

## Artificial Intelligence potential within airlines: a review on how AI can enhance strategic decision-making in times of COVID-19

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### Abstract

**Purpose:** The purpose is to explore the potential of Artificial Intelligence (AI) applications regarding strategic decision-making in airlines in times of COVID-19 and to depict a roadmap to encourage scholars and practitioners to jointly deploy these tools within corporations.

**Design/methodology:** This study firstly reviews the state-of-the-art regarding transport organization trends with focus on airline Strategy, Finance and Marketing as well as AI tools, supported by interviews to a former airline digitalization strategist. Secondly, the potential of the latter to be applied in those functions is analyzed, considering different Machine Learning (ML) methods and algorithms.

**Findings:** Some pathways are identified as of particular interest for the airlines' strategic decision-making process. Most of them are based on ML algorithms and training methods that are currently underused or disregarded in certain business areas, such as Neural Network models for unsupervised market analysis or supervised cost estimation.

**Research limitations/implications:** Focus is on airline Strategy, Finance and Marketing, keeping engineering or operational applications out of the scope.

**Practical implications:** Proposed guidance may promote the deployment of AI tools which currently lack practical implementation in certain business areas.

**Social implications:** Showcased guidance may revert into a closer collaboration between business and academia.

**Originality/value:** Comprehensive review of current airlines' strategic levers and COVID-19 impact as well as identification of promising AI pathways to be further explored.

**Keywords:** Airlines, COVID-19, Artificial Intelligence, Machine Learning, Strategic decision-making

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## 1. Introduction

The strategy of transport organizations is a key element that is responsible for identifying the actions that are necessary for the company to maintain a valuable competitive position or even increase its capabilities in the long term. At the time of its formulation, understanding the past and current situation of the organization as well as the environment trends is essential. Once this is understood, future targets and the actions that are necessary to achieve them must be identified and defined. Numerous surveillance and technological intelligence tools have been developed for these tasks (Campos & Rubio, 2017).

At the same time, an indispensable requirement for the definition of the aforementioned objectives is the estimation of the future market evolution. As indicated in Castilla (2017), the industrial prospective is born with this aim through the analysis of possible technological events with a temporal perspective. In fact, these advances will be those dictated by the company of the future (Erro & Pérez, 2017) and managers must be aware of their relevance (Camus & Raapke, 2017).

Historically, transport and travel managers have based their strategic decisions on control or commitment principles (Gustafson, 2013); the former standing upon actions oriented towards the aforementioned surveillance while the latter focusing on employee involvement and responsibility. Either way, technological innovations seem to show potential for decision-making related to both approaches.

While technical advances are typically integrated relatively fast in engineering departments (such as design, manufacturing or service), other divisions in the organization seem to suffer from more momentum and lack of agility to assimilate new technological tools within their processes. For this reason, corporate innovation must be promoted as generator of competitive and adaptative advantages at different business levels (Bueno & Morcillo, 2016). This affects on a particularly critical way to Information Technology (IT) or computer science innovation (McKenney, Copeland & Masonn, 1996), which can thoroughly reshape markets and competition.

Several industries have already had to face major IT transformations such as banking (Bueno, Iongo, Paz & Morcillo, 2017) or education (Costa, Sá, Barros & Arantes, 2017). In transport and travel, as in those, new technologies will be introduced to automate dispensable tasks or to optimize other activities along the entire customer journey (Ascolese & Llantada, 2019).

Additionally, while defining the IT strategy to achieve this, the 17 Sustainable Development Goals (SDGs) proposed by the United Nations within the 2030 Agenda for Sustainable Development (United Nations, 2015) must be also taken into account given the increasing societal concerns in this regard. In particular, decent work and economic growth (#8), industry innovation (#9), climate action (#13) and partnerships for the goals (#17) are some of the SDGs that the aviation sector must address with special attention.

Within the transport and tourism sector, each mode (air, road, rail or maritime) features different opportunities and challenges. In this case study the focus is on airlines given their global impact on several factors (such as economic development, culture exchange or environment), their steady growth during the last decades which has led to several infrastructure and flow challenges (An, King & Hwang, 2019) as well as their pioneering leadership in the past introduction of disruptive technologies. Nevertheless, this study could be also extended to other means of transport in order to address in detail the particularities of each mode or subsegment.

In addition, the COVID-19 crisis is causing an unprecedented impact on the transport industry. This is not only due to the effect during the pandemic itself but as per the reshaped social relationships and behaviors related to the coming new normal. This effect is being especially noticeable in aviation where the current situation poses huge, diverse and dynamic challenges to organizations (Bolat & Ateş, 2020) in order to assure their survival (Amankwah-Amoah, 2020a).

Due to the fast dynamics and competitive environment of air transport business, airlines need to quickly adapt their organizations and adopt cutting-edge methodologies or tools in order to keep the pace of the industry. In fact, as stated by Orlikowski and Barley (2001), innovations may have an industry-wide impact, forcing airlines to perform extensive technological transformations.

A first IT disruption within the air transport took place in the mid-1900's. At that moment, American Airlines rolled out a Computerized Reservation System (CRS) which not only affected the air business but also other travel industries (Crowston & Myers, 2004). Another decisive technology was introduced in the 2000's. Since then, Internet has allowed airlines to be easier internationalized and reach a broader audience via their sales and distribution channels. In fact, Ramón, Moreno and Perles (2011) identify this as a relevant factor that impacts the bargaining power of suppliers and customers, two out of the five competitive forces by Porter (1980).

Nowadays a new IT technology is aiming to become the new game-changer. Although its fundamental mathematical principles and algorithms were firstly introduced in the first decades of the previous century, Artificial Intelligence (AI) has recently gained popularity because of the enhanced computational capabilities of existing hardware (Central & Graphics Power Units, CPU & GPU) and increased availability of large amounts of data. While AI term may be used in an ample sense, it is mainly related to several tools and algorithms based on Machine Learning (ML), Data Mining (DM) or Big Data (BD) techniques with high potential for cross-sector applications.

Other reason that is causing AI to expand is the emergence of user-friendly software applications based on this type of algorithms. Until the 2000's, only practitioners with high knowledge in programming and mathematics (commonly found in engineering departments) were capable of using these methods (Escorsa, 2017). Nevertheless, some software developer companies are creating Business Intelligence (BI) applications which embed AI tools into user-friendly interfaces in order to ease the data management, analysis and visualization. Howson, Richardson, Sallam and Kronz (2019) develop a method in which existing BI tools are analyzed via assessing their ability to execute and completeness of vision, among other features. These applications are eventually the ones which will speed-up the transference of AI technologies to managerial, administrative or finance departments.

In fact, and in line with that stated before, while the application of AI tools to non-managerial tasks in air transport firms (such as network optimization, delay avoidance, pilot decision-making or maintenance scheduling) has been extensively analyzed in the literature, there is still room for innovation in order to obtain more managerially interpretable knowledge through these techniques (Akpınar & Karabacak, 2017). The use of BI tools and data as a very valuable asset within the industry will define the future of airline management (Akerkar, 2014).

For these reasons, a methodological review of the potential applications within this field is essential. It allows to identify the main opportunities for organizations to leverage these technologies both in the near future and in the long-term, which features plenty of uncertainty due to the COVID-19 crisis.

The objective of this analysis is to identify potential areas in transport organizations which are related to strategic decision-making in which AI could be deployed. The study focuses in the commercial air transport industry and, more precisely, on airlines regardless of their business model approach. In fact, although some of the statements

are only applicable to air passenger carriers, most of the results presented here are also suitable for freight or cargo airlines or even for other modes such as road, rail or maritime transport.

Other spillover objective is to review the state-of-the-art regarding airlines organization and management (focusing on past and current trends for Strategy, Finance and Marketing) as well as AI tools (whose popularity has exponentially grown during the last decade). After analyzing the potential of the latter to be applied in the air transport managerial and finance departments, applications which show certain room for innovation and performance improvement are depicted along with some use cases that have been recently published during the pandemic.

The resulting potential guidelines or roadmap may revert into a closer relationship between business and academia, which sometimes suffer from lack of mutual alignment due to divergent overall ambitions. In fact, this is the ultimate goal of the work: to align both researchers and practitioners and to help the whole community to deal with the existing challenges during these times in crisis.

## 2. Methodology

The following paragraphs describe the methodology which has been implemented in order to achieve the aforementioned objectives and whose stages are linked to the structure of the paper itself through the successive sections.

Firstly, the airline organizational trends, the COVID-19 challenges and the AI tools are analyzed in section 3. The goal is to understand the baseline status from where needs and solutions could be identified. For this purpose, a comprehensive literature review is conducted with focus on those topics and, specially, on those studies including the development of qualitative and quantitative (not only AI-related) models applied to the strategic decision-making and related financial tasks.

In both cases (COVID-19 airlines trends and AI, section 3.1 and 3.2 respectively) a general introductory overview of the topic is presented initially. Then a deep-dive particularizing in the most relevant aspects from each subject matter is carried out.

The air transport sector, being one of the most adversely affected by the COVID-19 crisis, shows both threats and opportunities for airlines. The study includes references to the effect caused by the pandemic both during the initial phases after the outbreak as well as at later stages in the near future once the new normal is established.

The bibliography and references are selected mainly based on systematic searches on the Web of Science database. Specific keywords for each of the topics were used and the results were filtered by restricting the works to those included within the Transport research area.

Due to the fact that AI tools show currently a low penetration within these functions and that these top-management departments are not usually prone to disclose their confidential methodology or procedures, direct information from airlines is difficult to obtain in this regard. However, with the objective of complementing the aforementioned review, the authors were able to collaborate with a former strategist specialized in digitalization and the deployment of innovative technologies from one of the biggest European airlines (Iberia/IAG).

The information exchange was based on two semi-structured interviews, thus addressing the main topics presented a priori by the interviewer but also giving room for the expert to freely express his opinions and adding new topics to the discussion. This was achieved by means of a flexible protocol to guide the expert into linking the predefined topics with his experience and disclosing relevant insights. The comments and suggestions were used both to complement the information already identified through the literature review as well as to reveal additional areas for research.

Eventually, once the airlines organizational trends and the main AI tools have been independently identified and assessed, in section 4 some specific applications or pathways are discussed and proposed as potential research lines. These applications are basically comprised by (i) a functional area, analysis or task which is prone to

optimization via the deployment of AI and (ii) the specific AI tool, learning method or algorithm which should fit best for that requirement or purpose.

These potential use cases are, whenever possible, illustrated with recent studies and practical examples that have been developed after the outbreak and that address some of the challenges that the COVID-19 has posed over the aviation industry. For this reason, references included in this section are selected not only based on specific keywords and research area, but also including a publication filter, ensuring that they fulfil the condition of being released after the COVID-19 outbreak at the beginning of 2020.

### 3. Analysis

This section is subdivided into two parts. The first section 3.1. aims to illustrate the past and future evolution of airlines and, more specifically, some strategic, financial and marketing levers and how they have been impacted by the COVID-19. The second part (section 3.2.) focuses on the current development status of the most used AI tools, including the fundamental principles and applications of their learning methods and algorithms. A deeper discussion on how AI algorithms can address the current strategic challenges in the aviation industry is performed in the following section 4.

#### 3.1. Airline organization trends and COVID-19 challenges

Air transport shows some distinct characteristics, both intrinsic (strong competitiveness, low profitability margins, strict safety standards, cutting edge technology or globalized operations) and extrinsic (competition from other means of transport, geopolitical risks, environmental concerns, fluctuations of traffic demand or fuel costs, supply and energy shortages or impact of financial or health crises, etc.).

The combination of these features has prompted a diversity of business models which leverage the different conditions of each market in order to increase the success of the company and to create or maintain valuable competitive advantages. Several business models have been employed within the air transport industry including Full Service Network Carrier (FSNC), Low Cost Carrier (LCC), charter or regional for passenger service as well as freighter or integrator for freight service.

In particular, an in-depth analysis by Sengur and Sengur (2017) has shown how airlines tend to strategically build their business model based on four main concepts: value proposition, market segmentation, value chain and profit structure. In fact, the way each carrier leverages each of these concepts varies significantly from one model to another.

Focusing on the two main business models, a method to classify airlines within a spectrum from LCC to FSNC is developed in Mason and Morrison (2008). The procedure is based on the Product and Organizational Architecture (POA), considering that these two elements are the main factors determining the business model of an airline.

While the authors in Mason and Morrison (2008) apply their method to only 6 European LCCs, Lohmann and Koo (2013) apply the POA model to 9 US airlines featuring different models: 2 LCCs, 3 FSNCs and 4 hybrid. Data is selected for the 2008-2009 years, when the global financial crisis took place. In this case, 6 indexes are used of which revenue and labor show high correlation with LCC-FSNC classification while comfort and convenience do not fit the expected stereotype, probably due to the complexity to define objective measurement indicators for them.

Using data from 2011-12 (3 years later), Jean and Lohmann (2016) study the evolution of the previously analyzed carriers. By comparing results from both periods (08-09 and 11-12), divergent movements are observed in the spectrum (from LCC to FSNC and vice versa) but a tendency towards FSNC is observed in most merged companies.

The aforementioned air transport inherent features and the different business models that compete within the same habitat constitute a complex environment. This forces airline organizations to be flexible and fast-

responding in order to be able to successfully tackle sudden and abrupt changes in the market, taking into account the company characteristics and its available resources.

Particularities of each business model have also proven to determine to a certain extent the airlines resilience to the COVID-19. It seems that regular passenger carriers (LCCs and FSNCs) will struggle in the coming years to restore pre-crisis volumes, although LCCs have shown more flexibility in order to adapt to the abrupt demand decrease suffered during the first months of the pandemic (Pérez-Campuzano, Rubio Andrada, Morcillo Ortega & López-Lázaro, 2021). On the other side, business operators have already recovered to pre-pandemic volume and air freight transport has even increased their operations since the first phases of the outbreak. A clear example of this is shown in EUROCONTROL (2020).

Lynch (1984) emphasizes that any airline organization must relate and integrate three interdependent elements: Strategy (corporate planning and information management), Resourcing (finance, procurement and personnel) and Operations (marketing, flight and ground operations and maintenance). This paper focuses on three of these: Strategy as main function and Finance and Marketing as necessary secondary functions for the planning of the resources to be used within the implementation of the strategy.

### **Strategy**

According to Lynch (1984), a suitable organization structure should be achieved by means of designing a proper corporate strategy based on the current status of the company (including its distinctive competences and available resources), the desired future targets and the methods for the accomplishment of those goals.

In addition, Teece (2010) also evidences the relevance of a complementary strategy in order to maintain a sustainable business model. Furthermore, strategic actions must be specifically designed to extract value from technological innovation both for the customer and for the organization itself.

Air transport organization and strategy as well as their relationship with competitive inertia are analyzed in Miller and Chen (1994). There, two organization learning models are depicted: reactive, in which managers act based on awards and punishments, and experimental, which happens when strategic actions are mainly motivated by the desire to seize opportunities rather than the risk of performance deterioration. In addition, it is also concluded that, while for tactical actions the antecedents for inertia are past performance and diversity of market environment, for strategic actions, market growth seems more relevant.

Not only for air carriers, but for any transport organization, dynamic strategy has been also proven as a beneficial practice (Juan, Olmos & Ashkeboussi, 2012). Decisions based on this technique are constantly reevaluated as constraints evolve and the boundary conditions are modified, featuring a more flexible behavior against changes in the environment.

The design, and also implementation, of a precise strategy is key for an airline to be profitable and survive within this aggressive environment. In addition, the development of the strategy must guarantee the airline service quality in order to enhance the brand image and customer satisfaction (Suki, 2014). Otherwise, aspects such as deficient or inadequate strategy execution, opportunistic decision-making or systematic public intervention have been proved as factors that do not allow for a proper performance. An evidence of this can be found in Akbar, Németh and Niemeier (2014) for Central and Eastern Europe carriers.

Some key strategic aspects or levers in the sector are analyzed below, such as internationalization, alliances, or diversification within the value chain. These levers, along with the interrelationships between them and some additional topics originated by the crisis, are represented in Figure 1.

One of the key topics for airline strategy is the ability to grow in new markets due to the fact that cross-country demand increases year over year mainly due to economic growth (Brida, Lanzilotta & Pizzolon, 2019) and competition from other means of transport is fewer for longer distances.

During the pandemic itself, lockdowns and border closures throughout the globe thoroughly decreased cross-border demand. It is still to be proven how the new normal along with sustainable commitments will impact this segment (Amankwah-Amoah, 2020b). It seems that the reshaped social relationships (both related to leisure and business travels) and social concerns over aviation respectively may have a negative burden in the near term.

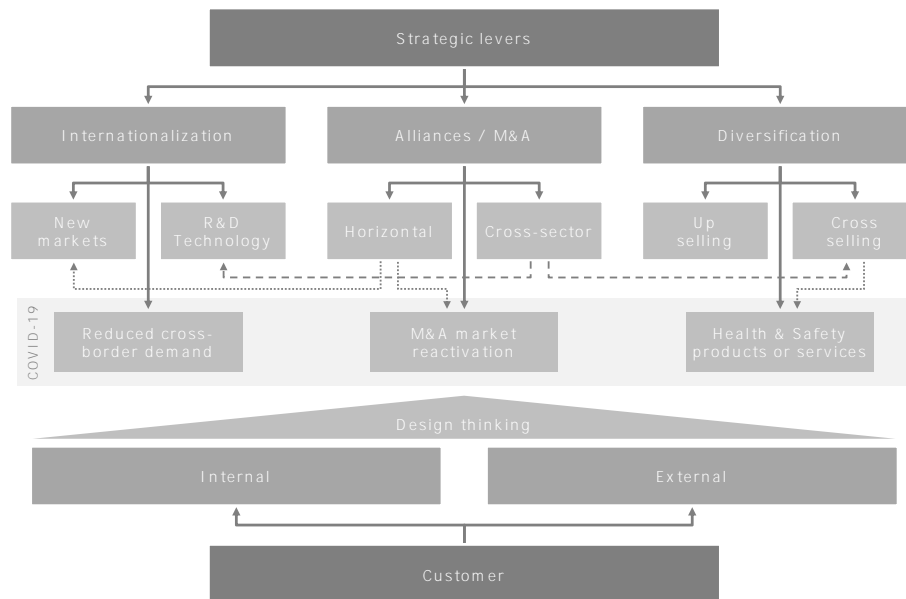


Figure 1. Main strategic levers in the air transport sector and their relationships

International competitiveness is assessed in Clougherty (2006) from an industrial organization perspective. In this case, domestic merger and acquisition activity in 20 countries proves its international impact via network-enhancement and network-consolidation, i.e. extensive networks and reduced competition in the domestic markets increase international efficiency.

Different theories for internationalization are also analyzed in Ramón et al. (2011) and applied to air transport. It is stated that, while FSNCs use measures such as alliances and code-sharing for penetration in new markets, LLCs rely on other factors. In addition, technology and R&D investment are seen as drivers for advantage when internationalizing a company.

Alliance development, which in addition is one of the fundamental principles to achieve the aforementioned Sustainable Development Goals (#17 partnerships for the goals), is one of the decisive topics within the strategy of many airlines. Given the high market growth and globalization of the operations, carriers have been forced to cooperate in order to strength their competitiveness via offering a more complete service to the customer.

Mergers & Acquisitions (M&A) is also another strategic tool widely employed within the air transport sector. In the past, several operations of this kind were executed in order to achieve scale to overcome critical situations, to enhance penetration in new markets or simply to lessen the threat from competitors. After the COVID-19 crisis, it seems clear that the M&A market will eagerly reactivate in order to ease carriers to financially survive. In fact, a market environment overhaul is expected in this regard in the coming years.

The selection of suitable partners for either alliances or M&A operations is one of the key discussions within the corporate strategy departments of air carriers. The eventual decision or selection must be based on the objective of the operation (market share growth, entrance in new markets, economy of scale, etc.) and on the potential synergies to be achieved (complementary markets, interrelated resources of both organizations, etc.). It must be also pointed out that the overestimation of synergies and the underestimation of implementation costs are usually the main reasons behind failures in M&A operations (along with overpricing, commonly caused by price wars between potential bidders).

On the one hand, those partnerships made between two airlines (same sector) are identified as horizontal alliances. Due to the trend towards consolidation in the market, in recent years there has been a great volume of activity in this area and in particular between airlines from complementary regions (mainly North America, Latin America, Europe, Middle East and Asia) to complement their flight networks and provide more connectivity options to passengers. A hybrid model which addresses the lack of comprehensive data or the differences of criteria between departments in order to select horizontal alliance partners is developed in Liou (2012).

On the other hand, cross-sector alliances (those made between companies from different sectors) are expected to allow airlines to expand their service portfolio to the customer and their knowledge network. In this field, stakeholders that stand out among others are technological partners (start-ups or consolidated companies that allow the introduction of new value proposals to the passenger and the development of more efficient processes) as well as intermodal allies (road, rail or cruise carriers).

In addition to partnering, some carriers opt for creating subsidiaries, also known as Airlines-within-Airlines (AwAs). This mechanism is usually employed by FSNCs, which establish daughter LCCs, with the goal of reducing the risk that other LCCs represent for the traditional business. There is high disparity regarding the profitability of this model (Pearson & Merkert, 2014), being the managerial autonomy from the parent, the leadership based on a clear strategy as well as the cost and efficiency similarity with pure LCCs the main factors for success.

The profitability for FSNCs due to the adoption of an AwA strategy (whether retaining the original hub-and-spoke network or not) is modelled in Lin (2012). Factors impacting on the final decision are the existence of an LLC in the rim routes or the passenger differentiation between one-stop and non-stop services.

Finally, another way to generate growth apart from the ones already mentioned is to enter different stages of the transport or tourism value chain. In fact, diversification via ancillary services (cargo, maintenance, catering or travel services) and monitoring the end-to-end consumer journey can increase profit margins, transfer value to the group or conglomerate and feed the core passenger business (Redpath, O'Connell & Warnock-Smith, 2017).

Two practices that are being increasingly applied by airlines are the up-selling (payment services to be added to the base product and generate higher revenues) and the cross-selling (other products or complementary services to extend the commercial proposal to the customer).

The up-selling techniques are related to the perception of the customer towards the airline brand. As stated in Laming and Mason (2014), the customer experience and overall satisfaction are highly influenced by additional services that are offered within the cabin such as inflight food and drink. On the other hand, the aforementioned cross-sector alliances are closely associated to cross-selling procedures. In this regard, some studies have already addressed the passenger preferences when consuming related products or services in the airport (Tseng & Wu, 2019).

In addition, airlines are undergoing a transformation in which, gradually, the commercial offering includes different small ancillary services that provide a large unitary benefit margin (in general, because their marginal cost is low) instead of a single product with low margin based on volume (as air transport has traditionally been).

This trend seems aligned with some opportunities unveiled by the COVID-19. Particularly, the different Health & Safety (H&S) protocols already enforced or to be developed by air transport associations or state governments include the implementation of several measures. These include both potential ancillary services (e.g. viral, immunologic or temperature tests and certificates) and products (e.g. face masks, gloves, wipes or hydroalcoholic gel).

Nowadays, the regulatory travel conditions and requirements are relatively complex and fast-changing due to different situations and implemented measures related to the pandemic evolution depending on the geography (e.g. vaccination level or COVID passport obligation). Airlines and transport organizations can also play a relevant role on providing clear and up-to-date information to the passenger on the current requirements by regulatory agencies in the different regions or countries.



It should also be noted the continuous search for improvement of the customer (both internal and external) experience and its satisfaction as a final goal to be achieved through the strategic actions defined by the company (Waguespack & Rhoades, 2014). In relation to this, it is becoming increasingly common, and advisable, to invite the client to participate in the process of defining, designing and developing those strategic actions. This collaboration takes place mainly in initiatives related to product development through programs known as design-thinking and can involve not only the design of the product but also the sales channels (Pasupa & Cheramakara, 2019) among others.

### **Finance and Marketing**

Finance is a function within organizations that allows the corporation to effectively manage its available resources. It is also responsible for estimating their evolution in the future, thus impacting the strategic definition. Definitively, the consequences of the COVID-19 pandemic have put much pressure on airlines' financials and they would need to rely on unprecedented measures in order to reduce its burden. Government support may be also required in many cases (Abate, Christidis & Purwanto, 2020).

The structure of this department may change from company to company depending on ownership (subsidiary company, state ownership) or political (foreign revenue) factors (Lynch, 1984). While certain organizations may give more importance within their structure to the form of reporting, others will give more relevance to the department in charge of rates or foreign currency exchange. However, in most of the cases the financial organization chart includes five main areas: Control, Accounting, Treasury, Budget and Internal Audit.

One of the functions with higher potential for AI application within these departments is accounting. It is in charge of the proper analysis and reporting of allocations such as revenue or expenses and it shows high relevance when the activity of the company is communicated to the market and investors. Eventually this aspect is fundamental in order to obtain the required resources of funding to implement the actions that are needed to pursue the overall strategic guidelines.

In fact, a high correlation is found between accounting results and stock returns (Riley, Pearson & Trompeter, 2003). In the past, there have been several events in which the management and communication of accounting results have been deficient. This has led to some scandals due to misleading representations of the company performance that are not in accordance with reality (Jorissen & Otley, 2010).

Moreover, accuracy in some Marketing activities such as forecasting (both demand and revenue) as well as optimization of pricing tactics show room for innovation and improvement given the current low-fare environment and interconnection between pricing, schedule and revenue management (Klophaus, 2006). In fact, the author of that study proposes a model for LCC pricing policies and he also analyses tools such as overbooking, expected marginal seat revenue, nested seat allocation or multi-leg seat inventory control.

The LCC pricing strategies have been extensively analyzed due to the high impact they have caused on the transport industry, modifying behavior of main stakeholders such as customers and competitors (Costantino, Di Gravio, Nonino & Patriarca, 2016). Apart from analyzing price dynamics, the authors in that study also identify the dependence on regulation and the evolution of business models as the main topics that have been addressed within the literature.

Another comprehensive review of techniques developed in the airline industry for revenue management is carried out by Cleophas, Frank and Kliever (2009). In addition to that, the increment of available information for customers via internet is assessed and models for demand forecasting are also reviewed. It has also been assessed how intermodal rivalry can impact air traffic demand (Demizu, Li, Schmöcker, Nakamura & Uno, 2017) and how airlines should try to recover from COVID-19 through a proper revenue management strategy planning (Mohamed, 2020).

Other pricing techniques have been developed within the air transport industry by airports in order to design optimized tariffs for flights to use their installations. Particularly, Zhang, Ye and Lili (2020) explore possibilities

for enhancing these strategies in airports with high level of traffic, including the improved management of tolls when airport is congested.

On the other hand, costs also represent a key piece for airlines accounting and determines their profitability. They are subject to a great variety of both, internal and external factors. Particularly, operating costs have been broadly analyzed in the literature. Several estimation models for them have been designed through the aviation history with the aim of comparing profitability of different fleet, routes or operating models.

To name but a few, (ATA, 1967) is one of the first models that was developed, (Harris, 2005) uses 1999 data from US airlines to statistically determine several allocations of the cost structure, Rashid and Al-Shamma (2014) compare some of these methods and López-Lázaro, Pérez-Campuzano, Benito and Alonso (2018) analyse the financial impact of biofuel introduction using updated versions of those models.

As showed by these models and other analyses from different airlines around the globe, although the cost structure has usually a very common architecture, it also shows certain level of elasticity depending on several factors. Aspects such as non-scheduled activity or flight delays have been identified as causes for variations in cost structure (Zou & Hansen, 2012).

Within this structure, fuel has always been a determining factor in the profitability of airlines, reaching between 30%-50% of the total operating costs depending on the business model and the price of the raw material. In fact, fluctuations of the latter have a high impact on airlines, which has led them to develop techniques for price protection (fuel hedging) with different time horizons (Carter, Rogers & Simkins, 2004).

### 3.2. Artificial Intelligence (AI)

This section represents an overview of the main AI tools that are currently being developed by scholars and also implemented in different industries. AI is commonly divided into two classes depending on their capabilities (Russell & Norvig, 2016):

- Weak AI (also narrow AI): machines that act simulating intelligence. They are usually designed for a specific task and cannot be applied outside of their field or scope due to inherent design limitations. Their usage is mainly related to the automation of time-consuming and repetitive tasks or to the extraction of wisdom from large databases.
- Strong AI (also general AI or super AI): machines that really have intelligence. Hypothetically they would be able to learn or adapt to carry out different tasks autonomously with an efficiency similar or superior to that of a human. Currently, no system with these capabilities has been developed yet.

Table 1 has schematically compiled the most representative features of the two types of AI mentioned.

	Intelligence	Scope
Weak AI	Simulated	Specific tasks for which it has been designed
Strong AI	Real	Autonomous learning capabilities for diverse tasks

Table 1. Artificial Intelligence (AI) classes: *Weak AI* and *Strong AI*

Due to the current level of development and its potential applicability in the short term, this analysis focuses on the first type, weak AI. Specifically, the most used models to date are those based on Machine Learning (ML). This science develops algorithms that allow the computer to learn to perform a task without being explicitly programmed for it or to improve their estimates from data that is introduced during the training phase. The most typical purposes for which these tools are used are: forecasting, estimation, outlier detection, pattern recognition, clustering or control systems optimization.

In the remainder of this section, the main learning methods (unsupervised, supervised and reinforced) are firstly generically described and some of the characteristics that distinguish these models from other algorithms such as the training phase or continuous learning are also discussed. In second place, a brief review of the most common AI and ML algorithms is carried out along with some examples of application in the aviation sector. A deeper discussion on how these tools can be applied in order to address the strategic topics showcased in the previous section 3.1. is made in section 4.

### Learning methods

In most cases, ML algorithms require an initial training phase in which the parameters (or even architecture) of the engine or model is optimized based on a series of data provided a priori. The training algorithms are aimed at minimizing a certain error while meeting certain requirements or constraints, for example in order to avoid memorization of the data also known as overfitting. Although, due to the rise of these technologies, the different techniques are in constant evolution and new ones also arise, in general there are three main learning methods (Pérez-Campuzano, Gómez-de-las-Heras, Gallego-Castillo & Cuerva, 2018):

- **Unsupervised.** The data set used during the training stage does not include output values (or labels). Given this, the model tries to find patterns, intrinsic structures, information relationships or different types of correlations between the provided inputs. In general, the variables or individuals are divided into groups with similar properties, so it can be used as a technique for extracting variables in a smaller dimensional space (feature learning); for classification or clustering or for anomaly identification (aiming to find individuals which have some distinctive characteristics).
- **Supervised.** The model is fed with a set of data that includes known inputs and outputs during the training. In this period, the parameters of the model are optimized to find the configuration that achieves the best results and minimizes the estimation error for the training set. Therefore, this learning method can only be used in those cases where a representative set of paired input and output data is available.
- **Reinforced.** In this case, during each iteration of the training phase, the algorithm, after evaluating the current situation, carries out a randomized action which is awarded or not based on the success achieved on certain previous hypotheses and targets. This way, the model interacts dynamically with the environment in order to achieve an optimal behavior (the one that gets the highest reward) to reach the final goal. Particularly, reinforced learning is often used for the design of control systems.

In addition to these learning methods that are commonly carried out during the design phase of the model, there is another type of learning, also known as continuous learning, which is carried out once the model is used during the implementation phase. Specifically, continuous learning algorithms modify the parameters of the model as it is put into operation and running with new input data. It is intended to correct deviations of the model which could have been created during the initial training phase or to dynamically adapt it to changes in the nature of the phenomenon being simulated.

Table 2 shows a summarized comparison of the learning methods that have been described above, based on the optimization method and its main applications.

	<b>Optimization method</b>	<b>Main applications</b>
<b>Unsupervised</b>	Unknown values or labels	Clustering, dimensionality reduction
<b>Supervised</b>	Known values or labels	Classification, forecasting
<b>Reinforced</b>	Rewarded actions based on targets	Control systems
<b>Continuous</b>	Dynamic training during implementation	Adaptation to changes in the system nature

Table 2. Learning methods for Machine Learning (ML) algorithms: unsupervised, supervised, reinforced and continuous

## Algorithms

Throughout the last decades numerous algorithms based on ML techniques have been developed and enhanced with new functionalities as explained by Mohammed, Khan and Bashier (2016) or Dey (2016). In this section, some of the most widely used in various industries are presented along with use case examples in the air transport business.

To begin with, one of the most pragmatic algorithms due to its simplicity is the k-means. Its main application is to segregate a multidimensional data set into groups or clusters based on the similarity of its characteristics. In fact, once the segmentation is done, the model could be also fed with new data to be classified. For example, Goldsberry and Scavette (2018) employ this method in order to optimize flight networks and hubs considering stopover airports as potential destinations.

Another algorithm whose applications are similar to those from the previous one is the Support-Vector Machine (SVM). Its functioning is based on the identification of hyperplanes that segregate the original data. This classification is made taking into account certain restrictions in order to achieve an optimal distribution. This algorithm is applied in Liu, Liu, Hansen, Pozdnukhov and Zhang (2019) in order to optimize ground delay strategies considering weather and arrival demand as the main impact factors.

Decision trees are also widely used due to their versatility to deal with different tasks. The foundation behind this algorithm is the identification of conditions or limits that separate the data in an optimal way, which eventually represent the division of each tree branch. They have been used in Wong and Chung (2007) with the objective of analyzing passengers and favoring their retention by airlines.

On the other hand, one of the tools that has shown more potential are the Neural Networks. This model is inspired by the human nervous system and is based on the connection of a certain number of neurons, fundamental element of these algorithms. There are numerous morphologies, structures and configurations, as well as mathematical models for their optimization. Due to their universal capabilities to represent any kind of non-linear relationships, their performance is usually very competitive. As an example, Cheng, Cui and Cheng (2003) design a model based on Neural Networks in order to forecast air traffic flow in China.

Recommender systems or engines are a group of algorithms dealing with the task of predicting customer preferences over a certain product or service. Some of the existing algorithms are collaborative filtering, content-based recommendations or matrix factorization. Although using different approaches and learning methods, all of them base their estimations on information from similar users which has been previously gathered. An extensive review on how these systems can support the airline business is performed in Bahulikar, Upadhye, Patil, Kulkarni and Patil (2017).

As mentioned at the beginning of this section, the algorithms mentioned here are just a representative sample, but the number of ML algorithms is high and also constantly growing. Sometimes this increase is given by the creation of completely new tools from scratch or, more commonly, by the evolution or combination of already existing algorithms or methods.

## 4. Discussion: how can AI address the COVID-19 challenges?

Once the current trends regarding airline decision-making and their main levers have been analyzed along with the COVID-19 impact, this section identifies some areas with room for innovation in the field of Artificial Intelligence (AI). The exploration in this study is based on the current needs and requirements within those functions (Strategy, Finance and Marketing) considering the crisis particularities as well as on the purpose and suitability of the AI algorithms both in theory and currently in practice in other industries or sectors.

In the following paragraphs some potential applications within the airline industry for the three Machine Learning (ML) methods explained before (unsupervised, supervised and reinforced) are showcased. These promising use cases are presented along with some examples of their application within the aviation industry which have been published after the COVID-19 outbreak. The applications oriented to technological solutions

or those related to other functions such as manufacturing or technological design are beyond the scope of this analysis.

In terms of specific applications that could be used this way, unsupervised learning (such as data clustering or description) shows high potential as a research line in the field of market and value chain analysis (competitors, customers and suppliers). This sort of assessment could enhance the internationalization or horizontal alliances strategy by means of grouping different target regions or potential allies according to the level of interest for the company. In addition, these methods gain relevance given the fact that air transport is a highly globalized industry with a large number of daily operations, which creates large amounts of information of very different nature: flight, operations, finance, etc.

In fact, airlines' financial data feeds an unsupervised clustering model for the airline market analysis which is developed in Pérez-Campuzano et al. (2021). In particular, a Self-Organizing Map is used in order to classify and visualize the last-years evolution of the top European carriers and the impact of the COVID-19 on their financial statements.

Business Intelligence (BI) applications (which are designed to structure and analyze this data) would be essential for airlines in order to get a better understanding of the past and future market trends. For example, insights obtained this way can prevent a carrier to lose share due to a shift of customer preferences or to implement cross-selling initiatives to both improve the customer experience and avoid losing potential passengers.

Another possibility for these kinds of tools is to complement the work of experts during the process of selecting another airline or company that must be merged or acquired in order to address a specific niche and take full advantage of the potential synergies. Nowadays the interest for this has increased given the effect of COVID-19 on the industry. The pandemic effects will reactivate the M&A market in the near future due to profitability pressure and other opportunities arisen due to high stock fluctuations of air transport corporations and enforced state aids (Suau-Sanchez, Voltes-Dorta & Cugueró-Escofet, 2020).

New potential markets or destinations which are not properly managed or those that may hold growth potential due to some particularity occurring inside or outside the sector (e.g. a particular destination fostered by the entertainment industry), could also be identified by anomaly detection techniques. This would be also applicable to sharp disease disruptions or outbreaks as well as epidemic behavior irregularities in certain regions, which could eventually led to reduced cross-border demand or increased epidemic control restrictions.

Processes related with these restrictions have also caused certain changes in airport operations. In fact, the flow of passengers at the airport has been also a topic that has been subject to machine learning analysis. This is the case of Rodríguez-Sanz et al. (2021), which proposes a random forest model with the objective of improving passenger services and their waiting times at queues.

On the other hand, within the Human Resources field, the application of these techniques for the management of the organization culture or for the design of collaborative spaces may be explored. They could also be useful for the search of information inside or outside the organization, as well as for the identification of key people that may be related to sources of valuable information and which is sometimes difficult to obtain. In this case, the participation of internal stakeholders through a design thinking process should be advisable

Other possible applications include the design of models to support the negotiation of hedging contracts (mainly fuel for airlines) or aircraft leasing. The relevance of this topics has increased considering the high volatility and supply bottlenecks that the pandemic and its consequences have caused in the commodity markets. This way, an estimate of which is the best time, price and time horizon to carry out this type of agreements would be available as support information for during the contract negotiation. This use case is explored in Chen, Rehman and Vo (2021), which leverages the potential of clustering and manifold learning to evaluate commodity markets.

Supervised learning techniques could be also one of the most promising tools to be applied in this industry. Particularly, Neural Networks (both deep and shallow) are being applied in several industries and achieving

relatively high success. Potential research lines in aviation include route or network optimization as well as traffic, performance or cost estimation based on historical data and certain a priori assumptions. Flexibility and adaptability in this regard is paramount given the changing demand, restrictions and costs (mainly fuel) caused by the pandemic.

In order to assess the capabilities of ML algorithms to estimate the performance of enterprises after the pandemic, Tsa and Hung (2021) compare the results from different engines such as Neural Networks and SVMs. Another performance estimation model is proposed in Stefanovic, Strimaitis and Kurasova (2020), which also applies several algorithms (Neural Networks, decision trees, SVMs, etc.) to predict deviations in flight time.

Regarding the evolution of the pandemic, a forecasting algorithm could be trained with data from previous epidemics (such as SARS or MERS) or even with recent past data from COVID-19 (e.g. from regions with an advanced level of epidemic evolution or vaccination percentage). Then the models should be fed with current data in order to estimate the near future evolution. Epidemiologic evolution and transport demand fluctuations could be anticipated by these means.

A recent study that focuses on the unpredictability caused by the COVID-19 among other sources of uncertainty is presented in Lohne and Skrbo (2020). The assessment also discusses the potential use of ML to associate air traffic and Gross Domestic Product.

The strategic lever related with diversification (up-selling, cross-selling and potential ancillary services or products derived from the new COVID-19 H&S protocols) could be also analyzed using another AI tool, the recommender systems. Strategic decisions involving this opportunity could be assessed leveraging information previously gathered regarding passenger preferences over other existing products and services. It is worth mentioning that these tools can rely on supervised or unsupervised learning, or even on both, depending on the particular algorithm to be developed.

For example, a deep assessment of six different recommender systems is conducted in Dadoun, Defoin-Platel, Fiig, Landra and Troncy (2021). They cover various stages of the customer travel experience and a robustness analysis is proposed for these tools considering the sparseness and rapid evolution of the data during this type of crises.

The ability of all these tools to be updated as new data is fed through the already-trained model (also known as continuous training) can also tackle one of the main drawbacks of the models that are being currently designed: their short-term validity. Technological advances in aircraft design, airlines transformation, growth of emerging markets or external factors such as financial crisis, natural hazards, oil price, geopolitical risks... make air transport a fast-changing business. Due to the fast dynamics of this industry as well as the accelerated pandemic evolution, models get outdated too soon and lose accuracy over time. Continuous learning allows the model to get automatically adapted to these changes, avoiding the need for a complete model redesign or retraining on a frequent basis.

Considering that reinforced learning applications are mainly based on the development of control systems, such as that developed in Zhen and Hao (2020), it seems that the potential for this type of tools to be applied in organizational tasks is lower than the aforementioned methods. However, reinforced learning models could be trained for such applications if a proper objective function and rewarding method could be established.

A possible application could be the use of this model to choose among different strategic actions to be taken in the company. Nevertheless, the simulator that would be needed to assess the impact of each decision would be too complex to be built or too biased by intrinsic design constraints.

However, Neural Networks based on reinforced learning have already been proven to be capable of supporting, for example, revenue management tasks. This is the case studied in Bondoux, Nguyen, Fiig and Acuna-Agost (2020), which avoids the necessity of designing a model to estimate future demand in order to manage and optimize pricing policies for airlines.

## 5. Conclusions and next steps

In this study it has been carried out a review of the state-of-the-art regarding the COVID-19 impact on airlines organization (past and current trends of Strategy, Finance and Marketing) as well as weak Artificial Intelligence (AI) algorithms whose popularity has exponentially grown during the last decade. Given the current low development level of strong AI tools, they have not been included within the analysis.

After assessing the potential of the AI tools to be applied within the air transport industry, and specifically on managerial departments, some applications are identified as of particular interest for the strategic decision-making process. Neural Network models for market analysis, cost estimation or hedging negotiation are some examples. On the other hand, two Machine Learning (ML) methods (supervised and unsupervised) have already demonstrated high potential in the field while reinforced learning techniques would have to deal with more barriers for its implementation, although some use cases have been already developed.

It is clear that the COVID-19 crisis has thoroughly stressed the sector and that the current situation poses huge challenges to air transport organizations, whatever their value proposition or business model. However, some AI algorithms (such as estimation models or recommender systems) have been identified as promising tools for strategic decision-making in order to deal with new threats and opportunities created by the pandemic, both in the near and long term.

To sum up, given the fast-changing needs of airline organizations, especially in these times of disruptive crisis, and the current capabilities of weak AI tools, several research lines could be addressed. Specifically, the methods with the highest potential seem to be mainly unsupervised and supervised learning. Additionally, many of the applications envisaged in this study show potential for transferability to other transport organizations or sectors such as road, rail or maritime. Hopefully the guidelines showcased throughout this paper may encourage scholars and practitioners to jointly develop a suitable environment for the deployment of these tools within corporations.

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