A Hybrid Modeling Framework for Airport Passenger Decision Making: A Markov Decision Process Approach

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***Abstract*—The end-to-end air passenger journey, from travel planning to arrival at the destination airport, encompasses a series of interdependent processes in which passenger behavior and airport infrastructure continuously influence one another. Passenger decision-making, such as arrival timing, use of services, and queue preferences, plays a central role in shaping these dynamics. Conversely, the design and efficiency of airport infrastructure can constrain or facilitate behavioral patterns, creating a feedback loop that is often overlooked in conventional modeling approaches. This study addresses the critical need to better understand the bidirectional relationship between passenger behavior and airport infrastructure. A hybrid modeling framework is developed, where Discrete Event Simulation (DES) for airport infrastructure is used to develop a passenger Agent-Based Model (ABM) via Markov Decision Process (MDP) formulation and optimal policy search. The model is informed by empirical data on passenger profiles, infrastructure configurations, and behavioral preferences. Preliminary analytical results highlight how small variations in passenger behavior can impact decision-making and infrastructure operation. The proposed framework will facilitate the design of behaviorally-informed, data-driven planning strategies for more resilient airport systems.**

Keywords-Markov Decision Process; Agent-Based Modeling; Airport infrastructure; Airport passenger; State machine; Decision-making; SysML; Discrete-Event Simulation; Dynamic Programming; Reinforcement Learning.

I. INTRODUCTION

The passenger journey in air travel encompasses a continuous sequence of phases, from initial planning and booking to airport arrival, check-in, security screening, boarding, and ultimately arrival at the destination. This journey represents a complex dynamic system where passenger decisions and airport infrastructure dynamically influence one another [1]. Central to this system are key airport infrastructure components, including check-in counters, security checkpoints, boarding gates, and waiting lounges, which play a critical role in determining the overall efficiency of airport operations [2][3]. However, airport infrastructure is increasingly challenged by systemic issues such as congestion, bottlenecks, and service delays, especially during peak periods. These challenges not only reduce operational performance and increase costs, but also have broader implications for airlines and aircraft manufacturers, impacting turnaround schedules and prompting new aircraft design considerations aimed at faster boarding [4]. On the other hand, passenger behavior acts as both a contributor to and a consequence of these challenges. Decisions about arrival times, use of on-site services, and queue selection can compound delays or alleviate pressure on infrastructure. For example, the tendency for last-minute queuing or congregation around certain kiosks can strain already-limited terminal resources [5]. These feedback dynamics and emergent behavioral patterns highlight the need to better understand the reciprocal relationship between passenger behavior and airport infrastructure capabilities.

Simulation-based approaches have emerged as important tools to enable a detailed yet scalable analysis of both behavioral and operational dynamics [6]. Formal methods, such as Markov Decision Processes (MDP), offer structured frameworks for modeling sequential decision-making in environments characterized by uncertainty and time constraints [7]. In addition, Agent-Based Modeling (ABM) provides a bottom-up approach by representing individual passenger agents and their interactions, while Discrete Event Simulation (DES) is adept at modeling process-driven phenomena such as service durations and queue dynamics. A hybrid approach combining these modeling paradigms enables the integration of behavioral insights with operational realism, thereby addressing both strategic and tactical dimensions of airport management [6].

Several studies have examined how passenger behavior and infrastructural design shape check-in performance. A simulation-based analysis of fifteen check-in configurations is conducted in [8], revealing that single-queue systems combined with variable counter allocation significantly reduced waiting times and operational costs. ABM is applied in [9] to investigate group travel dynamics, demonstrating that passengers traveling together often wait for one another, leading to longer dwell times and increased congestion. A mesoscopic simulation-optimization framework that incorporate infrastructure layout, stochastic passenger behavior, and resource constraints is proposed in [10] to minimize both staffing costs and passenger discomfort. Although these studies use modeling and simulation to explore passenger-infrastructure interactions, none integrate MDP within a hybrid ABM and DES framework. Without such integration, it is difficult to represent how individual passengers make decisions in complex, changing airport environments with diverse agent behaviors.

MDP is a powerful tool for modeling decision-making scenarios characterized by sequential actions and inherent uncertainty. It provides a systematic approach to describing

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how decision-makers, in this context, passengers, transition between various states through the selection of specific actions. It facilitates the derivation of optimal policies under uncertain conditions by accounting for both the immediate consequences of decisions and their long-term ramifications, effectively capturing the probabilistic transitions that define system performance. The intrinsic strength of an MDP-based approach lies in its capacity to encapsulate the sequential nature of decision-making throughout the entire journey, from the initial selection of a travel route to real-time adjustments in departure times. In modeling door-to-door transport scenarios, MDP systematically accounts for the full sequence of actions, including route selection, mode choice, and responses to unexpected delays, that collectively determine the efficiency of the travel experience. This modeling framework effectively captures uncertainties in passenger behavior, where the outcomes of individual decisions are contingent upon both personal choices and broader operational contexts [5].

This research is motivated by three central problems: (1) persistent airport inefficiencies due to passenger-induced bottlenecks and infrastructure limitations; (2) the absence of integrated models that consider feedback between infrastructure and behavior; and (3) the need for data-driven tools to inform decisions by airport planners and stakeholders. The primary objectives of the research are to better understand how passengers are influenced by airport infrastructure and to identify operational inefficiencies to improve passenger experience and airport performance. This paper addresses the need to understand the bidirectional relationships between passenger behavior and airport infrastructure by using a hybrid modeling and simulation approach.

The main contributions are summarized as follows: (1) a unified hybrid modeling framework is proposed to capture airport infrastructure-passenger interactions, (2) a methodology, through an example, is presented to transform the integrated passenger-infrastructure model into an MDP for optimal policy derivation, and (3) an approach is introduced to integrate the passenger profile into the decision-making reward system.The framework is illustrated using the passenger check-in system and supported with numerical calculations.

The rest of the paper is organized as follows: Section II defines the passenger profile that is used to drive passenger decision-making. Section III explains the airport infrastructure system and the overall modeling framework. Section IV describes a sample model for the check-in system. Section V explains the MDP formulation and its connection to the developed infrastructure model and passenger profile. Section VI illustrates the decision-making policy. A numerical example is given in Section VII. The work is concluded in Section VIII.

II. Passenger Profile

Airline passenger decision-making depends in part on passenger attributes, such as age, gender, and travel purpose. The passenger profile is defined as a set of key relevant features that could impact passenger decision-making. For rational agents, these features shape the reward function that drives the search for an optimal agent policy. Table I shows some of the relevant attributes of a passenger profile, including percentage values as per [2][11]. One-hot encoding is used with categorical data.

TABLE I. Passenger profile as a set of personal features [2][11]. One-hot encoding is used for categorical data. Only the features used in the paper are assigned symbols.

Feature	Symbol	Data type
Age	A	Int
Gender	G_M, G_F	Cat
Travel purpose	B, T	Cat
Household		Bool
Visa-free	V, V_F	Bool
Travel frequency		Int
Flight destination		Cat
Travel class		Cat

Symbols corresponding to features in Table I are used to shape the reward functions in Section V. The passenger feature vector is designated by $\theta_p = [\ A \quad G_M \quad G_F \quad B \quad T \quad V \quad V_F\ ]$.

III. Passenger-Infrastructure Interaction

Figure 1 shows a simplified block diagram for airport infrastructure from the passenger's perspective. The first stage is the check-in system, where available passenger choices are shopping, self-check-in, or manual check-in. The second stage is security check-in. Passengers have very limited choices at this stage, if any. However, passenger profile plays a role in the security check-in system dynamics, e.g., passengers who are more likely to carry forbidden articles will cause check-in delays. The third stage is the departure lounge, where passengers' choices are shopping or waiting. The fourth stage is the boarding gate area, where passengers have almost no choices. Airport infrastructure dynamics, particularly flight delays, play a key role in passenger satisfaction at this stage. The final stage is the runway. Passengers have no choice, but runway delays impact total passenger waiting time, hence passenger satisfaction as well. Note that the infrastructure is shown as a pipeline, as this is the passenger's perspective, given that the passenger cannot go back to an earlier system once passed through it, e.g., security check-in. However, infrastructure subsystems can interact in other configurations.

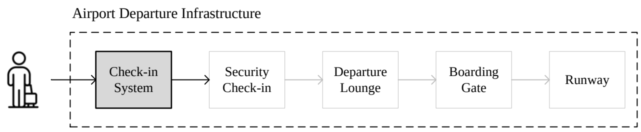

Figure 1. Airport infrastructure - Passenger's perspective

The modeling framework is summarized as follows: A DES model is developed for the airport infrastructure (Section IV). The DES model combined with the passenger profile is used to generate an MDP model (Section V). The MDP reward function is used to train the passenger agent (Section VI). The trained agent is finally represented in an ABM format.

IV. Airport Infrastructure Mathematical Model

This section presents a mathematical model for the check-in system that supports passenger decision-making. The rest of the infrastructure components in Figure 1 can be modeled very similarly and are not shown in the paper for brevity.

The check-in system is modeled as a DES, where state transitions occur at distinct points in time based on arrivals, service completions, and departures. The system includes one queue for manual check-in, a second queue for self check-in kiosks, and a third queue for baggage drop-off for passengers who checked in online. This follows recent airport organization, where each check-in system has a single queue that is served by multiple desks/kiosks. Figure 2 illustrates the check-in system architecture, and Table II summarizes the model parameters.

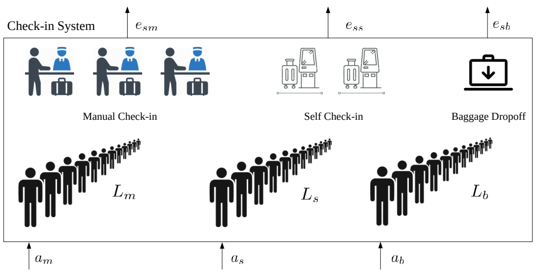

Figure 2. Airport check-in system

TABLE II. Check-in system model parameters

Parameter	Description
N_m	Number of serving desks for manual check-in
L_m	Queue length for manual check-in
N_s	Number of kiosks for self check-in
L_s	Queue length for self check-in
N_b	Number of serving desks for baggage drop-off
L_b	Queue length for baggage drop-off

The service time at each kiosk is modeled using an exponential distribution with rate parameter λ. This rate parameter depends mainly on the passenger profile, e.g., visa requirements, how many bags the passenger has, the number of family members checking in, or the fluency of using a computer system for self-check-in. For manual check-in, the rate parameter depends on the check-in agent's efficiency as well. For baggage drop-off, airline intervention is minimal, so it could be safely assumed that the rate parameter depends solely on the passenger profile.

The inputs to the check-in system, $A = [\ a_m \quad a_s \quad a_b\ ]$, represent the decision of a passenger to join/leave the manual check-in line, self check-in line, and baggage drop-off line, respectively. The state of the system is described by the length of each queue, $X = [\ L_m \quad L_s \quad L_b\ ]$, which is considered fully-observable by external agents. The output of the check-in system, $Y = [\ X \quad e_{sm} \quad e_{ss} \quad e_{sb}\ ]$, represents the events that a manual check-in customer, self check-in customer, and a baggage drop-off customer has been served, respectively. The service events are internal to the system, which impacts the number of passengers in each queue. As long as each queue length is observable by passengers, the system can be modeled with the state vector as the output. However, since the approach follows ABM, it is convenient to use these service events to simplify the queue position tracking performed by each passenger. For simulation, the passenger arrival rate is governed by passenger profiles instantiated according to profile population. To test the check-in system agent independently, a Poisson distribution could be assumed for passenger arrivals. Finally, a possible passenger action inside the system is to leave one queue and join another queue. This action could be achieved using the given action space by assigning two possible values to the input action, one for joining and another for leaving the queue, i.e., $a_m = 1$ to join the queue, and $a_m = -1$ for queue departure.

V. Passenger Agent and Decision-Making

To support passenger decision-making, an MDP is developed for the system [12]. The focus here is on the check-in system to present the technique, which could be extended easily to the rest of the infrastructure subsystems.

A. State Space

From the check-in perspective, two state variables could be identified for the passenger: the check-in status and the physical location in the check-in area. As per Section IV, the check-in system has three state variables representing the length of each queue. Also, the passenger may wish to track the length of the queue ahead of her position. Finally, a key factor impacting airline passenger decisions is the Time remaining To Departure (TTD). This variable is captured as a count-down timer that is represented as a global state variable T_d, allowing a compact representation of the state space. Table III summarizes the state variables and associated values.

TABLE III. Passenger decision-making - MDP States

State	Possible Values
Check-in status	{Online, !checked-in, Checked-in}
Location	{Lobby, Shopping, Check-in area}
Check-in area	{Waiting, Baggage, Self, Manual}
L_m, L_s, L_b, T_d	$\{x \in \mathbb{Z} \mid x \geq 0\}$
Queue position (P)	$\{x \in \mathbb{Z} \mid x \geq 0\}$

B. Action Space

While being in the check-in lobby, the passenger can decide to either go shopping or proceed to the check-in area. Once in the check-in area, the passenger has to choose between the different check-in queues. While standing in a queue, the passenger can also elect to switch queues.

C. Transition Function

Given the environment dynamics, a deterministic transition function is assumed, where $\forall(S, a)$ and a target state S':

$$P[S'|S,a] = 1, \quad P[S''|S,a] = 0 \quad \forall S'' \neq S' \tag{1}$$

D. Reward Function

To capture the influence of the passenger's profile on the decision-making process, the reward is designed to be a function of the passenger profile, as well as the current system state. For example, a business traveller could be more sensitive to time delays than a tourist, and a female traveller may select a shopping decision with higher probability. The following section defines the reward function for the shopping and queue selection decisions.

1) Shopping reward: Shopping reward comes from enjoying the experience, but the time spent during shopping, and the time remaining for boarding, play a role in the shopping decision. This could be captured given the following reward function:

$$R = \underbrace{G_M + 50G_F}_{\text{Pleasure}} - \underbrace{T_{sh}(\lambda_p)}_{\text{Shopping time}} - \underbrace{100(1 - \frac{T_d}{120})}_{\text{Time to board}} \tag{2}$$

where T_d is measured in minutes. T_{sh} is the shopping time, which is a random variable assumed here to have an exponential distribution with rate λ that depends on the passenger's gender [13][14], hence the reward is stochastic:

$$\frac{1}{\lambda_p} = 15G_M + 30G_F \quad \text{min} \tag{3}$$

2) Baggage Drop-off: This decision is driven by the time remaining to board as well as the baggage drop-off queue length. A longer queue urges the passenger to complete the check-in faster:

$$R = \underbrace{L_b T_s(\lambda_b)}_{\text{Queue time}} + \underbrace{100(1 - \frac{T_d}{120})}_{\text{Time to board}} \tag{4}$$

where the model assumes a constant service rate $1/\lambda_b = 3$ min, independent of the passenger profile.

3) Check-in and Security screening: These decisions are driven solely by the time remaining to boarding, assuming absence of additional information about queue lengths:

$$R = \underbrace{100(1 - \frac{T_d}{120})}_{\text{Time to board}} \tag{5}$$

4) Queue Selection: For manual check-in, the service time depends on both the passenger profile and the airport service rate. For self-check-in, the service time depends mainly on the passenger's profile. We model the service time with an exponential distribution as well. For the switching action, the same formulae below apply to the relevant queue, where the length of the queue reflects the current length at the switching time:

$$R = \begin{cases} -L_m T_s(\lambda_m) & \text{Manual check-in} \\ -L_s T_s(\lambda_s) & \text{Self check-in} \end{cases} \tag{6}$$

$$\frac{1}{\lambda_m} = 3G_M + 5G_F - B + 2V \text{ min} \tag{7}$$

$$\frac{1}{\lambda_s} = \begin{cases} 3 \text{ min} & 20 \leq \text{age} \leq 50 \\ 0.1A - 2 \text{ min} & \text{age} > 50 \end{cases} \tag{8}$$

For manual check-in, the service rate takes into account passenger gender (reflecting baggage need), a need for a visa (reflecting time to check the proper paperwork), and whether the passenger is a business traveler (reflecting light-weight travel). For self-check-in, the service rate reflects computer system fluency measured by age group.

Figure 3 is a state diagram representation of the MDP, where orthogonal region representation is used for the concurrent state variables `Check-in Status` and `Location`. The Check-in Area is a superstate that comprises four states representing the passenger location in the check-in area. The remaining Time to departure is initialized when entering the initial state, and globally decremented as the state diagram is executed. When a specific queue is served, an internal transition is triggered, and the passenger's position is updated. Reward functions are omitted to simplify the diagram. Dotted lines are used to distinguish actions due to environmental dynamics. For more details on SysML state diagram semantics, the reader is referred to [15].

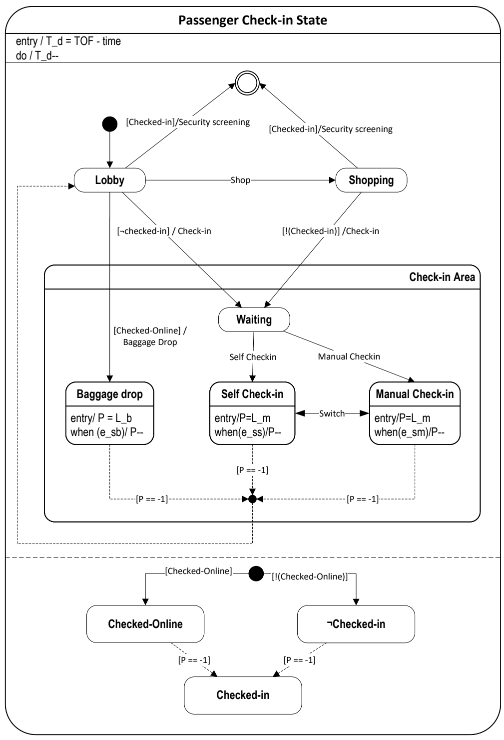

Figure 3. Check-in system state diagram. While waiting in a check-in queue, there is a decision at every time step whether to continue in the queue or switch queues. This loop-back transition is omitted to simplify the diagram.

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VI. Decision-Making Policy

A rational agent maximizes the expected cumulative reward from the initial state (here airport check-in lobby) to final state (boarding) [12]:

$$v_\pi(s) = E_\pi \left[\sum_{k=0}^{n} \gamma^k R_i | S = s \right] \quad (9)$$

where n is the number of decisions the passenger takes from airport arrival to boarding, and γ is the reward discount factor. This is a classical dynamic programming problem that can be solved using a variety of algorithms [12]. In reality, passengers would take decisions to maximize the immediate reward due to the lack of information about subsequent infrastructure state, i.e., $\gamma = 0$, which simplifies the problem significantly, as the optimal action at each state is the one with the highest average immediate reward, producing a deterministic policy.

Figure 4 shows the decision tree for the system MDP that enumerates all possible decision paths, assuming no online check-in. Due to space limitations, the decision sub-tree following the initial shopping decision is omitted, as it is identical to the sub-tree with Waiting state as its root. Every edge is annotated with its expected reward. The cumulative reward is the sum of all rewards starting from the initial state to the final state. Numbers shown are related to the numerical example explained in the next section.

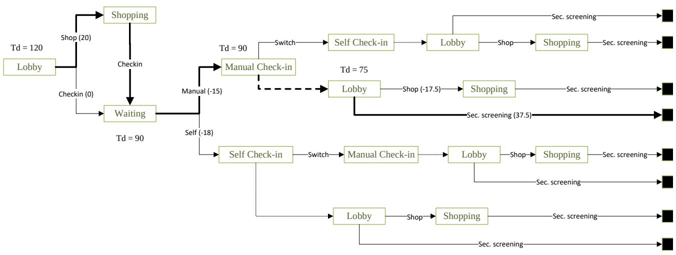

Figure 4. Decision tree for the airline passenger. Switching decision from Manual to self check-in and vice versa is not shown explicitly due to the compact representation of the state space. Dashed lines designate environmental actions not under the control of the passenger.

VII. Optimal Policy: A Numerical Example

Optimal policy of a cumulative reward system is often obtained using numerical algorithms along with interactions with the real system or a simulated version of it. An ABM approach guides the development of the airport infrastructure components. The trained agent with the optimal policy is then developed using ABM and integrated with the rest of the infrastructure environment. The presented work demonstrates the decision-making process using a numerical example and analytical techniques. This is mainly possible because of the assumption of immediate reward maximization, i.e., zero reward discount factor γ.

Assume a female, tourist, visa-free passenger profile, i.e., the feature vector is given by $\theta_p = [\ 40\ \ 0\ \ 1\ \ 0\ \ 1\ \ 0\ \ 1\ ]$. It is further assumed that the passenger arrives at the airport 2 hours before flight departure, i.e., initial $T_d = 120$ min. Furthermore, the queue lengths are $L_m = 3$ and $L_s = 6$ at the time of passenger arrival. The decision-making policy that maximizes the immediate reward results in the trajectory highlighted in bold in Figure 4, comprising Lobby $\rightarrow$ Shopping $\rightarrow$ Manual Check-in $\rightarrow$ Security screening. A passenger with the same profile who arrives 30 minutes late, encountering a longer manual check-in queue $L_m = 10$, even with matching self check-in queue length $L_s = 10$, will have the optimal path Lobby $\rightarrow$ Self check-in $\rightarrow$ Security screening.

This illustrative example highlights the benefits of a deeper understanding of passenger decision-making. Airport management can optimally allocate resources and redesign operational processes to minimize end-to-end travel time and passenger stress, ultimately enhancing overall satisfaction.

VIII. Conclusion and Future Work

This paper presents a framework that integrates ABM, DES, and MDP for studying decision-making for airline passengers. Different dynamic models can be transformed into an MDP that can be solved using a variety of dynamic programming and reinforcement learning algorithms to find the optimal policy for different discount factors. The framework facilitates the joint representation of individual decision-making and process-level system dynamics, which are often treated separately in existing studies. The contribution lies not only in the technical integration of modeling methods, but also in the application of this hybrid framework to analyze behavior-informed check-in processes under varying passenger conditions.

The analytical results demonstrate that even small variations in passenger decision-making, such as arrival time, queue preference, or check-in method, can lead to significant differences in airport performance. These decision patterns affect key metrics including queue lengths, waiting times, and passenger satisfaction. The hybrid framework, combining ABM and DES supported by MDP, provides an effective means of capturing both individual decision logic and operational flow dynamics. For airport operators, the model offers practical insights into how targeted, low-cost interventions, such as adaptive counter allocation or improved wayfinding systems, can reduce congestion as well as enhance service quality. Airlines benefit from increased predictability of passenger processing, which supports more efficient gate allocation and boarding schedules. Aircraft manufacturers may use this modeling approach to evaluate the likely impact of infrastructure-related delays on passenger behaviors and preferences.

Some simplifying assumptions are made in the presented model. Date and time of flight are important since they impact the number of passengers that are simultaneously at the airport, hence the passenger decision and experience. On the other hand, date & time also influence how the airport infrastructure functions, e.g., service rate. Moreover, flight delays and cancellations, and airport disruptions, are quite common and would significantly impact both the infrastructure dynamics and the passenger decision-making. Therefore, interfacing the developed model with external information sources, such as urban mobility networks and real-time flight scheduling, and capturing the impact in the system model are essential for realistic high-fidelity modeling and simulation. Also, we used the practical assumption that passengers seek to maximize the immediate reward, i.e., no look-ahead strategy. Lookahead strategy for decision-making would require algorithmic solutions, but may reveal counter-intuitive decisions that could be informative for both passengers and infrastructure operation. A service rate is also assumed to follow an exponential distribution, with arrival rate to follow a Poisson distribution. For a more sophisticated stochastic behaviour of the infrastructure obtained from available data, a high-fidelity simulation for the infrastructure combined with numerical algorithms would be needed to find the optimal policy, particularly for end-to-end policy optimization.

Several challenges represent the future work. First, the reward function formulation is challenging, particularly taking into account the passenger profile. Although the presented reward functions are intuitive from frequent travel experiences, tuning such reward functions is not an easy task. Available datasets could help, but there is no single integrated dataset that combines all the presented features; hence, data aggregation with practical assumptions is needed. Inverse reinforcement learning, where the reward is learned from observed behavior, is currently under investigation. Second, modeling decision-making for humans is a difficult task. Although the passenger profile presented can help significantly, modeling human behavior using a set of features may introduce bias and reduce the resulting accuracy. For example, assuming that all female passengers prefer shopping may be a biased assumption and inaccurate. Adding additional attributes may help, e.g., age and origin, but this complicates the problem due to the increased number of features that further require additional data. Finally, measuring passenger satisfaction is important for both airport operation and airline decision-making. Overall time from check-in to flying is one metric that is captured in the presented model. However, other factors can be considered, such as comfort and emotional stress, which are challenging to capture, yet significantly impact passenger behavior. Future research will aim to include the aforementioned modeling elements and to relax the simplifying assumptions for the complete airport infrastructure for wider model applicability. Also, available datasets will be used for model refinement and validation. Sensitivity analysis will be carried out to identify the most critical assumptions. Finally, the passenger agents will be explored to better understand the passenger-infrastructure interactions in modern airport systems.

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