the design team to compare proximity, privacy, access, and dedicated versus distributed options. Patient-flow records contain no fatigue measures, break-use observations, or room geometry, so the index cannot determine how many staff-support rooms are required. The card format supports several planning roles. Facility planners can inspect scenario inputs and editable weights; clinical operations leaders can review congestion and provider-load signals; graphic designers can develop warning hierarchy, evidence labels, and route-review prompts (Xu et al., 2025); and healthcare design researchers can trace each displayed claim to a dataset variable, derived measure, model output, external context source, or scenario assumption (Jin, 2025a).

In the prototype, model support is limited to pattern summarization and predicted-satisfaction prioritization (Zhang & Zhang, 2025a). Spatial inputs and weights remain visible and stakeholder-controlled, and the interface does not infer geometry, code compliance, room dimensions, or the effectiveness of a proposed layout. This bounded role positions machine learning as one input to the card hierarchy rather than as an autonomous design system (Chen & Xu, 2026).

Limitation

The study has six limitations. First, the patient-level analysis uses a public synthetic healthcare simulation dataset. The results therefore describe internal patterns in the simulation rather than observations from a built emergency department. Second, the files contain no floor plan, path geometry, staff-only boundary, nurse-station coordinate, bed coordinate, visibility measurement, collaboration observation, or respite-room geometry. Wayfinding friction, walking load, visibility coverage, collaboration continuity, nurse-station count, and respite-room count are scenario inputs used to evaluate interface logic, not measured architectural outcomes.

Third, patient type 4 is a simulated pathway category rather than a clinical acuity scale such as the Emergency Severity Index. Its contribution to the staff-support index represents pathway mix only. A deployment study would require validated triage acuity, staffing rosters, workload and fatigue measures, and clinical governance review. Fourth, the simulated satisfaction outcome takes a limited set of values, and the model was evaluated only within the same synthetic source. The cross-validation results demonstrate internal predictive consistency rather than external validity in a real ED. The annual HCAI records provide facility-level context but cannot be merged directly with the patient-level simulation. Fifth, both the scenario inputs and their weights are normative rather than empirically estimated. Weight sensitivity reveals dependence on stakeholder priorities but does not validate the inputs. Sixth, the decision-card prototype was not evaluated with clinicians, facility planners, or UI/UX practitioners; its effects on comprehension, trust, and planning decisions remain unknown (Chen & Xu, 2026; Xu et al., 2025).

CONCLUSION

This study presents a data-informed UI decision-card prototype that separates simulation-derived operational triggers from model-derived priority cues and configurable spatial scenario inputs. CheckPatientType produced the highest mean wait, Triage the highest recorded mean provider utilization, and gradient boosting achieved mean five-fold RMSE 4.119 and R^2 0.944 in internal cross-validation; the prediction serves only as a secondary priority cue for congestion and provider-load cards. Under the prespecified base-case inputs and weights, Scenario C received the highest support score and highest collaboration risk, while a collaboration-priority profile favored Scenario B. The visual decision-card logic brings patient-flow signals, model outputs, evidence classes, editable weights, and spatial assumptions into one interface, supporting transparent comparison of renovation priorities.

FUTURE RESEARCH

Future research should combine local ED logs with floor-plan coordinates, route observations, staffing and break-use data, and should evaluate the cards with clinicians, facility planners, and UI/UX professionals (Chen & Li, 2025; Li et al., 2025). Such studies could test whether evidence labels, warning hierarchy, editable weights, and card ordering improve comprehension and planning decisions.

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