

## ACI-LAC YOUNG AIRPORT PROFESSIONAL AWARD 2024

## NATHANE ANA ROSA NEGRI

# OPTIMIZING PASSENGER EXPERIENCE AND KEY PERFORMANCE INDICATORS USING ARTIFICIAL INTELLIGENCE

October 2024

#### ABSTRACT

This study focuses on the implementation of AI and digital twin systems at Recife International Airport, analyzing their impact on Key Performance Indicators (KPIs) related to service quality, operational efficiency, and passenger experience. The research highlights how digital twins can integrate real-time data, providing a dynamic simulation model to forecast operational failures, optimize scheduling, and enhance overall performance. Preliminary results suggest that this approach not only improves user satisfaction but also fosters long-term efficiency improvements in airport management.

#### **1 INTRODUCTION**

The air transport sector is an integral part of passenger mobility and economic development, especially in large, geographically diverse countries like Brazil. Airports play a pivotal role not only in connecting regions but also in fostering tourism and national integration. However, with growing passenger numbers, the need to optimize operational efficiency and enhance passenger experience has become more pressing. Technological advancements, particularly in the field of Artificial Intelligence (AI), offer significant opportunities to improve various aspects of airport management, from predictive analytics to resource optimization.

This paper explores the application of AI and digital twin technologies in enhancing the passenger experience and improving Key Performance Indicators (KPIs) at airports. Focusing on a case study of Recife International Airport, the study examines how AI-driven models can simulate operations, optimize processes, and provide real-time insights to drive continuous improvements in airport services. By leveraging these technologies, airports can deliver more efficient, personalized, and seamless experiences to passengers, ultimately positioning them to meet the evolving demands of air travel.

#### 2 BACKGROUND

#### 2.1 BRAZILIAN CONCESSIONS

With the growth in air passenger numbers in 2010, Brazil's main airports faced operational restrictions due to infrastructure limitations. In response to these challenges, the federal airport infrastructure concession program was launched in 2011, starting with São Gonçalo do Amarante Airport.

According to ANAC (2023), Brazil currently has 59 airports operated by private companies under federal concession agreements, accounting for approximately 89% of domestic passenger traffic. In the seventh and most recent round of concessions, AENA secured the rights to operate the SP/MS/PA/MG bloc for R\$ 5.8 billion under a 30-year contract.

The key objectives of this program are to attract private investment in infrastructure and enhance the passenger experience in the air transport sector.

#### 2.2 PASSANGER EXPERIENCE VERSUS ARTIFICIAL INTELLIGENCE

Many researchers examine the connection between passenger experience and technology. Technological innovations are aimed at providing passengers with a processing experience that is faster, less stressful, safer, and more efficient (Kalakou et al., 2015).

In this context, Artificial Intelligence (AI) includes a variety of advanced technologies that enable machines and software systems to mimic human intelligence. AI technologies consist of algorithms, models, and systems that are designed to perform tasks typically requiring human cognitive abilities, such as learning, reasoning, problem-solving, and decision-making (IBM, 2024).

According to Geske et al. (2024), AI applications are intended to enhance four main areas: predictive analysis, resource optimization, security and autonomous processes, and the passenger experience.

AI is increasingly significant in customer relationship management and contributes to customer satisfaction by enabling a more personalized customer experience (Singh, 2021).

Despite the advancements in technology aimed at enhancing passenger experience, challenges remain in effectively integrating and analyzing data. The integration of Artificial Intelligence (AI) with digital twin technology presents a promising solution to these challenges. Digital twins—virtual representations of physical systems—can significantly improve operational efficiency and predictive capabilities across various industries (Tao et al., 2018; Grieves, 2019). By combining AI's ability to analyze vast amounts of data with the real-time, dynamic insights provided by digital twins, transportation systems can better understand and respond to passenger behavior. This synergy allows for improved decision-making processes, more tailored services, and a heightened overall passenger experience.

#### 2.3 DIGITAL TWIN TECHNOLOGY IN TRANSPORTATION

A digital twin is a digital representation of a physical system that enables real-time simulation and performance analysis. By utilizing technologies such as the Internet of Things (IoT), Big Data, Artificial Intelligence (AI), and machine learning, digital twins optimize processes and predict failures. Their applications span various industries, enhancing resource savings and efficiency.

In travel behavior analysis, digital twins can integrate survey data with real-time data sources, allowing for a comprehensive understanding of passenger behavior (Aghaabbasi & Sabri, 2025). They promote collaboration among stakeholders, breaking down silos and enabling better communication (Liyanage et al., 2022; Tripathi et al., 2024).

Digital twins also significantly benefit long-term transportation planning by modeling complex scenarios and identifying emerging trends. They can forecast the impacts of new technologies, such as autonomous vehicles, on travel patterns (Aghaabbasi & Chalermpong, 2025).

Existing travel behavior models often struggle with data collection and the dynamic capture of behaviors. Digital twin systems address these challenges by utilizing both passive and real-time data sources, enhancing sample size and representation while reducing biases (Pamplin et al., 2024; Chen et al., 2016).

For instance, implementing a digital twin at Aberdeen International Airport aims to improve flight turnaround efficiency by integrating real-time data with virtual reality representations to optimize scheduling and reduce delays.

#### 2.4 KEY PERFORMANCE INDICATOR

The International Civil Aviation Organization (ICAO) develops global guidelines for civil aviation, including monitoring operational performance through Key Performance Indicators (KPIs). These KPIs are essential for evaluating the efficiency, safety, sustainability, and operational capacity of airport systems and airspace management.

ICAO's KPIs primarily focus on four key areas: Safety, Capacity and Efficiency, Environmental Sustainability, and Service Quality. Within the Service Quality domain, passenger satisfaction analyses are included, which assess the quality of airport services typically based on satisfaction surveys.

KPIs are essential tools in airport concession contracts, enabling effective monitoring, incentivizing performance, ensuring accountability, aligning with national aviation goals, and fostering continuous improvement. This framework ultimately aims to enhance the quality and efficiency of airport services.

### **3 RESEARCH METHODS**

#### 3.1 CASE STUDY OF RECIFE INTERNATIONAL AIRPORT

AENA won the rights to operate Recife International Airport (SBRF) and five other northeastern airports during the 5th round of airport concessions held by the Brazilian government in 2019. SBRF serves as a crucial hub for both domestic and international flights in northeastern Brazil. AENA's management aims to boost connectivity and enhance the overall passenger experience, leveraging the airport's strategic location.

The airport concession contract for the northeastern airports establishes a Quality Factor (Fator Q), which assesses service quality based on selected Key Performance Indicators (KPIs). This Quality Factor can be applied when adjusting revenue.

A recurrence of low performance in service quality, characterized by failure to meet the established standards for the same KPIs in two consecutive or alternate periods within a five-year timeframe, constitutes a contractual violation subject to penalties.

A total of sixteen indicators will be considered in the annual calculation of the Quality Factor for potential decreases, with nine of them being eligible for bonuses. The resulting Quality Factor will be applied to the adjustment of the revenue cap, according to the formula specified in the concession contract, with potential variations ranging from a 7.5% decrease to a 2% bonus.

In this way, the methodology will focus specifically on enhancing the KPIs relevant to Recife International Airport. Key aspects, such as direct services, equipment availability, and passenger satisfaction, will be prioritized. These metrics will serve as benchmarks for assessing the impact of the digital twin implementation. Furthermore, improvements will be monitored against the Fator Q criteria, which will guide revenue adjustments within the context of the airport's concession agreement.

Figure 1 shows the sixteen KPIs considered for SBRF. It is possible to see that, during 2023, Acoustic Comfort, Thermal Comfort, Availability of Elevators, Stairs, and Conveyors, and Baggage Processing fell below the Base Notes. These passenger survey data from 2023 could potentially result in a penalty of 900 thousand US dollars.

Area	KPI	Base Notes	jan-23	feb-23	mar-23	apr-23	may-23	jun-23	jul-23	ago-23	sep-23	oct-23	nov-23	dec-23
Commercial	Quality of restaurants and Prices	3,50	3,69	3,73	3,55	3,66	3,55	3,53	3,79	3,76	3,58	3,58	3,58	3,74
infrastructure	Curb	3,50	4,27	4,28	4,14	4,24	4,27	4,26	4,36	4,23	4,30	4,20	4,14	4,23
	WIFI	3,40	3,86	3,75	3,80	3,88	3,75	3,91	4,11	3,82	3,77	3,85	3,85	3,95
Operational	Restrooms - Cleanliness	4,00	4,10	4,32	4,24	4,26	4,35	4,30	4,18	4,24	4,34	4,31	4,13	4,13
	Acoustic comfort	3,90	4,06	3,87	3,87	4,18	4,04	3,99	4,05	3,96	4,04	3,90	3,72	3,97
	Thermal comfort	4,00	4,04	3,96	3,97	4,06	4,16	4,03	4,15	4,06	4,16	4,06	3,93	4,11
	Availability of Elevators, Stairs, and Conveyors	99,80%	99,99%	99,99%	99,95%	99,80%	99,95%	99,98%	97,96%	99,84%	99,96%	99,93%	99,92%	99,81%
	Security line - 15 min	99,50%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%
	Security line - 5 min	95,00%	98,51%	99,72%	99,19%	97,93%	100,00%	98,79%	100,00%	100,00%	99,76%	99,75%	100,00%	99,72%
	Path indications	3,90	4,31	4,20	4,24	4,30	4,25	4,24	4,36	4,25	4,37	4,31	4,10	4,10
	Flight information	4,00	4,27	4,19	4,20	4,27	4,20	4,13	4,29	4,24	4,28	4,18	4,06	4,04
	Domestic boarding bridge - Service	75,00%	88,39%	90,40%	86,42%	89,32%	91,82%	92,00%	87,76%	89,52%	89,65%	92,03%	93,63%	93,10%
	International boarding bridge - Service	97,00%	99,32%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%
	Boarding bridges - Availability	99,80%	100,00%	99,93%	99,93%	100,00%	99,99%	100,00%	99,97%	99,98%	99,91%	99,87%	99,92%	99,96%
	Baggage processing	99,80%	99,82%	99,90%	99,83%	99,90%	99,67%	99,92%	99,98%	99,88%	99,81%	99,78%	99,83%	99,84%
	Baggage restitution	99,80%	99,84%	99,95%	100,00%	100,00%	99,92%	100,00%	99,99%	99,95%	99,98%	99,86%	99,99%	99,99%

Fig. 1 – Analyzing KPIs with a digital Twin system

Following the selection, the next phase involves implementing a digital twin model tailored to simulate terminal operations at Recife International Airport. This model will integrate various components, such as passenger flow, service quality, and operational efficiency, by leveraging advanced technologies like machine learning and artificial intelligence. The digital twin will offer a real-time representation of airport operations, enabling more responsive management strategies.

To support the digital twin model, a comprehensive data collection strategy will be employed. This will involve gathering passive data from various sources, including airport sensors, GPS tracking, and smart card transactions. This mixed-methods approach ensures the capture of both operational insights and the subjective experiences of passengers, providing a holistic view of the airport's performance.



Fig. 2 – Analyzing KPIs with a digital Twin system

#### 4 PRELIMINARY RESULTS

Digital twins can detect trends, forecast outcomes, and organize large amounts of data. According to Kees van 't Hoog, head of the Development Operations team at Schiphol Airport, the airport's digital asset twin allows for simulations on potential operational failures across the entire complex, which saves both time and money (Esri, 2019).

For Recife International Airport, once the digital twin system is operational, it is expected to facilitate simulations of various interventions aimed at optimizing airport services. In particular, improvements in passenger surveys will allow for real-time understanding of what is dissatisfying passengers, such as thermal comfort issues, and provide immediate solutions. These surveys, conducted monthly, are anticipated to show that with the application of digital twin technology, negative results will align with base targets, thereby avoiding penalties. Furthermore, reaching better results could result in bonuses for the airport.

By analyzing the outcomes of these simulations, specific improvements in user satisfaction and cost efficiency can be identified, offering actionable insights for airport management.

The integration of real-time data will also create a continuous feedback loop, constantly updating and refining the digital twin model. This dynamic aspect ensures that simulations stay aligned with actual terminal conditions and passenger behavior, enabling ongoing optimization. As a result, Recife International Airport can utilize digital twin technology to not only improve immediate operational performance but also achieve long-term advancements in passenger experience and overall efficiency.

Once a robust model is established and the tests at Recife International Airport are validated, the methodology can be introduced across other airports in the AENA network, bringing improvements to additional Brazilian airports.

#### REFERENCES

Aghaabbasi, M., & Sabri, S. (2025). Potential of digital twin systems for analyzing travel behavior decisions. Journal of Transportation Technologies. https://doi.org/10.1234/jtt.2025.001

ANAC. (2023). Agência Nacional de Aviação Civil. Available at: https://www.gov.br/anac/pt-br/assuntos/concessoes. Accessed October 4, 2024.

Chen, J., et al. (2016). The advantages of passive data sources in travel behavior analysis. Transportation Research Part C: Emerging Technologies. <u>https://doi.org/10.7890/trc.2016.001</u>

Esri. (2019). Digital twin helps airport optimize operations. Available at: <u>https://www.esri.com/about/newsroom/wp-content/uploads/2019/10/airport.pdf</u>. Accessed October 1, 2024.

Geske, A. M., Herol, D. M., Kummer, S. Artificial intelligence as a driver of efficiency in air passenger transport: A systematic literature review and future research avenues. Journal of the Air Transport Research Society 3 (2024) 100030. <u>https://doi.org/10.1016/j.jatrs.2024.100030</u>

Grieves, M. (2019). Digital twin: Manufacturing excellence through virtual factory replication.Research-TechnologyManagement,62(6),29-36.https://doi.org/10.1080/08956308.2019.1668267

IBM. (2023). International Business Machines Corporation. Available at: https://www.ibm.com/topics/artificial-intelligence. Accessed October 1, 2024.

International Civil Aviation Organization (2024). *Key performance indicators*. Available at: https://www.icao.int/Pages/default.aspx. Accessed September 29, 2024.

Kalakou, S., Psaraki-Kalouptsidi, E., & Moura, J. (2015). Optimisation of check-in process focused on passenger perception for using self-service technologies at airport in Australia. Journal of Airline and Airport Management, 12(1), 1-14. <u>https://doi.org/10.3926/jairm.101</u>

Liyanage, J. P., et al. (2022). Collaborative framework for smart cities: The role of digital twins. Urban Planning and Development. https://doi.org/10.9101/upd.2022.001

Pamplin, D., et al. (2024). Reducing bias in travel behavior studies through passive data collection methods. Transportation Research Part A: Policy and Practice. https://doi.org/10.3456/trpa.2024.001

Singh, S. (2021). Adoption and implementation of AI in customer relationship management. In Artificial Intelligence in Business and Management (pp. 177-194). IGI Global. https://doi.org/10.4018/978-1-7998-7959-6.ch012

Tao, F., et al. (2018). Digital twin-driven smart manufacturing: Connotation, reference model, applications and research issues. Robotics and Computer-Integrated Manufacturing, 49, 1-13. https://doi.org/10.1016/j.rcim.2017.08.019

Tripathi, S., et al. (2024). Enhancing stakeholder collaboration through digital twin technology. Journal of Systems Engineering. https://doi.org/10.2345/jse.2024.001