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A 32-year meta-analysis on Artificial Intelligence research in aviation

Disclosing past success, unlocking next
challenges

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ABSTRACT

Artificial Intelligence (AI) and its related disciplines (Machine Learning, Data Mining, Big Data...) offer opportunities whose practical implementation pose complex challenges. Their fast evolution evidences potential but has caused a gap between academia and certain areas of the industry – which seem to lack the required agility to implement such technologies. This study aims to suggest some recommendations and a roadmap aligning both communities through a comprehensive quantitative meta-analysis and visualization of the existing literature. Although four modes of transport are initially compared, the focus is placed on AI within air transport (273 works since 1987) and its relationship with organizational areas. Results show that the most popular topics are Machine Learning and neural networks. Nevertheless, as many documents only mention one AI-related term, visibility is hindered in specific-keyword searches. Operations seem to be thoroughly explored while there is room for research in Strategy and Resourcing.

KEYWORDS

air transport, algorithms, Artificial Intelligence (AI), Machine Learning (ML), neural networks, organizational areas

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OBJECTIVE

Review and suggest a roadmap aligning academia and industry to facilitate the implementation of Artificial Intelligence (AI) tools in the air transport sector.

METHODOLOGY

Comprehensive quantitative meta-analysis and visualization of the existing literature in the aviation sector related to AI.

RESULTS

Most popular topics are Machine Learning and neural networks in the area of Operations, while there is still room for research in Strategy and Resourcing.

LIMITATIONS

The study is a high-level overview, for this reason detailed review of the past analyses, comparison between business models or image processing tools were not considered.

PRACTICAL IMPLICATIONS

Provided guidelines may encourage scholars and practitioners to jointly develop a suitable environment for the implementation of AI tools within corporations.

1. INTRODUCTION

This meta-analysis on Artificial Intelligence (AI) in air transport seeks to get an integrated view involving technological potential and business aims. For this reason, the search focuses on AI algorithms as well as on organizational areas. With the final goal of identifying a potential roadmap for future innovative research on these topics and its implementation within the industry, the existing work is used as the baseline. Additionally, guidelines showcased throughout this paper may also result in a closer relationship between scholars and practitioners, which is another main objective of the study.

Secondary goals include the benchmark of aviation among other modes of transport (i.e. road, rail and water) as well as the assessment of the popularity of different AI tools (e.g. neural networks, nearest neighbor or random forests). This may help in the identification of research trends and gaps that may bring about potential opportunities to be explored.

In order to help the spread of the research knowledge throughout the industry, this study also aims to feature and analyze the existing conferences on the topic and the geographical distribution of the scientific production. A comprehensive view of the different existing AI techniques and tools provides a holistic picture of the methods used in the literature. This visibility is usually fragmented due to the wide variety of algorithms and the recent abrupt emergence of these innovative technologies.

More precisely, the work aims to answer questions such as: What has been the degree of penetration of AI within the sector? How does this compare to other modes of transportation and regarding the different organizational areas? Which algorithms have been mostly employed? How has AI influenced the popularity of the research? Where and how are the scientific works spread? Which are the emerging future challenges in the industry?

In order to address these objectives and questions, the meta-analysis relies on a quantitative view of the research already conducted in the air transport sector related to AI and, specifically, in its links to the different areas of the organizations (namely, Operations, Strategy and Resourcing).

The paper presents a high-level overview of the state-of-the-art and does not aim to make a detailed review of the type of analyses conducted in the past or of the specific content of the works. It must be also pointed out that a deep-dive on the different types of air transport (e.g. passenger, cargo or unmanned) as well as on their different business models (e.g. low-cost, charter, regional or full-service network carriers) is out of the scope of this research. AI tools related to image processing (such as computer vision or augmented reality) were not considered in this study.

2. BACKGROUND

In the past, some innovative digital technologies have caused disruptions within the air transport business. The Computerized Reservation System (Crowston & Myers, 2004) or even the Internet (Ramón, Moreno & Perles, 2011) are clear examples. Some of them were able to reshape the industry by modifying the relationships and competitive forces between the different stakeholders, hence transforming the structure of the sector (Porter, 1980). The industry-wide impact caused by these innovations may, in addition, force aviation organizations to perform extensive technological transformations (Orlikowski & Barley, 2001).

Nowadays, the potential of AI along with other related disciplines (Machine Learning, Data Mining or Big Data) offer several opportunities whose implementation, in turn, pose complex challenges (Pérez-Campuzano, Morcillo Ortega, Rubio Andrada & López-Lázaro, 2019). Surveillance tools are being implemented

(Campos & Rubio, 2017) but the fast growth of these technologies has shaped an environment where a certain gap is perceived between business and academia. While scholars tend to quickly develop intricate models and tools that seem to have a high-accuracy performance, practitioners and executives show certain lack of agility to adopt and implement these innovative tools into their daily tasks. This difference seems to be even more noticeable in some organizational areas than others. For this reason, corporate innovation should be promoted in order to benefit from these competitive and adaptative advantages (Bueno & Morcillo, 2017).

In recent years, some literature reviews have already addressed the application of AI tools in the air transport business. For example, Akerkar (2014) analyzes the use of Big Data for the extraction of knowledge in aviation. Some cases of Data Mining applied to airlines and airports are assessed too in Akpınar & Karabacak (2017). The most recent study, Beecroft (2019), addresses the current situation and future challenges for security in the public transport.

These reviews have assessed the work already conducted within their respective scopes. However, none of them has broadened their research goal to the general AI field and has focused neither on the specific AI algorithms applied nor on the potential organizational areas yet to be exploited. In fact, some of their conclusions show that there is still room for innovation in order to obtain more operationally interpretable knowledge through these techniques, and that the use of AI tools and data, as a very valuable asset within the industry, will define the future of airline management. Following these premises, this meta-analysis carries out a quantitative review aiming to give comprehensive visibility on AI in order to help practitioners understand the state-of-the-art and the different existing AI methods and algorithms.

3. METHOD AND MATERIALS

In order to get an overview of the past research conducted on the topics addressed within this study, certain literature searches were carried out using the database by ISI Web of Science. In this regard, all the searches were made applying additional search conditions or filters to the basic query, which included the following criteria:

- **Research area (SU):** Transportation
- **Document type (DT):** Article or Proceedings paper
- **Publication year (PY):** 1987-2019. Initial year (1987) was selected following the first publication of a work fulfilling the previous conditions (SU and DT) as well as including some of the AI and Air Transport keywords (k^{AI}) and (k^{AT} , see below).

3.1. Keyword selection

In this section, the terms selected for the different filters are defined. These were used as keywords to be found within the field Topic (TS) in the database. These words were chosen after consulting the most popular terms used in the literature and are supported by relevant publications whenever possible.

Firstly, for each of the modes; air (AT), road (RO), rail (RA) and water (WT); ten terms were chosen as keywords for the search. They were iteratively selected and modified with query rules by checking the search results to minimize false negatives (e.g. overlooked documents) while also avoiding false positives (e.g. mistakes due to similar or polysemic words such as train or due to intermodal words such as traffic or vehicle).

$$k^{AT} = \{air\ tra^*, aeronautic^*, aviat^*, aerial^*, airlin^*, airport^*, airplane^*, aircraft^*, helicopter^*, drone^*\}$$

$$k^{RO} = \{road^*, highway^*, automo^*, car^*, taxi^*, bus, truck^*, motorcycl^*, *bike^*, bicycl^*\}$$

$$k^{RA} = \{^*rail^*, train\ station^*, ^*speed\ train^*, rapid\ transit^*, subway^*, underground^*, metro\ lin^*, tram^*, streetcar^*, locomotiv^*\}$$

$$k^{WT} = \{^*mariti^*, ^*marin^*, ^*ocean^*, sea, port$, harbo$, ^*boat^*, vessel^*, ship, cruise\}$$

Secondly, for the case of AI topics (AI), five general terms (GE) that are usually employed in the Computer Science literature were identified using sources such as Russell & Norvig (2016) or Pérez-Campuzano, Gómez-de-las-Heras, Gallego-Castillo, & Cuerva (2018). Then, ten different AI algorithms (AL) were also selected for the meta-analysis. This list of popular tools was built based on the common nomenclature used in Mohammed, Khan, & Bashier (2016) or Dey (2016).

$$k^{AI} = \{k, k^{AL}\}$$

$$k = \{artificial\ intelligence, machine\ learning, data\ mining, knowledge\ discovery, big\ data\}$$

$$k^{AL} = \{linear\ regression^*, logistic\ regression^*, principal\ component^* analys^*, decision\ tree^*, random\ forest^*, naive\ bayes^*, k-means^*, ^*nearest\ neigh^*, support\ vector\ machine^*, neural\ network^*\}$$

Thirdly, regarding the different organizational areas (OA) and according to (Lynch, 1984), any air transport organization must relate and integrate three interdependent systems: Operations (OP), Strategy (ST) and Resourcing (RE). Each of these may comprise other sub-functions such as maintenance, market intelligence, procurement, etc. In order to preliminarily evaluate the potential level of research already conducted for each system and function, six terms per system were used as keywords:

$$k^{OA} = \{k^{OP}, k^{ST}, k^{R}\}$$

$$k^{OP} = \{Operation^*, Marketing, Flight op^*, Ground op^*, Engineer^*, Maintenance\}$$

$$k^{ST} = \{Strateg^*, Market intel^*, Corporate dev^*, Business dev^*, M\&A, Merger^*\}$$

$$k^R = \{Resourcing, Financ^*, Purch^*, Procu^*, Human Res^*, Personnel\}$$

3.2. Exclusive, mixed and nil mentions

Some of the terms or categories (i.e. modes of transport, AI algorithms or organizational areas) in the searches did not meet the MECE principle, as they were neither mutually exclusive nor collectively exhaustive. This means that some documents in the searches could fit into one category, into more than one or into none. For this reason, the search queries were designed in order to address this by considering Exclusive mentions (EM, works where only one category is mentioned), Mixed mentions (MM, works where more than one category is mentioned) and Nil mentions (NM, works where none of the categories are mentioned).

In order to obtain the number of documents, d , corresponding to the aforementioned classification for the modes of transport, the following Boolean operations were applied for the search into the field Topic (TS):

$$d_{EM}^{\alpha} = ik_i^{\alpha} - \beta \neq \alpha ik_i^{\beta}$$

$$d_{MM}^{\alpha} = ik_i^{\alpha} - d_{MM}^{\alpha} \left(theequivalent : d_{MM}^{\alpha} = ik_i^{\alpha} \square \beta \neq \alpha ik_i^{\beta} \right)$$

$$d_{NM} = -aik_i^{\alpha}$$

where $\alpha, \beta \in \{AT, RO, RA, WT\}$ represent each mode of transport, $i=1,2,...,10$ represents each term within the category and k_i^{α} represents the documents mentioning keyword i from category α .

Similarly, for the AI and organizational areas terms, as only one term was used per category, the Boolean operations were applied as follows:

$$d_{EM}^{\square} = k_i^{\square} - j \neq ik_j^{\square}$$

$$d_{MM}^{\square} = k_i^{\square} - d_{EM}^{\square} \left(theequivalent : d_{MM}^{\square} = k_i^{\square} \square j \neq ik_j^{\square} \right)$$

$$d_{NM}^{\square} = -ik_i^{\square}$$

where $\gamma \in \{AI, OA\}$, $i=1,2,...,m$ represents each term within the category (considering that $m^{AI} = 15$ and $m^{OA} = 18$) and k_i^{α} represents the documents mentioning keyword i from category γ .

4. RESULTS

This section shows the outcome of the meta-analysis, obtained by applying the aforementioned search methodology within the database by ISI Web of Science. The first subsection compares the four modes of transportation while the following section focuses on the aviation sector and the AI implementation.

4.1. Comparison with other modes of transport

First, in order to get the overall picture of the transport sector, four modes of transport (road, rail, water and air) are compared both in general terms and regarding AI. For this purpose, **Figure 1** represents the number of documents published within those areas during the analyzed period.

In both graphs from Figure 1, bars have been divided into two segments. Exclusive mentions apply to those works where only one mode is referred to. Mixed mentions denote that the respective mode is cited along with at least another mode in

Figure 1. Transportation works in general (a) and regarding AI (b), segregated by mode of transport

the document; hence a document with Mixed mentions must be repeated in at least two mode bars while only appearing once in the total pie chart. The pie charts on both sides gather all the modes and also those works that, although included in the Transportation research area, show Nil mentions, publications that do not include any of the keywords used for the modes (see the methodology section).

It is noticeable how the road mode gathers the majority of works, representing at least 35% of the documents in (a). This is even more acute in the AI case (b), where the road contribution rises to 47%. The reason for this could be the high popularity of AI in the research topic of autonomous driving (Sportillo, Paljic, & Ojeda, 2019). The predominance of the road could be even higher than shown given the fact that some intermodal keywords (such as “traffic” or “vehicle”) are often used exclusively

for this mode but have not been included in this meta-analysis as search keywords.

On the other hand, the rest of modes show a significantly lower number of records. Rail represents 6-4% of the works and water and air modes only 3-2%, which seems to indicate that there still exists room for research and innovation in these modes. While this gap between the road and the rest of the modes could be explained by its higher direct economic impact, number of users/passengers, and accessibility (e.g. for testing and knowledge), other modes (e.g. water or air) also show a very relevant influence in terms of secondary economic or environmental impacts (López-Lázaro, Pérez-Campuzano, Benito & Alonso, 2018).

Regarding the ratios between Exclusive and Mixed mentions, road also shows the highest levels of unique research, 83% in (a)

and 91% in (b), while the rest of modes show a more balanced share (circa 60%). This means that rail, water and air are present, or at least cited, in a relatively higher number of analyses including multimodal comparisons or benchmarks. It is also worth noting that the vast majority of the works with Mixed mentions include references to the road mode. This is why the Mixed mentions in both Total pie charts are only slightly larger than the Mixed mentions in each road bar.

It seems interesting to analyze how much of the “Exclusive” research (which is only attributed to one specific mode of transport) is mode-agnostic and could be extrapolated (with either none or minor modifications) to other modes. For example, maybe a relevant portion of the extensive road literature could be used for rail, water or air solutions. This could help these scarce-literature modes when implementing knowledge already developed for the road transport.

Above each bar on (b), the value in square brackets represents the percentage of the AI related works within the general works in the respective bar on (a). For road transport, AI represents a 5.5% of the works while for the other three modes this ratio decreases to 3.0%, thus averaging a 4.5% in the Total transport documents. However, it should be noted that the popularity of AI has increased in the last decade and this ratio reaches an 11% when the comparison is restricted to works published during 2019.

Focusing on aviation, the total number of samples is the lowest of all the modes of transport and only 273 are related to AI, as shown in (b). In the following sections, these publications are analyzed.

4.2. Research overview of AI within aviation

The assessment focusing on the works regarding both air transport and AI (with a total of 273 samples) begins with their chronologi-

cal publication depicted in **Figure 2**. The 273 works identified using this methodology address a wide variety of topics including flight delays (Pérez-Rodríguez, Pérez-Sánchez & Gómez-Déniz, 2017), fuel consumption (Khan, Chung, Ma, Liu & Chan, 2019), trajectory analysis (Hurter, Conversy, Gianazza & Telea, 2014) or airlines’ business models (Thanasupsin, Chaichana & Plian-karom, 2010), to name but a few.

The first of these documents is Gosling (1987), which marked the starting year for this study. The work explores certain applications within the air traffic control which could be carried out or optimized by the implementation of AI techniques. The second publication in this subset corresponds to Rengaraju & Arasan (1992), which applies multiple regression analysis for air travel demand forecasting.

During the 1994–2003 decade, the academic production was low but stabilized at 1.9 documents per year. It must be pointed out that four different conferences were held in 1998, which contributed with a total of 5 proceedings papers in that year.

After a publication dip in 2004–2005, from 2006 to 2011 the average article production raised to a steady rate of 3.5 samples per year. In addition, regarding conference works, the ASME Turbo Expo contribution with 8 papers in 07–08 (half of the accumulated proceedings papers in the spike during those two years) deserves recognition.

Through the last eight years the production pace has increased four times since 2012, up to 52 documents in 2019. It is also noticeable that this increase in popularity has also prompted the publication of some reviews in the last years. This evidences the high potential that this technology shows for the coming years as one of the most promising research topics in the industry.

In order to understand which sources have been the most active during the whole period, **Figure 3** and **Figure 4** represent

Figure 2. Historical evolution of air transport and AI related works

Figure 3. Main journals by number of articles

the journals and conferences (respectively) with the highest number of issued records.

The Journal of Air Transport Management, the only pure-aviation journal among the top 11 depicted in Figure 3, is the scientific

magazine with the highest number of AI-related papers issued. However, the aggregated number of articles of all the Parts from Transportation Research (Part C, E, D and A in order of quantity) raises to 56 samples (28% of the total 199 articles that were identified).

Figure 4. Main conferences by number of proceedings papers

The IEEE's ITSC has been the major forum for AI applications within air transport, as shown in Figure 4. Its contribution started in 2003 but has accelerated since 2017 with 6 papers in the last three years. The ASME Turbo Expo stays in second place but, as mentioned before and although still active, its eight publications were all issued in 2007 and 2008 (conferences held in Canada and Germany respectively). It is followed by another IEEE event, the VTC, a biannual conference that has contributed with 6 documents since 2016.

Regarding specialized events, only one of the top 7 forums appearing in Figure 4 is purely dedicated to aviation, the Conference for Remote Sensing Applications for Aviation Weather Hazard Detection and Decision Support. Nevertheless, it was held in 2008 and its scope was rather restricted to the particular use case of weather forecasting.

The aforementioned journals and conferences, proven to be the mainstream sources of novel research, represent the place where scholars and practitioners should meet in order to promote further development in the industry. This may be achieved by either collaborating with new studies (researchers), by monitoring the published work (professionals), or by

attending the events in order to align academic potential and business needs (both).

However, this seems to show certain difficulty for air transport experts due to the lack of specialized journals and events. Despite the fact that many of the AI business applications show intermodal potential, it would be desirable to promote the creation of at least one (even biannual) scientific conference focused on AI and aviation.

The search conducted in this study also allowed the authors to evaluate the geographical distribution of the previous research. **Figure 5** shows that these topics have raised the most interest in the US and China (84 and 38 publications respectively). In addition, other 40 countries throughout the different regions and continents have also contributed to the topic.

For those corporations willing to introduce AI technology and based on countries with a higher number of publications, it should not be difficult to engage existing local Universities or research centers in order to jointly develop research programs with parallel goals. Those firms whose countries still show a low AI research penetration may first start developing local expertise by leveraging the already developed knowledge abroad.

Figure 5. Regions and countries by number of publications

4.3. Popular AI terms and algorithms

To get a sense of the popularity of various AI algorithms or tools applied within the air transport sector, **Figure 6** represents the number of works which mention any of the 15 terms chosen as a representation of AI. Although the search criterion is the same for all of them, for visualization purposes they have been divided into two groups: (b) AI Generic (hypernyms) and (c) AI algorithms (hyponyms). A definition of these terms along with an example from the literature (according to popularity and representativeness for each of the topics) can be found in the glossary in section 6.

The pie chart in Figure 6 (a) represents the total works divided into those which only mention one term (Exclusive) or those which show mentions to two or more terms (Mixed). It can be observed that only 14% of the documents showed Mixed

mentions. This illustrates how difficult it could be to find any of these studies even using generic terms as search keywords (which only represent a 26% of the papers). In other words, if a search were conducted using only AI generic terms, at least 61% of the research would be overlooked. This strengthens the relevance of including different terms in the paper referring to both tools used (hyponyms) but also to other generic terms covering a broader meaning (hypernyms) in order to increase the visibility of the publication.

In this case, given the fact that one of the a priori criterion used for the selection of this subset of 273 works was that all the publications should contain any of the AI terms, the groups are collectively exhaustive. For this reason and in contrast with other figures in this paper, works without mentions to any of these terms (Nil mentions) cannot be found.

Figure 6. AI terms (both generic and algorithms) by number of mentions

Focusing on the hypernyms in Figure 6 (b) it seems that the generic term that shows more popularity is Machine Learning being mentioned in a total of 37 works. On the other side, it is confirmed that Knowledge Discovery is rarely used (usually substituted by Data Mining) as its only mention is found in Wong & Chung (2007).

Looking at the results from hyponyms in Figure 6 (c), Neural Networks is clearly the most used term (82 mentions). The high potential of these algorithms relies on their universal capabilities to represent any kind of non-linear relationships and their competitive results have prompted their massive application in the last decade. It is not unusual either to find Linear regression as one of the most used tools. It is one of the oldest as well as simplest algorithms and it has been employed extensively in several research themes, either standalone or as a benchmark to compare the accuracy of other types of models.

It is not unexpected from some algorithms (such as Linear regression, Logistic regression, Principal Component Analysis or k-means) to show a high ratio of exclusive mentions, as they are methods which are sometimes used outside the pure AI environment. However, the ratio of exclusive mentions is also high in Neural Networks (79%) while it is clear that these tools are always linked to some hypernyms such as AI or Machine Learning. This again emphasizes the relevance of including in the articles not only explicit references to the tools themselves but also to their related hypernyms. The objective is to increase the visibility of the publications, which are usually found by searches through specific keywords.

To assess the impact of the number of mentions to different AI terms on the popularity or success of the papers, Figure 7 represents (b) the number of uses in the last 180 days and (c) the number of times cited differentiating between publications

Figure 7. Popularity (usage and citations) by number of mentions

mentioning only one AI term (Exclusive) versus those which mention at least two terms (Mixed).

Although the population size might not be representative (note that the total number of samples per category is shown in (a)) and the publication date has a noticeable impact on the numbers, some observations can be extracted from the figures. In particular, regarding the number of times the works have been used (b), papers with mixed mentions feature 13% higher usages. On the other hand, citations behave in the opposite way: studies with more than one mention are an 8% less cited (c).

Nevertheless, it is worth mentioning that the work with the highest number of AI terms mentioned is Wang, Liang & Delahaye (2018), which includes quotes to seven AI terms out of the 15 search keywords used in this analysis. In fact, it is aligned with the previously observed trend since its usage sums up to 5 while it has been cited only 7 times. The authors in that paper develop a hybrid machine learning model for Estimated Time of Arrival forecast based on neural networks and decision trees (using data previously processed through Principal Component Analysis). In addition, linear regression and k-means are used as comparison models.

4.4. Organizational systems and functions

A similar analysis to that carried out in the previous section is performed below. However, the most popular organizational systems or functions are selected as keywords for the search instead of using the AI terms. The purpose, based on the results in Figure 8, is to examine the extent of AI research undertaken through the different areas within the air transport organizations and, eventually, to find disregarded areas with high research potential.

The high number of works without any mention to organizational areas (Nil, 56% of the total) in Figure 8 (a) represents that most of the research does not focus on these particular topics (or at least not explicitly). This suggests that more research should be conducted in this regard, or that, at least, references to the related areas should be included in order to ease visibility within these topics.

Most of the works including any of these terms refer to Operations and its related functions (more than 25% of the total). The keywords Operations, Engineering and Maintenance are the most popular in the field as shown in Figure 8 (b). In fact, most of the common IA purposes (such as classification, forecasting, anomaly detection or control systems) show straightforward

Figure 8. Organizational systems and functions by number of mentions

applications in those areas (e.g. operations optimization or predictive maintenance).

In contrast, both Figure 8 (c) and Figure 8 (d) feature a much lower number of positives. Some examples of the few works included in these areas address issues such as the airline strategy to meet environmental commitments (Cui & Li, 2018), the impact of airline mergers in the definition of their hubs (Ryerson & Kim, 2013) or the assessment of the personnel service at an airport (De Oña, Eboli & Mazzulla, 2014). Most of the functions (e.g. Business Development or Human Resources) do not have even a single mention in the selected subset of 273 works. The exception is the term Strategy which in turn is a term that can be used in many senses, not only referring to the organizational function, so it is not representative for the purpose of this analysis.

These figures suggest that there is still extensive room for innovation since it is very difficult to find any paper dealing

with the application of AI tools within organizational areas such as Strategy or Resourcing (and all of their related functions). This could be partially explained because usually professionals working within Operations areas (especially engineers) are more used to dealing with technical software (e.g. programming and numeric computing applications). This trend may be balanced in the near future as business intelligence software is getting more popular and simpler to use with basic statistic knowledge, thus easing its practical implementation across different departments along the organization (e.g. Strategy and Resourcing).

5. CONCLUSION

This meta-analysis assesses the past and potential research regarding the application of Artificial Intelligence (AI) algorithms within the air transport industry. The literature meta-analysis is based on the results from searches in the database by ISI

Web of Science. Since another objective is to understand the integrated relationships between technological potential and business aims, the study relies on a quantitative visualization of the research already conducted in aviation related to AI and, specifically, linked to the different areas of the organizations (i.e. operations, strategy and resourcing).

Firstly, it is observed that the literature in the transportation area shows a significant bias towards road transport, whose number of scientific publications (both in general and in particular for AI) more than doubles the sum of the works in the air, water and rail modes of transport. This difference is even more meaningful in the research related to AI (probably due to the high popularity of technologies such as the autonomous driving), which raises the question of how much of that research is mode-agnostic and could be extrapolated to the rest of modes (with either none or very little modifications).

Focusing on the aviation field, the scientific production related to AI (273 works identified since 1987) has experienced a quick increase in popularity in the last decades, especially from 2010 onwards. This evidences the high potential that this technology shows for the coming years as one of the most promising research topics in the industry, which additionally has shown high appetite to introduce this kind of tools into its processes.

Regarding the channels for dissemination of the knowledge, circa 5 journals seem to gather an important portion of the articles published. However, it has been also observed that the publication material is quite scattered and most of the work is published in non-pure aviation sources. This is even more noticeable in terms of scientific conferences, where some of them have been very irregular or sporadic throughout the years. It would be advisable to concentrate the dispersed conference landscape

maybe through the promotion of one (even biannual) specific event for focused on AI in the air transport sector. This could serve as a meeting point for scientists and professionals from the industry and also help in the alignment and collaboration between them.

Particularly, in the air transport sector, the most popular AI-related topics already addressed seem to be Machine Learning (hypernym) and Neural Networks (hyponym). Most of the documents, developed in more than 40 countries, only mention one of the terms used for the search. This stresses the relevance of including different terms in the paper referring to both tools used (hyponyms) but also other generic terms (hypernyms) that seems to increase the visibility of the publication, making it easier to be found through searches in scientific databases.

In regards to the AI research conducted for each of the organizational areas in aviation, Operations (including engineering and maintenance) seems to be the most popular function. On the other side, Strategy (including corporate development or Mergers & Acquisitions) and Resourcing (including finance, procurement or human resources) have been barely explored at present.

Taking the past work as baseline, a potential roadmap for future innovative research in these topics may comprise the application of AI algorithms within the Strategy and Resourcing functions. Although this implementation seems to be less straightforward than for the Operations function, the versatility of AI tools should also retain high potential and may disclose unrevealed opportunities. In terms of particular AI algorithms to be further explored, the random forest, Naïve Bayes and nearest neighbor show very low utilization yet. It must be pointed out that commercial business intelligence software may also contribute to the penetration of these tools.

In order to further optimize or complete this meta-analysis, a review could evaluate the impact on the business models of different aviation companies (airports, cargo/passenger or traditional/low-cost airlines, handling firms, manufacturers...), be applied to the rest of modes of transport (such as road, rail or water) or even include the AI tools related to image processing (such as computer vision or augmented reality), which were not considered in this study.

To conclude, it is clear that AI and its related technologies will play a very relevant role in the next decades of air transportation research. Whether this will turn into a closer relationship between business and academia is yet an enigma. Besides, the guidelines provided throughout this paper may encourage scholars and practitioners to jointly develop a suitable environment for the development and application of these tools within corporations.

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8. DECLARATION OF COMPETING INTEREST

The authors declare that they have no conflicts of interest with the contents of this paper.

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APPENDIX: GLOSSARY

	Term	Definition	Example
AI Generic (hypernyms)	Artificial Intelligence	Theory and development of computer algorithms or systems able to perform tasks normally requiring human intelligence, such as forecasting, visual and speech recognition, decision-making or language translation.	(Goodall, 2014)
	Machine Learning	Development of data-based computer algorithms or systems able to learn and adapt without being explicitly programmed to do so, by using algorithms and statistical models to analyze and draw inferences from the data.	(Alligier, Gianazza, & Durand, 2015)
	Data Mining	Practice of mathematically and statistically analyzing large databases in order to generate or extract new information and wisdom through anomalies, patterns or correlations.	(Li, Hansman, Palacios & Welsch, 2016)
	Knowledge Discovery	Process of extracting useful information from large sets of data using sophisticated algorithms or methods usually through identifying novel and understandable patterns.	(Wong & Chung, 2007)
	Big Data	Extremely large data sets that may be analyzed computationally to reveal patterns, trends, and associations (e.g. relating to human behavior and interactions).	(Lin, Hu, Zhang & Yu, 2016)
AI algorithms (hyponyms)	Linear regression	In statistics, linear approach to modelling the relationship between a scalar response and one (simple) or more (multiple) explanatory variables.	(Suzuki, 2000)
	Logistic regression	In statistics, the logistic model is used to model the probability of a certain class or event existing such as pass/fail, win/lose, alive/dead or healthy/sick.	(Chen, 2006)

	Term	Definition	Example
	Principal Component Analysis	Process of computing the principal components and using them to perform a change of basis on the data, sometimes using only the first few p. components and ignoring the rest.	(Rehman, Qianli, SongBo, Zaman & Zhang, 2017)
	Decision tree	Decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility.	(Williams, Steiner, Ahijevych & Dettling, 2008)
AI algorithms (hyponyms)	Random forest	Ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. The output of the random forest is the class selected by most trees.	(Siddiqui, Abdel-Aty & Huang, 2012)
	Naïve-Bayes	Family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong (naïve) independence assumptions between the features.	NA
	k-means	Clustering method of vector quantization that aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean.	(Ryerson & Kim, 2013)
	Nearest neighbor	Non-parametric method used for classification (classes) or regression (values) in which the input consists of the k closest training examples in the original data set.	(Chen, Dang, Liang, Zhu & He, 2018)
	Support Vector Machine	Supervised learning models with associated algorithms that analyze data for classification and regression analysis based on finding high-dimensional hyperplanes that distinctly classify the data points.	(Wanke & Barros, 2017)
	Neural Networks	Algorithms that mimic the operations of a human brain (based on the mathematical interconnection of a network of neurons) in order to recognize relationships between vast amounts of data and used in a variety of applications.	(Barros & Wanke, 2015)