



## Passenger Experience Optimization in Smart Airports: A Human-Centered Design Approach

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**SUMMARY:** *This paper presents a human-centered computing design approach for passenger experience optimization in smart airports. Based on WiFi traces, security check queue logs, self-service check-in records, indoor positioning streams, and 186,420 groups of passenger-service events and interactive feedback from the three terminal areas, a unified multi-source service computing framework is constructed. Passenger states are encoded by timing diagram features, context embedding, and service touch point representation, and the service decision module generates adaptive guidance, window diversion, and interactive prompts. The feedback-driven collaboration layer updates the service policy based on real-time satisfaction signals and waiting time changes. Experimental results show that the proposed method achieves 91.8% experience score, 89.6% response consistency and 0.914 F1 value, which is better than BiLSTM, GCN and Transformer benchmarks, and maintains high response stability and consistency in multi-period scenarios. The average reasoning delay of this method is maintained at 84 ms, which shows strong applicability of human-centered service computing in a large terminal operating environment.*

**KEYWORDS:** *Smart airport; Passenger experience optimization; Multi-source sensing computing; Human-centered service design*

### 1 Introduction

With the implementation of intelligent perception, edge computing and data linkage technology in aviation travel scenarios, airport services are shifting from process-driven to experience-driven. The behavior data formed by passengers in check-in, security check, waiting, boarding and transit has become the computing basis for service configuration and spatial scheduling. Passenger experience is no longer just an outcome variable in a satisfaction survey, but a service representation that can be continuously computed through perception modeling, state recognition, and interactive feedback. Rubio-Andrada et al. studied the difference of passenger satisfaction in the use of smart airport technology, indicating that the configuration of technical facilities has affected the experience evaluation [1]. Li et al. used the crowdsourcing data method based on sentiment analysis to study the change of airport service quality, and showed that online feedback can be an important data source for experience measurement [2]. Kilic et al. used topic modeling and sentiment analysis to identify opportunities for airport service improvement, indicating that text data can reflect the real feelings of passengers at touch points [3]. Booranakittipinyo et al. studied the characteristics of passengers' perception of smart airport facilities and showed that there was a relatively stable correlation between the perception of digital facilities and service cognition

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[4]. Alanazi et al. proposed the prediction method of airport service quality feedback rate, which provided support for the quantitative modeling of passenger response behavior [5].

Existing research has provided a data foundation for airport experience analysis, but computational modeling still focuses on a single dimension. Oliveira et al. studied the perceived difference of service quality under the condition of flight delay, indicating that psychological state and situational factors would jointly change the evaluation results [6]. Lopez-Valpuesta et al. analyzed the changes of airport satisfaction after the epidemic, indicating that the experience structure has obvious temporal and scenario-specific characteristics [7]. Song et al. proposed a passenger satisfaction prediction model combining wide network and deep network to improve the prediction accuracy in delay scenarios [8]. Kim et al. studied the behavioral intention of passengers to use the airport biometric system and revealed the role of technology acceptance and trust perception in the interactive experience [9]. Wongyai et al. analyzed the adoption behavior of self-service check-in devices and showed that the design of service terminals would change passengers' subjective judgments on efficiency and convenience [10]. These results show that passenger experience has the characteristics of multi-source input, dynamic evolution and interactive dependence, and it is difficult to rely on questionnaire statistics or single evaluation to support real-time service adjustment in smart airport.

Aiming at the above research gaps, this paper defines passenger experience optimization as a continuous modeling process that integrates perception computing, behavior representation, service decision-making and feedback collaboration, and proposes a human-centered design method. This method takes multi-source airport sensing data as input, integrates location trajectory, queue length, device interaction, service touch point log and feedback text under a unified spatio-temporal framework, and constructs a multi-dimensional representation of passenger status. On this basis, the linkage mechanism of experience representation learning and service decision-making was introduced, so that the system could generate adaptive guidance and resource allocation strategies according to the passenger's location, congestion level and interaction history. At the same time, the feedback-driven dynamic collaborative update is combined to realize the real-time response linkage between different service units, so as to enhance the computational perception ability of the airport service system to experience fluctuations.

The main contributions of this paper are summarized in three aspects: (1) a multi-source perception computing framework for passenger experience optimization in smart airports is constructed, and the unified modeling of passenger behavior, service nodes and scene states is realized. (2) Design a human-centered experience interaction representation and service decision-making mechanism to complete passenger experience state recognition and service response generation without relying on a static rule base. (3) Form a feedback-driven dynamic service collaboration method, so that the airport service configuration can be continuously adjusted with real-time experience signals, and provide a technical basis for the computable experience design in smart airport.

## 2 Related Research

Passenger experience research in smart airports is shifting from service evaluation to computational modeling. Balaž et al. proposed the concept of smart airport mobile application and discussed its usage in predictive analysis, indicating that mobile interaction data can be used as an important entry point for passenger behavior modeling [11]. Vieira et al. studied the optimization method of airport indoor navigation based on visible light communication,

and proved that high-precision positioning and path guidance could directly affect passengers' experience in the terminal [12]. Chen et al. proposed a passenger biometric security implementation scheme based on distributed ledger technology, which makes a more stable technical balance between identity authentication, privacy protection and customs clearance efficiency [13]. Karamitsos et al. constructed a blockchain smart contract framework for airport security inspection process, which improved the efficiency of link collaboration and also provided a new path for trusted interaction in the experience link [14]. Such research shows that the smart airport experience is no longer limited to subjective satisfaction description, but gradually enters the stage of digital computing with perception, authentication, navigation and response as the core.

In terms of coupling modeling of airport operation and experience, Attar et al. proposed a simulative digital twin framework covering multiple operation links of the airside, which provides a unified computing environment for linkage analysis of complex airport business flows [15]. Hopfe et al. compared the performance of time series model and neural network model in short-term passenger flow prediction, and pointed out that passenger flow modeling under fluctuating periods needs stronger dynamic adaptability [16]. Li et al. proposed a spatio-temporal graph convolutional network guided by physical constraints to predict the spatio-temporal distribution of passengers in terminal buildings, and further analyzed the influence of this distribution on the adjustment of indoor environment [17]. AlKheder et al. constructed an airport terminal passenger flow simulation model to reduce delays and improve service levels, indicating that passenger experience is directly related to spatial organization efficiency [18]. Anagnostopoulou et al. proposed a passenger flow analysis and decision tool combined with artificial intelligence simulation to form a computable mapping between passenger movement status, congestion section and service configuration [19]. Oprea et al. established a discrete event-driven passenger flow analysis model in terminal buildings, which provides a reproducible experimental basis for process measurement and response verification in complex scenarios [20].

In order to more clearly compare the differences of existing studies in data access methods, computational modeling paths and scene adaptation levels, Table 1 summarizes the technical characteristics and applicable boundaries of representative studies related to passenger experience in smart airports.

*Table 1: Summary of relevant studies on passenger experience at smart airports*

Reference	Method	Research Subject	Computational Features	Limitations
Baláz et al. [11]	Mobile Application Predictive Analytics	Passenger Interaction	Mobile Data Access	Lack of Multi-source Joint Modeling
Vieira et al. [12]	Visible Light Navigation Optimization	Indoor Passage	High-Precision Positioning	Focus on Navigation Single-Loop
Chen et al. [13]	DLT Privacy Protection	Biometric Authentication	Secure Computation	Insufficient User Experience Representation
Karamitsos et al. [14]	Blockchain Smart Contracts	Security Check Collaboration	Trustworthy Process Execution	Lack of Feedback Loop
Attar et al. [15]	Digital Twin Simulation	Airside Operations	Multi-Linkage	Weak Focus on Passenger Experience
Hopfe et al. [16]	Time-Series/Neural Network Prediction	Passenger Flow	Dynamic Prediction	Limited Interaction Features
Li et al. [17]	Spatiotemporal Graph Convolutional Networks	Terminal Distribution	Graph Structure Modeling	Focus on Distribution Prediction
AlKheder et al. [18]	Passenger Flow Simulation	Delays and Service Level	Process Simulation	Lack of Real-Time Interaction Learning
Anagnostopoulou et al. [19]	AI Passenger Flow Simulation	Decision Support	State Mapping	Insufficient Human-Centered Design Expression
Oprea et al. [20]	Discrete Event Model	Terminal Passenger Flow	Scenario Replication	Lack of Adaptive Service Mechanism

From the perspective of research evolution, existing methods have promoted the airport experience from questionnaire statistics to data-driven analysis, but the experience objects are still divided into discrete indicators such as navigation efficiency, queuing time, safety perception or terminal adoption, and the continuous cognitive changes of passengers during the same trip have not been fully described. The passenger experience in smart airport has significant spatio-temporal coupling, service touch point dependence and feedback lag. It is difficult to support people-oriented dynamic service design by relying solely on passenger flow prediction or local process optimization. Multi-source representation learning, graph structure modeling, and real-time cooperative control in the computer field provide a scalable technical foundation for this task. Therefore, the extension direction of related research is not only to improve the accuracy of single prediction, but also to organize passenger location, interaction record, service resource status and instant feedback as a unified computing object, and complete experience recognition, response generation and policy update in the same model. This also constitutes the starting point of the relevant research in this paper, that is, to re-understand the passenger experience optimization in smart airport from the three levels of perception, computability and collaboration, and form the fulcrum and basis of the method.

### **3 Research Methods**

#### **3.1 Overall architecture of smart airport for passenger experience optimization**

In order to make passenger experience optimization in smart airport have the ability of continuous perception, real-time judgment and linkage execution, this paper constructs a people-oriented overall architecture. In this architecture, passengers are no longer regarded as pure traffic objects, but the mobile status, waiting perception, terminal interaction, environmental feedback and service response of passengers in the process of check-in, security check, waiting, boarding and transit are organized as a computable event chain. The system input consists of indoor positioning trajectory, queue length of security channel, self-service check-in device log, gate screen trigger record, inquiry and counter service log, mobile terminal interaction record and instant feedback text. After all kinds of data enter the edge access layer, time alignment, anomaly removal, identity anonymization and contact normalization are completed, and then sent to the central computing layer to form a unified experience event stream. In this way, the coding separation between different systems is avoided, and the continuous behavior of the same passenger in different service units can be tracked uniformly.

In the computing backbone, the whole framework is divided into perception and access layer, state modeling layer, service decision-making layer and collaborative execution layer. The sensing access layer is responsible for gathering multi-source heterogeneous data and mapping original records into standard event units through lightweight protocol conversion. The state modeling layer constructs a spatio-temporal correlation representation around passengers, service nodes and spatial regions, which is used to describe the change of passengers' experience status in a certain service stage. According to the current congestion density, flight time constraints, passenger attributes and resource loads, the service decision-making layer generates personalized strategies, which not only give path recommendations, but also synchronize the calculation of window diverting, interactive prompts, information display methods and manual assistance trigger conditions. The collaborative execution layer distributes the policy synchronously to the security check, counter, boarding gate, navigation screen and mobile terminal, and writes the execution result

back to the state modeling layer, forming a closed loop. The overall architecture formed in this way not only retains the stability of the airport operation system, but also completes the fine-grained dynamic adjustment for experience in high concurrency scenarios.

As shown in Fig. 1, the overall smart airport architecture for passenger experience optimization consists of five parts: multi-source data access, event alignment and anonymous mapping, experience state modeling, service decision generation, and collaborative execution feedback. All kinds of trajectory, queuing, terminal interaction and feedback data are uniformly preprocessed in the access layer, and then enter the central computing layer to form a continuously updated experience event stream. Then, the state modeling module characterized the spatio-temporal states of passengers in different service contacts, and the service decision module generated personalized response plans according to the passenger states and resource loads. Finally, the collaborative execution layer completed the interaction of multiple service nodes, and wrote the execution results back to the status update link. This diagram is not a single business process, but an overall computing architecture with experience perception, decision calculation and feedback loop as the core.

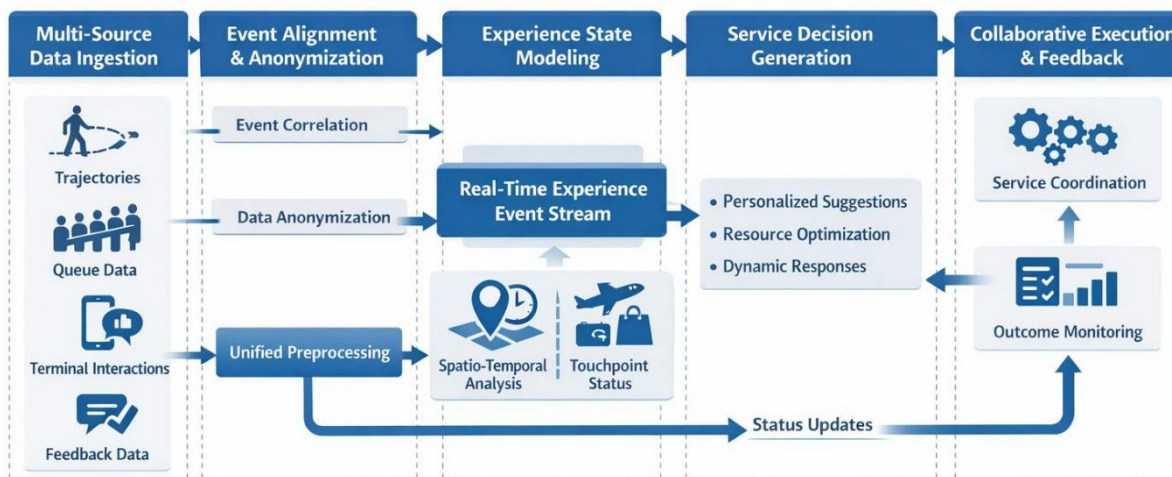


Figure 1: General architecture diagram of smart airport for passenger experience optimization

To make the input, computational tasks and output results of each module in the overall link clearer, Table 2 summarizes the core units in the overall architecture of this paper.

Table 2: Illustration of the core units of the overall smart airport architecture

Module	Input Content	Computational Processing	Output Results
Perception Access Layer	Trajectory, Queuing, Device Logs, Feedback Text	Cleaning, Alignment, Anonymization, Touchpoint Mapping	Experience Event Flow
State Modeling Layer	Event Flow, Spatial Units, Service Nodes	Spatiotemporal Aggregation, Cross-Modal Encoding, State Update	Passenger Experience State Vector
Service Decision Layer	State Vector, Flight Density, Resource Load	Path Inference, Diversion Matching, Interaction Orchestration	Personalized Service Strategy
Collaborative Execution Layer	Service Strategy, Terminal Capabilities, Job Status	Instruction Issuance, Node Interaction, Result Write-back	Real-Time Service Response

In general, the focus of this architecture is not to stack more subsystems, but to organize the continuous experience of passengers in the terminal into learnable, updatable, and collaborative computing objects. Therefore, the subsequent representation learning, service decision making and feedback-driven collaboration all have a unified data entry and execution boundary.

### 3.2 Multi-source perception data construction and passenger experience representation learning

Before constructing the representation of passenger experience, this paper first performs time-slot slicing and contact mapping on the multi-source perception data of the airport. Based on the minuter-level timestamp, the system uniformly divides the indoor positioning trajectory, the security check queue length, the check-in stay time, the screen interaction record, the query log and the feedback text into continuous Windows. The passenger state in each time window is no longer determined by a single behavior, but is composed of location, service contact, terminal interaction and feedback strength. In order to ensure that the data from different sources can be aligned in the same computing plane, this paper adopts the event coding method to establish the experience event unit, and organizes the passengers, service nodes and spatial units into a spatio-temporal correlation graph, and then obtains the experience state vector that can be used for subsequent service decision-making through cross-modal fusion.

As shown in Fig. 2, the multi-source sensing data construction and passenger experience representation learning process includes five stages: event slicing, modal reliability estimation, spatio-temporal correlation construction, cross-modal fusion, and representation constraint update. Firstly, the original records from different sources form experience event units according to a unified time window, and then calculate the modal weight according to the data integrity and noise level. Finally, the spatio-temporal correlation relationship between passengers, service nodes and spatial units is established. The fusion module further compresses the location, service contact and feedback information into a unified low-dimensional state vector, and maintains the consistency of adjacent events on the association graph through representation constraints. This figure corresponds to the generation of passenger experience states from raw data to computational representation.

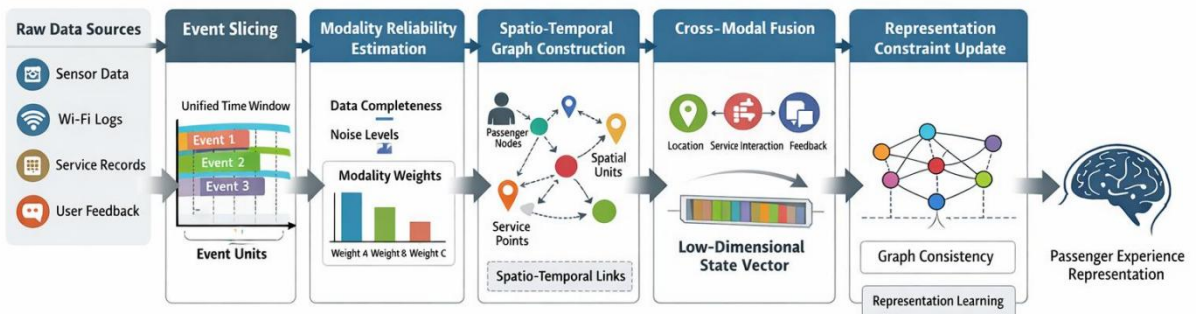


Figure 2: Flowchart of multi-source sensory data construction and passenger experience representation learning

In order to enable the raw records of different service touch points to participate in the calculation in the same time frame, this paper first defines a unified encoding method of experience events as follows, so as to compress the decentralized log into a standard state input with computable meaning:

$$r_{\mu,\tau} = [\alpha_{\mu,\tau}, \beta_{\mu,\tau}, \gamma_{\mu,\tau}, \delta_{\mu,\tau}, \epsilon_{\mu,\tau}] \quad (1)$$

Here,  $r_{\mu,\tau}$  denotes the original event vector of passenger  $\mu$  in the time window  $\tau$ .  $\alpha_{\mu,\tau}$  denote the spatial position encoding;  $\beta_{\mu,\tau}$  denotes the service contact type;  $\gamma_{\mu,\tau}$  denotes the terminal interaction strength;  $\delta_{\mu,\tau}$  denotes the queued or stay state; Let  $\epsilon_{\mu,\tau}$  denote the immediate feedback signal. The function of this formula is to map the records in different systems to the same event space, and provide consistent input for subsequent modal fusion.

In order to control the contribution difference of different perception sources in experience modeling, this paper sets reliability adaptive weights for multimodal signals to avoid too strong perturbation of the final representation caused by low-quality data:

$$q_m = \frac{\exp(\sigma_m/(\theta_m + \epsilon))}{\sum_{n=1}^M \exp(\sigma_n/(\theta_n + \epsilon))} \quad (2)$$

Here,  $q_m$  denotes the normalized weight of the  $m$  mode;  $\sigma_m$  represents the information completeness of the mode in the current window. Let  $\theta_m$  denote the noise sensitivity. The  $\epsilon$  is a trace constant that prevents the denominator from becoming zero;  $M$  denotes the total number of modes. This formula is used to suppress data sources with severe missing or high noise, so that representation learning can rely on effective information more stably.

In order to incorporate passenger mobility, service contacts and spatial constraints into state learning, this paper defines the spatio-temporal correlation strength matrix as follows, which is used to measure the neighborhood effect and service correlation between events:

$$\Omega_{\mu,v} = \exp\left(-\frac{d_{\mu,v}}{\rho_\mu}\right) \cdot \exp\left(-\frac{|\Delta\tau_{\mu,v}|}{\kappa_v}\right) \cdot \zeta_{\mu,v} \quad (3)$$

Here,  $\Omega_{\mu,v}$  denotes the correlation strength between passenger event  $\mu$  and service event  $v$ .  $d_{\mu,v}$  denote the spatial distance;  $\Delta\tau_{\mu,v}$  denote the time interval;  $\rho_\mu$  and  $\kappa_v$  are the spatial and temporal decay scales, respectively. Let  $\zeta_{\mu,v}$  denote the service semantic consistency. This formula enables the model to simultaneously identify experience events with close proximity, high timeliness and strong semantic association.

In order to generate a low-dimensional representation that takes into account the semantics of location, service and feedback, this paper uses cross-modal gated fusion to form the experience state vector, so that signals from different sources can be effectively distinguished in the shared space:

$$u_\mu = \tanh\left(P_1 r_\mu^{(loc)} + P_2 r_\mu^{(srv)} + P_3 r_\mu^{(fb)} + b_\mu\right) \odot \sigma(g_\mu) \quad (4)$$

Here,  $u_\mu$  denotes the experience state vector of passenger  $\mu$ .  $r_\mu^{(loc)}$ ,  $r_\mu^{(srv)}$  and  $r_\mu^{(fb)}$  denote the location, service, and feedback components, respectively.  $P_1$  to  $P_3$  are projection matrices;  $b_\mu$  is the bias term;  $g_\mu$  is the gating vector;  $\odot$  indicates element-wise multiplication. This formula is used to form a compact state representation while maintaining the diversity of multiple sources.

In order to make the learned state vector smooth and distinguishable in local event clusters, we introduce a representation constraint term to stabilize the state propagation on the association graph:

$$\mathcal{J}_{\text{enc}} = \sum_{\mu=1}^N \left\| \mathbf{u}_{\mu} - \sum_{\nu} \Omega_{\mu,\nu} \mathbf{u}_{\nu} \right\|_2^2 + \lambda \sum_{\mu=1}^N \|\mathbf{u}_{\mu}\|_1 \quad (5)$$

where,  $\mathcal{J}_{\text{enc}}$  represents the representation learning loss;  $N$  denotes the total number of passenger events in the window; Let  $\lambda$  denote the sparsity control coefficient. The former term constrict the smooth agreement of adjacent events on the association graph, and the latter term controls the redundant components in the representation dimension. Through this setting, the experience representation not only retains the fine-grained differences of passenger states, but also has the stable input ability for subsequent decision modules.

After completing the above modeling, the system gets not a simple passenger flow vector, but an experience state representation that can simultaneously reflect spatio-temporal location, service contact, behavioral response and feedback strength. This representation provides a distinguishable, updatable, and traceable input basis for subsequent human-centered decision computations.

### 3.3 Human-oriented service decision-making and experience interaction design mechanism

After obtaining the passenger experience state vector, this paper further constructs the human-oriented service decision-making and interaction design mechanism. The goal of the mechanism is not only to compress the average travel time, but to form a computable balance among passenger mobility burden, waiting perception, interaction friction, environmental comfort and service coherence. For the airport scene, the same type of service action has different effects on the experience of different passengers. Transit passengers pay more attention to the path coherence and clear prompts, passengers with large luggage pay more attention to the moving distance and manual assistance, and ordinary departure passengers in peak hours are more sensitive to the queuing time. Therefore, the decision module must integrate the experience representation, scene load and resource state into the unified evaluation framework.

As shown in Fig. 3, the human-centered service decision and experience interaction design mechanism consists of four parts: experience utility evaluation, action candidate generation, interaction intensity calibration, and optimal service scheme selection. The system first calculates the comprehensive utility according to the current passenger experience state, and then generates the executable action set combined with the service resource conditions. On this basis, the interactive adaptation calibration is carried out on the prompt density, interface form and manual assistance trigger intensity. This figure shows that the service decision in this paper does not simply pursue efficiency maximization, but makes a balance calculation among experience benefits, resource constraints and interaction burdens.

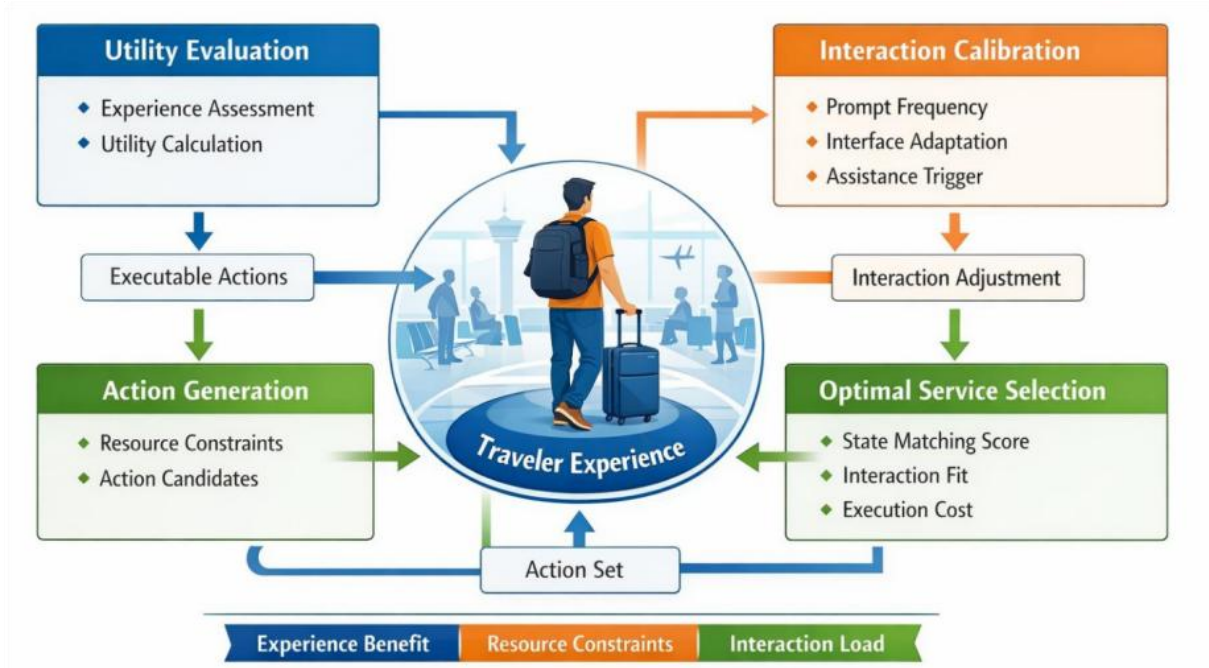


Figure 3: Human-centered service decision and experience interaction design mechanism diagram

In order to transform the subjective feelings of passengers in different service stages into optimized objectives, this paper defines the single service utility as the following comprehensive function, which is used to uniformly measure the influence direction of different actions on the experience:

$$U_{\mu} = \omega_{\mu}^{(1)}(1 - \hat{q}_{\mu}) + \omega_{\mu}^{(2)}(1 - \hat{\ell}_{\mu}) + \omega_{\mu}^{(3)}\hat{c}_{\mu} + \omega_{\mu}^{(4)}\hat{s}_{\mu} - \omega_{\mu}^{(5)}\hat{r}_{\mu} \quad (6)$$

Here,  $U_{\mu}$  represents the comprehensive experience utility of passenger  $\mu$  in the current window.  $\hat{q}_{\mu}$  denotes normalized wait-sensing;  $\hat{\ell}_{\mu}$  denotes the mobility burden;  $\hat{c}_{\mu}$  denotes environmental comfort;  $\hat{s}_{\mu}$  denotes service coherence;  $\hat{r}_{\mu}$  is the interaction resistance; Let  $\omega_{\mu}^{(1)} - \omega_{\mu}^{(5)}$  denote the individualized weights. This formula enables the decision-making module to calculate the experience benefit according to the demand focus of different passengers.

In order to match the candidate service actions with the current state and resource conditions, this paper gives the action scoring function as follows, so that different policies can be compared in the shared space.

$$\Pi_{\mu,\xi} = a_{\xi}^T \tanh(B_1 u_{\mu} + B_2 m_{\xi} + b_{\xi}) \quad (7)$$

Here,  $\Pi_{\mu,\xi}$  denotes the matching score of passenger  $\mu$  to candidate action  $\xi$ .  $u_{\mu}$  represents the passenger experience state vector;  $m_{\xi}$  denotes the resource and scene description vectors corresponding to actions.  $B_1$  and  $B_2$  represent the mapping matrix;  $a_{\xi}$  denotes the action projection vector; Let  $b_{\xi}$  denote the bias term. This formula is used to project passenger states and action conditions into a unified scoring space.

In order to make the prompts of the interactive interface adapt to the cognitive endurance range of passengers, this paper further defines the calibration function of interaction strength

to avoid information overload or insufficient prompts in high-pressure scenes:

$$\Gamma_{\mu,\xi} = \eta_1 \text{softplus}(\Psi_{\mu,\xi}) + \eta_2 \text{sigmoid}(\Phi_{\mu}) - \eta_3 \text{ReLU}(\kappa_{\mu,\xi} - \bar{\kappa}) \quad (8)$$

Here,  $\Gamma_{\mu,\xi}$  denotes the interactive adaptation strength of action  $\xi$  on passenger  $\mu$ . Let  $\Psi_{\mu,\xi}$  denote cue validity; Let  $\Phi_{\mu}$  denote the passenger's acceptance of the current terminal;  $\kappa_{\mu,\xi}$  denote cognitive load;  $\bar{\kappa}$  is the acceptance threshold;  $\eta_1$  to  $\eta_3$  are the calibration coefficients. The purpose of this formula is to keep the interaction design clear, restrained, and adaptive.

In order to select the service plan that can best improve the current experience among multiple types of actions, this paper defines the final decision rule as follows, so that the candidate actions are output in the unified benefit framework:

$$\Lambda_{\mu}^* = \arg \max_{\xi \in \Xi} (\Pi_{\mu,\xi} + \Gamma_{\mu,\xi} - \varsigma_{\xi}) \quad (9)$$

Here,  $\Lambda_{\mu}^*$  denotes the optimal service action of passenger  $\mu$ . Let  $\Xi$  denote the set of candidate actions;  $\varsigma_{\xi}$  represents the action execution cost, including resource occupancy, post load, and handover cost. The formula takes state matching, interaction adaptation and execution cost into the screening criteria at the same time, so that the service actions are closer to the implementable scheme in the real airport environment.

Through the above mechanism, the output of the decision module in this paper is not only a static recommendation, but a combined service strategy including path guidance, window diversion, prompt mode and manual assistance trigger. The design logic thus formed not only retains respect for passenger differences, but also ensures the computational feasibility and execution consistency of the system during busy hours.

### 3.4 Dynamic service collaboration mechanism driven by passenger experience feedback

In the smart airport scenario, the short-term effectiveness of a single service action does not mean that the overall experience has been stable. After receiving guidance, checking in or passing through security, passengers' subsequent feelings will still be affected by the response speed, information consistency and channel linkage degree of adjacent service nodes. Therefore, this paper introduces a feedback-driven dynamic service collaboration mechanism after the decision-making module, which considers security check, check-in, inquiry, boarding gate, mobile terminal and screen terminal as linkable service units, and continuously updates the collaboration strategy according to real-time feedback. The core of the mechanism is not to simply write back the satisfaction score, but to transform the feedback signal into the coordination trigger strength, the strategy modification range and the overall benefit evaluation, so that the service system can form an adaptive closed loop among multiple nodes.

As shown in Fig. 4, the dynamic service collaboration mechanism driven by passenger experience feedback includes five links: feedback collection, feedback status update, service unit coupling calculation, collaborative trigger and policy correction. The subjective feedback and objective execution results of passengers in the process of check-in, security check, waiting and boarding are synchronously written into the feedback state vector. Then the system identifies the linkage demand according to the coupling strength between different service units, and calculates the collaborative trigger amplitude of the current period. After the policy modification, the update results will return to the execution nodes such as security check, counter, gate and mobile terminal, forming a continuous rolling service closed loop.

This figure reflects the linkage update mechanism of the airport multi-node service system driven by experience.



Figure 4: Dynamic service collaboration mechanism diagram driven by passenger experience feedback

In order to aggregate passengers' immediate feedback and system execution results into updatable states, this paper first defines the feedback state update rules as follows, so that short-term feelings and execution effects can enter a unified memory space:

$$f_{t+1} = \alpha_t f_t + (1 - \alpha_t)[y_t \oplus r_t \oplus o_t] \quad (10)$$

Here,  $f_{t+1}$  represents the feedback state vector at the next time.  $f_t$  denotes the current feedback memory;  $\alpha_t$  is the time decay factor;  $y_t$  indicates subjective satisfaction feedback;  $r_t$  stands for objective waiting for change;  $o_t$  represents the result of service execution.  $\oplus$  denotes the concatenation of vectors. This formula is used to incorporate short-term subjective feelings and objective operation results into dynamic feedback memory.

In order to identify the linkage strength between service units in the current period of time, this paper constructs the service coupling matrix as follows, so that the coordination requirements between nodes can be quantitatively described:

$$\Xi_{c,d} = \frac{\exp(\iota_{c,d} + \vartheta_{c,d})}{\sum_{d'} \exp(\iota_{c,d'} + \vartheta_{c,d'})} \quad (11)$$

Here,  $\Xi_{c,d}$  denotes the normalized coupling strength of service unit  $c$  and  $d$ . Let  $\iota_{c,d}$  denote the historical linkage frequency; Let  $\vartheta_{c,d}$  denote the state correlation of the current time period;  $d'$  represents other cooperative units at the same level. This equation can identify which nodes are more likely to form linkage effects in the propagation of experience changes.

In order to determine whether a service unit needs to initiate cross-node collaborative adjustment, this paper gives the calculation formula of collaborative trigger strength as follows, which summarizes the experience diffusion and load spilt of neighboring nodes:

$$\Theta_c = \sum_d \Xi_{c,d} \cdot \max(0, \bar{\ell}_d - \ell_d^*) \cdot \nu_d \quad (12)$$

Here,  $\Theta_c$  represents the collaborative triggering strength of service unit  $c$ ; Let  $\bar{\ell}_d$  denote the real-time load of cell  $d$ ;  $\ell_d^*$  denotes the target load threshold of cell  $d$ ;  $\nu_d$  represents the sensitivity coefficient of the unit to experience fluctuations. This formula is used to summarize the congestion diffusion and experience influence of adjacent nodes into an executable linkage signal.

In order to control the scope of policy modification and avoid system oscillation in high-frequency scenarios, this paper defines the service policy modification rules as follows, so that node adjustment can maintain a balance between responsiveness and stability:

$$\Delta p_c = \beta_c \Theta_c (r_c^+ - r_c^-) - \gamma_c n_c \quad (13)$$

Here,  $\Delta p_c$  represents the amount of policy adjustment for unit  $c$ ;  $\beta_c$  denotes the response gain;  $r_c^+$  and  $r_c^-$  represent the forward and reverse service effect vectors respectively. Let  $\gamma_c$  denote the suppression coefficient;  $n_c$  represents the node switching noise. The function of this formula is to dynamically adjust the service strategy according to the cooperation strength and feedback direction, and suppress the side effects caused by frequent handoffs.

In order to evaluate the collaborative benefits of the overall airport service after a round of linkage update, this paper sets the overall objective function as follows, so that the local optimization results can be verified back to the global experience scale:

$$\mathcal{G} = \sum_c (\chi_c^{\text{sat}} + \chi_c^{\text{tim}} + \chi_c^{\text{syn}}) - \sum_c \chi_c^{\text{cost}} \quad (14)$$

where,  $\mathcal{G}$  represents the total synergy benefit; Let  $\chi_c^{\text{sat}}$  denote the satisfactory payoff of unit  $c$ ;  $\chi_c^{\text{tim}}$  represents the revenue from aging;  $\chi_c^{\text{syn}}$  represents the linkage consistency gain; The  $\chi_c^{\text{cost}}$  denotes the collaborative execution cost. This equation is used to evaluate whether the feed-back driven update actually improves the overall airport experience, rather than optimizing only local aspects.

Through this mechanism, the system can continuously adjust the service configuration according to the feedback status, node coupling and revenue changes without relying on a fixed script when the passenger experience fluctuates. The collaborative mode formed in this way extends the experience optimization in smart airport from single-point recommendation to cross-node linkage control, and also provides a clear calculation object and execution boundary for the performance verification and complexity analysis of the subsequent experimental part.

## 4 Results and discussion

### 4.1 Experimental Design

The experimental data in this study come from the multi-source service records formed in the

continuous operation cycle of the three terminals of an international airport, including WiFi track, security check queue log, self-service check-in record, indoor positioning stream, screen interactive information and instant feedback text. A total of 186420 passenger-service events were sorted out. To ensure privacy security, all identification fields are processed by anonymous mapping. The data preprocessing is divided into four steps. The first step is to align the different system logs according to the uniform timestamp. The second is to map events into five state units according to service touch points: check-in, security check, waiting, boarding and transit. Thirdly, neighborhood smoothing and window completion strategies are used to correct the missing segments. Fourth, the minute-level experience sequence is generated by combining flight plan and regional load. Three representative methods, BiLSTM, GCN and Transformer, are selected for experimental comparison models. BiLSTM is used for temporal state modeling, GCN is used for spatial correlation propagation modeling, and Transformer is used for global interaction dependence modeling. The evaluation indicators are Experience Score, Response Consistency and F1-Score, and the average reasoning delay and perceived waiting time are recorded to comprehensively measure the accuracy of experience recognition, service response consistency and deployment feasibility. In the training phase, the samples were divided according to the time order, the first 70% were used for training, and the last 30% were used for validation and testing. The batch size is set to 256, the initial learning rate is set to 0.001, the optimizer uses Adam, the maximum number of training rounds is 120, the state vector dimension is 128, and the sliding window length is 15 min. All the models are run under the same data partition, resource constraint and unified hardware environment to ensure that the experimental results are comparable. The experimental platform is configured with Ubuntu22.04, Python3.10, and PyTorch2.1, the processor is Intel Xeon Silver, the graphics card is NVIDIA RTX4090, and the video memory is 24GB. To reduce random fluctuations, all experiments are run five times in duplicate and the average results are reported.

## **4.2 Overall passenger experience optimization performance comparison**

In order to evaluate the comprehensive performance of the model in the overall passenger Experience optimization task, this paper selects Experience Score, Response Consistency and F1-Score as the core indicators, and records the changes of average reasoning delay and perceived waiting time. It is used to investigate the overall ability of the method in terms of accuracy, response consistency, and deployment feasibility. The multi-index comparison results of different methods on the unified test set are shown in Fig. 5.

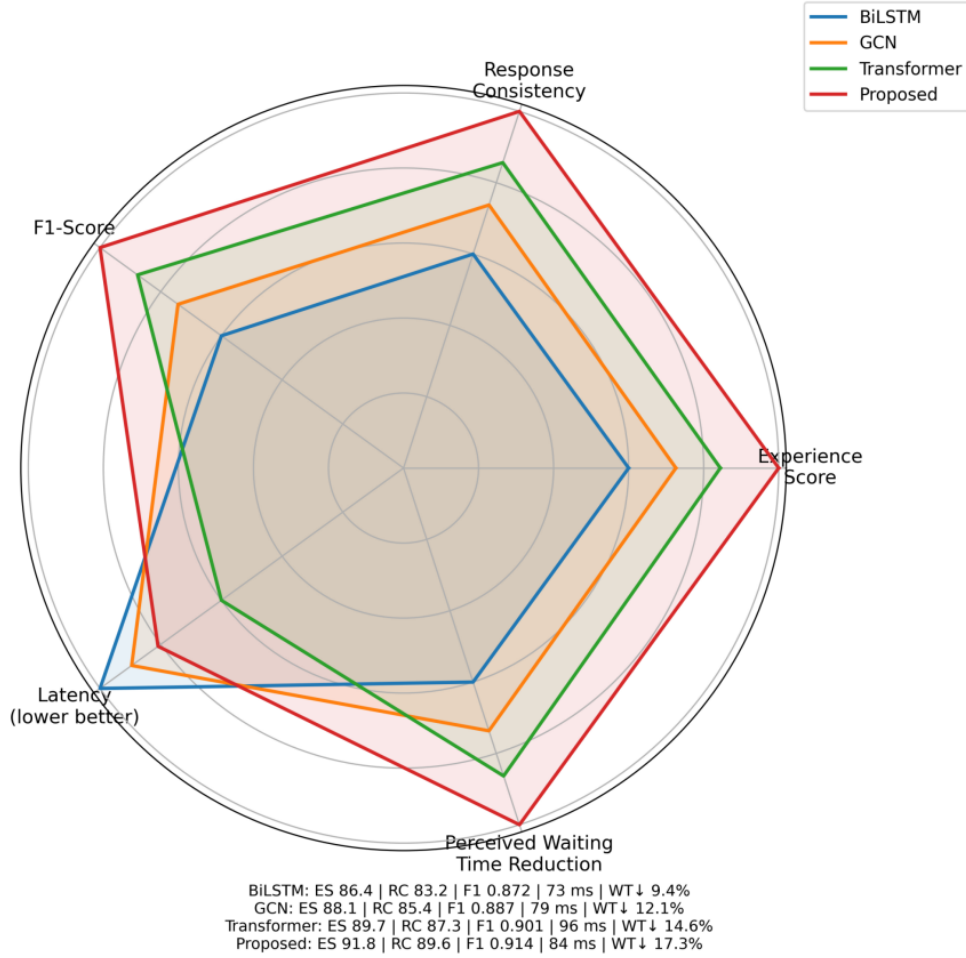


Figure 5: Radar heat zone plot of overall passenger experience optimization performance for different methods

In Fig. 5, the radar contour is used to represent the relative performance of each model on the three indicators of Experience Score, Response Consistency and F1-Score, and the color of the central hot area reflects the decrease of the average perceived waiting time. Fig. 5 shows that the proposed method achieves the best results on the three main indicators, and the Experience Score reaches 91.8%, which is 5.4, 3.7 and 2.1 percentage points higher than that of BiLSTM, GCN and Transformer, respectively. The Response Consistency reached 89.6%, indicating that the multi-node service action maintained a higher consistency in the continuous execution process. The F1-Score reaches 0.914, indicating that the system is more stable in identifying samples experiencing fluctuations in high-pressure scenarios. Compared with the comparison methods, the proposed framework maintains an average inference delay of 84 ms, and does not introduce unacceptable additional overhead due to multi-source sensing and collaborative computing.

Further analysis shows that BiLSTM can better describe short-term temporal changes, but the expression of spatial contacts and service interaction is limited. GCN can reflect the regional correlation, but it is difficult to deal with the rapidly changing time dependence. Transformer has strong global modeling ability, but it is easy to generate response smoothing under high-frequency local disturbance conditions of airport. Through unified experience representation, individualized service decision and feedback-driven collaborative update, the proposed method makes experience benefit and system response form a closed loop, so it shows higher stability in the overall index.

### 4.3 Robustness evaluation of experience response in scenarios with different time periods

In order to test the response stability of the model under different operating hours and service pressure conditions, this paper divides the test samples into four scenarios: morning peak departure, noon peak flat, intensive transit and evening centralized boarding. The changes of Experience Score, Response Consistency and average perceived waiting time of each model in different scenarios were recorded. The comparison results of the robustness of the experience response in each scenario are shown in Fig. 6.

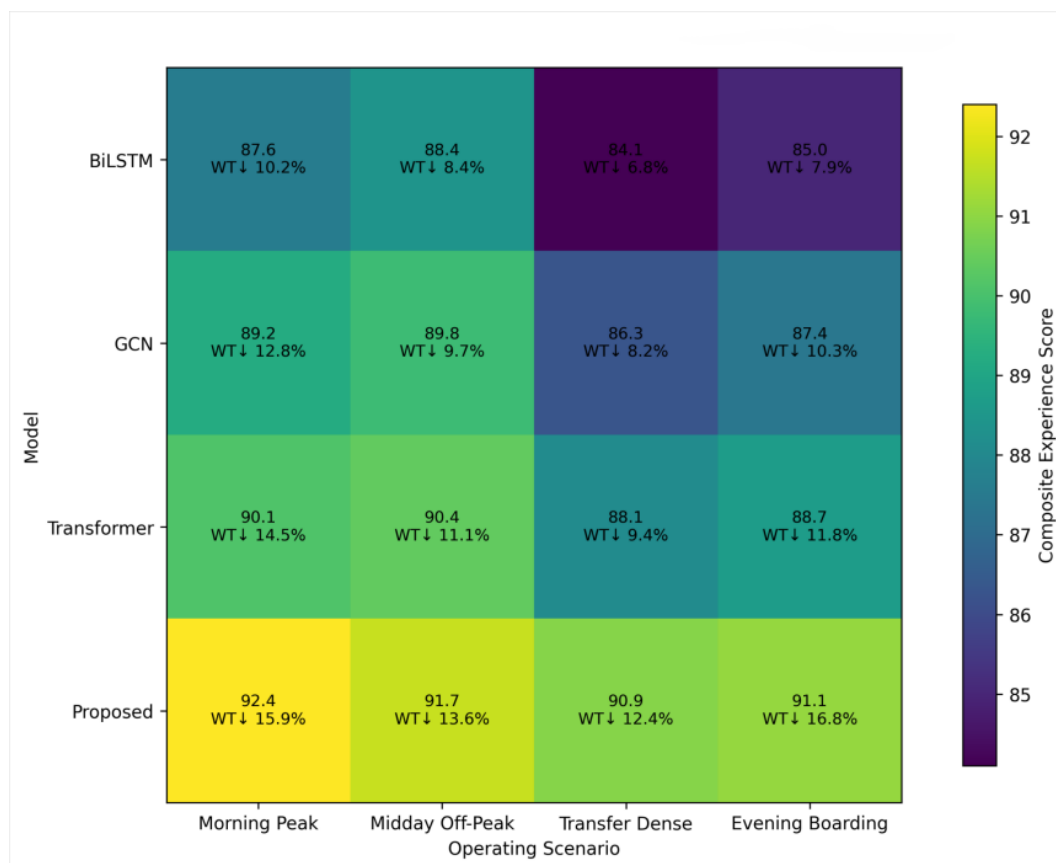


Figure 6: Thermodynamic matrix plots of experience response robustness in different time period scenarios

In Fig. 6, the horizontal axis represents four types of operation scenarios, the vertical axis represents different models, the color block intensity is used to represent the level of comprehensive experience indicators, and the corner mark of the color block corresponds to the decrease proportion of the average perceived waiting time. It can be seen from Fig. 6 that all models can maintain relatively stable performance in low-load periods, but with the increase of passenger density, window switching frequency and path crossing intensity, the index fluctuations of the comparison methods are significantly increased. The Experience scores of the proposed method in the four types of scenarios remained at 92.4%, 91.7%, 90.9% and 91.1%, respectively, with a maximum fluctuation of only 1.5 percentage points. Significantly lower than BiLSTM (4.8 percentage points), GCN (3.9 percentage points) and Transformer (2.7 percentage points).

In terms of Response Consistency, the proposed method still maintains 88.8% in the transit dense scenario, which indicates that the feedback-driven coordination mechanism can

maintain the service action consistency when the load of multiple nodes changes. Further observing the average perceived waiting time, the proposed method is 15.9% and 16.8% less than GCN in the morning peak and evening centralized boarding scenarios, respectively, showing strong congestion adaptation ability. The key reason for this difference is that the proposed framework does not only respond passively to the current passenger flow state, but also adjusts the path guidance, screen prompts, and manual service allocation in advance through state representation learning and collaborative trigger mechanism, so that part of the slow release has been completed before the load fluctuation spreads.

#### 4.4 Analysis of the influence of multi-source perception structure on experience optimization effect

In order to analyze the actual contribution of the multi-source sensing structure to the experience optimization process, this paper designs four input configurations, namely, location trajectory only, location trajectory plus queuing log, location queuing plus terminal interaction, and the complete multi-source sensing structure, while keeping the decision module and collaborative update mechanism unchanged. The purpose of this setting is not to simply compare the difference in the number of inputs, but to observe the supporting effect of different information levels on the learning process of passenger experience states after entering the model. Considering that the final optimization effect depends not only on the output results of the testing phase, but also on whether the representation is stable, the gradient is smooth, and the convergence is sufficient during the training process, this paper further uses the validation loss curve to compare the four configurations. By gradually introducing service contacts and feedback information, the influence of different perception levels on model convergence behavior and training stability can be observed more clearly. The convergence comparison results under different input configurations are shown in Fig. 7.

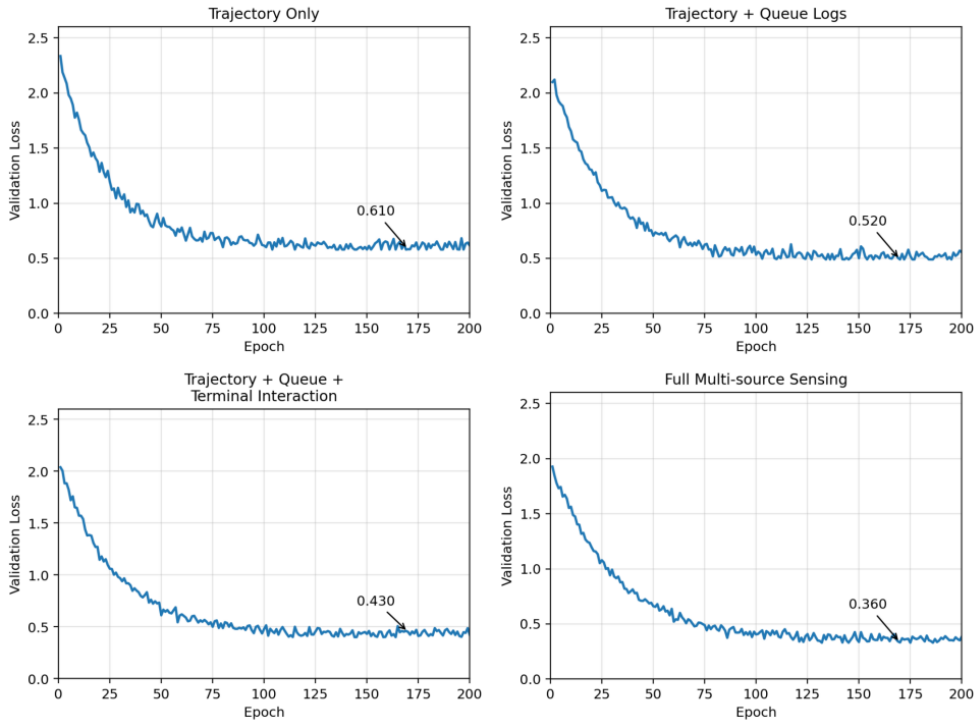


Figure 7: Comparison plots of validation loss convergence for different multi-source sensing configurations

As can be seen from Fig. 7, when only the position trajectory is used, the loss curve can continue to decrease, but the fluctuation is still obvious in the later stage, and it is stable at 0.610 at the end of the training, indicating that the structure can describe the passenger movement trend, but the expression of waiting perception and interaction friction is still limited. After the queuing log is added, the curve descent speed and the stability of the posterior section are improved, and the final loss is reduced to 0.520, which indicates that the load information has a direct support effect on the state identification. After adding the terminal interaction, the oscillation amplitude of the model in the middle and late stages was further reduced, and the late loss dropped to 0.430, indicating that the behavioral characteristics such as screen touch, self-service device stay and inquiry frequency enhanced the discrimination of experience representation. When the feedback text and the instant evaluation are jointly connected, the convergence curve of the complete structure is the lowest and the smoothest, and the final loss is further reduced to 0.360, which is significantly better than the first three configurations. The above results show that the joint modeling of subjective feedback and objective events can significantly enhance the system's fit to real experience. Furthermore, the value of the multi-source perception structure is not only to increase the number of inputs, but also to organize mobility, queuing, interaction and feedback into a unified state space, so that the model can learn the internal laws of passenger experience changes more stably in the training process, and accurately apply the optimization ability to the corresponding service nodes.

#### 4.5 Analysis of ablation experiments

In order to verify the specific contribution of each component module in the passenger experience optimization task, this paper conducts ablation experiments and compares the performance of the full model with different truncated versions under the same data partition and training parameters. The pruning scheme includes removing the multi-source perception fusion module, removing the experience interaction design module, removing the feedback driven collaboration module, and removing the interaction design and feedback collaboration module at the same time. The results for the different model variants are shown in Table 3.

*Table 3: Results of ablation experiments*

Model Version	Experience Score (%)	Response Consistency (%)	F1-Score
Complete Model	91.8	89.6	0.914
Without Multi-source Perception Fusion	88.4	85.9	0.887
Without Experience Interaction Design	89.1	84.8	0.893
Without Feedback-Driven Collaboration	88.7	86.2	0.881
Without Interaction Design and Feedback Collaboration	87.3	83.9	0.869

It can be seen from Table 3 that the full model achieves optimal values in all three indicators, indicating that there is an obvious complementary relationship between state representation, service decision making and dynamic collaboration. After removing the multi-source perception fusion, the Experience Score decreased from 91.8% to 88.4%, indicating that single source input is not enough to support fine-grained experience recognition, and the differences in waiting, moving and terminal contact cannot be fully expressed. After removing the experience interaction design, the Response Consistency decreases most obviously, which reflects that even if the state is judged correctly, without the

calibration of interaction intensity for different passengers, the service actions will still have inconsistent rhythms in the continuous execution. After removing the feedback-driven collaboration, the F1-Score decreases more significantly, which indicates that the system's recognition of fluctuating samples in high-voltage scenes relies on cross-node linkage updates.

After the simultaneous removal of the two modules, each index further decreases, indicating that the proposed method is not supported by a single technical point, but forms the performance gain through representation learning, interaction design and feedback collaboration. By further comparing the change range of different pruned versions, it can be found that multi-source perception fusion determines whether the model can form a real and usable experience state basis, experience interaction design determines whether service actions can fit individual differences, and feedback-driven collaboration determines whether nodes can maintain a consistent response under load fluctuations.

#### 4.6 Computational complexity analysis

In order to evaluate the feasibility of the proposed method in the actual deployment of smart airport, this section analyzes the computational complexity of the model from two aspects: training phase and inference phase, and compares it with three types of baseline methods: BiLSTM, GCN and Transformer. The main overhead of the proposed framework comes from multi-source event alignment, state vector update, action score computation, and feedback co-propagation. The comparison results of different methods in terms of training, inference and resource occupancy are shown in Table 4

Table 4: Complexity comparison results

Model	Training Complexity	Inference Complexity	Peak Memory (GB)	Average Latency (ms)
This Method	$O(N_e \cdot d + N_s \cdot k + C_s \cdot g)$	$O(N_e \cdot d + C_s \cdot g)$	8.6	84
BiLSTM	$O(T \cdot d \cdot h)$	$O(T \cdot h)$	6.1	73
GCN	$O(E \cdot d \cdot h)$	$O(E \cdot h)$	7.4	79
Transformer	$O(T^2 \cdot h + T \cdot d)$	$O(T^2 \cdot h)$	10.9	96

Table 4 shows that the training complexity of the proposed method is higher than that of BiLSTM, but lower than that of Transformer dominated by global self-attention structure. In the inference stage, due to the constraint screening of the candidate action set, the proposed method remains within the acceptable range, and the average inference delay of a single batch is 84 ms, which can meet the requirements of the airport service system for minute level rolling update. GCN has low overhead on structure aggregation, but lacks time and interaction modeling capabilities, so the overall accuracy is limited. Although BiLSTM has low training cost, it is difficult to express spatial contact associations. Transformer has strong global modeling ability, but its video memory occupation increases significantly under the condition of high-frequency service events.

In general, after introducing multi-source perception, human-centered decision making and feedback collaboration, the proposed method does not cause uncontrollable complexity expansion, but maintains a stable balance between accuracy improvement and deployment cost, which is more suitable for online experience optimization and continuous service orchestration in smart airport.

## 4.7 Discussion

In the aforementioned experiments, the proposed smart airport passenger experience optimization method shows advantages in terms of overall metrics, scene stability, structural gain, and deployment efficiency. Compared with BiLSTM, GCN and Transformer, Experience Score reaches 91.8%, Response Consistency reaches 89.6%, and F1-Score reaches 0.914, indicating that this method not only improves the accuracy of experience state recognition, but also improves the accuracy of experience state recognition. It also enhances the action consistency of multiple service nodes in the continuous execution process. Fig. 6 shows that in the face of load fluctuation scenarios such as morning peak departure, intensive transit, and centralized boarding at night, the fluctuation range of model indicators is always controlled in a small range, indicating that the multi-source perception representation and the feedback driven coordination mechanism can jointly absorb the disturbance caused by local congestion and path conflict. Fig. 7 further shows that the multi-source perception structure is not simply superimposed input, but organizes the position, queuing, terminal interaction and feedback information into a unified state space, which reduces the final convergence value of the model from 0.610 to 0.360, and weakens the synchronization of invalid shocks in the training process. Ablation results also support this judgment. After removing multi-source fusion, experience interaction design or feedback collaboration, the three main indicators all decline, indicating that there is a stable functional complementary relationship between state modeling, service decision making and cross-node linkage. From the perspective of computation, the proposed method achieves high accuracy and strong generalization ability while maintaining the average inference delay of 84 ms and the memory occupation of 8.6 GB, which indicates that the framework has the application foundation in the smart airport service orchestration. It should also be noted that there is still room for improvement in the adaptation ability of the current method to extremely sparse feedback samples and sudden large-area flight fluctuations. In the future, cross-period memory constraints and text semantic joint modeling can be further introduced to enhance the response ability under complex operating conditions.

## 5 Conclusion

### 5.1 Research Contributions

In this study, a human-centered computing framework is constructed around the task of passenger experience optimization in smart airports, and multi-source perception, state representation, service decision making and feedback collaboration are incorporated into a unified link. At the method level, based on trajectory, queuing, terminal interaction and instant feedback, this paper forms a continuously updated experience event stream, and realizes the fine-grained modeling of passenger status. At the mechanism level, we design a service decision and interaction adaptation method for individual differences, so that path guidance, window diversion and prompt trigger can be generated dynamically according to experience status. Experimental results show that the proposed method outperforms BiLSTM, GCN and Transformer in Experience Score, Response Consistency and F1-Score, and maintains stable output in multi-period scenarios. This shows that the proposed framework not only has good calculation accuracy, but also has the application value of service orchestration and online rapid deployment, which provides a methodological basis for the computational experience design for real passenger feelings in smart airport. At the same time, experience optimization is extended from single-point efficiency evaluation to cross-node collaborative control. The dynamic adaptation ability and collaborative resilience of the service system to complex

operating states are enhanced.

## 5.2 Limitations and Future research Directions

Although the proposed method has achieved stable and reliable results in the passenger experience optimization task of smart airport, there is still room for further expansion. The current framework mainly relies on trajectory, queuing, terminal interaction and immediate feedback to construct the state representation, and the description of sudden flight fluctuations, super-density transit congestion and low-frequency feedback samples can still be strengthened. At the same time, although the joint computing of multi-source perception, interactive decision and feedback cooperation improves the overall performance, it also brings additional training cost and video memory pressure, and it still needs to improve the reasoning efficiency under larger scale area and higher concurrency conditions. The follow-up research can be carried out from three directions. First, the cross-temporal memory constraint and stronger spatio-temporal compression mechanism are introduced to enhance the expression of experience states in long time scales. Second, it combines text semantics, speech cues and visual passenger flow characteristics to form a richer multimodal input structure. Thirdly, the parameter scale and policy update method are optimized for edge deployment, so that the model has stronger real-time response ability and scene migration ability while ensuring accuracy. In addition, the current method is still weak in modeling the causal transfer relationship between service nodes, and there is still room for improvement in the ability to identify cross-regional linkage and abnormal chain diffusion in advance, which is also an important direction and research focus for subsequent engineering improvement.

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