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From Descriptive to Prescriptive Analytics: Turkish Airlines Case Study

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Abstract
Recent years, evolving technologies have increased importance of data analytics and have extended the potential of using data-driven for decision-making process in different sectors as it has also been shown in civil aviation. The aviation industry supports $2.7 trillion (3.5%) of the world's GDP thus, it has always been seen to have an inherently strategic role. Propose of this study is an integrated model that combines descriptive analytics (multidimensional analytics) predictive analytics (data mining and more) and prescriptive analytics (MCDM/DEMATEL) in order to extract the critical factors for the improvement of airline baggage optimizations. The data has taken from Turkish Airlines which is one of the biggest 10 airlines in terms of the passenger number. Descriptive analytics results have set a precedent implication of multidimensional reports for service sector. In addition, rules that arise as outcomes of predictive analytics have really significant knowledge for marketing and planning department in civil aviation. Furthermore, they will help to solve some optimization problem in air transportation sector. Owing to prescriptive analytics, displayed results supported by the MCDM (DEMATEL) methods. Therefore, all stages of the analytics have been shown step by step on the real-world data implementation.

Keywords
Analytics, Decision Support Systems, Air Transportation, Civil Aviation, Descriptive, Predictive, Prescriptive

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Tanımlayıcı Analizden Öngörüsel Analize: THY Vaka Çalışması

Özet

Son yıllarda gelişen teknolojiler, veri analitiğinin önemini artırmış ve sivil havacılıkta da görüldüğü gibi farklı sektörlerde karar verme süreçlerinde veri odaklı kullanım potansiyelini genişletmiştir. Havacılık endüstrisi, dünya GSYİH'sının 2,7 trilyon dolarını (%3,5) desteklemektedir, dolayısıyla her zaman doğası gereği stratejik bir role sahip olduğu görülmüştür. Bu çalışmanın önerisi, havayolu bagaj optimizasyonlarının iyileştirilmesi için kritik faktörleri çıkarmak amacıyla tanımlayıcı analitiği (çok boyutlu analitik), tahmine dayalı analitiği (veri madenciliği ve daha fazlası) ve normatif analitiği (MCDM ve DEMATEL) birleştiren entegre bir modeldir. Veriler, yolcu sayısı bakımından en büyük 10 havayolundan biri olan Türk Hava Yolları'ndan alınmıştır. Tanımlayıcı analitik sonuçları, hizmet sektörü için çok boyutlu raporların emsal teşkil etmesini sağlamıştır. Ayrıca öngörü analitiği sonucunda ortaya çıkan kurallar, sivil havacılıkta pazarlama ve planlama departmanı için gerçekten önemli bir bilgi birikimine sahiptir. Ayrıca, hava taşımacılığı sektöründeki bazı optimizasyon problemlerinin çözülmesine yardımcı olacaklardır. Öngörü analitiği sayesinde, MCDM ve DEMATEL yöntemleri tarafından desteklenen sonuçlar görüntülenir. Bu nedenle, analitiğin tüm aşamaları gerçek dünya veri uygulaması üzerinde adım adım gösterilmiştir.

Anahtar Kelimeler

Analitik, Karar Destek Sistemleri, Hava Taşımacılığı, Sivil Havacılık, Tanımlayıcı, Öngörücü, Kuralcı

Introduction

Developing computer and software technologies and analytics techniques are one of the biggest supporters of aviation (Enrico and et al., 2019). The sector encompasses a huge amount of data, and many airlines and airports cannot manage and process the amount of data they receive, but such data could be used to increase profitability or to revolutionize the passenger experience (Gössling and et al., 2019; Insaurralde and et al., 2022). The vast amount of data produced related to passenger flow, cost reduction and revenue enhancement is too much to handle for most small airline IT departments (Akerkar, 2014).

Air transport has always been seen to have an inherently strategic role (Abdi & Càmara-Turull, 2022). It has obvious direct military applications, but it is also highly visible and, for a period, and in some countries still, was seen as a "flag carrier", a symbol of international commercial presence (Mlepo, 2022). From its earliest days, airlines were seen as having potential for providing high-speed mail services, and subsequently medium and long-term passenger transport. With 35 million flight departures per year, data is critically important for any planning decision made by airlines and airports (Schultz and et al., 2022). Air traffic control, navigation, cargo and airport facilities have also improved considerably, and more recently the underlying management structure of the supplying industries has enhanced efficiency (Yilmaz and et al., 2022).

Air transportation is a major industry in its own right and it also provides important inputs into wider economic, social and political processes. The aviation industry supports $2.7 trillion (3.5%) of the world's gross domestic product, GDP (Hubbard & Williams, 2017) with contributes $664.4 billion directly from airlines, $892.4 billion from tourism and more other such us subsidiary manufacturing industries. Compared with the GDP contribution of other sectors, the global air transport industry is larger than the automotive industry, which accounts for 1.2% of global GDP and chemicals manufacturing 2.1% (Káposzta, 2016). The world's airlines carry over three billion passengers a year and 50 million tons of freight (Kumar, 2022). Providing these services generates 9.9 million direct jobs within the air transport industry and to global GDP (Piccioni and et al., 2022).

Hiding Cost for Airlines

While airlines set the fares and fees for air travel, carrying all materials also come with extra costs. Every item on board makes a plane heavier, which burns more fuel (Bussemaker and et al., 2022). An airliner's cost of operating rises with every laptop (33 cents per flight), pillow (6 cents), or magazine (5 cents) passengers bring along. According to MIT aeronautical engineers Luke Jensen and Brian Yutko researches, used a set of typical flight conditions to analyze how specific items add up on airlines over a normal day. It's shows that during one year on a Boeing 737-800 (which is a one of the most popular narrow body aircraft), even small things add up to big costs on table 1. (Stone, 2017)

Table 1. Carriying Items Cost (calculated based on THY flights in 2017).

Items	One Cost	All Cost (For all Flights)	Total Cost (For all Passengers)
Carry-on Bag (8 Kg)	USD 464,00	USD 148.944,00	USD 32.767.680,00
Video Console	USD 216,00	USD 69.336,00	USD 15.253.920,00
Suitcase (22 Kg)	USD 1.545,00	USD 495.945,00	USD 109.107.900,00
Meal Tray	USD 31,00	USD 9.951,00	USD 2.189.220,00
Water Bottle (500 Ml)	USD 37,00	USD 11.877,00	USD 2.612.940,00
Laptop (2 Kg)	USD 138,00	USD 44.298,00	USD 9.745.560,00
Cell Phone	USD 12,00	USD 3.852,00	USD 847.440,00
Magazine	USD 22,00	USD 7.062,00	USD 1.553.640,00
Total	USD 2.465,00	USD 791.265,00	USD 174.078.300,00

Aviation Business Analytics

Before elaborate the business intelligence (BI), there is a need for mentioning Business Analytics (BA) in order to resolve incomprehensibility. Business intelligence and analytics are two processes that involve different tools and serve different purposes (Patriarca and et al., 2022). BI is the main topic which has cover infrastructure of the systems, analytics, reporting and visualization. At this point, BA is one of the stage the business intelligence process (Baars & Kemper, 2008). In fact, BI includes all components of the data operation, from when data is collected to when it is accessed (Minelli, 2012). Analytics, on the other hand, is the process performed on data that has been delivered by BI for the purpose of generating insights to drive decisions, actions and, eventually, revenue or other impacts (Enholm and et al., 2022).

Recent years, evolving technologies have increased importance of data analytics and have extended the potential of using data-driven in decision-making process (Elgendy and et al., 2022). Business Intelligence (BI) represents analytical tools and systems that allow a company to gather, store, access and analyze corporate data to aid in decision-making models and strategic planning process. BI encompasses internal system and external sources to access the data that enable both decision support applications and databases (Moss & Atre, 2003). Business Intelligence tools are handling spread several service industries; such as “Finance and Insurance, Health, Tourism, Telecom, Transportation” in order to improve operational efficiencies, increase customer retention and develop a solid Customer Relationship Management strategy (Yalcin and et al., 2022). This paper will focus on the all different dimension Business Analytics: Descriptive, Predictive and Prescriptive Analytics respectively and will be shown the applications of civil aviation industry.

Descriptive and predictive analytics are beneficial for decision maker not only aviation industry but also all services sectors (Chen and et al., 2012). Notwithstanding, there’s novel data-driven solution about the operational problems that’s poised to make positive changes: prescriptive analytics. Moreover, prescriptive analytics will start replacing and improving the classic model of predictive analytics (Salah & Srinivas, 2022). Today, much of the airline industry uses data for predictive analytics. For example, predictive works can give specific information in order to operations such as flights profiling with personnel data and statistics. Prescriptive analytics, on the other hand, goes further than making predictions (Susnjak and et al., 2022). It applies business intelligence to prescribe optimal solutions for an operational problem. That is, it clearly tells manages what the next steps should be at any given moment – such as, to optimize is or make a decision depending on multi creation techniques for a simplified example. While using good judgement should always be a priority for airline decision makers, it doesn’t hurt to have an intelligent system that prescribes the next steps (O’hare, 1992).

Briefly, the purpose of the paper demonstrates the application from descriptive to prescriptive analytical process in order to improve usable result examples in air transportation. The subsequent sections of the study are organized as follows: the literature on business analytics in civil aviation industry will be examined in the second part and the methodological framework will be presented in the third section. The empirical findings will be provided in the subsequent part and the evaluation and inferences of the findings will take place in the final section.

Business Analytics and Civil Aviation

Nowadays increasing of the globalization and integration of the world, one of the most notable part of the transportation sector is civil aviation sector, has grown at an average annual 5% since 1980 (IATA, 2016). Air transport provides a significant boost to economic development. An ongoing increase in unique city-pair routes has helped to enable the flow of goods, people, capital, technology, and ideas. The number of unique city-pair connections exceeded 18,400 in 2016, over 700 more than in 2015 and almost double the connectivity by air 20 years ago (Zheng and et al., 2018). It is estimated that aviation supported 67.7 million supply-chain jobs in 2016 and underpinned $3.0 trillion in value-added output globally. IATA estimates that air travelers spent around $650 billion in 2016. The value of international trade shipped by air, meanwhile, was $5.5 trillion in 2016 (O'neill, 2017).

Civil aviation sector is generated large amounts of data that are flights information, passengers' data, cost expenditure input mainly based upon fuels prices and employee cost, the information of airspace of countries and other political relations (Tian and et al., 2021). The huge amount of data lead to utilize of Business Intelligence tools especially diverse Data Mining technics and applications in an aviation industry.

The development of computerized reservations systems (CRSs) began in the 1950s, when American Airlines partnered with IBM in order to that purpose. (McKenney & et al., 1995). To illustrate, "Semi Automated Business Research Environment" which is called as SABRE; supplied airline reservations agents to manage the distribution process, both as well as centralized reservations office and other ticketing offices which are can be city, airport or another country. SABRE was "the first real-time business application of computer technology, an automated system with complete passenger records available electronically to any agent connected to the SABRE system" (Smith & et al., 2001). The airline companies operate to both predictions future customer behavior using historical data and improve a scalable analytics service based on their current requirements (Ayhan & et. al., 2013). In this respect, BI can be very useful in involving several decision-makers with multiple criteria to arrive at optimal operational and financial solution. To illustrate, the empiric analytics studies examples in civil aviation sector in last three years and their main features has shown in Table 2

Table 2. Empirical Analytics Studies in Civil Aviation Sector in last Three Years

Cite	*Type*	*Domain*	*Technique*	*Scope*
Mobarakeh et al., 2017	Predictive	Spare Parts	Neural Network	Airport
Amirkolaai et al., 2017	Predictive	Spare Parts	Neural Network	Unspecified
Hazen et al., 2017	Descriptive	Operation	Reporting	Country
Yuan et al., 2017	Predictive	Passenger	Clustering	Country
Jacquillat and Odoni, 2017	Descriptive	Operation	Visualization	Airport
Kasturi et al., 2016	Predictive	Operation	Heuristic Algorit-hms	Continent
De Luca et al, 2016	Predictive	Spare Parts	Clustering	Airport
Hansman et al., 2016	Predictive	Operation	Clustering	Country
Kalakou et al., 2015	Prescriptive	Airport	Simulation	Airport
Denman et al., 2015	Descriptive	Queue	Exploratory	Airport
Guerra-Gomez et al, 2015	Descriptive	Passenger	Visualization	Country

The descriptive analytics includes historical data analytics using data aggregation and data mining (Belhadi and et al., 2019). Descriptive analytics, which describes the raw data in an intelligible form, is used by 90% of organizations. In this study, not only include descriptive analytics but also contain predictive and prescriptive analytics. In civil aviation and air transportation' studies about business analytics in the last three years has listed on Table 1. Regarding all those empirical studies, descriptive type of studies is predominant and predictive and prescriptive papers have sparsely an impact the relevant literature.

Descriptive analytics

Descriptive analysis is an important first step for conducting Business Analytics (Ain and et al., 2019). It gives an idea of the distribution of data, helps detect outliers, and enable to identify associations among variables, thus preparing for conducting further statistical analyses. The best approach for conducting descriptive analysis is to first decide about the types of variables and then use approaches for descriptive analysis based on variable types. Broadly, variables can be classified into quantitative and categorical. Quantitative variables represent quantities or numerical values while categorical variables describe quality or characteristics of individuals (Kaliyadan & Kulkarni, 2019).

Descriptive statistics are used to describe the basic features of the data in a study (Mishra and et al., 2019). They provide simple summaries about the sample and the measures. Together with simple graphics analysis, they form the basis of virtually every quantitative analysis of data. Descriptive techniques often include constructing tables of means and quantiles, measures of dispersion such as variance or standard deviation, and cross-tabulations or "crosstabs" that can be used to examine many disparate hypotheses.

One of the most popular descriptive analytics is multidimensional data graphs which is also known data cubes. A data cube refers is a three-dimensional (3D) (or higher) range of values that are generally used to explain the time sequence of an image's data. It is a data abstraction to evaluate aggregated data from a variety of viewpoints. It is also useful for imaging spectroscopy as a spectrally-resolved image is depicted as a 3-D volume. A data cube can also be described as the multidimensional extensions of two-dimensional tables. It can be viewed as a collection of identical 2-D tables stacked upon one another. Data cubes are used to represent data that is too complex to be described by a table of columns and rows. As such, data cubes can go far beyond 3-D to include many more dimensions (Hoffmann and et al., 2019).

Predictive analytics

Predictive analytics is a category of data analytics aimed at making predictions about future outcomes based on historical data and analytics techniques such as statistical modeling and machine learning (Selvan & Balasundaram, 2021). The science of predictive analytics can generate future insights with a significant degree of precision. With the help of sophisticated predictive analytics tools and models, any organization can now use past and current data to reliably forecast trends and behaviors milliseconds, days, or years into the future.

Predictive analytics draws its power from a wide range of methods and technologies, including big data, data mining, statistical modeling, machine learning and assorted mathematical processes (Amalina and et al., 2019). Organizations use predictive analytics to sift through current and historical data to detect trends and forecast events and conditions that should occur at a specific time, based on supplied parameters. With predictive analytics, organizations can find and exploit patterns contained within data in order to detect risks and opportunities. Models can be designed, for instance, to discover relationships between various behavior factors. Such models enable the assessment of either the promise or risk presented by a particular set of conditions, guiding informed decision-making across various categories of supply chain and procurement events. Thanks to predictive analysis, it may predict the impact of specific maintenance operations on aircraft reliability, fuel use, availability and uptime (Ren and et al., 2021).

One of the most popular predictive analytics technics is Data mining (Abu Saa and et al., 2019). It is the process of finding anomalies, patterns and correlations within large data sets to predict outcomes. Using a broad range of techniques, you can use this information to increase revenues, cut costs, improve customer relationships, reduce risks and more. Clustering analysis is a data mining technique to identify data that are like each other (Gupta & Chandra, 2020). This process helps to understand the differences and similarities between the data. The aim of the clustering is to identify homogenous subgroups of instance in a population. In this tutorial, we implement a two-step clustering algorithm which is well-suited when we deal with a large dataset. It combines the ability of the K-Means clustering to handle a very large dataset, and the ability of the Hierarchical clustering (HCA – Hierarchical Cluster Analysis) to give a visual presentation of the results called "dendrogram". This one describes the clustering process, starting from unrefined clusters, until the whole dataset belongs to one cluster. It is especially helpful when we want to detect the appropriate number of clusters.

Cluster is a group of objects that belongs to the same class. In other words, similar objects are grouped in one cluster and dissimilar objects are grouped in another cluster (Jiang and et al., 2020). Clustering is the process of making a group of abstract objects into classes of similar objects. Data mining covers a lot of different tools include Two-Step algorithms. Two–Step Clustering method which is developed in recent years and one of the best methods for data sets containing mixed types of variable.

Prescriptive analytics

Prescriptive analytics is the area of business analytics (BA) dedicated to finding the best course of action for a given situation (Frazzetto and et al., 2019). Prescriptive analytics is related to both descriptive and predictive analytics. While descriptive analytics aims to provide insight into what has happened and predictive analytics helps model and forecast what might happen, prescriptive analytics seeks to determine the best solution or outcome among various choices, given the known parameters (Lepenioti and et al., 2020).

Prescriptive analytics can also suggest decision options for how to take advantage of a future opportunity or mitigate a future risk and illustrate the implications of each decision option. In practice, prescriptive analytics can continually and automatically process new data to improve the accuracy of predictions and provide better decision options. All of that data being amassed by businesses can be used to describe current trends, predict what's going to happen next, and most importantly, prescribe the proper course of action a business should take to ensure success in the most efficient way possible through the process of prescriptive analytics.

DEMATEL technique can convert the interrelations between criteria into an intelligible structural model of the system and divide them into a cause group and an effect group (Chen Shyu and Huang, 2017). DEMATEL is a practicable and benefcial tool to analyze the interdependent relationships among elements in a complex framework and grade them for decision making. Tus, this technique can be used in prescriptive analytics.

DEMATEL is an exhaustive prescriptive method for setting up and analyzing an organic model involving casual correlations among complicated criteria. DEMATEL technique has two main advantages: It effectively analyzes the mutual influences which are direct and indirect effects among separate criteria and understands the complicated cause and effect relations in the decision-making problem. DEMATEL can be used not only to determine the ranking of alternatives, but also to find out critical evaluation criteria and measure the weights of evaluation criteria.

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The formulating steps of the classical DEMATEL (Fontela and Gabus, 1976) can be summarized as follows;

Step 1: Generating the direct-relation matrix. For example, five scales for measuring the relationship among different criteria are used: 0 (no influence), 1 (low influence), 2 (normal influence), 3 (high influence) and 4 (very high influence). Decision makers prepare sets of pair-wise comparisons in terms of effects and direction between criteria. The initial data can be obtained as the direct-relation matrix which is a n × n matrix A where each element of a_{ij} is denoted as the degree in which the criterion i affects the criterion j.

Step 2: Normalizing the direct-relation matrix. Normalization is performed using the following formula,

$$X = k \times A \quad (1)$$

$$k = \frac{1}{max_{1 \le i \le n} \sum_{j=1}^{n} a_{ij}}. \ i, j = 1,2\ldots, n$$

Step 3: Attaining the total-relation matrix. Once the normalized direct-relation matrix X is obtained, the total relation matrix T can be acquired by using Eq. (3), where I is denoted as the identity matrix,

$$T = X(I-X)^{-1} \quad (3)$$

Step 4: Producing a causal diagram. The sum of rows and columns are separately denoted as vector D and vector R through equations (4-6). The horizontal axis vector (D + R) named as “prominence” is made by adding D to R, which reveals the relative importance of each criterion. Similarly, the vertical axis (D - R) called as “relevance” is made by subtracting D from R, which may divide criteria into a cause and effect groups (Chen, 2012). Generally, when (D - R) is positive, the criterion belongs to the cause group, (D - R) is negative, the criterion represents the effect group. Therefore, the causal diagram can be obtained by mapping the dataset of the (D + R, D - R), providing some insight for making decisions.

$$T = [t_{ij}]_{n \times n} \quad i, j=1, 2, \ldots, n \quad (4)$$

$$D = \left[\sum_{j=1}^{n} t_{ij} \right]_{n \times 1} = [t_i]_{n \times 1}$$

$$R = \left[\sum_{i=1}^{n} t_{ij} \right]_{1 \times n} = [t_j]_{1 \times n}$$

where vector D and vector R denote the sum of rows and columns in total-relation matrix $T = [t_{ij}]_{n \times n}$.

Step 5: Obtaining the inner dependence matrix. In this step, the sum of each column in total-relation matrix is equal to 1 by the normalization method, and then the inner dependence matrix can be acquired.

Methodology

The study being reported in this paper follows a sequential procedure composed of the steps: (1) data selection and transformation; and (2) model building and interpretation.

In this paper, data has taken from Turkish Airlines which is one of the biggest 10 airlines in terms of the passenger number. Although this airline is not the most points in the globe, but it is the airline that flies to most different countries. Because of this, they have very different passenger and baggage profiles. Dataset is consisted of 855.250 different flights and has included 115.629.955 passengers from 2014 to 2015. The time phrase and domestic flights knowledge, international and local pass passenger information take part in dataset that picked out the flights which are departure from Istanbul. International flights were selected as the most likely to be able to explain the pattern of operation therefore only left about 230.000 records. Lastly, some of them was deleted because of validation and incompletion of the data as it mentioned before and eventually has been left 229.465 flights which are from Istanbul to international point in during in 2014 and 2015. This flight has different types of attributes such as; time, location, number of the total passenger, number of the luggage, business and infant passenger rates and the distance of arrival airports. The dataset consists of 21 different attributes and more than two hundred flights were questioned on their operational feature. The most accurate, holistic and appropriate data for analysis are considered as 2014 and 2015 data due to reasons such as airport terrorist incidents, moving to a new airport, and pandemics that occurred after 2015.

In data preprocessing step, data has both outlier due to the compressive flights and missing value however they are removed after checking flights codes, because only scheduled flights were taken into account (Ahmad and et al., 2022). Approximately, 21 different flights are omitted because of no passenger and baggage information, which is less than 0.003 % of whole flights. Moreover, for the study, some missing distance and some region values were added which is identified on the Turkish Airlines website. After data preprocessing step, this study focusses on about 230.000 flights from Istanbul to 247 different airports. All these flights took place to 4 continents, 11 regions and 112 different countries.

The three research methodology paradigms and using business intelligence tools are shown on Table 2 detailed with the form of the headings.

Table 3. Summary of the Method.

Types of Analytics	***The Main Purpose***	***Questioned Answers***	***BI Methods / Techniques and Tools***	***Variables Used***
Descriptive	To describe the data for state main data structure	What is the data pattern of passenger luggage based upon the number and weight?	Exploratory Data Analysis and Multidimensional Reporting / OLAP Cubes	All attributes
Predictive	To determine customer profile and discovering insights about the future	What will be happened on the future behavior that relates to the profile of passenger baggage for different country and flight type?	Data Mining / Twostep Clustering & K-Means Clustering and Association Rules	Number of Baggage Weight of Baggage Arrival Information CI rate, Yclass Rate Number of Passengers
Prescriptive	To support the predictive results, define the attributes' degrees of impact and feeding advice for decision makers with meaningful results	What should be done to give an advice on possible outcomes using optimization and simulation algorithms, such as put forth some association rules depending on all those analytics and their results?	Multiple Criteria Decision Making / DEMATEL	Average Passenger Baggage Quantity Baggage Weight Y (Economy) Class Rate Infant + Child Passenger Rate Flights Number Distance Region Cluster Numbers

In addition to our primary questions above, we may also be looking for answers of the following question: Can be used an online analytical processing and multidimensional cubes in civil aviation sector and is it possible to promotes and support predictive analytics outputs such as association rules, with Decision-Making Trial and Evaluation Laboratory (DEMATEL) method for making futuristic analytics?

The aim of this study is to follow from descriptive to prescriptive analytical process in order to improve usable result examples in air transportation. In descriptive analytics phase, descriptive statistics are employed to describe the basic features of the data in a study and help the systems what happen in the past (Trochim & Donnelly, 2001). Second phase is predictive analytics, which tries to give a recommendation for key decisions based on future outcomes and focuses on answering the question: "What is probably going to happen in the future?". Predictive analytics provides organizations with actionable insights based on data and estimation regarding the likelihood of a future outcome via a variety of techniques, such as machine learning, Data Mining, modelling and game theory (Dhar, 2013). Firstly, TwoStep clustering technique is used to the determined the cluster number. Secondly, K means is one of the common algorithm which uses unsupervised learning method to solve all known clustering issues (Krishna & Murty, 1999; Jain, 2010). It is appropriate for large datasets and it has strong sensitivity to any outliers (Huang, 1998; Zhao, Ma & He 2009). Lastly, about the association rules, the more then 75 % of the results have taken notice. Prescriptive analytics could have a huge effect on all business and how determinations are made and it can impact any industry, organization and systems and help them become more effective and efficient (Delen & Demirkan, 2013). To demonstrate, prescriptive analytics can optimize your scheduling, production, inventory and supply chain design to deliver the right products in the right amount in the most optimized way for the right customers on time. Taking the results from the descriptive and prescriptive analytics throughputs, attributes have been assessed in order to interview with sectoral experts. For the prescriptive analytics phase, DEMATEL method has been developed interview questionnaire and also results reliability and their validity.

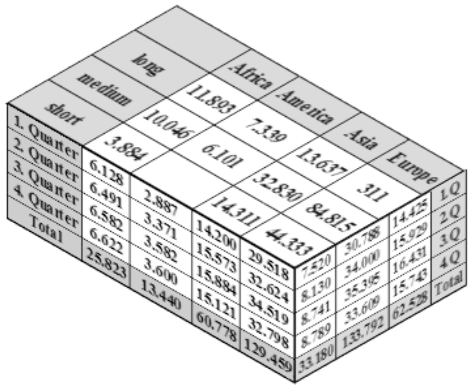
Results of Analytics

Descriptive Analytics Results

It is a common knowledge that every item on board makes a plane heavier therefore burns more fuel. An airliner's cost of operating rises with every laptop (33 cents per flight), pillow (6 cents), or magazine (5 cents) you bring along (Stone, 2017). The luggage values in the different flights have difference between them based on distance and countries. To better understand this state of affairs, it is necessary to make the country and the distance-based profiling.

According to dataset, there are about 31 million passengers on 229,465 flights in 2014 & 2015. Their average luggage quantity is 1.12 per person and its weight is 19.21 kg. The multidimensional cubes such as Figure 1, which include 3 main layers; region, time and distance, shows that company's main target is Middle Europe, Middle East and South Europe which have more number of passengers and flights. However, these are more than half of the company flights the business rate of the America flights has reached about 11 percent therefore the firm can increase the business class seat number or they may focus for the business passenger.

Figure 1. Descriptive Analytics Cube by Flights.



There is relationship between distance and luggage weights. When people fly long haul, they need more luggage. To explain the data pattern of luggage, the relationship between the distance and luggage have not enough the power of knowledge. For this reason, predictive analytics is used to discover of data pattern.

Predictive Analytics Results

Clustering is the process of grouping the data into clusters, so that objects within a cluster have high similarity in comparison to one another but are very dissimilar to objects in other clusters (Han and Kamber, 2006: 381). Many clustering algorithms exist in the literature. It is difficult to categorize the clustering methods because each category may overlap, so that a method may have features from several categories. In this study, hierarchical methods and partitioning methods are used to determine the clusters.

TwoStep clustering algorithm is a popular algorithm that falls into hierarchical methods. A hierarchical method creates a hierarchical decomposition of the given set of data objects. Partitioning algorithms are clustering techniques that subdivide the data sets into a set of k groups, where k is the number of groups pre-specified by the analyst. There are different types of partitioning clustering methods. The most popular is the K-means clustering (MacQueen 1967), in which, each cluster is represented by the center or means of the data points belonging to the cluster. The K-means method is sensitive to outliers.

In this study, the strategy that is to first apply a hierarchical agglomeration algorithm, which determines the number of clusters and finds an initial clustering, and then use iterative relocation to improve the clustering. Initial cluster number was determined by using two-step technique as three clusters. K-Means classify technique applied that the cluster numbers picked 3, and iteration numbers picked 100, but only 34 iterations took places. The number of cases in each cluster is shown Table 4.

Table 4. Number of Cases in each Cluster.

Cluster	1	126795.0
	2	85879.0
	3	16791.0
Valid		**229465**.0

And the average value of clusters is shown in Table 5.

Table 5. Average Values of Cluster

	Cluster		
	1	**2**	**3**
Average Baggage Quantity	.9475	1.2386	1.7746
Average Baggage Weight	15.3741	21.8942	34.4425

Lastly, its derived some association rules with generalized rule induction (GRI) algorithms with the cluster results. Association rules meaning is, created by analyzed data for frequent if/then and using some criteria in order to identify support and confidence for most important relationships. Table 5 shows the accuracy rates and the amount of support of the rule occurs.

Table 6. Rules Derived from Generalized Rule Induction (GRI) Algorithms.

Number	**Cluster Number**	**Rules**	**Support %**	**Confidence %**
1	CN = 1	Child Passenger < 4,5	57.2	78.79
2	CN = 1	Baggage Quantity < 141,5	54.22	76.09
3	CN = 1	Average Child Rate < 0,0272	45.89	77.12
4	CN = 1	Child Passenger < 4,5 and Passenger Number > 73,5	45	78.12
5	CN = 1	Baggage Quantity < 141,5 and Continent = Europe	36.61	86.5
6	CN = 1	Child Passenger < 4,5 and Passenger Number > 73,5 and Continent = Europe	29	84.21
7	CN = 1	Average Child Rate < 0,02725 and Continent = Europe	27.3	85.59
8	CN = 2	Child Passenger Number > 10,5	24.21	76.21
9	CN = 2	Average Child Rate > 0,0819	16.85	77.18
10	CN = 3	Baggage Quantity > 405,5	15.3	80.46

To illustrate the rules, they are related baggage weight and number, child passenger rate, business and economy passenger rate, total passenger number and also concerning location like country or region. Those rules have really significant knowledge for marketing and planning department. Moreover, they will help to solve some optimization problem in air transportation sector.

According to Table 5, in cluster number 1, total number of child and infant passenger is less than 4.5 what confidence rate is approximately 79. This is also important for airlines since they can arrange their flights take into consideration that., The cluster number 2 is included the more than 10,5 child and infant passenger per flight (Confidence rate is 76.21). While cluster number have less than 141 baggage per flight at %77 confidence rate, cluster number 3 have more than 405.5 baggage quantity in each flight at %81 confidence rate. Additionally, there are also lots of different types of rules, such that business class passenger number is less than 8.5 per flight in cluster number 2.

Prescriptive Analytics Results

In this study, the factors to be evaluated are considered based upon expert interviews. Propose of this study is an integrated model that combines descriptive analytics (multidimensional analytics) predictive analytics (data mining and more) and prescriptive analytics (MCDM and DEMATEL) in order to extract the critical factors for the improvement of airline baggage optimizations. We apply the dominance-based rough set approach to extract the essential factors. The decision-making trial and evaluation laboratory method (DEMATEL) with the clustering results are then used to construct the new evaluation and assessment system.

At first step of DEMATEL, attributes impact values have already asked to 8 different experts on working this field. The impact value which is from 0 to 4 (0 means that there are not any affect and 4 means that there are relations with those attributes a very dramatically effective) has collected each different specialist. 8 experts are asked to identify the degree of influence between the factors or elements (criteria) to calculate the average matrix of influence matrix.

Table 7. Total Influence Matrix.

Conditional Attributes	A	B	C	D	E	F	G	H	Total (Y)
A. Average Passenger (Number)	0.466	0.584	0.661	0.564	0.413	0.391	0.604	0.493	**4.176**
B. Baggage Quantity (Number)	0.610	0.510	0.719	0.521	0.406	0.527	0.658	0.619	**4.571**
C. Baggage Weight (Kg)	0.559	0.590	0.564	0.559	0.469	0.499	0.633	0.606	**4.479**
D. Y (Economy) Class Rate (%)	0.671	0.654	0.733	0.492	0.444	0.421	0.687	0.636	**4.738**
E. Infant + Child Passenger Rate (%)	0.229	0.241	0.338	0.228	0.145	0.161	0.223	0.281	**1.846**
F. Flights Number (Time)	0.588	0.549	0.597	0.449	0.348	0.328	0.477	0.548	**3.883**
G. Distance (Km)	0.654	0.614	0.674	0.596	0.360	0.405	0.496	0.506	**4.305**
H. Region	0.709	0.677	0.757	0.647	0.438	0.535	0.651	0.523	**4.937**
Total (B)	**4.486**	**4.420**	**5.043**	**4.056**	**3.023**	**3.267**	**4.428**	**4.211**	

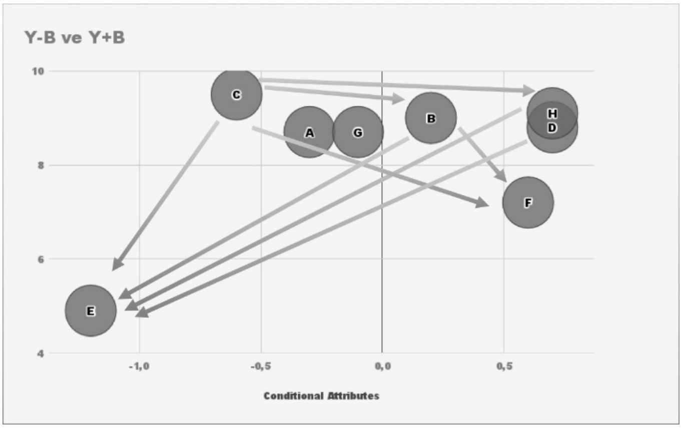
Following the step of DEMATEL method is created the total influence matrix. The total influence matrix is defined the sum of the rows and the sum of the columns separately which can be denoted as vector r and c. There shows the sum of the direct and indirect effects that factor has received from the other factors. Let $i = j$ and $i, j \in \{1,2,...,n\}$; the horizontal axis vector ($r_i + s_i$) is then made by adding r_i to s_i, which illustrates the importance of the criterion. Similarly, the vertical axis vector ($r_i - s_i$) is made by deducting r_i from s_i, which may separate criteria into a cause group and an affected group. In general, when ($r_i - s_i$) is positive, the criterion is part of the cause group. On the contrary, if ($r_i - s_i$) is negative, the criterion is part of the affected group. Therefore, a causal graph can be achieved by mapping the dataset of ($r_i + s_i$, $r_i - s_i$), providing a valuable approach for decision-making. The sum of influences is given and received on criteria will be shown in Table 7.

Table 8. Sum of Influences Given and Received on Criteria.

	Y	B	Y+B	Y-B
Average Passenger (Number)	4.176	4.486	8.663	-0.310
Baggage Quantity (Number)	4.571	4.420	**8.991**	0.151
Baggage Weight (Kg)	4.479	5.043	**9.522**	-0.564
Y (Economy) Class Rate (%)	4.738	4.056	8.794	**0.682**
Infant + Child Passenger Rate (%)	1.846	3.023	4.869	-1.177
Flights Number (Time)	3.883	3.267	7.151	**0.616**
Distance (Km)	4.305	4.428	8.733	-0.124
Region	4.937	4.211	**9.148**	**0.726**

The direction of influence between dimensions and criteria can be visualized in Figure 2. After all those analytics, the Integrated Natural Resource Management (INRM) indicates that Baggage Weight (C) is the most effective attributes can be understood from Figure 2. Moreover, Region (H) factor also may be one of the most effective and also affected ones.

Figure 2. Evaluating the Conditional Attributes Systems.



As a result of the prescriptive analytics, the conditional attributes' degrees of impacts have been identified. Moreover, predictive analytics results (cluster and rule outcomes) have been supported with DEMATEL technique. All those outcomes would give advices for decision makers with meaningful results.

Conclusion

Civil aviation as a notable part of transportation is a growing and a highly competitive sector (Abate and et al., 2020). Air transportation cover excessive different kind of job and department, like engineering issues, marketing, planning, micro/macro-economic issues and optimization. Consequently, the analytics and reporting have become crucial because aviation sector has developed rapidly via the use of information systems and they cannot be unconcerned about all kinds of business analytics. Moreover, automatically and manually accumulating information is impracticable, due to the mass amount of data produced on each flight. Airlines have adapted several business intelligence and analytics implementations in order to support decision-making activities (Phillips-Wren and et al., 2021). However, when we compared, application of business intelligence is insufficient academically. The aviation industry has been rapidly developing and evolving over the years, with a growing demand for air travel and the emergence of new technologies. As a result, airlines are facing increasingly complex challenges in various areas of their operations. Business analytics and reporting have become essential tools for airlines to improve their decision-making process and enhance their overall performance. However, the academic literature on the application of business intelligence in the aviation sector is still limited.

To address this gap, this study proposed an integrated model that combines descriptive, predictive, and prescriptive analytics to extract critical factors for improving airline baggage optimization. The findings of the study demonstrate that descriptive analytics can provide useful insights into passengers' behaviors and preferences, which can be leveraged to develop more effective marketing and planning strategies. Predictive analytics can help airlines forecast potential problems and optimize their operations, while prescriptive analytics can provide actionable recommendations for improving decision-making. The results of the study can have important implications for airlines, as they can help to optimize flight profiling, improve customer satisfaction, and enhance overall performance. However, the study also has some limitations, such as the difficulty of obtaining and handling large amounts of data, and the impact of external factors, such as political and economic crises, on airline operations.

Civil aviation is vital in many industries such as tourism, exotics, and hi-technology. Regarding the developing technology, business analytics process monitoring aims at forecasting potential problems during process execution before they occur so that these problems can be handled proactively. Several predictive monitoring techniques have been proposed in the past (Huang, & Kuo, 2019). However, so far, those prediction techniques have been assessed only independently from each other, making it hard to reliably compare their applicability and accuracy. We empirically analyze and separately put forth that, the three different types of analytics with air transportation secondary data.

Descriptive analytics results have set a precedent implication of multidimensional reports for service sector. In addition, rules that arise as outcomes of predictive analytics have really significant knowledge for marketing and planning department in civil aviation. Furthermore, they will help to solve some optimization problem in air transportation sector. Owing to prescriptive analytics, displayed results supported by the MCDM and DEMATEL methods. Therefore, all stages of the analytics have been shown step by step on the real-world data implementation.

Especially, the issued rules as a result of all analytics can be beneficial for flight profiling and optimization. The descriptive analytics consequences make an impression for profiling passengers and their behaviors. Furthermore, especially regional analytics may serve for purpose of not only long term but also short-term planning. In phase, the framework of the results obtained this article, airlines should use current and difference analytics techniques and they should adapt to evolve data technologies. And also, this study can expand by adding previous years data and it can be more effective for predicting next year situations.

This study has some of limitations and restriction. One of the most significant restraint is acquisition and attainment of the data. Because unlike the USA reach and compass the aviation data is not easy in Turkey or some developing country. Because their operation system and data statistics have open system and have public accessibility. On the other hand, in Turkey, it is very hard to attain this kind of secondary data which has gathered by company own system and acquire them. Especially it is difficult find data which has cover some financial record and passenger or employee personal data. In addition, because of the data has over 1 million rows, it's difficult to handle and contemplate.

And also, external factors have changed the data in these years. Because of the THY is the flag carrier of the Turkey, they are most affected airline company depending on political and peripheral factors. According as geopolitical circumstance in middle east and north Africa, that data was so impressed. Especially civil war in Syria, Libya and Yemen, the company has closed more than 10 flight point which has include one of the busiest line like; Istanbul-Damascus. Furthermore, terror attacks on different place and time in Turkey also affected air transportation in short term. That is also can be different study with these flights and passenger data. Political issues were not taken into account which are not close the work in this area. Besides, also some economic crisis and situation in neighborhood such as, Greece, also could affect the company flight slightly.

To further improve the application of business intelligence in the aviation industry, airlines need to adapt to evolving data technologies and develop more sophisticated analytics techniques. Additionally, future studies could expand on this work by incorporating previous years' data and examining the impact of external factors on airline operations. Overall, the findings of this study demonstrate the potential benefits of integrating different types of analytics in the aviation industry and highlight the need for further research in this area.

Discussion

Data analytics can play a critical role in the air transport sector, as it can help airlines and other companies in the industry make data-driven decisions that can improve efficiency, increase revenue, and reduce costs. Here are a few examples of how data analytics can be used in the air transport sector (Bartle and et al, 2021; Belhadi and et al., 2021; Serrano & Kazda, 2020):

- Flight scheduling and fleet management: Data analytics can be used to optimize flight schedules and fleet management. By analyzing data on flight patterns, weather conditions, and maintenance schedules, airlines can make more efficient use of their aircraft and crew, which can help reduce costs and increase revenue.

- Passenger demand forecasting: Data analytics can be used to forecast passenger demand, which can help airlines plan their schedules and inventory more

effectively. By analyzing data on historical passenger demand, airlines can predict future demand and make more accurate decisions about how many flights to schedule, how many seats to allocate, and how much cargo to carry.

- Pricing and revenue management: Data analytics can be used to analyze data on pricing, passenger demand, and competitor behavior to develop dynamic pricing strategies that can help airlines increase revenue. For example, using data analytics, airlines can optimize pricing based on factors such as flight time, route, class of service, and passenger demand.

- Maintenance and operational performance: Data analytics can be used to monitor and analyze data on the operational performance and maintenance of an airline's fleet. This can help identify trends, patterns and potential issues with the fleet and help the airline to schedule maintenance and repairs more efficiently, reducing downtime and costs.

- Customer Relationship Management: Data analytics can also be used to analyze data on customer behavior and preferences, which can help airlines improve their customer service and create personalized marketing campaigns. With the help of data analytics, airlines can understand customers' preferences and behaviors and tailor their services to better meet customers' needs.

On the other hand, the COVID-19 pandemic has had a significant impact on the civil aviation industry (Li, 2020; Su and et al., 2022; Arora and et al., 2021). Many countries have implemented travel restrictions and quarantine measures, leading to a significant decline in the number of flights and passengers. This, in turn, has resulted in a decline in revenue for airlines and other related businesses. Many airlines have had to reduce their flight schedules and even temporarily ground their fleet of aircraft. This has led to job losses and furloughs for many employees in the industry, including pilots, flight attendants, and ground staff. Additionally, many airlines have had to seek financial assistance from governments and other organizations in order to stay afloat during the crisis.

Data analytics is revolutionizing the air transport industry by providing insights that enable companies to make data-driven decisions that improve efficiency, increase revenue and reduce costs. However, the COVID-19 pandemic has presented unprecedented challenges to the industry, and it has underscored the need for data analytics to help companies navigate these challenges. The pandemic has led to significant changes in consumer behavior, with many people opting for remote work and virtual meetings. This has impacted the demand for air travel and created uncertainty for the industry's future. However, companies that are leveraging data analytics to monitor these changes in consumer behavior will be better positioned to adapt and thrive.

One area where data analytics can be particularly useful is in predicting passenger demand. With the help of data analytics, airlines can make more accurate decisions about how many flights to schedule, how many seats to allocate, and how much cargo to carry. This can help reduce waste and improve operational efficiency, resulting in cost savings and increased revenue. Data analytics can also be used to optimize pricing strategies by analyzing data on pricing, passenger demand, and competitor behavior. Dynamic pricing can be implemented based on various factors such as flight time, route, class of service, and passenger demand. This can help airlines increase revenue and remain competitive in a challenging market. In addition to passenger demand and pricing, data analytics can also help airlines optimize flight schedules and fleet management. By analyzing data on flight patterns, weather conditions, and maintenance schedules, airlines can make more efficient use of their aircraft and crew, which can help reduce costs and increase revenue. Finally, data analytics can help airlines improve customer relationship management by analyzing customer behavior and preferences. With this information, airlines can create personalized marketing campaigns and improve customer service, resulting in higher customer satisfaction and loyalty.

The decline in air travel has also had a ripple effect on other industries, such as tourism and hospitality (Abrar and et al., 2021; Yu and et al, 2020). Hotels, resorts, and other tourism-related businesses have seen a decline in revenue as fewer people are traveling for leisure or business. Airports, too, have seen a decline in revenue from decreased traffic and from concessions and other airport businesses shutting down.

The pandemic has also affected the long-term demand of air travel. Many companies and individuals have found that they can conduct business remotely, and this may permanently impact the need for frequent business travel. The long-term effects on the civil aviation industry are still uncertain, but it's likely that the industry will fully from the impact of the pandemic rapidly. In short, data analytics is becoming a powerful tool for airlines and other companies in the air transport sector. By leveraging data, companies can improve efficiency, increase revenue, and reduce costs, which can help them better compete in a challenging and rapidly changing market. In conclusion, the air transport industry can benefit significantly from data analytics. By leveraging data, companies can improve efficiency, increase revenue, and reduce costs, which can help them better compete in a challenging and rapidly changing market. The COVID-19 pandemic has created unprecedented challenges for the industry, but companies that continue to invest in data analytics will be better positioned to adapt and thrive in the post-pandemic world.

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