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Machine learning and mixed reality for smart aviation: Applications and challenges

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ABSTRACT

The aviation industry is a dynamic and ever-evolving sector. As technology advances and becomes more sophisticated, the aviation industry must keep up with the changing trends. While some airlines have made investments in machine learning and mixed reality technologies, the vast majority of regional airlines continue to rely on inefficient strategies and lack digital applications. This paper investigates the state-of-the-art applications that integrate machine learning and mixed reality into the aviation industry. Smart aerospace engineering design, manufacturing, testing, and services are being explored to increase operator productivity. Autonomous systems, self-service systems, and data visualization systems are being researched to enhance passenger experience. This paper investigate safety, environmental, technological, cost, security, capacity, and regulatory challenges of smart aviation, as well as potential solutions to ensure future quality, reliability, and efficiency.

1. Introduction

The aviation industry has undergone a massive transformation as technology advanced and new digital capabilities have been developed. Intelligent solutions can enhance effectiveness, reduce costs, and boost productivity in the industrial sector. Advanced systems integrate a variety of cutting-edge technologies including automation, robotics, artificial intelligence (AI), machine learning, mixed reality, and the Internet of Things (IoT) (Menouar et al., 2017; Siegel et al., 2017; Zhu et al., 2018; Andreoni et al., 2021; Menezes et al., 2022). Digitization has changed the industry paradigm for smart aviation. The recently adopted innovative digital approaches promote efficiency, safety, and security in the operating process, and raise passenger satisfaction by better understanding their needs, preferences, and habits (Abeyratne, 2020; Molchanova, 2020; Xiong and Wang, 2022). Digitalisation has enhanced cooperation and communication among airlines, airports, and other aviation stakeholders (Kuisma, 2018). With machine learning and mixed reality, the aviation industry has the chance to transform aerospace engineering and enhance passenger experience.

Machine learning is crucial for digitalisation, interpreting and identifying features, patterns and trends in digital data to gain valuable insights and make informed decisions (Mahdavinejad et al., 2018; Adi et al., 2020; Brunton and Kutz, 2022). Machine learning provides powerful tools for creating efficient, reliable, and safe aircraft designs, manufacture, and training. Machine learning applications in the digital twin, aerospace design, aerospace production, aerospace verification and validation, and aerospace services has increased automation and streamlined processes in aviation industry (Mackall et al., 2002; Zhu et al., 2012; Allen, 2016; Brunton et al., 2020; Chinchanikar and Shaikh, 2022; Rodrigues et al., 2022; Xiong and Wang, 2022). Transformative machine learning has an effect on the manufacturing, automation, and data analysis in the aerospace industry with the use of digital modelling and simulation (Hey, 2009; Donoho, 2017; Brunton and Kutz, 2019). The data-rich aviation industry is poised to capitalize on the machine learning revolution. Machine learning optimises transportation networks, predicts customer behaviour, and provides tailored services to improve the passenger experience. Airlines can optimise operations, improve loyalty, and increase revenue by analysing passenger data (Akerkar, 2014; Duraisamy et al., 2019; Brunton et al., 2020). Machine learning tracks and analyses numerous passenger transit phases, including the arrival, departure, and waiting periods to reduce delays and improve the customer experience. Airlines use mobile applications to offer real-time updates and individualised services. Smart services such as customized tickets, baggage tracking, and flight tracking are provided by airlines (Avram, 2017; Bor, 2017; Molchanova, 2020; Pereira et al., 2022). Machine learning is a useful technology that makes travel more pleasant and gratifying.

Virtual reality (VR), augmented reality (AR), and mixed reality are

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all related technologies that use computer-generated content to enhance the user experience. VR is an innovative technology that enables users to engage with a simulated environment, creating a fully immersive experience. This technology is designed to generate a completely artificial world that can be navigated and interacted with in a seemingly realistic way. By wearing a VR headset such as the Oculus Rift, HTC Vive, Google Daydream, and Oculus Quest, users are transported to a digital environment that completely blocks out the real world. These headsets are equipped with high-quality screens that display images in 360°, allowing users to look around and explore the virtual environment. Additionally, users may interact with the digital environment using controllers or sensors that track their movements and gestures, allowing them to manipulate objects and engage with the environment in a natural way. VR technology can be utilized for training aviation professionals such as pilots, air traffic controllers, and maintenance technicians in a simulated environment. Through the creation of 3D models of aircraft, VR can simulate their performance, aerodynamics, and engineering, providing a platform for testing and refinement before building actual prototypes. Unlike VR, which creates a completely artificial environment, AR enhances or augments the existing environment with digital content that appears as if it is part of the physical world. AR technology is accessible through various devices, including smartphones, tablets, and smart glasses, such as HoloLens. These devices use cameras and sensors to identify and monitor the user's environment, enabling them to display digital information in real-time. AR can overlay digital images onto physical components, providing visual guidance, simplifying the process, and identifying issues in real-world. Mixed reality is sometimes used synonymously with Extended Reality (XR). Mixed reality combines both VR and AR to create a cohesive and interactive blend of virtual and real-world elements (Rokhsaritalemi et al., 2020; Rauschnabel et al., 2022a). This technology allows users to seamlessly perceive and interact with both virtual and real-world environments. Mixed reality experiences can be achieved using various technologies, such as sensors, cameras, and advanced graphics processing capabilities. Mixed reality applications may require the use of headsets or mobile devices such as Microsoft HoloLens. Mixed reality creates rich, immersive, interactive, and engaging experiences.

Mixed reality can be applied in aviation through a combination of robotics, analytics, mobility, and visualization (De Crescenzio et al., 2010; Tran et al., 2022). Mixed reality has the potential to revolutionise aerospace engineering (Van Krevelen and Poelman, 2010; Safi et al., 2019). Using mixed reality, aerospace engineers can easily develop virtual worlds where they interact with physical objects in a lifelike manner (Frigo et al., 2016; Mourtzis et al., 2022). Mixed reality transforms manual labour into digital assistance for smart maintenance, visualising intricate parts, and achieving problem-solving in a virtual environment (De Crescenzio et al., 2010). The cost and time associated with developing and testing physical prototypes are reduced. Using mixed reality, pilots can undergo safe and cost-effective training in a highly efficient visualization environment (Schaffernak et al., 2020, 2022). Virtual instructions are overlaid on physical items for training, allowing staff to gain hands-on experience (De Crescenzio et al., 2010). Mixed reality merges virtual and physical worlds to create immersive and interactive passenger experiences. Some airlines use mixed reality for indoor navigation, advertising recommendations, information notification, and immersive entertainment (Pucihar and Coulton, 2015; Safi et al., 2019). Mixed reality increases the effectiveness of airport infrastructure, such as baggage handling and security checks. Additionally, passengers can enjoy a more user-friendly and convenient experience (Gupta and Sandhane, 2022; Jiang et al., 2022; Rauschnabel et al., 2022b). The potential of mixed reality in the aviation industry is virtually limitless.

This paper contributes to the aviation industry by researching and analysing innovative applications and services, as well as discussing current industry issues and challenges. This paper offers practitioners, academics, airlines, airports, and other stakeholders insights into how to shape the industry globally to make it more efficient, agile, sustainable, and safe. This paper makes the following contributions:

i) Investigating the applications and challenges of machine learning and mixed reality in the aviation industry with digital solutions.
ii) Exploring machine learning based intelligent tools for more efficient and reliable aerospace engineering through design, manufacturing, testing, and services.
iii) Researching mixed reality based applications, which combines digital information with physical objects to visualise the entire aerospace engineering process, identify potential issues, and provide immersive training experience, from product design to production.
iv) Studying machine learning solutions for improving the passenger experience by leveraging data from customer surveys, ticketing, and reservation systems to better understand passengers, anticipate their needs, and provide personalised services.
v) Exploring mixed reality services, which immerse passengers in a multidimensional experience, provide real-time flight information, and expand passenger entertainment options.
vi) Discussing future opportunities of smart aviation as well as potential digital solutions for efficiency, productivity, automation, convenience, safety, and collaboration.
vii) Investigating a variety of aviation industry challenges, including safety, environmental, technological, cost, security, capacity, and regulatory issues.

The remainder of the paper is organized as follows: Section 2 reviews machine learning and mixed reality for aerospace engineering, including recent advances, methods, and applications. Section 3 discusses machine learning and mixed reality for passenger experience enhancement, including recent developments, services, and solutions. Section 4 presents advanced digitalisation solutions for the future aviation industry. Section 5 investigates safety, environmental, technological, cost, security, capacity, and regulatory challenges of smart aviation. Finally, a conclusion is provided in Section 6.

2. Smart aerospace engineering

2.1. Machine learning

Machine learning provides powerful analysis and optimization tools for complex problems in aerospace engineering. Advanced machine learning in aerospace design, manufacturing, testing, and services is covered in this section (see Fig. 1).

Machine learning has become an integral part of modern aircraft design. Aircraft designers can create more efficient and safer aircraft, as well as optimise aircraft performance, by utilising powerful algorithms. The proliferation of data science and model-based engineering has made modern aircraft design possible (Bowcutt et al., 2008; Bons and Martins, 2020). Multidisciplinary design employs data analytics and dimensionality reduction to deal with high-dimensional design parameters. Data reduction improves calculation accuracy and interdisciplinary interactions in jet propulsion, swept wings, and composite construction (Henderson et al., 2012; Martins and Lambe, 2013). The design of an aircraft is a multi-objective optimization problem (Cramer et al., 1994; Booker et al., 1999). The objective functions, prediction algorithms, and analytic tools have transformed aerodynamics, structures, and control systems in aircraft design (Baran et al., 2017).

Application of machine learning in aerodynamics optimization results in more fuel-efficient, stable, and easy-to-control flight. The data collected from wind tunnel tests, flight tests, and simulations is trained in a machine learning model, which can then be used to determine the optimal design parameters. These parameters are used to generate 3D models of the aircraft, which are then tested in a virtual environment to ensure the desired aerodynamic performance (Dong et al., 2021;

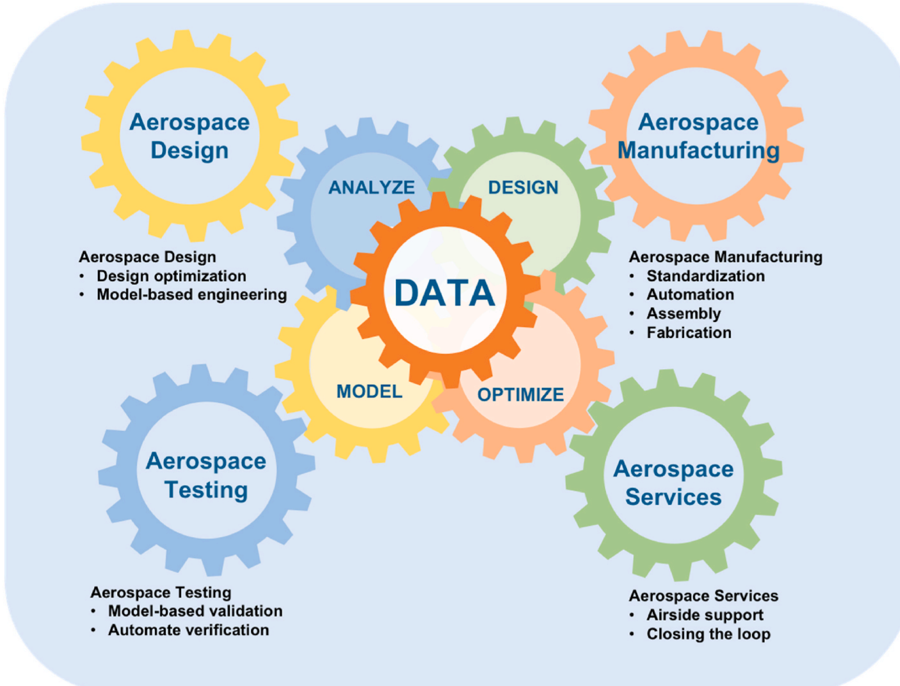

Fig. 1. An overview of smart aerospace engineering.

Clainche et al., 2022; Sabater et al., 2022). Machine learning can generate new aircraft structures and optimise their performance for much lighter and stronger aircraft. A large data set of existing aircraft structures, including materials, aerodynamics, structural, and cost, is collected and analysed using machine learning. Based on the patterns identified in the data set, the trained model generates new aircraft structures. The generated aircraft structures are evaluated in a computer simulation environment. The designed aircraft structures achieve the desired performance and safety through an iterative process (Salehi et al., 2018; Ai et al., 2021). Machine learning can create and optimise control systems that make aircraft more manoeuvrable and easier. Data from the aircraft control system is collected and analysed, such as aircraft performance and safety records. A mathematical model is designed for aircraft control systems to reveal the relationships between input and output variables. The trained model is tested on a simulator or a real aircraft to make further adjustments (Eroglu et al., 2020; Ravaioli et al., 2022).

Model-based engineering supports accurate prediction and optimization of complex aircraft designs. The digital twin system captures physical world information accurately and ensures standard data format. Diverse signals from hundreds of subsystems are modelled, and physical operational systems are effectively represented with virtual portrayals (Singh et al., 2018). Airbus and Boeing are investing heavily in machine learning platforms. Airbus created aircraft design solutions that combines 3D modelling and machine learning (Airbus, 2023a). The solutions can analyse aircraft components such as wings and fuselages, optimise weight, performance, and other metrics to determine the best aircraft design, and diagnose potential aircraft problems. Boeing uses machine learning to analyse the design of various aircraft components, allowing engineers to design aircraft components quickly and accurately (Boeing, 2023a). The utilization of machine learning is causing a paradigm shift in aircraft design, resulting in improved aircraft performance and enhanced safety for the future of aviation.

Aircraft manufacturing is a complex process that involves the manufacture of components, assembly, testing, and inspection. Machine learning reduces costs, improves safety, and boosts efficiency in the aircraft manufacturing. In process control, autonomous detection, and material selection, machine learning plays a significant role. Machine learning identifies trends, detects abnormal behaviour, suggests corrective actions, recommends optimal assembly sequences, assumes expected performance, and suggests potential modifications, allowing manufacturers to make better decisions (Caesarendra et al., 2019; Brunton et al., 2021; Shafi et al., 2023).

Machine learning redefines standard data formats and assists in robust cross-platform data transfer. Data analysis of aircraft parts parameters shortens the material manufacturing cycle and accelerates the parts assembly process. Parts parameters are used in aircraft standardization, which has informed future decisions and streamlined processes. Machine learning uses sensors and data logs to detect abnormalities in the process, reducing downtime and improve safety and reliability of the aircraft. Automated machines produce detailed aircraft parts with higher accuracy and lower cost.

In autonomous detection, machine learning monitors and controls manufacturing processes (Malik et al., 2020; Brunton et al., 2021; Lu et al., 2023). Machine learning recognises patterns in data, analyses deviations from expected output, and identifies invisible manufacturing defects such as cracks and warping. To improve the accuracy and reliability of aircraft manufacturing, supervised learning, unsupervised learning, and deep learning are used in autonomous detection. Machine learning measures error to shorten operation times and increase operator efficiency. Sensors detect faults in real time, recognise repetitive patterns, and predict abnormalities. Outliers are detected using principal component analysis and feature extraction to improve the quality of automated inspections (Manohar et al., 2018).

Machine learning improves material selection by detecting parameter changes, filtering out suitable materials, shortening testing times, and determining the best options (Chinchanikar and Shaikh, 2022). Digital models are used to simulate new materials or structures based on a variety of criteria such as cost, strength, weight, and durability (Conduit et al., 2017; Verpoort et al., 2018; Brunton and Kutz, 2019). Sparse regression is used to investigate the relationship between various parameters such as material characterization, structural characterization, friction, pressure resistance, and temperature sensitivity. The use of digital simulations reduces the cost of developing new materials significantly (Sachs, 2014; Conduit et al., 2018; Green et al., 2018). Computer vision and thermal detection are used in new material diagnostics and defect detection.

Machine learning-based systems are gradually taking the place of manual labour (Juarez et al., 2018; Sacco et al., 2019). GE Aviation employs machine learning in aircraft manufacturing (GE Research, 2023). The AI-powered analytics tools are used for predictive maintenance and performance optimization of its jet engines. GE Aviation is also using machine learning to improve the efficiency of its jet engine production lines.

Machine learning provides efficient and accurate data analysis for aircraft testing, allowing for the development of better aircraft models and the improvement of aircraft performance. Data-driven methodologies streamline the testing process while also ensuring testing quality. Machine learning is used at the subsystem and integrated system levels to reduce the dimension of sensor collected data, extract main features, analyse parameter relationships, and visualise optimised data patterns. There are many different types of aircraft and multi-modal signal data, such as accelerometers, temperature sensors, and pressure sensors. Each process of the complex and dynamic integration system has been significantly improved through data modelling and constraint optimization. Automatic verification and validation have reduced the need for time-consuming manual labour and alleviated the problem of staff shortages. A large amount of real-time discrete data is processed by aviation industry to ensure flight safety. Automated flight testing allows staff to refocus on critical information, detects abnormal activities quickly, increases testing efficiency, and shortens testing cycles. Data simplification converts messy sensor data into regular patterns. Data visualization reduces the cognitive burden on engineers. Active learning algorithms simplify multi-dimensional and multi-objective verification models. Digital twin seamlessly connects verified digital models with physical entities (Cohn et al., 1996). Machine learning incorporates prior testing experience into data analysis and physical information to perform real-time decision-making during the testing phase. Lockheed Martin is developing novel machine learning applications for testing and evaluating aircraft designs (Lockheed Martin, 2023a). Engineers and test pilots are capable of conducting structural, propulsion, avionics, and environmental testing. Aircraft testing ensures that the tested aircraft meet the highest possible standards and provide passengers with a safer experience. Boeing offers competitively priced, timely, accurate, consistent, and repeatable test results in wind tunnels, propulsion, environmental, electromagnetics, and structures (Boeing, 2023b).

Aerospace stages can be improved in reverse by utilising service data, including enhanced predictive maintenance, optimised performance, and improved safety, reliability, efficiency. Potential problems are identified and addressed before they occur, resulting in lower maintenance and operating costs. The information gathered from the services fleet improves the digital models of the aircraft, allowing for more accurate predictions and simulations of performance, maintenance, and other operational aspects. The service data further optimises sensor processing, allowing for more accurate and precise aircraft designs. Furthermore, the service data can be used to quickly evaluate and modify existing aircraft designs to make them more efficient and safer. Many passengers lose confidence in the airline as a result of flight delays caused by aircraft failures (Ariyawansa and Aponso, 2016; Mangortey et al., 2020; Huang and Zhu, 2021). Machine learning recognises data patterns in previous flights to predict the likelihood of a flight delay. Machine learning identifies the delay caused by mechanical problems, allowing them to be resolved quickly and avoided in the future. Machine learning processes massive amounts of aircraft system data to support quick self-diagnosis, identify real-time faults, and make accurate decisions. Airport services generate a large amount of data, including passenger check-in information, cargo details, flight schedules, security logs, and weather updates, which can be used to optimise airport operations and ensure passenger safety (Muelaner and Maropoulos, 2011; Muelaner et al., 2013; Mamdouh et al., 2020; See et al., 2022). Autonomous systems based on machine learning make informed decisions for airport staff and provide better services to passengers. These systems optimise operations to reduce delays, improve flight schedules, and predict passenger needs.

2.2. *Mixed reality*

Mixed reality has a significant impact on aerospace engineering. Advanced interfaces and visualization systems are developed for product design, complex assembly, accurate maintenance, and assisted training.

Mixed reality has the potential to improve the efficiency and effectiveness of the design process, thereby shortening the time to market for new aircraft designs. Designers create immersive simulations of aircraft to test and evaluate virtual prototypes in a controlled environment. This approach saves time and money that would otherwise be spent on traditional physical design methods (Regenbrecht et al., 2005; Shen et al., 2010; Ng et al., 2013; Mei et al., 2019; Kent et al., 2021). Mixed reality has the capability to evaluate different design concepts quickly and easily. It can build virtual prototypes in hours or days, which is a drastic reduction from the weeks or months required for physical prototypes. As a result, mixed reality can significantly accelerate the design process (De Crescenzio et al., 2019). By utilising mixed reality, engineers can optimise the performance of aircraft designs, identify potential issues, and construct convincing product lifecycles (Mourtzis et al., 2018; Lallai et al., 2021).

Mixed reality improves the way teams collaborate (Utzig et al., 2019; Cooper et al., 2021). Instead of relying on physical models or drawings, which can be difficult to share and collaborate on. With mixed reality, designers can work together in a virtual environment, allowing for real-time collaboration and communication. Mixed reality is integrated into the current development platform and workflow. Based on the feedback, the mixed reality based product is refined and tested until the desired results are obtained. Boeing leverage Microsoft's mixed reality, cloud platform, and AI capabilities to modernise critical infrastructure, streamline processes, and accelerate digital aviation innovations (Airforce Technology, 2023). Boeing visualises and optimises aircraft designs in real time using Microsoft HoloLens device (Microsoft, 2023a). Airbus uses Microsoft Hololens hardware and software to speed up production. The designing is 80 percent faster than traditional methods due to the ability to test designs in 3D before manufacturing (Computer World, 2023). Lockheed Martin develops new simulations to revolutionise the way engineers design advanced systems from satellites to aircraft. Rather than utilising an expensive and time-consuming process to create new aircraft modifications and add-ons, engineers use a virtual workspace to craft digital parts and modify designs (Lockheed Martin, 2023b).

The utilization of mixed reality is revolutionizing aircraft assembly and providing numerous advantages to aircraft builder teams. The application of mixed reality enables the accurate and quick assembly of thousands of parts (Tang et al., 2003; Luxenburger et al., 2019; Dong et al., 2021; Wang et al., 2022). During product assembly, manual instructions must be laboriously studied and constantly referred to. However, mixed reality offers hands-free and voice-controlled operations with detailed 3D instructions (Gavish et al., 2015). The task of installing electrical wires on an aircraft is difficult and must be executed with absolute precision. Nevertheless, interactive 3D wiring diagrams have made this task possible (Wang et al., 2016; Yin et al., 2018). Using 3D manufacturing, engineers have achieved a 90 percent improvement in first-time quality as compared to 2D information, as well as a 30 percent reduction in the time required (Baird and Barfield, 1999; Mizell, 2001; Barfield and Caudell, 2001; Davies and Sivich, 2011). Mixed reality applications superimpose 3D models on physical parts, providing a more consistent and accurate assembly process.

Mixed reality makes aircraft assembly more engaging and interactive, allowing engineers to practise and fine-tune their skills before performing the actual task (Wang et al., 2021). Engineers first determine the specific area of aircraft assembly before designing and laying out the mixed reality environment. They then integrate the hardware and software components into the existing assembly line. The systems are tested for functionality and accuracy to ensure their proper operation. Following testing, assembly line workers are trained to optimise performance. Boeing uses mixed reality to accelerate aircraft assembly (Boeing, 2023c). 3D digital models of aircraft components are visualised, interacted, and assembled in a physical environment. The Boeing mixed reality system can detect errors in the assembly process quickly and easily, as well as virtually simulate and review assembly operations. Mixed reality guides and trains aircraft assembly technicians, enabling them to quickly become acquainted with the assembly process. Teams from across the Boeing are working to transform aircraft assembly to assist in the resolution of difficult and real-world problems (Boeing, 2023d).

Mixed reality improves maintenance process efficiency and reduces downtime, making aircraft maintenance safer and more cost-effective (Hincapié et al., 2011; De Marchi et al., 2014; Palmarini et al., 2018; Hebert Jr, 2019; Siyaev and Jo, 2021). Mechanics have traditionally relied on paper manuals to assist with thorough maintenance. Mixed reality overlays instructions on over the actual product, allowing operators to visualise machine status in real time (Scurati et al., 2018). Rigorous quality screenings identify problems at an early stage, reducing machine downtime and airline costs (Ceruti et al., 2019). Human-based defect detection cannot ensure optimal quality assurance because human errors are unavoidable. Mixed reality projected digital overlays over the product to accurately identify defects and inefficiencies (Eschen et al., 2018). Engineers solve complex problems by interacting with 3D models of aircraft, viewing their parts and systems, and simulating maintenance activities. Mixed reality provides interactive step-by-step instructions for maintenance activities to reduce the time required for training and onboarding new employees (Mustapha et al., 2021). The inventory of aircraft parts is tracked and managed using mixed reality. Engineers scan, identify, and check the availability of parts to make maintenance processes faster, safer, and more cost-effective (Utzig et al., 2019). Airbus creates mixed reality systems that provides 3D models of aircraft components to facilitate maintenance process (Airbus, 2023b). The 3D models assist technicians in rapidly and precisely identifying the parts and components requiring repair or replacement. Simultaneously, they provide a more extensive overview of the aircraft structure. Mixed reality provides technicians step-by-step instructions, allowing them to complete maintenance tasks quickly and safely. Mixed reality uses holograms to transform digital information from two-dimensional to a three-dimensional experience. Airbus employs the Microsoft HoloLens headset to interact with holograms in physical space (Microsoft, 2023b). The HoloLens 2 enhances the mixed reality experience by including eye tracking to detect digital information, automatic scrolling for user reads, iris recognition login, and secure sharing among multiple people. HoloLens significantly speeds up the maintenance process, cutting time spent by 80 percent, while improving quality.

Mixed reality is used for aircraft ground navigation, assisted piloting, and operator training (Schaffernak et al., 2020). Mixed reality creates a virtual environment that is overlaid with the physical environment for ground navigation. The terrain, navigation, air traffic, weather, instrumentation, and airspace information are visualised in a simple 3D format. Mixed reality creates virtual landmarks to assist pilots in orienting themselves in their surroundings and guiding them to destination. Microsoft Flight Simulator creates systems for pilot navigation simulation (Flight Simulator, 2023). Mixed reality assisted piloting allows pilots to view a more realistic and accurate surrounding representation, access real-time data about the aircraft, and make split-second decisions with greater accuracy and confidence (Oh et al., 2021; Schaffernak et al., 2022). The head mount display (HMD) assists pilots during flight, takeoff, and landing. The mixed reality systems show a corridor overlay to show the pilots the proper path from takeoff to landing (Wu et al., 2012; Zollmann et al., 2014). Mixed reality has the potential to reduce pilot fatigue and stress by providing an immersive, realistic experience. Without the need for actual flight, mixed reality for piloting training allows pilots to experience a realistic simulation of flying a real aircraft, better understand different scenarios, and practise more in less time. Thorough and extensive training is required for airline personnel before they work in a real-world environment. However, preset manual training is insufficient to meet the growing needs. Mixed reality enables operators to gain hands-on experience, making the equipment easier to learn and use (Macchiarella et al., 2008; Kaplan et al., 2021; Kaplan et al., 2021). The utilization of remote mixed reality can reduce both training and execution costs. This is achieved by enabling experts to view through the technician's eyes, facilitating remote expert support, and permitting inspections without any distance restrictions (Schneider et al., 2017; Utzig et al., 2019). Delta Air Lines trains airport staff in mixed reality using Microsoft HoloLens. The HoloLens headset is capable of simulating a wide range of scenarios, including emergency situations (Foundry, 2023).

3. Passenger experience enhancement

3.1. Machine learning

In the aviation industry, machine learning is becoming increasingly prevalent. Its usage enhances security, improves passenger experience, and streamlines the travel process, ultimately providing a more efficient, secure, seamless, and enjoyable journey from the entrance to the boarding gate (Zheng et al., 2016; Din et al., 2019; Guo et al., 2022). The journey of passenger through an airport is shown in Fig. 2.

Before traveling, passengers can easily plan journeys, book tickets, and buy ancillary products online with machine learning. Machine learning provides passengers with personalised recommendations based on their preferences and location (Kumar and Zymbler, 2019; Heidari and Rafatirad, 2020; Hasib et al., 2021; Guo et al., 2022). Passengers' past travel patterns and preferences are analysed by algorithms. The algorithms can recommend routes, destinations, and attractions tailored to their specific needs and desires (Jain and Pamula, 2021; Noviantoro and Huang, 2022). Through machine learning, passengers are offered a range of options, including the most suitable modes of transportation, lowest fares, and most comfortable journeys. This empowers passengers to make informed decisions and choose the most suitable option for their journey, resulting in time and cost savings.

Machine learning updates traffic in real time, suggests alternate routes, and ensures passengers arrive on time (Khaksar and Sheikholeslami, 2019). Machine learning optimises routes by taking into account real-time traffic, weather, and other conditions to ensure the quickest and most efficient route, making journey planning more enjoyable and stress-free. Uber has developed scalable, reliable, easy-to-use, and automated machine learning tools to predict approximate arrival times. This process involves data management, data training, model evaluation, model deployment, prediction, and prediction monitoring (Uber, 2023). Machine learning is utilized by Google Maps to optimise routes for passengers. Passengers are informed of any delays or changes in their route in real-time, and alternative routes based on current conditions are recommended (Google, 2023). Delta Air Lines uses machine learning to price tickets, analyse passenger behaviour, and provide self-service experiences (Harvard Business School, 2023).

During check-in, machine learning is rapidly transforming the airline industry, with self-service, self-tagging, bag dropping, and streamlining processes (Rostworowski, 2012; Yau and Tang, 2018; Thamaraiselvan et al., 2019; Antwi et al., 2021; Jamaluddin and Rahmat, 2023). Self-service check-in machines are gaining popularity as a means of providing more accurate and efficient processes. Machine learning can recognise various types of passengers and provide a more personalised check-in experience. By automating the process, airlines can save money on labour while also analysing data to gain insights into passenger preferences to improve service and increase loyalty. The passengers

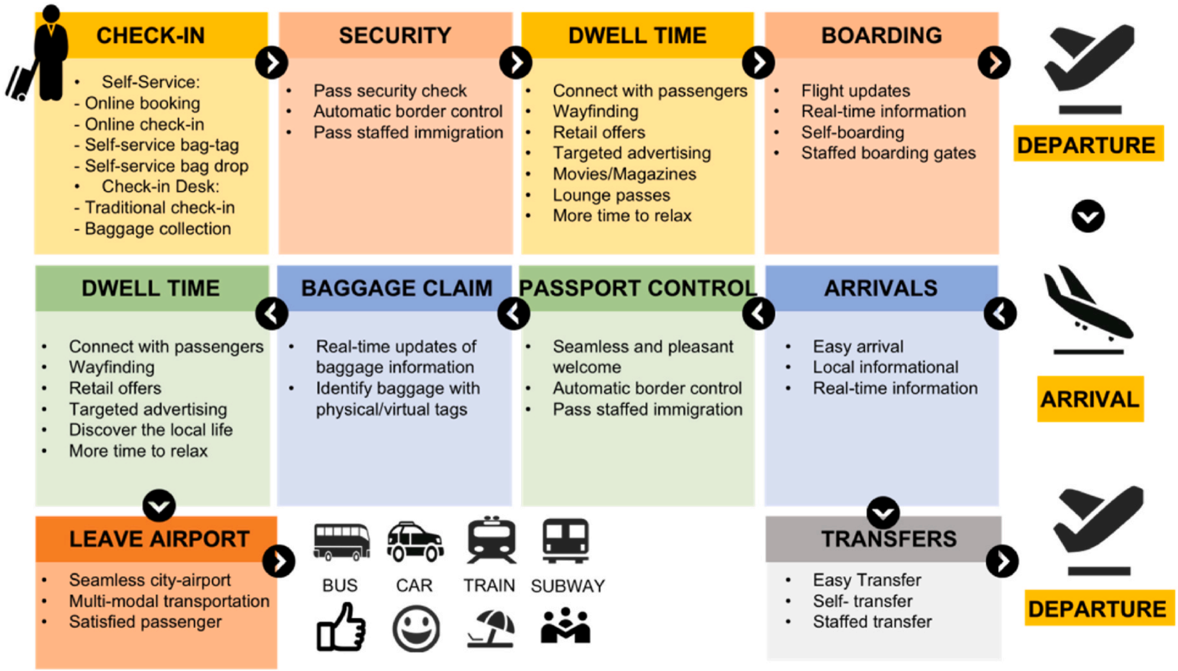

Fig. 2. The journey of a passenger through an airport.

enter their information, such as their name and flight number, into the self-service kiosk. The system then accesses a database of stored passenger information and uses machine learning to quickly identify the passenger and check them in for their flight without the need for manual verification, reducing the possibility of human error, shortening wait times, and providing more cost-effective solutions. Hong Kong International Airport is using machine learning to automate its self-service airport check-in system. The airport uses a combination of facial recognition, passport scans, and other biometric data to verify passenger identities, and facilitate a faster, more secure check-in process (Hong Kong International Airport, 2023a). These technologies can reduce long queues at entry points and optimise passenger service efficiency.

Machine learning with self-tag baggage improve airport processes while reducing manual labour and passenger wait times. The system quickly recognises the shape and size of baggage, assigns a unique code, and labels it accurately. The code then is used to track the baggage and ensure their safely arrive. Singapore Changi Airport employs machine learning for self-tagging, which recognises passengers, assigns them a unique boarding pass, and assigns an identification tag to their baggage (Changi Airport Group, 2023). Cathay Pacific requires passengers to obtain their boarding pass and baggage tag from the kiosk before proceeding to the bag drop counter (Cathay Pacific, 2023). The implementation of self-service bag drop has the potential to considerably decrease passenger wait times at airports while eliminating the need for airport personnel to manually check in passengers. This allows passengers to allocate their time to more critical tasks. Computer vision systems read the ticket information and compare it to the information on the passport. Once the information has been validated, the machine learning-based facial recognition system identifies the passenger. The system retrieves flight information quickly and generates the appropriate bag tags. The passenger then places their bags on the conveyor belt, and the machine scans the tags to route the bags to the correct destination. Cathay Pacific and Hong Kong International Airport have implemented self-service bag drop facilities to assist passengers in printing bag tags and checking their baggage on their own, reducing the bag drop process to approximately 1 min (Cathay Pacific, 2023; Hong Kong International Airport, 2023b). The Heathrow and Los Angeles international airports adopt advanced system to make the check-in process easier for passengers (Heathrow, 2023; Transportation Security Administration, 2023). Machine learning can streamline the check-in process and reduce wait times by analysing the time of day, number of passengers, and other factors. The daily data is used to optimise staffing and check-in station layout, improving passenger experience.

Machine learning analyses massive amounts of data to identify patterns, predict potential security threats, detect fraudulent documents, inconsistencies, and anomalies. Airports can use machine learning to identify potential risks and take preventative measures to ensure traveller safety (Zheng et al., 2016; Gota et al., 2020; Rodríguez-Sanz et al., 2021; Zhang, 2022). Machine learning learns from datasets and recognises patterns of behaviour to detect and prevent security issues at airports. Airports treat each passenger as a data point, creating a personal profile for each one. Booking information, travel history, and individual details are used as predictive analysis parameters. These structured and unstructured data are used in unsupervised learning, and the airport assigns a risk rating to each individual. The Gaussian distribution is used in mathematical modelling to learn complex non-linear relationships between the characteristics of passengers. In a classification system, each passenger is assigned a different category, and the higher risk is easily identified. Computer vision algorithms analyse data from security cameras to detect suspicious behaviour, illegal activities, and potential threats. Airports use facial recognition technology to identify people who have been flagged as potential security threats. The system allows airports to quickly and accurately identify individuals who may pose a threat, preventing terrorism, smuggling, and other criminal activities. Machine learning identifies travellers who may pose a risk based on their travel patterns, such as whether they have visited specific countries or websites.

Automated baggage detection and self-screening systems, including explosive detection systems, prohibited items detection systems, and 3D CT technologies, are extensively employed in airports (Gui et al., 2019). These systems aid operators in identifying suspicious items for further examination (Liang et al., 2018). The Transportation Security Administration (TSA) detects suspicious items, potential explosives, and other prohibited items in carry-on bags and airports using 3D imaging technology and machine learning models (U.S. Department of Homeland Security, 2023). Machine learning utilises synthetic training data sets and simulants to mimic real and diverse threats. Airport application scenarios are rapidly and thoroughly studied, recreated, modelled, and understood to create synthetic augmentation libraries to fully train and test algorithms for complex threat propertises. Machine learning is increasingly being used to automate border control processes that are more efficient and secure than manual methods, such as emigration, passenger data verification, and other regulatory requirements. Biometric information such as fingerprints, photographs, iris scans, passport and visa numbers are collected from traveller for automated border control (Ariyawansa and Aponso, 2016). Based on the collected data, traveller profiles are created to proceed automatically. When machine learning detects unusual patterns in data, such as suspicious behaviour or potential security threats, it alerts authorities and initiates an investigation. The Munich Airport is developing the Information Security Hub (ISH) to assist in combating the threat, which ranges from preventing simple data theft to simulating risk scenarios (Munich Airport, 2023).

Machine learning enhances the boarding and baggage experience by reducing wait times, optimising traffic flow, and providing passengers with intelligent services (Abdelaziz et al., 2010; Altexsoft, 2023). Machine learning analyses booking information, passenger number, aircraft size, baggage number to determine an efficient boarding order that minimises boarding time. Machine learning tracks passengers by analysing data such as arrival and security check times to adjust the boarding process accordingly. Machine learning detects patterns in the boarding process, such as boarding priority, boarding speed, and boarding time, to maximise efficiency. Machine learning analyses the current boarding process to identify bottlenecks, reduce congestion, and improve passenger flow. Machine learning provides personalised boarding experiences by analysing passenger data such as travel history, preferences, and previous flight experiences.

Automated baggage solutions using machine learning provide streamlined and efficient air travel. Airports benefit from machine learning by using less time and resources to transfer baggage, which cuts costs and enhances the traveller experience. Airports can determine the best baggage routes and the most effective loading and unloading techniques by evaluating data from baggage scanners and passenger information. Machine learning identifies potential issues that may occur throughout the baggage handling procedure to foresee consumer complaints and deal with them beforehand (Sørensen et al., 2020). Rapid identification, sorting, and delivery of baggage at the airport are required. Automated baggage handling eliminates the need for manual sorting and reduces the potential of human error. Using machine learning, airport staff can more precisely and efficiently track passenger and baggage information. After baggage tags are scanned, machine learning algorithms evaluate the scanned data and assign the correct passenger to the information. Anomalies, damaged, and lost baggage can be identified using image recognition algorithms. Krasnodar International Airport uses robots to automate the baggage picking and loading process, reducing human error, loss and damage amount, and the time required to load and unload aircraft. The robot is a manipulator outfitted with cameras, bar code scanners, detectors, and advanced algorithm. The first prototype can lift up to 42 kg and load one piece of baggage every 40 s in a specific order (Simple Flying, 2023a). An automated object detection system based on computer vision detects prohibited items in X-ray images. The system can detect prohibited items in black-and-white 2D X-ray images, colorized X-ray images, and 3D CT scan images at up to 30 baggage images per second. The system detects threats more precisely and efficiently, reducing false alarms, saving valuable time, increasing passenger safety, and removing human error from the baggage-screening process (Community, 2023). Machine learning improves the accuracy, sustainability, and cost-effectiveness of the baggage process. Eindhoven Airport is testing a machine learning-powered baggage handling system that allows passengers to simply take photos of their baggage, deposit it, and collect it when they arrive at the destination without the need for labels. The image recognition algorithm links to the baggage system. Algorithms categorize baggage and then compare it to the registered image dataset, retrieving precise data such as the origin, type, color, IATA classification, manufacturer, and baggage dimensions. The baggage system based on machine learning eliminates the need for baggage tags and label printing machines, making Eindhoven Airport more environmentally friendly (Community, 2023). The combination of bag tracking data generated and collected under Resolution 753 and machine learning tools has the potential to significantly increase efficiencies in baggage operations. Air Canada integrates Amazon Alexa, cloud platform and AI brain, into their system to provide baggage status to passengers (SITA, 2023). The air transport industry is undergoing digital transformation. The use of machine learning to revolutionise baggage operations is still in its early stages of development.

Machine learning assists airport staff in making more informed operational decisions. Using sophisticated algorithms, airport staff can accurately predict and monitor flight arrival and departure times, as well as other pertinent information (Gui et al., 2019; Lambelho et al., 2020; Rodríguez-Sanz et al., 2021; Guo et al., 2022). Regression tree algorithms can be used to forecast real-time quantile. The algorithm recognises late connecting passengers and assists them in making connections. Large airports contain a vast amount of data from systems and equipment such as security, baggage, freight, traffic, and passengers. Machine learning collects all relevant data and converts them into actionable information, allowing operators to maximise their efficiency and optimises aiport effectiveness. Machine learning improves customer operations, provides personalised service, and allows individual strategies (Sridhar et al., 2020; Barakat et al., 2021). Passenger activities such as check-in, departure paperwork, security checkpoints, boarding and deboarding a plane are being simplified. Airports create customer profiles by analyzing passenger data to identify their needs and provide customized solutions. Customer service agents use customer profiles to identify customers with similar needs and provide them with the same solutions, reducing wait times and increasing satisfaction. The airport adjusts flight schedules, aircraft capacity, load factors, and transfer rates based on changing passenger patterns. During peak hours, the airport dynamically coordinates queue length and promptly opens spare idle service equipment (Zhang, 2009; Sims, 2019; Orsini et al., 2019; Guo et al., 2020). Machine learning is used at Amsterdam Airport Schiphol to provide personalised service as well as asset corrective and predictive maintenance. Amsterdam Airport Schiphol analyses customer behaviour and preferences using predictive analytics to provide tailored boarding gate recommendations, flight information, and travel advice. Schiphol employs IBM Maximo and IBM Watson IoT for asset management to provide passengers with a pleasant journey (IBM, 2023). Heathrow Airport analyses aircraft generated data, refines aircraft turnaround processes, and reduces passenger delays using machine learning (International Airport Review, 2023).

Autonomous robots and vehicles offer an efficient, safe, and cost-effective way to move passengers and goods throughout the terminal, such as passenger flow control, baggage delivery, passenger security, and passenger transportation. Machine learning chatbots are critical tools for airports to improve passenger experience. They respond in a human-like manner using natural language processing, providing information efficiently while reducing airport staff workload. These chatbots can monitor and manage airport operations, track customer feedback, identify improvements, and alert on issues. AirAsia created AirAsia Virtual Allstar (AVA) chatbots using machine learning to provide passengers with a more seamless and user-friendly experience, from bookings to browsing to shopping to customer support (Kasinathan et al., 2020; Future Travel Experience, 2023). Guide robots based on machine learning help travellers navigate airports by assisting with navigation and baggage handling. Using computer vision, guide robots are programmed to recognise various types of baggage and locate the appropriate conveyor belts. For baggage transportation, Frankfurt Airport employs guide robots known as FRANbots. The robots are designed to autonomously transport baggage to its final destination, eliminating the need for manual handling and improving baggage transportation efficiency. The FRANbots were outfitted with sensors, touchscreens, and computer vision technology to enable advanced navigation and obstacle avoidance. Passengers enter their flight information and destination into the FRANbots, which will navigate them to their destination and drop off their baggage (Simple Flying, 2023b). With the increased popularity of air travel and the increasing demand for on-time departures and arrivals, autonomous robots are increasingly seen as a viable solution to the challenge of airport punctuality. Incheon Airport in South Korea and Munich Airport in Germany deploy autonomous robots to help passengers move around the airport quickly and with ease. The robots are outfitted with advanced sensors and machine learning to track passenger movement, ensure passenger punctuality, keep passengers on time, and avoid delays. By providing passengers with faster and more efficient service, the airport is able to reduce the amount of time and manpower required for smooth operation (Airport Benchmarking, 2023; Airport Technology, 2023a). The autonomous vehicles are intended to be an efficient solution for baggage handling. Delta Airlines employs self-driving vehicles to assist with delayed baggage delivery. Self-driving electric wheelchairs improve accessibility for disabled passengers and represent a step forward in the travel industry. The self-driving electric wheelchairs are outfitted with various sensors and cameras to ensure equal access to air travel and a consistent travel experience for disabled passengers. All Nippon Airways (ANA), Etihad Airways, and Abu Dhabi Airports are testing the mobility of self-driving electric wheelchairs to provide disabled passengers with a comfortable and secure mode of transportation (ANA Group, 2023; Etihad Airways, 2023).

Entertainment plays an important part in the passenger journey. Passengers were used to rely on available options like books, magazines, or board games during flights (Alamdari, 1999). Today, there are numerous entertainment options available to make the journey more enjoyable. Airlines use machine learning to provide more personalised in-flight entertainment. Some airlines provide personalised music as a soothing and calming tool for nervous passengers (Portalés et al., 2010). By collecting passenger data, airlines customise flight offerings to best meet their individual tastes, provides passengers with their favorite movies and food options on flights. Customized services improve passenger satisfaction, help airlines better understand customer needs, build customer loyalty, and increase overall profitability (Steiner et al., 2016). Passenger data is collected, cleaned, and organized to train a machine learning model to provide personalised service. With the advancement of technology, airlines are seeking opportunities to reimagine the travel experience and enhance overall business efficiency. Cranfield Airport has embarked on an ambitious "Urban Turbine" project to redefine the relationship between the city and the airport. The project seeks to create an innovative and sustainable approach to airport expansion and development. The project envisions transforming the existing airport terminal facilities and surrounding area into a vibrant urban space that incorporates commercial, office, leisure, and residential elements. The project aims to create an environment that seamlessly integrates the airport into the surrounding area, reducing its environmental footprint and making it more accessible to the local community (Urban Turbine, 2023).

3.2. Mixed reality

Mixed reality, which combines the physical and digital worlds, provides passengers with a variety of benefits that enhance their airport experience. Mixed reality provides passengers with useful information and directions throughout their airport experience to speed up their travel efficiency. Passengers are shown advertisements and targeted recommendations while shopping. The virtual tags allow for faster baggage claims and reduce mishandled baggage.

Airports are large, complex spaces that can be difficult to navigate. Airports assist passengers by providing indoor navigation services that guide them through the building with ease. Traditionally, indoor airport navigation employs a variety of technologies, including signposts, GPS, Wi-Fi, Bluetooth, beacons, and QR codes (Huang and Gartner, 2009). Indoor mixed reality navigation has numerous advantages over other types of navigation. Mixed reality provides navigation cues in an interactive and immersive manner, making it much easier and more enjoyable to navigate through indoor spaces. Indoor mixed reality navigation is a low-cost solution that can be installed in existing indoor spaces without requiring costly renovations. Mobile phones can be used for mixed reality based indoor navigation. Users can download a mixed reality indoor navigation app on their phone. These apps use the phone's camera, GPS, and sensors to create a digital map of the indoor environment and overlay it with relevant information, such as directions, points of interest, and other relevant data. The users can then use their phone as a window to view the digital map and navigate through the environment. Indoor mixed reality navigation is a visual treat that makes it easier for visually impaired passengers by improving turn-by-turn audio prompts. A mixed reality navigation system can locate late-running passengers and send them text reminders (Kim and Jun 2008). Indoor mixed reality navigation app can display points of interest along the way. The retailers send promotional messages to nearby passengers informing them of current ongoing promotions. The indoor mixed reality navigation app can collect passenger information, which is then used to improve airport queue management and direct passengers to a less congested area. Passengers can use mixed reality navigation to get through the airport quickly, accurately find their way, and avoid missing their flight. Google Maps integrated mixed reality for indoor navigation to help people navigate more precisely and efficiently (CNBC, 2023; Google AR & VR, 2023; Resonai, 2023). Instead of relying on traditional signs and maps, passengers can now use their phones or tablets to access indoor navigation, which provides passengers with real-time maps and directions in 3D, making airport navigation more intuitive and engaging. Passengers can also access additional information such as flight times, gate information, and other relevant data.

Retail is an essential source of revenue for airports, accounting for a sizable portion of total revenue (see Fig. 3). Mixed reality retail boosts in-store and online sales while revolutionizing how customers shop and businesses interact with them. Virtual try-ons allow customers to get a realistic view of a product on their mobile devices. Customers can move and rotate the product to see it from various angles, and they can even change the color or fabric to create personalised products (Bonetti et al., 2018; Jiang et al., 2021a). Nike has launched a "Virtual Try-Ons" project, which uses mixed reality to allow customers to try on shoes without ever touching them (Forbes, 2023). Customers download the Nike app and then scan their feet with their phone camera. The app then generates a 3D model of their feet and overlays it with the shoe they want to try on. After that, the customer can change the size, color, and style of the shoes and receive feedback from the app. Mixed reality alters how businesses advertise their products and services. Customers can use phones to scan and access interactive videos rather than plain old print ads by implementing mixed reality markers on print advertisements. This technology brings a whole new dimension to marketing, allowing businesses to reach out to and engage new audiences. The mixed reality retail advertisement system directs passengers to specific products based on their interests and preferences. Retailers can use an indoor wayfinding system to give passengers a virtual tour of the store, allowing them to explore the various sections and shelves. Airports use mixed reality to provide interactive airport maps that show passengers their favorite shops and restaurants along their route as well as detailed information. Airports provide product information for a variety of prices and use guided arrows to direct customers to the correct location. The combination of mixed reality retail, advertisements, and indoor wayfinding gives passengers a more interactive and engaging airport shopping experience, allowing them to make more informed purchasing decisions and increasing sales for retailers.

Mishandled baggage and missed flights are both common sources of stress at airports, where mixed reality integrated solutions can help. Mixed reality can make flight information more interactive. Passengers

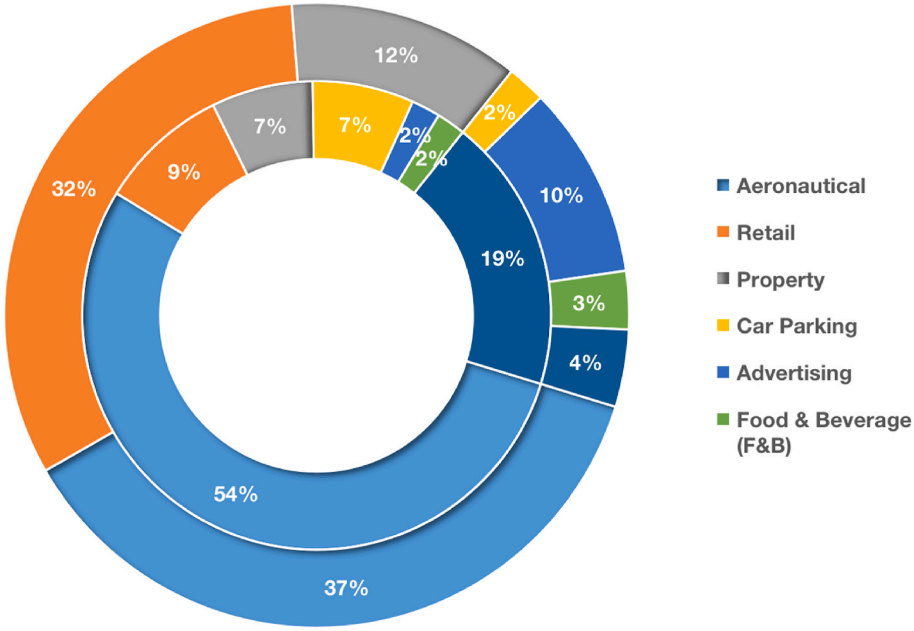

Fig. 3. The sources of airport revenue: From the inside out, the inner data comes from the 2019 annual report of Beijing Capital International Airport, and the outer data comes from the 2019 annual report of Flughafen Zurich AG (Zurich Airport Company).

can view flight information in a virtual environment on their smartphones or tablets, including departure and arrival times, departure gate, flight path, route taken, and other details. Prior to boarding, the airport can use mixed reality applications to notify passengers of the best boarding time and direct them to the gate. Gatwick Airport uses a mixed reality application to provide personalised flight updates and a frictionless experience for travellers. Late deliveries, damaged baggage, and mishandled baggage can all be red flags in baggage collection service (Zhang et al., 2008; Singh et al., 2016). Many airlines are eager to optimise their baggage handling process (see Fig. 4). Radio frequency identification (RFID), barcodes, QR codes, and mixed reality are used to track baggage and provide real-time information to passengers. However, barcodes only have 60–70% read rates, and RFID is costly and requires a separate reading scanner (Wyld et al., 2005; DeVries, 2008; IATA, 2023). Mixed reality with QR code allows passengers to track baggage with smartphone (Jiang et al., 2021b). The airlines assign a QR code to each baggage item and deliver it to the aircraft. When custody changes between carriers, an airline staff scans the QR code for verification. When the baggage arrives at its destination, the passenger can scan the QR code to confirm baggage-passenger information and avoid mishandling. The application reduces the number of lost, delayed, and mishandled bags and improves customer satisfaction. Smart glasses are used for baggage handling at Singapore Changi Airport (Coconuts Singapore, 2023). Staff can scan QR codes on baggage and cargo containers to instantly determine weight and unit data, reducing loading time from 60 to 45 min.

4. Opportunities

The COVID-19 pandemic has caused some problems in the aviation industry (Sun et al., 2020). Airlines have been forced to reduce capacity and cancel flights, resulting in significant revenue losses. To ensure the safety of passengers and crew, the aviation industry has had to grapple with new safety protocols and procedures. A digital transformation is underway in many airlines, with the potential to bring about cost savings, increased productivity, streamlined operations, and reduced risk (Serrano and Kazda, 2020).

Airlines are trying to achieve touchless and frictionless travel (Albers and Rundshagen, 2020; Gössling, 2020). Booking tickets, seat selection, and check-in via online reduce the contact and queue time. Machine learning-powered apps like Kayak, Booking.com, and Expedia assist travellers in planning and navigating their trip by providing affordable flights. Many airlines offer online services, including United Airlines, American Airlines, Delta Air Lines, Southwest Airlines, JetBlue Airways, Alaska Airlines, Virgin Atlantic, British Airways, and Air Canada, to help book ticket and self check-in. Airlines use travel history, previous behavioural patterns, and purchase history to create personalised travel packages.

Self-service systems with computer vision technologies, including biometric enrolment, facial recognition, and finger scanning, are applied in automated check-in and boarding. The US Transportation Security Administration recently installed computed tomography (CT) scanners, which use AI to help target threats, at Los Angeles International Airport, John F. Kennedy International Airport, and Phoenix Sky Harbor International Airport (Airport Technology, 2023b). Over the next five years, 77 percent of airports plan major biometric ID management programmes. Facial recognition technology is already being implemented at several major airports to scan passengers as they go through customs (Airport Technology, 2023b). Hartsfield-Jackson International Airport has opened a biometric terminal that includes facial recognition

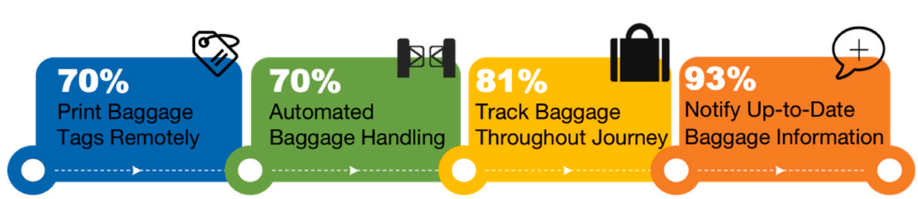

Fig. 4. The willingness of airlines to optimise their baggage handling process.

scanners at self-service kiosks, checkpoints, and boarding gates. Fingerprinting, facial recognition, and retinal scans are expected to be increasingly used for airport security.

Machine learning can predict future traffic flow and enable informed decision-making for airport operations. Predictive analytics is used to forecast the number of passengers and flights over specific time periods. Machine learning-based automated routing systems for aircraft to reduce operational costs and delays. Flight scheduling systems that are automated to maximise the number of aircrafts and flights. Automated air traffic control systems are used to optimise traffic flow. Machine learning-based incident detection systems can identify and address potential issues quickly. Real-time weather updates and forecasts will be provided by weather forecasting systems. Automated ground operations systems can optimise resource utilization and aircraft flow. American Airlines, Delta Air Lines, United Airlines, Southwest Airlines, and British Airways all utilize machine learning to predict flight delays and cancellations. They also use it to optimise their aircraft routes and maintenance schedules.

The airports use mobile applications to provide optimised queues and to ensure a safe distance between passengers. Passengers can use the apps to check in and receive their boarding passes, avoiding long lines at the airport. The apps deliver real-time updates on flight departure and arrival times, as well as other pertinent information. The apps provide details on airport amenities and services. Mobile applications are used by Ryanair, easyJet, Delta Air Lines, American Airlines, JetBlue Airways, and KLM Royal Dutch Airlines to create efficient wait lines, reduce wait times, and increase customer satisfaction.

Health screening and certificates are special operations during COVID-19 (Gold et al., 2019). The airports utilize the web, mobile, social media, kiosk, email, smartphone apps, and chatbots to assist the customer services. Machine learning algorithms are used to detect patterns and trends in passenger health data. The information gathered from the online system and social media helps identify passenger's risk of contracting the virus. It provides targeted intervention to reduce their chances of becoming infected. Machine learning can be used to generate COVID-19 certificates that verify passenger health status, reducing the risk of the virus spreading. IBM has created a COVID-19 screening and certification system that evaluates health screening questions using machine learning and natural language processing technology. Microsoft has developed a system that uses machine learning to provide personalised health advice and quarantine alerts. Google has created a machine learning-based system that uses questionnaires to determine whether an individual should be tested for COVID-19. Apple has created a system that detects potential COVID-19 symptoms in Apple Watch data using machine learning. Amazon has developed a system that analyses COVID-19 test results using machine learning. The health of each passenger is recorded in a digital form, and machine learning is used for abnormal data identification, identifying infected suspects in a timely manner. Data-driven real-time analytics ensure that potential patients are not missed. Machine learning analyses large datasets to find patterns in the data that can indicate an outbreak or provide additional information about the virus. Machine learning models can accurately predict the future spread of the virus by analysing data from previous outbreaks, such as the number of cases and the rate of spread. COVID-19 digital forms are used by Air Canada, American Airlines, Delta Air Lines, Emirates, JetBlue Airways, KLM, Lufthansa, Qatar Airways, Singapore Airlines, and United Airlines. Passengers authorise access by logging into the apps on their smartphones, using cameras to capture passport information, and adding their itineraries, vaccination certificates, and Covid-19 test results as a travel pass. As vaccination passports, health passports, and digital green certificates, the EU issued digital COVID certificates. The digital COVID certificate issued by the EU provides travelers with a QR code in both paper and digital formats. This code contains information about their vaccination and health status, ensuring their safety and facilitating their travel.

Data science is used to manage airport sanitization, ensuring high hygiene standards. It decreases human intervention while increasing fidelity, accuracy, and observations. Data is used to identify areas of the airport that are most at risk for disease spread, such as those with the most foot traffic and those touched by travellers. Machine learning determines the most effective sanitization methods, such as the types of cleaning products to use, the frequency of cleaning, and the best times of day to clean. Data science can track the effectiveness of sanitization efforts over time and make necessary adjustments. Temperature screening, contactless payment systems, and automated disinfection robots have been implemented at Shenzhen Bao'an International Airport in China, San Francisco International Airport in the United States, Heathrow Airport in the United Kingdom, and Changi Airport in Singapore.

Although airports will incur short-term losses during COVID-19, renewed digital aviation investments will increase long-term benefits (Adrienne et al., 2020). This paper promotes airport digitization while also emphasising environmental protection (Rolnick et al., 2022; Chaouk et al., 2020). Airports must prepare for an increase in passenger traffic in the future, as well as a faster recovery of the leisure passenger segment (Schultz et al., 2020). Passengers' modes of transportation to and from the airport have significantly changed in recent years (see Fig. 5). Public airport transportation necessitates substantial assistance, such as route subsidies (Mandle et al., 2000; Vuchic, 2002). A baggage-free airport terminal is considered a potential solution, as it moves baggage operations away from passenger terminals, reducing airport operator workload and encouraging passengers to use public transportation to airport terminals. The baggage-free airport terminal integration of the modified Clark and Wright savings heuristic and a density-based clustering algorithm for optimising logistic hub location and vehicle routes for baggage collection. The baggage-free airport terminal will have a significant impact on energy and the environment, resulting in lower fuel consumption and lower carbon emissions (Jiang et al., 2021b). Machine learning and predictive analytics are being used to monitor aircraft operations and identify potential environmental risks. Algorithms can be used to identify anomalies that could indicate potential pollution or other environmental risks by utilising data from flight patterns, fuel efficiency, and aircraft performance. The risks alert is sent to airport operators or other stakeholders so that they can take corrective action. Commercial air taxi services have been expanded at some airports. The Volocopter successfully completed its first manned flight over Singapore. Planned urban air mobility solutions were unveiled by Boeing, Bell, Embraer, Safran, Uber, Fraport, and Groupe ADP. Airports have joined forces to reduce their environmental impact. A new air transport industry has emerged, as has a new travel ecosystem.

5. Challenges

Machine learning and mixed reality are rapidly evolving fields, and their increasing popularity in smart aviation brings a slew of new challenges, including security and privacy, technology, cost, acceptance, and regulations (Helbing, 2015; Scholz et al., 2018; Helbing et al., 2019a; Helbing et al., 2019b).

Security and Privacy: Machine learning and mixed reality pose a distinct set of security and privacy challenges, as it becomes increasingly vulnerable to malicious attacks and manipulation. Machine learning algorithms are trained on data containing passenger personal information, from which sensitive information can be inferred. Malicious actors can design biased algorithms to influence decision-making and outcomes. Machine learning is vulnerable to cyber attacks and other malicious activities to gain access to sensitive data. Personalization service based on machine learning raises privacy concerns. Machine learning analyses massive amounts of data from various sources, including in-flight system, social media, web searches, and even physical locations. This allows to create detailed profiles of the passenger, which can then be used to provide personalised services. However, the information gathered can be abused. Machine learning-based personalised in-flight

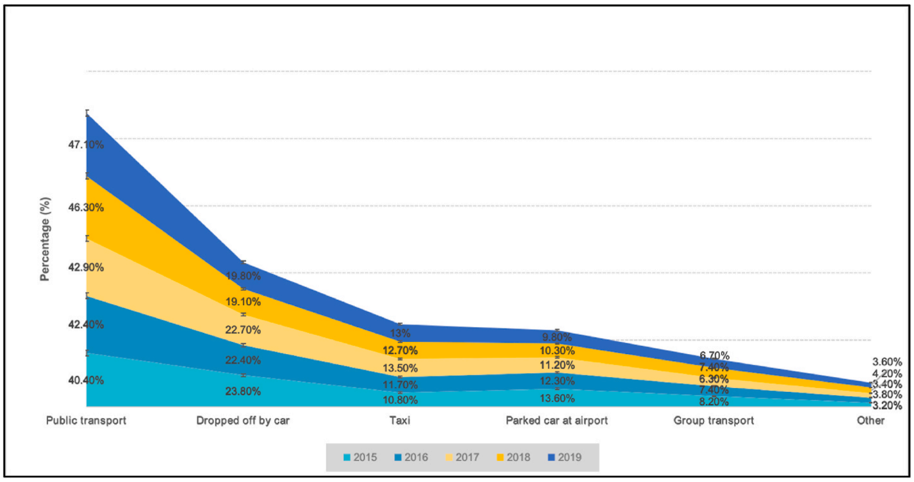

Fig. 5. Changes in the modes of transportation used by passengers to and from the airport over time.

service can result in unfair discrimination, including the creation of 'blacklists' of passengers who are deemed undesirable, denying them access to certain services or treating them differently. Algorithms can result in biased decision-making or unfair pricing. Airlines must follow strict privacy regulations to ensure that machine learning-based personalised services remain ethical. Before collecting and storing personal data on passengers, airlines should obtain their explicit consent. Airlines must be transparent about how data is used and ensure that any decisions based on data are fair and nondiscriminatory. These services should allow passengers to choose to opt out and have their data deleted.

The most significant security concern of mixed reality is the potential for malicious individuals to gain access to the actual environments of passengers. To provide a realistic and immersive experience, mixed reality technology requires access to personal data such as location, age, and gender. Attackers can potentially use this information to carry out targeted attacks, posing a security risk. Compliance with data privacy laws and clear policies for the use of passenger data should be established by mixed reality systems. Mixed reality technology can track passengers' physical movements and behaviours, which raises concerns about privacy. Airlines may collect and monetize this data, potentially leading to issues such as unwanted advertisement targeting. Virtual spaces created through mixed reality technology can be inaccessible to the public, and therefore not subject to regulations or laws. This can potentially allow airlines to collect and use passenger data without proper oversight, raising concerns about privacy and data protection. To ensure that the benefits of machine learning and mixed reality outweigh the risks, passenger security and privacy must be addressed.

Technology: As technology advances and becomes more sophisticated, the aviation industry must keep up with the changing trends. The data in the aviation industry is of high volume, velocity, variety, and veracity, making traditional data management tools ineffective. Aviation data is made up of a large amount of structured or unstructured data generated from various sources. Data is generated at a rapid rate from social media, web logs, and sensors. Machine learning has limited processing power and speed. There is often a lot of noise in aviation data. Machine learning algorithms frequently struggle to identify and learn from noise, resulting in inaccurate models. Machine learning lacks interpretability, making it difficult for humans to comprehend underlying processes and decisions of models. The lack of understanding can lead to mistrust, the interpretability causes problems with trust and reliability. Machine learning are prone to bias, which can lead to inaccurate and unfair outcomes. Machine learning models are trained on the real-world data, which can reflect societal biases. This type of bias can have serious consequences for algorithms, as it can lead to unfair or discriminatory decisions. To reduce the risk of bias in machine learning, the data used to train the model should be accurate and representative of the population it is meant to serve. Data scientists should use techniques such as stratified sampling. Regular bias testing should be performed on algorithms.

One of the major technological challenges for mixed reality is scalability. As mixed reality is still in its nascent stages, it is difficult to ensure that the content created is compatible with a wide range of devices and platforms. The non-scalability makes mixed reality applications struggle to provide a consistent and positive user experience across devices. Ensuring a smooth and engaging interactive experience with mixed reality content can be challenging due to the possibility of encountering glitches and delays. As technology continues to advance, the challenges and limitations can be addressed and overcome.

Cost: Deploying machine learning and mixed reality applications demands a considerable amount of computing power, software, and energy. The implementation cost of machine learning algorithms can depend on various factors, such as the complexity and size of the data set, the number of models and algorithms used, the required hardware and software, and the duration and resources needed for training and deployment. Hardware and software costs can be quite high, especially for deep learning algorithms and large datasets. The time and resources required to train and deploy models are costly, and they necessitate specialized knowledge. Aviation data used in machine learning algorithms must be accurate and up to date, which can be challenging due to changes in the environment and the data collection process. Maintaining and updating machine learning algorithms is a time-consuming and costly process. Airlines need to carefully consider the advantages and drawbacks of employing machine learning technology to ensure that their resources are being utilized efficiently.

The costs associated with mixed reality applications mainly stem from expensive hardware requirements, such as complex headsets, sensors, and controllers. In addition, users must have internet connectivity, which can result in extra charges. To stay current with the latest technology, the aviation industry must regularly update the hardware used in mixed reality applications, which can be expensive. The creation of virtual environments in mixed reality applications may also be costly due to the need for specialized software and expertise. These virtual environments must be maintained and updated, which can increase the overall cost. While machine learning and mixed reality are exciting technologies that have the potential to transform the way we interact with the world, it is essential to consider their associated costs.

Acceptance: Airlines face challenges in the acceptance of machine learning and mixed reality due to concerns about their potential impact on broader applications. To address this, airlines must ensure that their applications are explainable, providing insight into the underlying decision-making process. The quality of machine learning algorithms is highly dependent on the quality of the data on which they are trained, and any bias in the data can negatively affect even the most advanced sophisticated algorithms. Airlines must therefore take steps to identify and eliminate potential sources of bias in their data. To ensure that users trust machine learning algorithms, the data must be accurate and unbiased, the algorithms must be transparent and explainable, and the system must be secure against potential cyber attacks. However, machine learning algorithms are often complex and difficult to understand, and the datasets used to train them may contain errors or not be representative of the entire population, resulting in inaccurate or biased results. The algorithms are also constantly evolving, making it difficult to ensure consistent results.

The high cost of hardware needed for mixed reality still makes it expensive for users to adopt. In addition, the cost of mixed reality software can pose a challenge for developers to create and disseminate new applications. Mixed reality applications are intricate, and users need to learn new concepts and various tools, which can be time-consuming and hinder their acceptance. Furthermore, mixed reality applications can gather a significant amount of user data, which raises concerns about privacy and security. As mixed reality technology continues to develop, it is crucial to safeguard the security of passenger data and responsibly use this technology.

Regulations: Stringent government regulations and compliance are essential for the industry to remain safe and secure. Machine learning and mixed reality have numerous and diverse potential applications, and their impact on our lives is growing rapidly. However, there are several gaps in the current regulatory system that must be filled. Many regulatory bodies are struggling to define machine learning and mixed reality usage standards. To keep up with the ever-changing capabilities of technologies, these standards must be revised and updated. The inner workings of machine learning are largely unknown, making it difficult for regulatory bodies to ensure that the algorithms are not biased or discriminatory in their decisions. Much of the regulation is currently left to individual countries and organisations, resulting in a patchwork of laws and regulations. A global regulatory framework would ensure that all countries adhere to the same standards and provide a level playing field for the development and use of technology. Laws and regulations are required to address the ethical implications of machine learning and mixed reality. A framework must be in place to ensure that algorithms do not make biased decisions based on factors such as race or gender. There is a need for the implementation of worldwide regulations to oversee the progress and utilization of cutting-edge technology, alongside specialized laws and policies aimed at tackling the ethical concerns, data confidentiality, and possible negative impacts. Data regulation contributes to a more informed and engaged public by allowing individuals to use data to hold decision-makers accountable and exercise their rights. Data regulation promotes data producer and data consumer transparency and collaboration. Increased data accessibility can result in more equitable decision-making processes. Users are required to possess digital literacy, which includes an understanding of how the digital world operates and its impact on their lives, as well as the potential advantages and hazards of technology, and the usage of digital content in a responsible and secure manner.

6. Conclusion

This paper provided a review of machine learning and mixed reality applications and solutions in the aviation industry. This paper investigated intelligent tools based on machine learning for aerospace design, manufacturing, testing, and services. Mixed reality applications for product design, complex assembly, accurate maintenance, and assisted training were explored. This paper studies advanced machine learning techniques for improving passenger experience, such as self-service check-in and boarding, advanced passenger controlling, more efficient baggage claim processes, intelligent predictive analysis, and impressive in-flight entertainment. Mixed reality influences the passenger experience through visualised real-time information, indoor wayfinding, immersive retail, and virtual baggage tags. This paper discussed the opportunities and challenges faced by the aviation industry. With the breathtaking array of innovative digitization technologies, the aviation industry will open up a new era of "touchless, seamless and secure" operations and services.

Author statement

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