



Artificial intelligence as a driver of efficiency in air passenger transport: A systematic literature review and future research avenues

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ABSTRACT

Despite the claim that artificial intelligence (AI) has the potential to increase efficiency in and for airlines, current literature is limited concerning models and frameworks to assess AI applications and their implications for airline efficiency. In response, we a) conceptualize and propose an AI-Airline-Efficiency-Model (AAEM) that allows for a more structured management approach for a systematic review and analysis of existing literature, and b) present a framework explicating the identified areas of AI application for airline efficiency based on the AAEM model. In particular, using the four AI elements Machine Learning, Deep Learning, Reinforcement Learning and Natural Language Processing and their applications within six identified airline departments, we systematically review and analyze key attributes and characteristics of both AI and airline efficiencies to critically assess current research efforts. We found that AI applications are built around four overarching improvement areas predictive analytics, resource optimization, safety & autonomous processes and passenger experience, but lack a cross-department and inter-organizational focus and are often theoretical in nature. This study provides insight into most prevalent AI applications and the less popular applications applied in and for passenger transport, thereby presenting the dominating AI techniques that are covered by existing literature as well as highlighting a wide range of emerging AI techniques with the potential to become more influential for future studies. We discuss theoretical and managerial implications and offer avenues for future research.

1. Introduction

The application of artificial intelligence (AI) is expected to enhance human decision-making and increasing productivity by utilizing data to identify patterns, perform scenarios analysis based on predictions, learning from historic phenomena and suggest actions to maximize efficiency (Akerkar, 2019; Min, 2010; Pournader et al., 2021; Sun et al., 2023). However, various industries have only recently started leveraging the potential of learning from data, automation, AI bots or predictive analytics using data for instance generated by sensors, devices or users (Balakrishnan et al., 2020; Beer et al., 2022; Dantas et al., 2017; Herold et al., 2021b; Mikl et al., 2020; Sun et al., 2021, 2023). Yet, AI has manifested invaluable in industries like automotive, assembly, travel or retail and often delivers superior results compared to traditional analytical techniques (Dash et al., 2019; Herold et al., 2023; Stone et al., 2020; Weisz et al., 2023).

In airlines, the introduction of AI starts to reshape airlines' approaches to data, revenues and operations (Geske et al., 2024; Wandelt et al., 2024). Research indicates that AI and related machine learning techniques "have greater autonomy, deeper learning capacity, and are

more inscrutable than any of the intelligent IT artifacts that have come before" (Berente et al., 2021, p. 1433). As a consequence, the application of AI is expected to reduce manual workload and foster human capabilities in complex scenarios. Current actual of AI applications in airline management improve operational efficiency and customer satisfaction (Leong et al., 2015; Lucini et al., 2020; Olivares et al., 2023; Pilon, 2023; Sun and Wandelt, 2021; Wandelt et al., 2015; Xu et al., 2024), but may range from increasing efficiency to safety (Eurocontrol, 2020) to reducing operational costs by optimization through delay prediction. Studies show that AI could also be used in passenger and baggage identification, customer satisfaction, aircraft maintenance and safety or remote sensing (Vincent et al., 2021).

Eurocontrol (2020) suggests that the key areas of AI application opportunities in aviation are passenger experience, infrastructure monitoring, spacing/ separation, performance management, resource management/ optimization, traffic predictions and forecasts as well as workload/automation/autonomy. However, current usage is limited and is still lagging behind compared to other industries (Merkert, 2022; Vincent et al., 2021; Xiao et al., 2014). As there is only a little appli-

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cation of Machine Learning techniques in aviation (Ding et al., 2023; Maheshwari et al., 2018), the aim of this paper to analyze to what extent AI has been used in air passenger transport and identify gaps for future research, specifically asking the question:

RQ: What is the state-of-the-art of AI applications in air passenger transport to foster efficiency?

In order to identify current and potential AI applications in commercial passenger aviation, this study adopts a systematic literature review approach to provide an overview of the research articles published to date and to identify gaps in current research. This paper contributes in three ways. First, we present an AI-Airline-Efficiency-Model (AAEM), which provides a conceptual foundation for a structured systematic review and analysis of existing literature of AI applications in air passenger transport. The model combines both AI elements as well as the classic airline business functions, thereby representing a structured approach to categorize AI applications based on the respective airline departments. Second, we used the AAEM as a conceptual foundation for our systematic literature review on AI and airline efficiency to analyze the research that has been published to date and to identify overarching improvement areas for AI applications. Third, by analyzing and categorizing the current literature of AI in commercial passenger aviation, we do not only provide a state-of-the-art overview about current AI application in the airline sector, but also identify relevant gaps that need to be addressed to further foster efficiency.

The remainder of this article is structured as follows: The next section proposes a conceptual model and highlights the basics and scope of AI. In the next section, we outline the methodology used for our systematic literature review. This is followed by the findings of the literature review, which summarizes the literature on AI applications and commercial passenger aviation. We then discuss theoretical and managerial implications. Finally, we suggest a research agenda based on identified gaps in the current literature and provide directions for future investigation.

2. AI in and for airline efficiency: a model

In this section, we introduce the AI-Airline-Efficiency-Model (AAEM) to build a conceptual foundation for a structured systematic review and analysis of existing literature of AI applications in air passenger transport (see Fig. 1). The model consist of two main components: a) the airline business functions based on the efficiency model of Feng and Wang (2000), which distinguishes operations, marketing and execution efficiency, and b) the different elements of AI, namely *Machine Learning*, *Deep Learning*, *Reinforcement Learning* and *Natural Language Processing (NLP)*. In particular, we combine these two components not only to assess how the different AI elements contribute to or increase the overall operational efficiency in airlines, but also to allow a more structured recognition of AI in and for airline efficiency. In the following sections, we will elaborate on the two components of airline business functions as well as the AI elements.

2.1. Efficiency in airline business functions

To categorize efficiency in airline functions, Feng and Wang (2000) proposed a model that presented relevant functional areas of commercial passenger airlines, distinguishing operational efficiency, marketing efficiency and execution efficiency. The authors argue that higher efficiency for airlines is achieved when the decision-making from operators using the factor input (such as the capital and assets) leads to a higher output in the current period compared to the previous period. In other words, airlines simultaneously pursue a) more efficiency in operational activities, b) more efficiency in consumer spending, and c) more efficiency from the input-output ratio during the execution phase for the existing period, thereby determining the factor input ratio for the subsequent period.

Operational efficiency comprises the departments of *Ground Operations* and *Flight Operations* and relates to resources utilized in operations to produce output for economic sustainability (Feng and Wang, 2000). More specifically, Flight Operations involves dispatch, crew tracking, maintenance control/aircraft engineering, aircraft control and air traffic control coordination, while Ground Operations targets ramp or apron operations. Dispatch is responsible for the flight planning, which mainly covers the flight plan and fuel calculation. The functional area crew tracking reassigns crews in case of schedule disruptions and crew sickness. The maintenance control/aircraft engineering deals with aircraft malfunctions and performs scheduled maintenance. The function of aircraft control reacts to schedule disruptions by reassigning aircraft to flights in order to ensure schedule stability. The air traffic control coordination is involved in the air traffic management to make decisions collaboratively with all stakeholders involved (Cook and Billig, 2017; Kohl et al., 2007). In Ground Operations, ramp or apron operations involve the supervision of all activities around the aircraft such as cleaning, fueling, catering and baggage as well as cargo handling (Bruce, 2018).

Marketing efficiency comprises the activities of *Sales & Marketing* departments as well as *Customer Service* and measures the consumer consumption based on e.g. flights marketing capability, seat marketing capability or debts turnover (Feng and Wang, 2000). Under sales, we subsume pricing and revenue management, ancillary services and distribution channels. The objective of revenue management is to generate the maximum revenue possible using price discrimination and seat inventory management (Bazargan, 2010; Belobaba, 2016a, Belobaba, 2016b; Cook and Billig, 2017). Ancillary services shall increase the value of the airline's core product (Parker, 2018). The marketing department is closely interlinked with sales as it involves the product and its distribution, brand management, advertising and promotional policies or relationship marketing, but has also touchpoints with revenue management or the distribution channels (Shaw, 2016). The marketing comment also includes Customer Service, as there is a relationship between customer satisfaction and airline profitability (Steven et al., 2012). Therefore, we subsume under the functional area of Customer Service functions such as customer care departments, call centers, customer relations management or airline service centers. Customer care units in this respect support passengers in case of flight disruptions by (re-) accommodating affected passengers on other flights and/or by arranging accommodation and meal vouchers (Kohl et al., 2007).

Execution efficiency represents the efficiency of departments such as *Finance and Planning* (Feng and Wang, 2000), involving network and schedule planning (=network department), fleet assignment and aircraft routing as well as manpower planning and crew scheduling (=crew planning) (Bazargan, 2010). In other words, execution efficiency relates to the overarching fleet execution capability and the associated airline's shareholder value, asset turnover or the return of investment.

2.2. Artificial intelligence for efficiency

AI has been existing for more than half a decade, but recent advances in super computing and technologies targeting big data processing and analysis have strengthened its capabilities for increased efficiency (Duan et al., 2019). Rooted in computer-based technologies, AI is assigned to informatics as it ensures a systematic and automatic processing of data using computers to transform an input through programs to solve a problem. Advances in perception, cognition and problem solving have led to systems, which are outperforming human intelligence (Brynjolfsson and McAfee, 2017; Lanquillon, 2019). To define intelligence of a human or machine, Legg and Hutter (2007) have formulated two conditions: being able to initiate actions to support achieving the target and being capable to handle an environment that is not completely known. In general, AI is capable of analyzing and learning from data, human cognition (e.g. speech, text), emotions and thinking (Nishant et al., 2020). AI represents an alternative to traditional methods to deal with complex systems (e.g. transportation system), where the characteristics' relationships are dif-

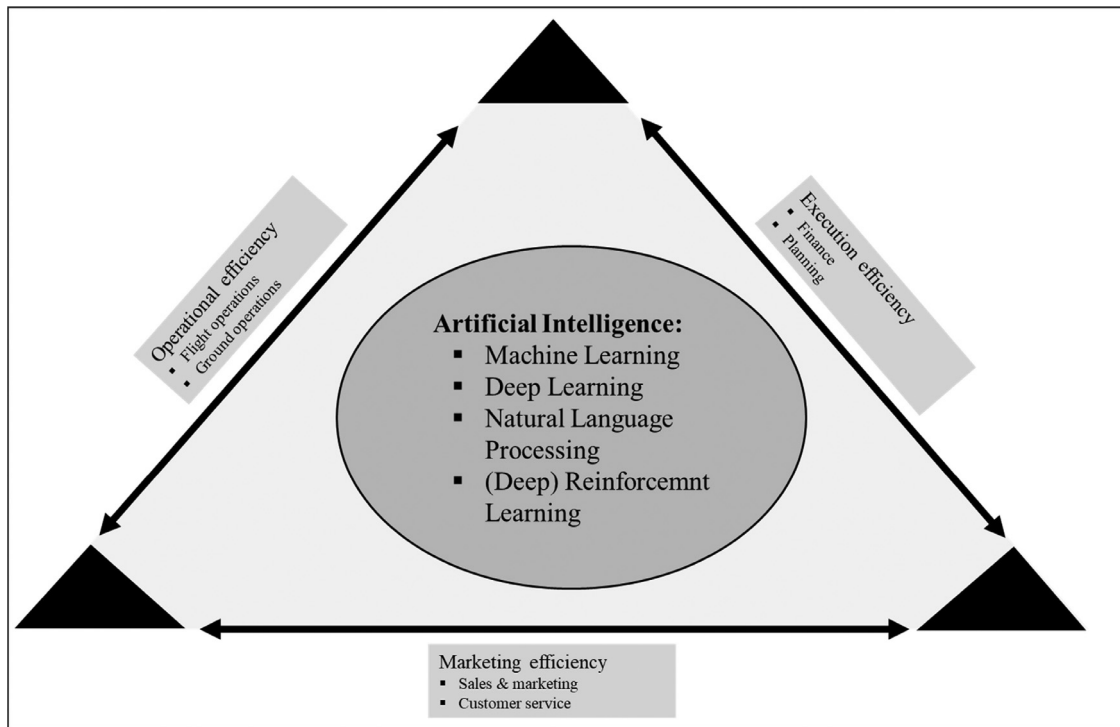


Fig. 1. the AI-Airline-Efficiency-Model (AAEM) (adapted from Feng and Wang, 2000).

difficult to understand (Herold et al., 2021a; Mikl et al., 2021; Thurner et al., 2018). It enables data acquisition as well as data base knowledge updates in automated processes and thereby supports human decision making or reduces manual labor requirements (Ogunsina and DeLaurentis, 2022).

Following Campesato (2020), we categorize the elements of AI into *Machine Learning*, *Deep Learning*, *Reinforcement Learning* and *Natural Language Processing*. Machine Learning refers to algorithms to enable a computer to learn from experiences, statistical regularities and patterns (Ayodele, 2010). Consequently, Machine Learning investigates how knowledge can be generated from data to solve problems (Nayal et al., 2021). Deep learning resembles an extended version of Machine Learning in which multiple layers of learning/processing are used to allow learning from data that have several abstraction levels. This kind of learning improves applications like recognition of speech or objects (LeCun et al., 2015). In Natural Language Processing the content of human language shall be learned, understood and reproduced by computational approaches (Hirschberg and Christopher, 2015). Due to the vast amount of text produced, which becomes difficult to process and to discover information by humans, Natural Language Processing algorithms enable machines to support (Chowdhary, 2020). Reinforcement learning in contrast, “provides both qualitative and quantitative frameworks for understanding and modeling adaptive decision-making in the face of rewards and punishments” (Dayan and Niv, 2008, p. 185). It involves the investigation of agents and their behavior within their environment to learn approaches that maximize the respective outcome (Henderson et al., 2018). Deep Reinforcement Learning constitutes a development towards the construction of autonomous systems that have an increased understanding of visual world (e.g. in robotics) (Arulkumaran et al., 2017).

AI tools can be broadly categorized into *perform* (Machine Learning, knowledge-based systems), *cognize* (Natural Language Processing, knowledge representation) and *sense* (computer vision, media processing). Thereby descriptive (what has happened?), predictive (what could happen?) and prescriptive (what could be done to realize the best re-

sult?) analysis can be performed (Akerkar, 2019). Applications in forms of computer vision (object-detection) or Natural Language Processing to improve language capabilities have progressed in recent years (Zhang et al., 2021). AI is also capable of acquiring, interpreting and reasoning data to set action in order to reach a given target (Eurocontrol, 2020).

Baryannis et al. (2019), in contrast, grouped techniques and methodologies that can be subsumed under AI into mathematical programming approaches, network-based approaches, agent-based approaches, automated reasoning as well as Machine Learning and big data analytics. Thereby, mathematical programming involves stochastic programming for optimization models under uncertainty, robust optimization for parameters with unknown uncertainty distributions as well as fuzzy programming, which uses fuzzy parameters and hybrid approaches. Network-based approaches present problems as sets of potential states and transitions between them, while agent-based approaches target problems dealing with interacting entities and potentially conflicting conditions. In automated reasoning, decisions are made based on available data, rules and cases, which were previously derived from expert knowledge (Baryannis et al., 2019). Besides Machine Learning and machine reasoning (e.g. planning, representation or optimization), AI is part of robotics to support perception, sensors, control and actuators or of augmented and virtual reality (Eurocontrol, 2020; Smith and Eckroth, 2017).

3. Methodology

Building on the AAEM model presented above, this paper employs a systematic literature review approach (see also Herold et al., 2020; Weisz et al., 2023). The replicability, rigor and transparency is the foundation for the high-quality evidence of systematic literature reviews (Tranfield et al., 2003), thus being a ideal method for the paper’s research aim, namely to provide a structured approach to examine AI applications in air passenger transport and identify future research avenues. We follow the established six-step (see Fig. 2) approach established by Durach et al. (2017) which we discuss below.

Table 1
Inclusion criteria.

Inclusion criteria	Rationale
Peer-reviewed articles	Quality of published peer-reviewed articles is higher (Denyer and Tranfield, 2009)
Selection of papers published 2015 to 2022	The year 2015 was selected as a starting point due to the emergence of AI (Pournader et al., 2021).
Summary must address an AI aspect (as identified in the AAEM model) within the context of airlines/aviation	The purpose is the analysis of existing airline and aviation management literature and the role of AI
Different type of article considered (e.g. empirical, conceptual)	Broad conceptual and methodological focus as the aim is analyze multiple approaches and topics in AI for airline efficiency
Article must be written in English	AI and airline management research articles are dominated by the English language

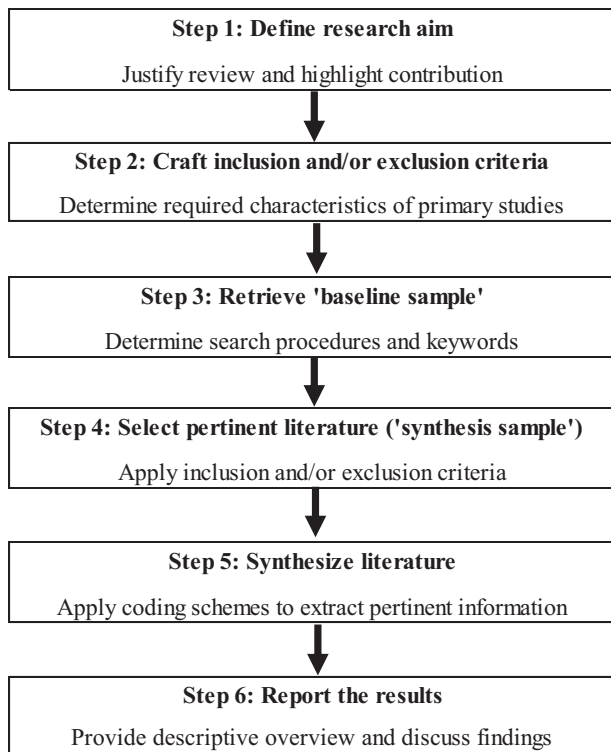


Fig. 2. Steps for conducting a systematic literature review (adapted from Durach et al., 2017).

3.1. Step 1: define research aim

The aim of this research is utilizing the AAEM model to analyze and synthesize existing airline and aviation management literature that examines the role of AI and highlight opportunities for future research for airline and aviation management scholars.

3.2. Craft inclusion and/or exclusion criteria

Following a rigorous methodological approach, the authors developed and agreed on an inclusion criteria list (see Table 1). As the goal of this paper is to identify AI applications in airline operations, the six departments from our model were also included in the search. As a consequence, relevant documents needed to demonstrate a focus on how AI and related technologies can be used in air passenger operations in general, and in the identified departments in particular. The review only included peer-reviewed articles due to their higher quality compared to non-peer-reviewed articles (Denyer and Tranfield, 2009). Moreover, we focused on the timeframe 2015 to 2022 as 2015 was the year when AI was becoming a popular among managers and academics (Pournader et al., 2021). All peer-reviewed articles not fulfilling these criteria were excluded.

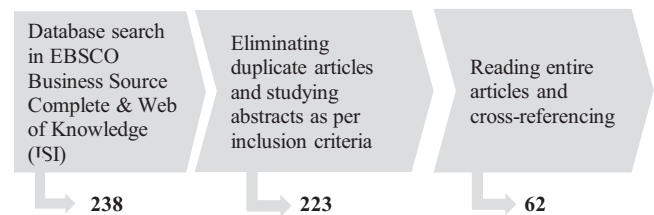


Fig. 3. Article selection process.

3.3. Retrieve 'baseline sample'

As a third step a 'baseline sample' of potentially relevant articles was retrieved. We focused on two databases for the search: Business Source complete (via EBSCO) and the Scopus-Database. We selected these databases were selected as both comprise large research repositories in management and business (Sandberg and Aarikka-Stenroos, 2014). Following Denyer and Tranfield (2009), a team of three researchers – specializing in AI and airline management – identified and validated initial search terms based on the research aim and the inclusion criteria. After agreeing on the initial search terms, the researchers identified incremental keywords and extended the search string by indicating synonyms to cover all relevant topics.

In line with other systematic literature reviews (e.g. Herold and Lee, 2017), we searched first for airline management articles in the databases by applying the keyword “airline” in combination with “artificial intelligence” and its elements of “Machine Learning”, “Deep Learning”, “natural language processing” and “Reinforcement Learning” (see Table 2). To expand our scope and include the departments, we repeated the search and replaced “airline” terms with “aviation”, “flight” and included the terms of the departments.

We adjusted the search string for each database to the database guidelines to capture all relevant documents comprising airline efficiency and AI, further conducting subsequent citation searches. The first search was carried out in February 2022 but repeated in December 2022.

3.4. Select pertinent literature

We identified 167 articles from Business Source Complete and 71 articles from Web of Knowledge in the initial search process including a significant overlap, thereby indicating consistency among the search strings. Duplicate documents were eliminated and two authors screened the abstracts based on the inclusion criteria. To ensure inter-coder reliability (i.e. multiple coders), a sample of 30 abstracts was screened by two authors. In case of doubt, a third researcher was involved. This resulted in a reduced amount of documents with 77 articles. Sharing the documents (Durach et al., 2017), two authors read the full content of the identified documents to evaluate relevance for the final sample. This stage, which was carried out again in July 2024, allowed us to detect additional 17 documents by using cross-referencing. At the same time, we also excluded all documents with no relevance to AI and airline issues. This led to a final sample of 62 articles (see Fig. 3).

Table 2
Keywords and search string.

Construct	Original search string	Databases
AI in and for Airline Efficiency	("artificial intelligence" OR AI OR "machine learning" OR ML OR "deep learning" OR DL OR "reinforcement learning" OR RL OR "Natural Language Processing" OR NLP) AND (aviation OR airline")	Business Source Complete Web of Knowledge (ISI)

3.5. Synthesize literature

We synthesized the final sample of 62 articles aiming for a comprehensive overview about the studies that increase airline efficiency using AI. Further, we analyzed the content of the documents against the AAEM model and in its two components of a) the AI elements and b) the above-identified departments of the airline business functions, an interpretative synthesis approach (Rousseau et al., 2008). For the categorization of the documents, we used the four AI elements of “Machine Learning”, “Deep Learning”, “Reinforcement Learning” and “Natural Language Processing” for the x-axis and used the six departments “Flight Operations”, “Ground Operations”, “Finance”, “Planning”, “Sales & Marketing” and “Customer Service” to build an AI-Airline-Grid in which the articles will be allocated. The allocation of the papers according to the AI elements and the respective departments provides also a solid foundation for identifying gaps and proposing directions for future research.

3.6. Report the results

The following section outlines the results from the identified studies reporting on how AI can increase airline efficiency.

4. Results

In presenting our study results, we first provide a snapshot of the 62 papers from our review based on the AI-Airline-Grid, consisting of the four AI elements and six airline departments (Table 3). To synthesize our findings, we present an integrative framework illustrating and subsequently categorizing the AI applications in air passenger transport that foster efficiency, thereby also answering the research question (see Fig. 4). The framework shows that airline efficiency (divided into operational, marketing and execution efficiency, see Feng and Wang, 2000) is represented through four overarching improvement areas, namely *predictive analytics*, *resource optimization*, *safety & autonomous processes* and

Table 3
AI-Airline-Grid.

Artificial Intelligence					
Machine Learning			Deep Learning	Reinforcement Learning	Natural Language Processing
Operations	Flight Operations	Atlioglu et al. (2020), Cai et al. (2019), Dattaram and Madhusudanan (2016), Di Ciccio et al. (2016), Diana (2018), Diana (2019), Esmailzadeh and Mokhtarimousavi (2020), Gui et al. (2020), Khan et al. (2019), Puranik et al. (2020), Khan et al. (2021b), Schultz and Reitmann (2019), Truong (2021), Verdonk Gallego et al. (2018), Vaze et al. (2017), Yang et al. (2021), Baumann and Klingauf (2020), Zhang and Mahadevan (2019), Liu et al. (2019b), Herrema et al. (2019), Shi et al. (2021), Yu et al. (2019), Ivanoska et al. (2022), Zanin et al. (2020)	Ai et al. (2019), Bao et al. (2021), Liu et al. (2019a), Pang et al. (2021), Tong et al. (2018), Yu et al. (2019), Zhang and Mahadevan (2020) Zhu and Li (2021), Zheng et al. (2016)	Cruciol et al. (2015), Ding et al. (2023)	
		Ground Operations	Felkel et al. (2021), Guo et al. (2021), Wang et al. (2018), Suh and Ryerson (2019)	Huang et al. (2021), Zheng et al. (2016)	
	Finance Planning	Atlioglu et al. (2020), Gui et al. (2020), Kuhn (2016), Mack et al. (2017)	Ai et al. (2019), Bao et al. (2021), Zhang and Mahadevan (2020)	Abdelghany et al. (2021), Hu et al. (2021), Bondoux et al. (2020), Lawhead and Gosavi (2019)	
	Sales & Marketing	Bondoux et al. (2020), Dadoun et al. (2021), Darrow (2021), Delahaye et al. (2017), Fiig et al. (2018), Firat et al. (2021), Gautam et al. (2021), Hwang et al. (2020), Kummara et al. (2021), Lheritier et al. (2019)	Acuna-Agost et al. (2021), Darrow (2021)		
Marketing	Customer Service	Gao et al. (2021), Hwang et al. (2020), Joshi and Sharma (2020), Lheritier et al. (2019)	Zheng et al. (2016)		Ahmed and Rodriguez-Diaz (2020), Jimenez-Barreto et al. (2021), Meyer-Waarden et al. (2020), Siering et al. (2018), Tian et al. (2020)

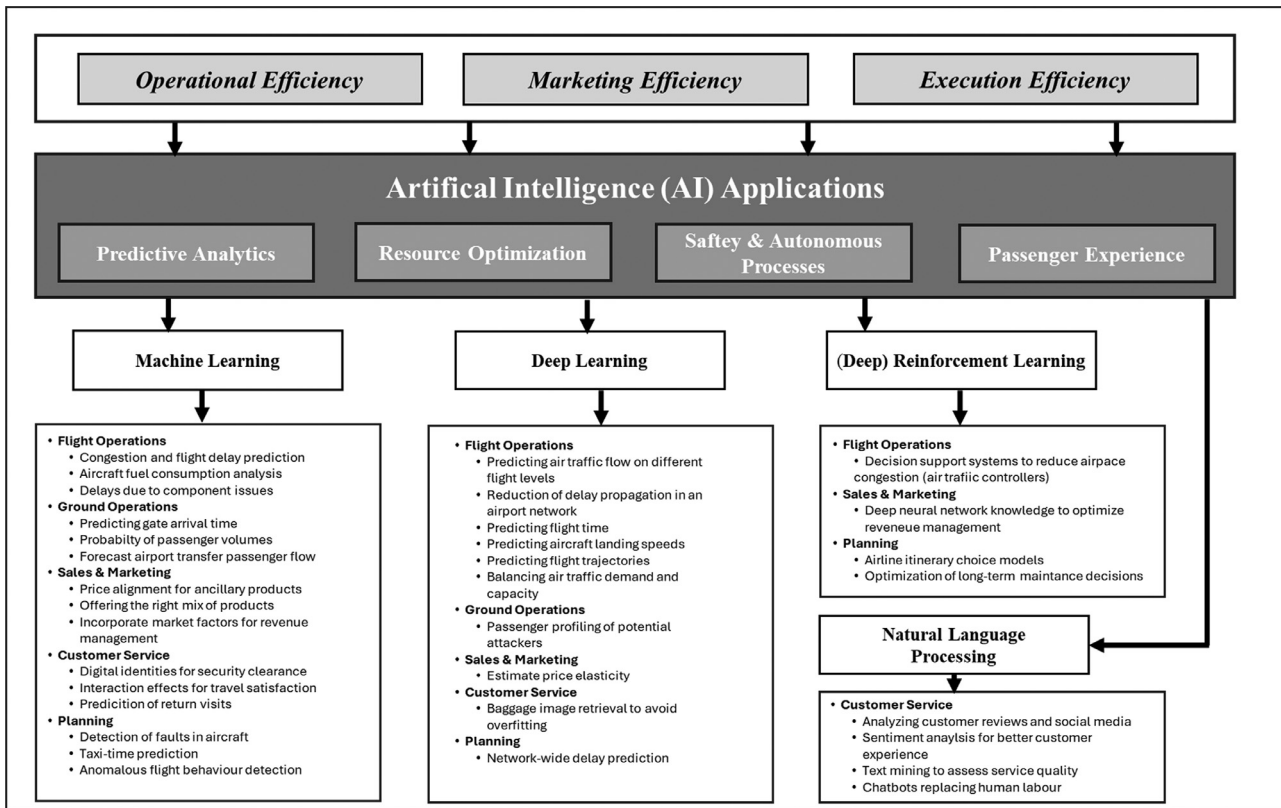


Fig. 4. Integrative framework for AI applications for airline efficiency.

passenger experience. To achieve airline efficiency in the improvement areas, we found multiple applications in the elements of AI, i.e. in Machine Learning, Deep Learning, Reinforcement Learning and Natural Language Processing. The framework categorizes and summarizes the identified applications per AI element as well as per business function. In the following section, we will further discuss the most significant findings and AI developments under each of the AI elements and its respective departments.

4.1. Machine learning

Machine Learning comprises the largest number of identified papers with 73 percent of all papers (45 out of 62). With 23 papers, the majority of the papers address Flight Operations, followed by ten papers examining Sales & Marketing issues. Machine Learning in Ground Operations has been addressed by four papers, as also Planning and Customer Service have been examined by four papers, respectively.

The most popular theme in Machine learning is the predictive ability of AI applications to foster efficiency, in particular predicting the on-time departure/arrival and its implications on congestions or delays. For Flight Operations, Gui et al. (2020) compared several Machine Learning models to predict flight delays not limited to a single route or airport for airline efficiency, while Khan et al. (2021a) used also various Machine Learning algorithms to predict departure delays and duration. Diana (2018) used Machine Learning to predict taxi-out time, while Di Ciccio et al. (2016) introduced a prediction model to detect anomalous behavior and a subsequent flight diversion. The authors used the airplane's position, speed and the intended destination to predict the diversion with excellent precision, thereby providing crucial information to ground for an appropriate response time.

Scholars also addressed other Flight Operations issues, using the predictive ability of AI for resource optimization. For example, Khan et al. (2019) used Machine Learning to predict and thus control aircraft fuel consumption by applying an orthogonal linear transformation of several operational parameters. Dattaram and Madhusudan (2016) used Machine Learning techniques to monitor and examine delays due to components issues in the aircraft. Similarly, Mack et al. (2017) investigated the differences between faults and symptoms for detection of faults in aircrafts, thereby not only optimizing passenger experience, but also improving airport resource management. In a broader approach, flight delays and their implications are also the dominating themes from a Planning perspective, with Kuhn (2016) using Machine Learning to select days for air traffic management initiative planning.

For Ground Operations, Felkel et al. (2021) examined the implications of Machine Learning at the Frankfurt Airport. The authors investigated specifically how to predict the arrival times more precisely at the gates, but found that not only technical challenges exist, but the matter of trust not also be addressed. From a passenger demand perspective, Suh and Ryerson (2019) used Machine Learning to predict the probability of a severe contradiction of passenger volumes by incorporating past forecast errors, thereby significantly improving accuracy of aviation demand forecasting models. In the same vein, Guo et al. (2021) forecasted airport transfer passenger flow using real-time data and a two-phased predictive system.

Sales & Marketing is also a popular research stream, with the majority focusing on pricing. For example, Fiig et al. (2018) used Machine Learning techniques to better align prices for ancillary products such as baggage, advanced seat reservations, meals as well as parking or insurance. From a revenue management perspective, Gautam et al. (2021) incorporated several market factors that influence customer behavior and thus can be used to determine optimal control policy. In con-

trast, [Kummara et al. \(2021\)](#) tailored airline prices based on the relations between several airline and customer characteristics, thereby learning new trends and patterns to provide the optimal mix of products and price that have the highest propensity for a given customer. [Firat et al. \(2021\)](#) used Machine Learning to forecast air travel demand based on the optimal the optimal seat capacity and thus the highest load factor, thereby also optimizing existing resources.

Only little research has examined Machine Learning in and for Customer Service and the associated passenger experience. For example, [Joshi and Sharma \(2020\)](#) investigated how Machine Learning can enhance the travel experience, e.g. how the automated booking can be more 'humanized' or how AI can help to build digital identities for a faster security clearance or ease the navigation in airports. [Lheritier et al. \(2019\)](#), on the other hand, examined how customer choose between different itineraries so that airlines can better predict market conditions and market needs, while [Gao et al. \(2021\)](#) looked at interaction effects of various determinates for airline travel satisfaction, using Machine Learning to providing cost-effective measures of promoting satisfaction. Return visits in airline services has been investigate by [Hwang et al. \(2020\)](#), who used Machine Learning to predict the customer's return visits by considering sentimental features from comments and satisfaction ratings.

4.2. Deep Learning

Deep Learning comprises the second largest number of identified papers with 25 percent of all papers (15 out of 62). With nine papers, research on Deep Learning also mainly addresses Flight Operations, followed by three papers examining Planning issues. Two papers address Deep Learning in Sales & Marketing and Ground Operations, respectively, while Customer Service has been discussed by only one paper. Finance has not been mentioned at all.

Similarly to the Machine Learning, the predominant theme in Deep Learning involves AI's predictive analytics capability to calculate air traffic flows and delay predictions. [Liu et al. \(2019a\)](#) suggest a Deep Learning approach to predict the air traffic flow on different flight levels. The examined method of [Yu et al. \(2019\)](#) does not only target delay prediction, but also supports the reduction of delay propagation within a network of connected airports. Even tough, [Zhu and Li \(2021\)](#) also include delay prediction in their work, the authors focus on the prediction of flight time to support the decision on fuel loading. Another application of Deep Learning is suggested by [Tong et al. \(2018\)](#) to predict aircraft landing speeds. [Zhang and Mahadevan \(2020\)](#) apply Deep Learning in forms of Bayesian neural networks for the prediction of flight trajectories to increase in-flight safety and thereby addresses issues involving Flight Operations and Planning. [Pang et al. \(2021\)](#) also examines the predication of flight trajectories by using a Bayesian Deep Learning approach, but incorporates weather, which increases the relevancy for Flight Operations. The application of Deep Learning in the temporal and special prediction of flight delays by [Ai et al. \(2019\)](#) targets Planning and Flight Operations departments. Similarly, [Bao et al. \(2021\)](#) also focus network-wide delay prediction.

Deep Learning techniques were also used for security and passenger experience. The publication of [Zheng et al. \(2016\)](#) conducted passenger profiling for Flight and Ground Operations as well as Customer Service. The authors use Deep Learning to classify potential attackers and normal passengers. While these security concerns may only have a low probability of occurrence, their impact on operational and consequently financial performance is significant. In the only publication on Ground Operations that is related to resource optimization, [Huang et al. \(2021\)](#) apply Deep Learning to foster efficiency in baggage image retrieval. In their neural networks, the authors avoid overfitting by using deep metric learning. In the category of Sales & Marketing, [Acuna-Agost et al. \(2021\)](#) estimate price elasticity using choice models based on Deep Learning, as those their

power in out-of-sample prediction is better. This proposal offers the flexibility to examine elasticity for different dimensions such as departure date and time or destinations. [Darrow \(2021\)](#) stress the need to implement autonomous processes and to move to systems capable of working with little data, to distributed AI and to marketplace approaches.

4.3. Reinforcement learning

Reinforcement Learning comprises the third largest number of identified papers with eight percent of all papers (6 out of 62). Papers on Reinforcement Learning are equally distributed with two publications each between Sales & Marketing and Planning, while Flight Operations are only examined two papers. For Finance and Customer Service, no papers were identified.

The majority of papers deals with the optimization of resources, with [Cruciol et al. \(2015\)](#) suggesting a decision support system based on Reinforcement Learning to reduce airspace congestions. While the authors mainly target air traffic controllers, the application has also an impact on the efficiency of Flight Operations. For Planning, [Abdelghany et al. \(2021\)](#) examined airline itinerary choice models using Reinforcement Learning. The authors applied a reinforcement algorithm to identify the input values for the parameters of the itinerary choice model, which aims at maximizing the reward function. In contrast, [Hu et al. \(2021\)](#) focus on safety issues and propose a maintenance strategy building on Reinforcement Learning to optimize maintenance decisions in the long-term, incorporating information such as repair costs, future aircrafts requirements or storage of pair parts.

In Sales & Marketing, [Bondoux et al. \(2020\)](#) propose a new revenue management system, which is based on Reinforcement Learning. This system can be used without demand forecasting. To overcome the obstacle that Reinforcement Learning requires a great amount of data to converge to the optimal solution, the authors display a model, which is incorporating knowledge from a deep neural network. [Lawhead and Gosavi \(2019\)](#) also address revenue management as the authors test a bounded actor-critic Reinforcement Learning algorithm and conclude that this algorithm outperforms the industry average.

4.4. Natural language processing

Natural Language Processing comprises the least number of identified papers with eight percent of all papers (5 out of 62). Every paper applying Natural Language Processing targets the passenger experience and in particular Customer Service systems.

Natural Language Processing in airlines is mainly used to analyze customer reviews and social media data in order to assess customers satisfaction and service quality. [Ahmed and Rodriguez-Diaz \(2020\)](#) use Natural Language Processing to propose an approach for the identification of significant labels as a representation of the sentiments of customers to assess customer experience. Also relying on sentiment analysis, [Siering et al. \(2018\)](#) identified the most relevant aspects of service, which were expressed in airline customer reviews. The authors also presented that these aspect-specific service sentiments affect the recommendation of airlines. [Tian et al. \(2020\)](#) apply text mining and sentiment analysis for the assessment of service quality based on social media data.

As the airline industry as part of the service industry is human-labor intense, we chose to also include papers on chatbots although these papers do not focus on the underlying AI. Consequently, papers of [Jimenez-Barreto et al. \(2021\)](#) and [Meyer-Waarden et al. \(2020\)](#) rather examine the motivation and acceptance to use chatbots. As chatbots may reduce labor force requirements, we consider them crucial to foster efficiency gains in the airline industry.

5. Theoretical and managerial implications

Our review revealed that airlines and its associated organizations employ AI tools for various business functions. Given the advancements in computing and software development in the last decade, AI applications are set out to be major contributors to airline efficiency for flight operations, but are also employed in a more limited form in sales & marketing and in customer service. As an overarching theme, we found that one of the main challenges is that the field of AI is extremely fragmented, which is also indicated by predominantly isolated AI studies in and for airline efficiency. Often, AI is not applied among airline partners and in cross-organizational processes due to non-availability of data, thereby highlighting the role of organizational silos and the lack of data exchange and integration in inter-organizational processes.

The results of our review have both theoretical and managerial implications that can be applied to practice and research for aviation management in general and in air passenger transport in particular. From a theoretical perspective, we conceptualized and presented a new framework to assess AI and its implications on efficiency on airlines and passenger transportation, demonstrating that AI applications are built around four overarching improvement areas: predictive analytics, resource optimization, safety & autonomous processes and passenger experience. By introducing the framework, we not only provide a conceptual foundation to assess the extent of AI applications in airlines, but we specify the AI techniques used to increase efficiency. More specifically, the model allows us to distinguish between the most prevalent AI applications applied and the less popular applications in and for passenger transport. In other words, the framework provides both a comprehensive perspective about the dominating AI techniques that are covered by existing literature and presents a wide range of emerging AI techniques with the potential to become more influential for future studies.

The findings, however, have also implications for practitioners and airline managers. First, the potential of NLP in for airlines efficiency. So far, NLP applications are mainly limited to virtual assistants or chatbots and is used for in customer service for data collection, branding, customer relationship management and online marketing campaigns (Hoyer et al., 2020). While NLP is already applied in this context in airline operations, its full potential has not been exploited. Studies show that NLP is one of the most promising AI applications to simplify and enhance human-machine interactions. By identifying relevant information through text mining, NLP can also be used as a facilitator to support logistics decision-making and to accelerate organizational processes. For example, NLP techniques can be designed to analyze aviation incidents and safety reports. As large airlines have to deal with approx. 600 aviation incidents reports per month, NLP provides an opportunity to extract useful information from the reports to accelerate decision-making and consolidate information of potential dangers (Tanguy et al., 2016). NLP may also be used to perform automatic text analysis for stored technical unstructured text to identify potential aircraft defects. As such, NLP provides an opportunity for better maintenance planning and the prediction of unscheduled repairs (Kála et al., 2022).

Second, the use of Reinforcement Learning AI techniques seems rather limited. Studies show that reinforcement learning techniques such as 'Tabu Search' or the 'Markov decision process' can be applied in machine scheduling or to optimize planning for transport networks (Toorajipour et al., 2021). According to EASA (2023), air navigation service providers develop applications that will adopt reinforcement learning to detect and resolve typical air traffic control conflicts or suggest alternative solutions. Another promising direction in Reinforcement Learning is to apply it to Revenue Management systems. In particular, Reinforcement Learning can be applied to better manage and control the seat allocation and the overbooking aspects. As Reinforcement Learning allows to scale up and handle complex modeling assumptions, it can be used for optimize seat planning (Alamdari and Savard, 2021; Gosavii et al., 2002). Furthermore, studies show that Reinforcement Learning can be used to maximize flight revenues. Based on market dynamics

and passenger behavior, the agent is capable to learn an optimal airline revenue management policy, surpassing the original seat revenue projections (Shihab and Wei, 2021). Consequently, we see Reinforcement Learning and its techniques as another significant application for airline managers.

Third, all AI applications seem rather isolated and related to a specific department or function, although the inherent network-based structure of airlines and their core transportation and logistics components provide a natural environment for further cross-department and inter-organizational applications of AI. While we could not identify a cross-department AI application in our review, applications in the real-world attempt to use AI on a cross-departmental level. For example, the airline group Lufthansa developed the so-called 'Operations Decision Support Suite' (OPSD) which uses AI to combine and analyze data (such as crew availability and locations, passenger demand, aircraft maintenance status and weather) to suggest scenarios to human controllers for decision-making support (Lufthansa, 2023). Lufthansa claims a 90 per cent acceptance rate of suggested scenarios, and while this indicates trust from operations controllers that AI makes the right decisions, OPSD can also pull relevant data for controllers to make more informed decisions. A good example for cost-effective decisions is whether an aircraft has its own or leased engines, as leased engine are more expensive, which is a detail that was not incorporated in the decision-making by operators prior to OPSD. As such, the associated networks of suppliers, partners and customers generate large datasets, thereby providing an opportunity for AI tools for big data analysis. Moreover, the network structure requires the orchestration not only between digital and physical networks, but also the asset coordination as well as time sensitive ground activities. AI applications can help to facilitate coordination and network optimization, thereby improving existing processes and practices. By analyzing big datasets, AI tools may be able to predict operational opportunities and challenges, thereby representing a tool for the transition from reactive organizational practices to proactive organizational practices (Mendes et al., 2022). For example, The Eurocontrol Maastricht Control Centre uses machines learning for 4D trajectories predictions based on aircraft position, speed and altitude (Eurocontrol, 2020). Current approaches to predict flight trajectories can be disturbed by e.g. future air traffic controller clearances, however AI can predict those deviations more accurately, which has led to a 50 per cent improvement. Predictive analytics may also be used for planning purposes both for ground and air operations (Rajendran et al., 2021). Furthermore, AI tools can be used to minimize and eliminate manual processes, thereby not only providing an opportunity for airlines to introduce autonomous processes instead, but also to achieve a greater ROI than through digitalization alone (Chung et al., 2020). And although AI is already playing an increasing role in and for customer relationship management and for customer satisfaction, it provides an opportunity for a more personalized customer experience (Singh, 2021).

Fourth, a glimpse into more practitioners-oriented reports shows that the use of AI applications is rapidly utilized or explored, thus these insights may also provide a foundation to conduct further research. A popular topic, which has been so far neglected in academic articles is the focus on environmental sustainability ranging from reducing carbon emissions by route and aircraft optimization to waste reduction in catering. According to Eurocontrol (2020), excess carbon emissions stemming from air traffic management inefficiencies account for approx. six per cent of all airline carbon emissions in Europe, putting pressures on airline managers to reduce these inefficiencies. As a response, Lufthansa Group, for example, used their OPSD and the associated AI analyses to optimize flight operations across multiple their airlines simultaneously to e.g. deploy smaller planes to minimize carbon output (Lufthansa, 2023). On the other end, Airbus is developing an AI-supported food scanner device tracking in-flight catering. With 1.5 kilogram cabin waste and per passenger and 20 percent of untouched food (IATA, 2002), AI helps to optimize the catering planning and the waste management (Airbus, 2022; Blachly, 2023).

Fifth, the use of NLP and Generative AI in the airline industry, in particular programs such as ChatGPT, is primarily employed to enhance customer service by analyzing customer reviews and social media data, as revealed in a synthesis of relevant research studies (Liu, 2024). This emerging field is significant for assessing customer satisfaction and service quality, which are pivotal in a sector as customer-centric as airlines (Wandelt et al., 2023). The utilization of NLP and sentiment analysis methods helps in deciphering the emotions and sentiments of customers from textual data, providing airlines with actionable insights to improve their services (Sun et al., 2021). For example, Tian et al. (2020) demonstrates how digital platforms can serve as valuable sources of customer insight. These studies collectively underscore the potential of LLMs to transform large volumes of unstructured text into structured data that can inform service enhancements and marketing strategies. LLMs can also be used on chatbots, which, although not directly related to the core artificial intelligence technologies underpinning NLP, are relevant due to their potential to enhance operational efficiency in the airline industry. Jimenez-Barreto et al. (2021) and (Meyer-Waarden et al., 2020) investigate the acceptance of chatbot usage, highlighting their role in potentially reducing labor costs and increasing efficiency, a critical aspect in the human-labor intensive airline industry.

6. Future research avenues

Although these existing studies and their implications provide insight into the AI applications in and for airline efficiency, we could also identify several gaps in the literature. Our literature review reveals that several topics related to AI in and for passenger transport are severely underrepresented. For example, the findings show that the majority of papers develop conceptual models and frameworks without actual real-world data and poor problem dimensionality. Furthermore, when AI is applied in a business environment, AI projects are often tested in isolation, i.e. without considering the broader organizational environment, or in ad-hoc pilots. We found, however, that AI applications can help airlines to better perform and orchestrate activities and networks with a higher level of efficiency than human thinking. To promote a deeper understanding of how AI tools can be used in future, we suggest the following recommendations for future research in particular:

6.1. Little attention has been given to comprehensive AI-driven decision-making tools for airline efficiency

While our literature revealed that AI in and for airline efficiency is an emerging topic in academia, the vast majority of all papers only address rather narrow areas in the respective airline departments. In other words, current research uses AI only to solve only specific topics and in isolation, i.e. it neglects intra- and interorganizational links and a comprehensive view how AI can help to make decisions on a cross-department level and across companies. For example, popular topics for Machine Learning identified in the review comprise both Flight Operations and Ground Operations, but although these departments have several operational overlaps, no paper addresses an overarching AI solution that combines the decision-making process. Future research could therefore incorporate a broader view of AI applications involving other departments and/or companies to foster efficiency among the entire organization or even the industry.

6.2. In academic literature, the understanding of AI processes in airline operations is often purely theoretical and lacks practical application

Although a number of papers have addressed real-life problems and using case study data, the extant research has yet to consider the specific processes and requirements of and for AI on an organizational level that are needed to contribute directly to airline efficiency. In other words, it is not clear how these AI models and their output can be applied or implemented in practice. The lack of research in this space may be

partly explained by the resistance of industry partners to share data and collaborate due to mono- and oligopolistic structures. Interestingly, AI applications are only implemented in areas where the data is generated, collected and processed internally, while AI applications depending on external data are rather of theoretical nature. Moreover, the identified models used to examine efficiency cover only partially variables that are relevant in practice, thereby only presenting a too simplified replication of operational processes. As such, we encourage future researchers to not only focus on theoretical AI models, but rather incorporate an interorganizational approach to facilitate data collection between organizations that have real-life impact on the efficiency of airlines operations and the aviation industry. Moreover, future research should not only focus on the model development / building itself, but formulate management requirements to actually implement those models in real-life situations or organizations.

6.3. Reinforcement learning have only partially explored and applied in and for airline efficiency

Out of the 62 papers identified in our review, only six papers deal with Reinforcement Learning techniques. This is particularly surprising, as Reinforcement Learning in the context of aviation, which represents a complex system dealing with a variety of different agents, can contribute to a better understanding of actions taken by different agents to automate adaptive decision-making processes. For example, Cruciol et al. (2015) used Reinforcement Learning to understand the behavior of different agents and subsequently improve and adapt decisions to reduce air congestion. In such environments with a high complexity stemming from a variety of interacting agents, and constantly changing system parameters, Reinforcement Learning provides an opportunity to maximize operational performance. Future research could use Reinforcement Learning to develop decision-support systems that incorporate different stakeholder and industry partners in the airline industry. Besides this, research on intra- and inter-organizational collaboration may support to overcome current challenges in terms of data availability, data sharing and protection as well as shared data usage and processing in order to exploit the full potential of Reinforcement Learning.

6.4. Airline processes are an ideal case for further development of AI models and applications

The applications identified in the papers often target issues with standardized processes with repetitive actions and patterns, thereby providing a reliable environment for the development and testing of AI models, in particular for Machine Learning. In many cases, the environmental conditions are deterministic with only a few stochastic elements such as weather conditions. The focus on these particular elements increases the reliability and performance of the underlying models. Given the inherent coordination and network-based structure of airlines and their core transportation and logistics components, the airline industry constitutes an ideal case for research and development of AI models and applications. We encourage future researcher to take a more holistic view and design AI models and frameworks that use the predictive ability of AI to develop cross-departmental processes to move from current reactive practices to proactive support for more efficient organizational decision-making.

6.5. Large Language Models (LLMs) hold substantial promise

The potential applications identified in recent studies highlight the capability of LLMs such as ChatGPT to enhance communication, customer service, and operational efficiency. LLMs can be trained on vast amounts of industry-specific data, enabling them to handle diverse inquiries, provide real-time information, and facilitate seamless interactions across different departments. These models can excel in under-

standing and generating human-like text, making them ideal for automating routine communications and providing personalized customer experiences. Furthermore, the ability of LLMs to analyze large datasets and generate insights can support decision-making processes, improve predictive maintenance, and optimize flight operations. Given the intricate network-based structure and the necessity for precise coordination within the airline industry, integrating LLMs can lead to significant advancements in efficiency and service quality. Future research should focus on developing robust LLM frameworks that not only automate tasks but also enhance strategic decision-making, driving the industry towards more proactive and intelligent operations.

7. Conclusion

The recent developments in computing power led to an increase of often complex AI applications. To better understand the impact of AI on airline efficiency, we set out to achieve three interrelated goals. First, we reviewed management literature specifically focused on how AI can help airlines to become more efficient and discussed its implications to date. Second, we proposed a new AI-Airline-Efficiency-Model (AAEM) that is based on the identified AI elements and the respective airline departments that can help to analyse the efficiency in and for airlines from an AI perspective. And third, we used the AAEM as the backdrop to our systematic literature review on AI and airline efficiency to synthesize the research that has been published to date around the four overarching areas of predictive analytics, resource optimization, safety & autonomous processes and passenger experience. By categorizing this research according to the AI elements, we were also able to identify gaps and propose future research directions that will contribute to further debate and investigation into this important yet neglected field of study.

The identification of the scope and characteristics shows that AI in and for airline efficiency can be defined by four AI elements: *Machine Learning*, *Deep Learning*, *Reinforcement Learning* and *Natural Language Processing*. Moreover, the management of AI and the efficiency of airline depends on three overarching pillars, namely operations, marketing and execution, which are defined by the six departments *Flight Operations*, *Ground Operations*, *Finance*, *Planning*, *Sales & Marketing* and *Customer Service*, which led to the creation of our AI-Airline-Grid, which helped us to synthesize and categorize existing literature and shed light on the current state how AI can increase airline efficiency. Our systematic review revealed that AI applications for airline efficiency to date comprise the four overarching areas of predictive analytics, resource optimization, safety & autonomous processes and passenger experience and provide plenty of opportunities for further research. In particular, we found that AI papers for airline efficiency usually investigate very narrow research areas and thus lack a comprehensive view for decision making on a cross-department level and for interorganizational exchange. Moreover, we also observed that most papers deal with AI modelling are rather of theoretical nature and lack practical applicability in and for real-life environments. Lastly, we consider Reinforcement Learning as a promising avenue for airline efficiency, however, research in this area is still heavily underrepresented.

Interestingly, the topic of generative AI or large language models such as GPT-4 seems to play a rather marginal role both in academic and in practitioner research. So far, as our review reveals, language models or generative AI are currently mainly used in customer service as chat assistants to answer an increasing number of customer queries or can be used to decipher maintenance reports for more efficient planning. While applications for generative AI and language models may be expanded to applications for baggage tracking, real-time flight information updates, booking and reservation and in-flight services and entertainment, it is so far not clear how these applications can be applied in other areas such as flight or ground operations with greater efficiency potential.

Overall, AI in and for airline efficiency seems to be a strongly emerging topic that has yet to resonate with airline managers and academics

alike. Our study provides therefore a critical first step to more structural recognition of this topic and we hope that both the gaps and challenges presented in this contribution will spark ideas, discussions, and projects on how to fill this largely open canvas.

Declaration of competing interest

The authors declare that there are no potential competing interests.

CRediT authorship contribution statement

Alexander M. Geske: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **David M. Herold:** Writing – review & editing, Writing – original draft, Validation, Conceptualization. **Sebastian Kummer:** Writing – review & editing, Supervision.

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