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Internet of Things and Artificial Intelligence for Smart Airports

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ABSTRACT

The Fourth Industrial Revolution, or Industry 4.0, promotes innovation and automation. In this new era, Internet of Things and Artificial Intelligence can drive the implementation of smart airports that will improve the airports' outcomes and productivity based on real-time and situation-specific conditions. The objective of this research is to propose a framework for implementing an Internet of Things based Artificial Intelligence (ITAI) system for smart airports and a research process for identifying and mitigating potential risks associated with ITAI implementation along with critical success factors.

KEYWORDS: Internet of Things, Artificial Intelligence, smart airport, innovation, machine learning, deep learning

INTRODUCTION

The Fourth Industrial Revolution, or Industry 4.0, promotes innovation and automation, in which machines are getting more advanced in predicting, learning, and managing themselves. In this new era, Internet of Things and Artificial Intelligence have driven the world to a new level of networked connection of people, systems, and smart products. They become the main drivers for innovation and automation to improve outcomes and productivity. Among public sectors, airports have a substantial contribution to economic growth. According to the FAA (2017), airports contributed \$76 billion in total output to the U.S. economy in 2014. Airports maintain communications and interactions within their own internal operations, and among themselves, the airlines, and the passengers and guests who arrive and depart. Airports have numerous facilities and components that can be connected, but the number of components and parties involved often creates difficulties in ensuring safe and effective operations and providing satisfactory customer services. Industry 4.0 provides technological capabilities to create smart airports. There is no consensus definition of a smart airport in the current literature. Zmud et al. (2018) describe a connected airport as a system using a "variety of technologies through the Internet of Things, with the goal of improving the passenger experience and bringing monetary benefits to the host airport." Smart airports are more than just connected airports. Essentially, a smart airport is a system that uses an Artificial Intelligence platform to collect and analyze real-time data in a connected airport ecosystem and automatically solves airport business problems through generating optimal solutions in a real-time manner to enhance the safety and security, operational optimization, environmental sustainability, and financing solutions of the airport. In a smart airport, manual processing and human interventions are minimized to avoid human errors and delays and ensure the automation or airport safety and efficiency.

Internet of Things and Artificial Intelligence are critical components of a smart airport. Internet of Things is the third wave of information-technology-driven competition and promises more

innovation, productivity gain, and economic growth (Porter & Heppelmann, 2014). The *Internet of Things* (IoT) is defined as “an infrastructure of interconnected objects, people, systems, and information resources together with intelligent services to allow them to process information of the physical and the virtual world and react.” (ISO, 2015). The IoT is characterized by monitoring capability (monitoring a product’s condition, operation, and external environment through sensors and external data sources), control capability (controlling through remote commands of algorithms built into the device or in the cloud), optimization capability (optimizing the performance through data analytics to improve output, utilization, and efficiency), and autonomy capability (incorporating autonomous product operation and enhancement, self-coordination, and self-diagnosis and service) (Porter & Heppelmann, 2014). An IoT system can create automatic and smart communications among objects, people, and systems, and IoT devices collect data in real-time and store them in the cloud.

The rapid growth of Artificial Intelligence (AI) creates a perfect combination with the IoT to enhance the automation. A combination of AI and IoT is a prerequisite for success in IoT-based digital ecosystems (Hwang, 2019). AI can be defined as a system that simulates human intelligence for either solving a problem or making a decision (Chowdhury & Sadek, 2012). AI can learn, predict, improve, and solve. Through training, an AI application is able to generate optimal solutions and apply them to novel situations not encountered before. Thus, AI can process a large amount of data provided by IoT devices to make a prediction and automatically produce an optimal solution and even take actions. An *Internet of Things based Artificial Intelligence (ITAI)* system can be defined as a system that senses, monitors, connects, controls multiple components, and processes the data to automatically produce an optimal solution and take actions to solve business problems.

An ITAI system can enhance innovation and automation in airport ecosystems to create smart airports by connecting airport components, passengers, and stakeholders in a synchronized system. In this system, machine learning algorithms can be used to analyze data to detect unknown patterns, based on which ITAI can automatically produce solutions to solve business problems and take actions. Such a smart system allows airports to maintain safe operations at the highest level of effectiveness and, at the same time, provide passengers with satisfactory services. In order to implement this system successfully, an operational framework is needed. The current literature on applications of IoT and AI in airport research seems to focus on the use of a specific IoT device for a specific task rather than a comprehensive framework that shows the linkage between IoT devices, data storage, machine learning, and AI applications. Such a framework is needed to enable airport authorities to develop, deploy, and implement ITAI to enhance airport safety and operations.

Despite its advantages, ITAI is not without challenges. Airports need to meet strict technical, process, and managerial requirements to be able to successfully implement the ITAI. The biggest challenges are to connect all components and store a very large amount of data, deal with the complexity of interconnecting multiple components and data sources, and process big data with the aging infrastructure. Additionally, the ITAI is often considered a black box, which may pose some serious threats, such as technical (system and application failures), security, and privacy risks (Lykou et al., 2018). The risks may cause serious issues for airports, such as system failure, unavailable customer services, cyber-attacks, security vulnerabilities, and identity thefts. Airport executives need to gain sufficient understanding of the ITAI’s applications and components, implementation processes, and requirements. They must also learn about potential risks associated with ITAI implementation and know how to manage and mitigate these

risks, so they can successfully implement the ITAI while ensuring the security and privacy of the airport and passengers.

The objective of this research is twofold: 1) to propose a framework for implementing ITAI for airports, including steps and requirements; 2) to propose a research process for identifying and mitigating potential risks associated with ITAI implementation at airports along with critical success factors.

LITERATURE REVIEW

IoT Studies for Airports

Despite the rapid growth of IoT in industries, IoT research studies in the airport environment are very limited. Cao et al. (2013) proposed a design for airport perimeter security system based on the IoT. The authors described the features and applicability of the airport perimeter security system using IoT. The authors conclude that IoT sensors provide a novel, low-cost, low maintenance choice to improve the capability to detect, locate, and classify intruders at airports. Wang et al. (2013) conducted a field survey that adopted IoT-based emergency monitoring and warning models to estimate the disaster losses and to prevent a secondary disaster from occurring. The authors used relative displacement sensing technology and Global System for Mobile Communications (GSM) technology to remotely monitor ground cracks in the landslide. Troiano and Pasero (2014) developed sensors to detect the presence of ice or water on the airport surface. They did experiments both in a laboratory and in the field to evaluate the repeatability, stability, and reliability of the sensor. Three sensors were embedded in the runway to check the state of the surface. Each sensor was connected to a GPRS modem to allow the data to be collected and stored. The state of the runway surface based on the collected data from the sensors is virtually represented the IoT features. Finally, Liu and Lu (2015) developed a perimeter intrusion detection system (PIDS) using sensors that detect illegal intrusion to an airport. The PIDS can accurately detect an intrusion, identify the type of intrusion, locate the intrusion target, and reduce false alarms due to unexpected interference. The PIDS has been successfully deployed and implemented by Shanghai Pudong International Airport. While these studies provide some interesting designs and applications of IoT systems for airports, they mainly focus on developing single systems using IoT sensors at airports. They lack the holistic view of airport systems and how AI can be used to support airport safety and effectiveness.

In order to determine the changes that airports need to make in a new era, Robinson (2017) explores the opportunities and challenges faced by airport authorities. The author indicates that the new digital age presents “the opportunity to not only reinvent the travel experience but also to develop solutions that result in cost-effective capital expenditure and optimize existing infrastructure.” The main challenge to the adoption on a global scale is the non-uniformity of the solutions. While digital solutions can be developed at an airport-by-airport level, the global air travel system will require strong collaborative initiatives across airports and stakeholders in different countries. In a more recent study, Zmud et al. (2018) developed a primer for airport operators and stakeholders in the Internet of things (IoT) within the airport environment. The authors described airport systems as a whole consisting of multiple connected components inside and outside of its boundaries. Additionally, the study described IoT enabling technologies that can be used for airports and obstacles to the implementation of connected devices and data sharing. The study also examined the passenger experience with IoT solutions at Atlanta International Airport (ATL), San Francisco International Airport (FSO) and Dallas Fort Worth International Airport (DFW).

Overall, the literature in IoT for airports seems to focus mainly on using a specific IoT device to accomplish a specific task, and the focus on a connected airport ecosystem is missing. As stated by Robinson (2017) and Zmud (2018), airport is a complex system consisting of multiple components that are connected to passengers and stakeholders. However, these studies are conducted at the conceptual levels and have not explored the role of AI in IoT systems for smart airports. A more comprehensive and robust system should be used at airports to take advantage of IoT and AI capabilities in the Industry 4.0 era. ITAI is a system that can automatically collect data, predict, learn, and generate solutions to help airport authorities solve business problems with minimal human intervention. Given the important role of this system for developing and deploying smart airports, further exploration and investigation are required.

IoT Components and Process

The objectives of IoT are to connect objects through smart technologies to be able to monitor and control these objects through a robust process. Table 1 presents the IoT components described in the literature. In an IoT system, physical objects are interconnected through a reliable network (Zmud et al., 2018). To connect physical objects and collect data in real-time, sensors, and communication devices are required (Madakam et al., 2015, Zmud et al., 2018, Deloitte Insights, 2018). Additionally, in order to ensure the consistency, validity, and usability of the data, uniform standards are needed for these devices (Deloitte Insights, 2018). Once the data are collected, they will be stored in cloud data storage, which should be large and powerful enough to manage the data and allows accessing data securely and effectively. Last, but not least, IoT requires analytics tools that can analyze the data to support the decision-making process (Madakam et al., 2015, Zmud et al., 2018, Deloitte Insights, 2018).

Zmud et al. (2018) and Meyers et al. (2015) also describe the IoT process, which typically starts with collecting data by smart sensors. Then data will be aggregated and analyzed to provide business insights, which in turn will lead to recommendations for decisions or acts. This process is to ensure the connected smart things can connect and operate smoothly in a connected system to support the decision-making process. Madakam et al. (2015) suggest some prerequisites for an IoT solution, including dynamic and real-time demand, access to data, end-user applications, security, and privacy.

Table 1: IoT components and process

<i>Madakam et al. (2015)</i>	<i>Zmud et al. (2018)</i>	<i>Meyers et al. (2015)</i>
<u>IoT Components</u> <ul style="list-style-type: none"> • Hardware (sensors, IP cameras, communication devices) • Middleware (demand storage and data analytic tools) • Presentation (visualization and interpretation tools) 	<u>IoT components</u> <ul style="list-style-type: none"> • Physical objects (person, luggage, or boarding pass) • Instrumentation (smart components such as sensors or data collection system) • Connectivity (network-based device facilitating the interconnection between an object, its 	<u>IoT components</u> <ul style="list-style-type: none"> • Sensors • Network • Standards • Augmented intelligence • Augmented behavior

	environment, and data management system) <ul style="list-style-type: none"> Analytics (information gained from data analysis) 	
<u>IoT Prerequisites</u> <ul style="list-style-type: none"> Dynamic resource demand Real-time need, exponential growth of demand Availability of applications Data protection and user Privacy Efficient power consumptions of applications Execution of the applications near to end-users Access to an open and interoperable cloud system 	<u>IoT Basic framework</u> <p>Data captured by sensors → Sensor data communicated and aggregated □ Sensor data analyzed to modify future acts</p>	<u>IoT process</u> <p>Business activities □ Sensors produce data □ Data is analyzed in the cloud □ Analysis leads to insights □ Decisions and actions</p>

Roles of Machine Learning, Deep Learning, and Optimization Modeling in Artificial Intelligence Applications

Artificial Intelligence (AI) can be defined as a system that simulates human intelligence for either solving a problem or making a decision (Chouwdhury & Sadek, 2012). AI can process data to learn, predict, improve, and solve problems. Through training, an AI application is able to generate optimal solutions and apply them to novel situations not encountered before. In the airport context, faced with the challenges of growing air traffic, resource demands, increasing uncertainties, and operational complexity, AI can automatically predict issues in an airport ecosystem and provide real-time optimal solutions and decisions under uncertainties, hence solving the problem. However, AI is not without limitations and challenges. Since AI is often regarded as a black box, there are concerns about AI's capabilities to generalize to new situations or how AI determines the best decisions, hence some skepticism on AI's capabilities. It is also a challenge to integrate AI to current airport systems. Furthermore, AI could also be a potential liability, given its autonomous nature (Chouwdhury & Sadek, 2012). Some key components of AI include machine learning, deep learning, and optimization modeling (Sadek, 2007; Tien, 2017).

Machine Learning

Machine learning is a key component of an AI system. SAS defines machine learning as “a method of data analysis that automates analytical model building. It is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns, and make decisions with minimal human intervention.”

(https://www.sas.com/en_us/insights/analytics/machine-learning.html). Machine learning is an important component of an AI system since it allows the AI to learn and uncover unknown patterns from large and noisy data and predict the desirable outcome (Sadek, 2007). The model can be adjusted and improved with real-time data feeding to the algorithms. Machine learning is usually used in a data mining process, which uses various machine learning algorithms to

analyze large and noisy data to uncover new patterns that would provide information for business decision making (Nisbet et al., 2009). Popular machine learning algorithms include, but not limited to, regression, decision tree, support vector machine, memory base reasoning, Bayesian network, neural network, random forest, and gradient boosting tree. Machine learning can be categorized into supervised learning and unsupervised learning. Supervised learning requires identifying a variable as a target variable and determines the relationships between the predictors and the target variable, hence, predicting this variable (Sarma, 2013). For example, prediction models can be used to predict the probability of an aviation incident. Truong et al. (2018) used decision tree and Bayesian networks learning algorithms to predict the probability of a flight delay between two cities. Additionally, Truong (2018) uses various machine learning algorithms to predict the risk of small unmanned aircraft systems (sUAS) violations in the National Airspace System. Unsupervised learning discovers probabilistic relationships among a large number of variables, without having to specify predictor and target variables (Sarma, 2013). For example, unsupervised learning can be used to detect anomalies in pilot behaviors during an unstable approach or passengers' perception of airport service performance.

Deep Learning

Deep learning is a growing field in the past few years and plays an important role in AI systems (Arel et al., 2010). Essentially, deep learning is an advanced class of machine learning algorithms that use Artificial Neural Network (ANN) to train the model. Unlike machine learning, which requires structured data through a data cleaning, coding, and variable identifying process to train the model, deep learning can automatically handle unstructured data without preprocessing. Deep learning learns the same way as the biological neural network of the human brain by using multiple hidden layers in ANN. Deep learning can automatically extract information from large and noisy data and detect patterns at a high level of accuracy (Smidhuber, 2015). Convolutional neural network (CNN), a commonly used algorithm in deep learning, is a multi-layer neural network designed for use on two-dimensional data, such as images, audios, and videos. Image recognition and classification are good examples of how CNN can be used to detect physical and human subjects in images or videos (Arel et al., 2010). Image or audio recognition can be used to improve passenger services at airports or to ensure airport security. Similarly, audio or text recognition can be used to detect anomalies in runway safety. While machine learning requires structured data, identified variables, and interferences of the data analyst, deep learning automates the entire process. In essence, deep learning makes AI work. Nonetheless, this does not necessarily mean machine learning is not useful in an AI system. In a system where a specific target variable is identified, a supervised learning model works best to predict the target variable and predictors contributing to this prediction. Such a prediction model would allow the system to predict the risk of a certain aviation incident, which can lead to a solution to mitigate the risk (Truong et al., 2018). Accordingly, when to use machine learning and when to use deep learning depends on the business problem and the organizational objectives.

Optimization Modeling

While machine learning and deep learning are great methods to discover unknown patterns which help detect a problem, an AI system needs to automatically generate a solution and even take actions. In order to do so, optimization modeling is needed to find the optimal solutions for the problem (Van Zuylen, 2012; Zhang and Xie, 2012). Optimization modeling is a decision science method that determines the optimal values of decision variables to achieve the objective function, given the constraints of resources. Methods such as linear programming,

integer linear programming, goal programming, non-linear programming, and dynamic programming have been used extensively in many areas. In an AI system, such an optimization model can be developed based on the outputs of machine learning or deep learning, business resources, and business objectives. The optimal solution of this model along with sensitivity analysis provide the AI system necessary information about what actions should be taken to solve the problem.

PROPOSED INTERNET OF THING BASED ARTIFICIAL INTELLIGENCE (ITAI) FRAMEWORK FOR AIRPORTS

The capabilities of IoT can be combined with AI to create a smart system that can connect, sense, monitor, and control objects, collect data in real-time, learn, predict, produce optimal solutions, and take actions to improve the safety and operational efficiency of an airport. Figure 1 presents the proposed framework for Internet of Things based Artificial Intelligence (ITAI) implementation for smart airports.

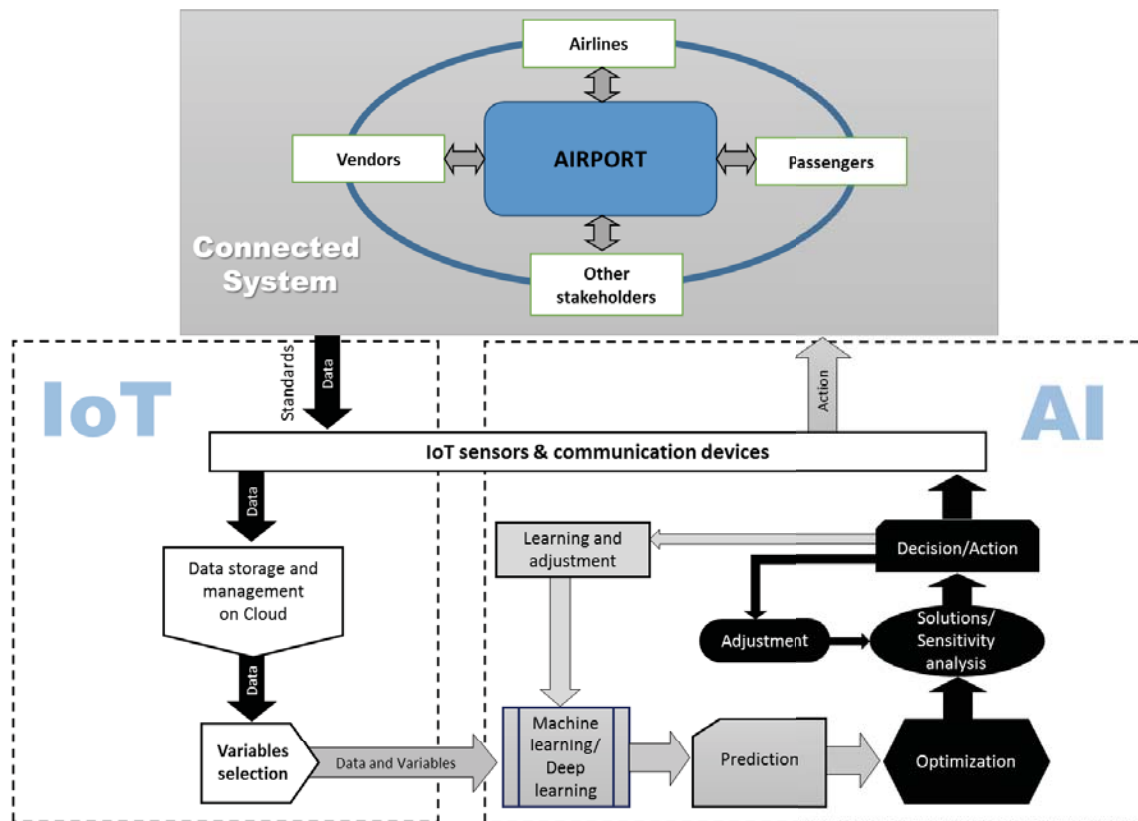


Figure 1: Internet of Thing based Artificial Intelligence (ITAI) framework for smart airports

The framework consists of the following components.

- **Connected airport system:** Airport is a complex transportation hub serving aircraft, passengers, cargo, and surface vehicles. An airport typically consists of airside facilities,

landside facilities, and the terminal building (Office of Technology Assessment, 1984). In a connected airport ecosystem, the airport is connected with airlines, passengers, vendors, and other stakeholders, to ensure the visibility and effectiveness of airport operations.

- **IoT system:** A wide variety of IoT sensors and communication devices are installed and deployed at the airport. These devices are able to sense, monitor, and control objects. They communicate with each other to share and collect data throughout all airport-related operations. Uniform standards are needed to make sure sensors and devices are seamlessly communicated, and data are consistently collected in real-time. The data are collected in real-time and stored in the cloud through an effective big data management system. This system plays a critical role in ITAI, given the tremendous amount of data is collected continuously (Tien, 2017). The data need to be stored effectively and securely, and at the same time, must be accessible. Cloud computing provides a scalable solution for big data management and allows accessibility (Truong, 2010). Nonetheless, given the sensitivity of the data, the system must guarantee the security and privacy for the stored data. Furthermore, the system must be reliable to ensure uninterrupted operations. Finally, various data analytic methods can be used to explore the data and identify relevant variables.
- **Artificial Intelligence:** ITAI framework takes the data analytics to the next level by automating the entire process so airport operations can be done with minimal human interference. The first component of the AI in the ITAI framework is machine learning, in which machine learning or deep learning algorithms are used to detect unknown patterns. The process requires to develop, train, and validate prediction models. Then, these models are evaluated and compared based on pre-determined selection criteria, and the best prediction model with the highest prediction accuracy is selected. Machine learning algorithms can handle large and noisy data to build a prediction model with high predictive power (Sarma, 2013). This prediction algorithm is used to make a prediction with real-time data feeding to the algorithm. The prediction model can be automatically adjusted to improve its performance with new data coming in. Supervised machine learning can be used to predict a specific target variable, such as runway safety incident, maintenance issue, flight delay, or security issue. If unstructured data, such as images, audios, videos, and texts are provided, deep learning can be used to detect anomalies or patterns (Arel et al., 2010). Image and audio recognition can be used to enhance airport security, provide passengers with directions, or help them find lost items or needed services. Similarly, audio and text recognition can be used to detect anomalies related to runway safety or maintenance errors. Finally, an optimization module in the AI system uses the results of machine learning or deep learning to find an optimal solution to the airport business problem, such as to either maximize the performance or minimize the cost of operations. The optimal solution usually includes the values of decision variables. Additionally, sensitivity analysis can be conducted to evaluate various what-if scenarios to determine the best course of actions needed to solve the problem. Then, the AI makes the decision and take actions by sending commands to IoT devices, which control the connected objects to take corrections. The information about the decision and results is sent back to the AI system to allow this system to learn and make an adjustment. The machine learning will be continuously improved.

In order to implement this ITAI framework, specific steps should be followed. Figure 2 presents a process consisting of specific steps. These steps are to allow airport authorities to correctly deploy and implement the system to meet the business objectives.

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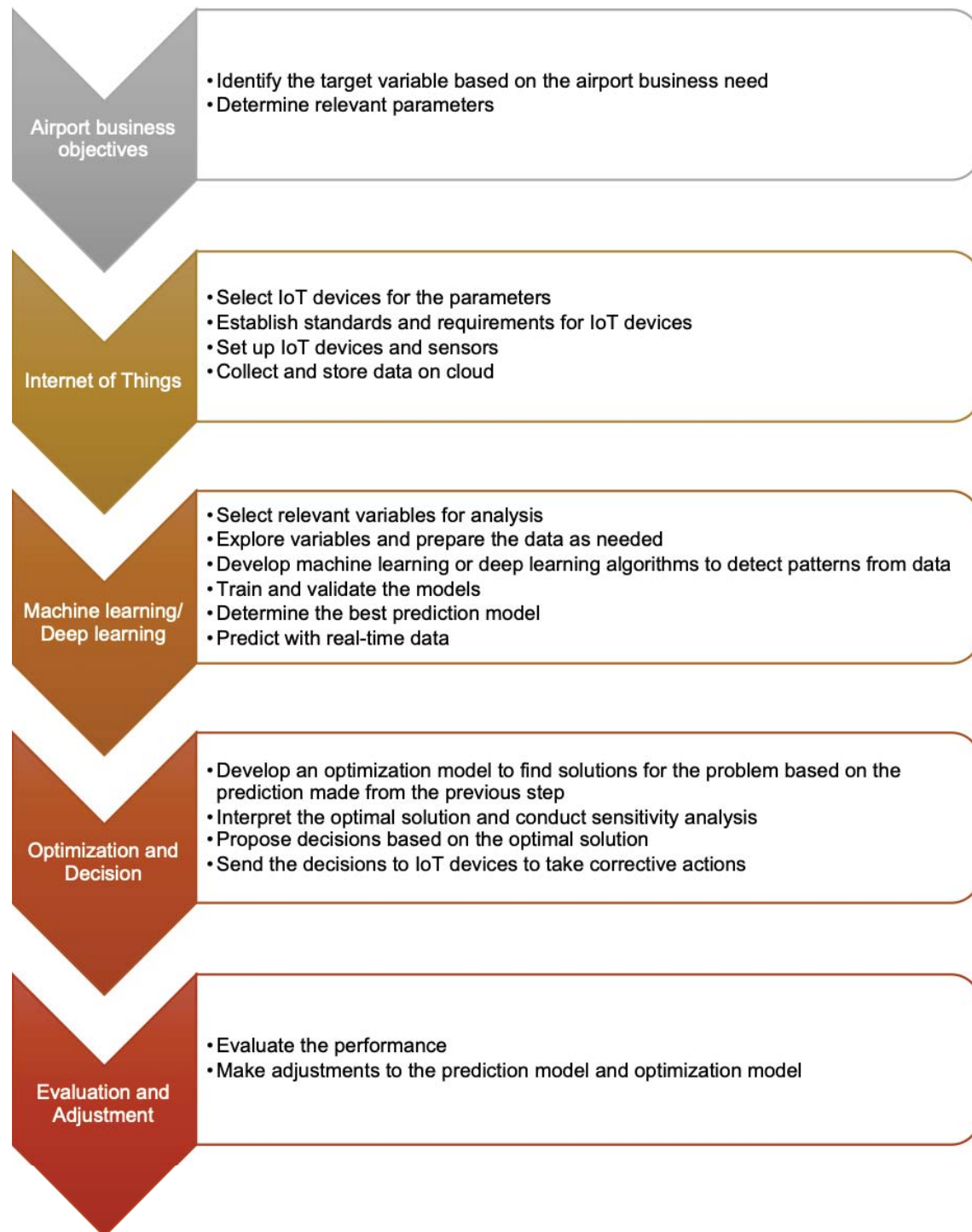


Figure 2: Steps for implementing the ITAI framework

PROPOSED RESEARCH PROCESS FOR IDENTIFYING AND MITIGATING RISKS

Since ITAI is considered a black box, there are risks associated with deploying and operating this system. In order to identify the risks and develop mitigation strategies, a combination of research synthesis and case study methods is proposed. In phase one, the research synthesis method will be used to collect information about the IoT, AI, and airport operations. The goal is to present the state of knowledge concerning innovation at airports through the implementation of ITAI and associated risks. This research will use seven steps proposed by Cooper (2010).

1. *Formulating the problem.* In this step, the specific objectives of the research will be identified. Important research questions include: What are the benefits and challenges of the ITAI? What are major applications of the ITAI at airports? What are technical and managerial requirements for ITAI deployment? How can airports successfully implement the ITAI to improve productivity and outcomes? What are the risks associated with using the ITAI, and how can they be managed and mitigated?
2. *Searching the literature.* Studies relevant to the objectives will be searched and collected from various resources: Embry-Riddle Aeronautical University's Hunt Online Library (which contains thousands of academic and professional databases), American Association of Airport Executives, Airport Services Association (ASA), The Internet Society, Internet of Things journals, Internet of Things Community IEEE, Artificial Intelligence journals, and Artificial Intelligence IEEE. Literature, including research articles, professional reports, technical reports, and cases will be collected and reviewed.
3. *Gathering information from studies.* The relevant information being gathered includes not only characteristics of the study, but also how the study was conducted and the results. The collected information will be stored and categorized for easy lookup and analysis. Bibliography and glossaries will be developed as well.
4. *Evaluating the quality of studies.* Quality of studies will be evaluated by examining the methodology to determine whether the data will be reliable and valid for addressing the research questions. Bad data will be discarded or given minimum credibility.
5. *Analyzing and integrating the outcomes of studies.* Collected data will be analyzed, summarized, and integrated into a unified picture.
6. *Interpreting the evidence.* The researchers will interpret the cumulative evidence and determine which conclusions are warranted by the data.
7. *Presenting the results.* Results will be presented to describe the investigation that answers the research questions.

In phase two, case studies will be conducted to provide best practices and lessons learned in implementing the IoT at airports. The results of phase one, along with case studies in phase two, will allow other airports to apply successfully the ITAI. Case studies will be conducted following Yin's (2009) process.

1. *Defining and designing case studies.* This research will use the two-case, embedded design to provide analysis of ITAI applications in airports (Yin, 2009). Since ITAI is new to airports, case studies will focus on collecting inputs from airport operators regarding smart airports and potential implementation of ITAI. US airports will be reviewed in order to identify two airports that have applied IoT sensors, big data analytics, and AI applications in their operations.
2. *Preparing case study evidence.* The case study protocol will be developed to ensure the quality of the data collection process. Interview questions and the survey questionnaire will

be designed to achieve the research objectives. The questions will be shared with subject matter experts for feedback to ensure the face and content validity.

3. *Collecting case study evidence.* Case study information will be collected through multiple sources, including interviews, survey, and archived records. To collect needed information and evidence, researchers will contact each airport manager, director of information technology, and director of operations. Data should include details of the ITAI applications, associated risks, risk management strategies, and critical success factors.
4. *Analyzing case study evidence.* Both quantitative and qualitative data analyses will be performed. Techniques such as pattern matching, explanation building, logic modeling, and cross-case synthesizing will be used in this research.
5. *Reporting case studies.* Results and findings of case studies will be reported to provide the audience with best practices in ITAI implementation and risk management. These results will be integrated and aligned with phase one results.

CONCLUSIONS

The rapid growth of IoT and AI in Industry 4.0 will drive airports to embrace automation and innovation to be able to improve and succeed. The results of this research will shed light on the applications of ITAI systems for smart airports. The requirements for ITAI implementation and deployment provide airport authorities and stakeholders with useful information about the investment needed to transform airports to smart airports to become more innovative and effective in the new era. The critical success factors, risk management strategies, and lessons learned are critical to airports' success in implementing and deploying the system. The findings of this research will also be useful for companies in other industries adopting an ITAI system.

REFERENCES

- Arel, I., Rose, D.C., & Karnowski, T.P. (2010). Deep machine learning-a new frontier in artificial intelligence research. *IEEE Computational Intelligence Magazine*, November, 13-18.
- Cao, X. M., Jing, C. M., & Zheng, X. D. (2013). Design of the airport perimeter security system based on the internet of things. *Applied Mechanics and Materials*, 361-363, 2276-2281.
- Chowdhury, M., & Sadek, A.W. (2012). Advantages and Limitations of Artificial Intelligence. *Transportation Research Circular E-C168: Artificial Intelligence Applications to Critical Transportation Issues*, November, 6-8.
- Cooper, H. M. (2010). *Research synthesis and meta-analysis: A step-by-step approach* (4th ed.). Los Angeles, CA: Sage Publications.
- Federal Aviation Administration (2017). The Economic Impact of Civil Aviation on the U.S. Economy. *Federal Aviation Administration Report*, September. Retrieved from https://www.faa.gov/about/plans_reports/media/2017-economic-impact-report.pdf
- Hwang, S. (2019). A network clock model for time awareness in the internet of things and artificial intelligence applications. *The Journal of Supercomputing*, February 9, 1-20.
- International Organization for Standardization (ISO) (2015). Internet of Things (IoT). *ISO/IEC JTC1 Preliminary Report*. Retrieved from http://www.iso.org/iso/internet_of_things_report-jtc1.pdf
- Liu, C. X., & Lu, K. (2015). A perimeter intrusion detection system based on sensor network for airport application. *Applied Mechanics and Materials*, 738-739, 50-55.
- Lykou, G., Anagnostopoulou, A., & Gritzalis, D. (2018). Smart airport cybersecurity: Threat mitigation and cyber resilience controls. *Sensors (Basel, Switzerland)*, 19(1), 19.
- Madakam, S., Ramaswamy, R. and Tripathi, S. (2015) Internet of Things (IoT): A Literature Review. *Journal of Computer and Communications*, 3, 164-173.

- Meyers, M., Niech, C., & Eggers, W.D. (2015). Anticipate, sense, and respond - Connected government and the Internet of Things. A GovLab report in the Deloitte Future of Government series, *Deloitte University Press*. Retrieved from <https://www2.deloitte.com/content/dam/Deloitte/tr/Documents/technology/iot-public-sector.pdf>
- Nisbet, R., J. Elder IV, and G. Miner. 2009. *Handbook of Statistical Analysis and Data Mining Applications* (1st Ed.). Burlington, MA: Academic Press/Elsevier.
- Office of Technology Assessment (1984). Airport System Development. *Office of Technology Assessment, OTA-STI-231*, August. Washington, D. C.: U.S. Congress.
- Porter, M.E. & Heppelmann, J.E. (2014). How Smart, Connected Products Are Transforming Competition. *Harvard Business Review*, November. Retrieved from <https://hbr.org/2014/11/how-smart-connected-products-are-transforming-competition>
- Robinson, J. (2017). Passenger terminal development in the digital age. *Journal of Airport Management*, 11(4), 355-368.
- Sadek, A.W. (2007). Artificial Intelligence Applications in Transportation. *Transportation Research Circular E-C113: Artificial Intelligence in Transportation Information for Application*, January, 1-6.
- Sarma, K.S. 2013. *Predictive Modeling with SAS Enterprise Miner – Practical Solutions for Business Applications* (2nd Ed.). Cary, NC: SAS Press.
- Schmidhuber, J. (2015). Deep Learning in Neural Networks: An Overview. *Neural Networks*, 61, 85–117.
- Tien, J. M. (2017). Internet of things, real-time decision making, and artificial intelligence. *Annals of Data Science*, 4(2), 149-178.
- Troiano, A., & Pasero, E. (2014). A runway surface monitor using internet of things. *Journal of Electrical Engineering*, 65(3), 169-173.
- Truong, D. (2010). How Cloud Computing Enhances Competitive Advantages: A Research Model for Small Businesses. *The Business Review, Cambridge*, 15(1), 59-65.
- Truong, D. (2018). Risk Assessment of Small Unmanned Aircraft System (sUAS) Operations. In C. Di Mauro (Ed.), *Decision Sciences Institute: 2018 Proceedings* (pp. 1-8). Chicago, IL: Decision Sciences Institute.
- Truong, D., Friend, M., & Chen, H. (2018). Applications of Business Analytics in Predicting Flight On-time Performance. *Transportation Journal*, 57(1), 24-52.
- Van Zuylen, H. (2012). Difference Between Artificial Intelligence and Traditional Methods. *Transportation Research Circular E-C168: Artificial Intelligence Applications to Critical Transportation Issues*, November 3-5.
- Wang, H., Tuo, X., Zhang, G., & Peng, F. (2013). Panzhuhua airport landslide (oct. 3rd 2009) and an emergency monitoring and warning system based on the internet of things. *Journal of Mountain Science*, 10(5), 873-884.
- Yin, R. K. (2009). *Case study research: Design and methods* (4th ed.). Los Angeles, Calif: Sage Publications.
- Zhang, Y., & Xie, Y. (2012). Traffic Signal Timing and Optimization. *Transportation Research Circular E-C168: Artificial Intelligence Applications to Critical Transportation Issues*, November, 11-21.
- Zmud, J., Miller, M., Moran, M., Tooley, M., Borowiec, J., Brydia, B., Sen, R., Mariani, J., Krimmel, E., & Gunnels, A. (2018). A Primer to Prepare for the Connected Airport and the Internet of Things. *Airport Corporate Research Program (ACRP)*. Washington, DC: The National Academies Press.