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A Business Intelligence Solution For Ticket Sales Management In Sintra's UNESCO Cultural Heritage

Yu Song

Project Work

presented as partial requirement for obtaining the Master Degree Program in Data Science and Advanced Analytics

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A BUSINESS INTELLIGENCE SOLUTION FOR TICKET SALES MANAGEMENT IN SINTRA'S UNESCO CULTURAL HERITAGE

by

Yu Song

Project Work report presented as partial requirement for obtaining the Master's degree in Advanced Analytics, with a Specialization in Business Analytics

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

[Yu Song]

[Lisbon, 2022/10/03]

ABSTRACT

The tourism industry has experienced huge growth of business volume in recent years leading to a rapid increase in the amount of data being generated. To leverage these data, tourism companies can greatly benefit from incorporating business intelligence tools in their daily operations, which can contribute to the creation of new value and to sustainable growth. In this work, we develop a business intelligence solution for Parques de Sintra - Monte da Lua (PSML), a public company that manages ticket sales for some of the most visited cultural attractions in Portugal, which are part of the UNESCO Cultural Heritage. We optimize their current transactional database structure for data analysis by following a dimensional modelling methodology. Then, we develop three dashboards on top of the resultant model. Each dashboard aggregates different visuals and provides information from different perspectives of the business, namely sales, attractions, and customers. We analyse the layout and visualization capabilities of the dashboards and provide insights regarding data interpretation. With this work, we provide the PSML team with a tool that can aid in the quick monitoring of their business at different levels and has the potential to inform decisions and strategies in the areas of sales, logistics, advertising, and customer satisfaction.

KEYWORDS

Tourism management; Data visualization; Business Intelligence; Ticket management; Cultural tourism

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1. INTRODUCTION

Companies that can retrieve insightful information from data stored in daily transaction activities have a competitive advantage in the industries and markets in which they operate (Nyanga et al., 2019). As such, information management systems and reporting tools that allow for insightful data visualization and analysis are increasingly being used. Companies and institutions that wish to apply these Business Intelligence solutions are required to continually store data and structure their databases to optimize the process of data reporting (Pencarelli, 2020). In this context, tourism companies that adhere to information management systems, at the level of database management (Lopes et al., 2019) and business intelligence solutions (Vajirakachorn & Chongwatpol, 2017), as means to improve their revenue (Fuchs et al., 2014), advertisement (Chugh & Grandhi, 2013) and customer satisfaction (Berezina et al., 2016), as well as cultural and landscape preservation (Yang & Han, 2020), can do so in a smart and sustainable manner, one that ensures present and future desirable outcomes (Fuchs et al., 2013). Business intelligence (BI) approaches have been applied in various aspects of the tourism industry such as hotel performance (Girsang et al., 2017; Lau, 2020; Lavrador & Laureano, 2019), tourism destination management (Höpken et al., 2015) and social media analysis (Hyseni, 2017; Marine-Roig & Anton Clavé, 2015b; Miah et al., 2017). Specifically, in culture tourism, BI techniques have also been applied in recent years for user-generated content analysis (Qi et al., 2018) and tourism information systems (Angelaccio et al., 2013; Lopes et al., 2019).

In this work, we follow current advances in the tourism industry and develop and implement a Business Intelligence solution for Parques de Sintra - Monte da Lua S.A. (PSML). PSML is a public company responsible for managing, promoting, and protecting the UNESCO cultural landscape of Sintra, Portugal. The company manages around 45% of the World Heritage area in Sintra, including the famous Parks of Pena and Monserrate, and important cultural buildings such as the Palaces of Pena and Monserrate, the Moorish Castle, and the National Palaces of Sintra and Queluz. These sites receive millions of visitors annually, mostly from other countries, and are a core part of the Portuguese touristic sector, both in terms of the revenue generated and cultural heritage. Currently, PSML is storing all the data generated in day-to-day business operations in a relational database format. The data stored is related to sales values and tickets sold for their cultural attractions, the different modalities of tickets and payment methods, as well as some information regarding their clients, including their origin. Since the data is managed in an OLTP environment, despite being able to query the data on-demand, PSML is lacking an overarching view of their business at different levels, namely for sales, customers, and cultural attractions. We created a new data model for the company, one that is optimized for data analysis and reporting. Moreover, we developed three dashboards compiling dynamic visualizations that aim at providing insightful information regarding ticket sales patterns. The implemented solution provides PSML with a tool for the company to incorporate practices of smart and sustainable tourism, by aiding decision making through the gauging of business metrics and supporting the formulation of business strategies that contribute directly to ticket sales management efficiency and, indirectly, to cultural heritage preservation.

We must say that during the development of this research, we have submitted a paper accepted to Journal on Computing and Cultural Heritage.

2. LITERATURE REVIEW

Business intelligence (BI) is a broad term that includes all the processes, applications and technologies required for gathering, storing, accessing, analysing and visualizing business data for the purpose of operative and strategic decision-making (Kimball & Ross, 2015). Therefore, it is widely applied in the tourism industry because of its ability to provide data-driven decisions in an industry that is increasingly complex, fast-paced and a competitive global business (King et al., 2000). Experts in the tourism industry can keep abreast of company dynamics by evaluating and monitoring touristic data, helping companies to improve revenue (Blagojević et al., 2020), estimate the market share (Ashiabor et al., 2007) obtain competitors' information (Vizjak et al., 2010) and support operational business decisions such as service positioning and pricing (Mariani et al., 2018).

Several studies have explored various aspects of business intelligence applications in the tourism sector (Vajirakachorn & Chongwatpol, 2017). For instance, to demonstrate how knowledge creation, exchange, and application procedures for the Swedish tourism destination can be enhanced, Fuchs et al. (2013) described a business intelligence method centred on online analytical processing (OLAP). By analysing more than 100,000 relevant travel blogs and online travel reviews, Marine-Roig & Anton Clavé (2015) studied the online image of Barcelona to support smart destinations. The author proposes a method of massive gathering, cleaning up, and analysis of tourism-related user-generated content data, leading to enhanced branding and positioning strategies among tourism and marketing firms. Miah et al. (2017) proposed an approach to extract, rank, locate and identify meaningful tourist information from social media-generated big data to support strategic decision-making in tourism destination management. The authors used geotagged photos uploaded by tourists on Flickr and Melbourne, Australia, demonstrating the applicability of the method in assisting destination management organizations in analysing and predicting visitor behaviour patterns in specific destinations. In a large hotel chain in Indonesia, Girsang et al. (2017) used Kimball's (1996) methodology to build a data warehouse to integrate the data sources for providing fast and accurate access to information and reports from each branch to make decisions. The reports were used to explain regional information such as rooms, guests and amounts to help with decision making. In Kosovo, (Hyseni, 2017) analysed the top thirty things to do based on the reviews on TripAdvisor[1]. The data were web scrapped and imported into Power BI[2] where visualizations were made to provide valuable information about specific attractions and to support the government and local companies in enhancing tourist satisfaction. Addressing similar problems, Lavrador and Laureano (2019) utilized the BI tools to monitor the performance of the Hotel Resort& SPA from the perspective of its financial officer. Dashboards were built focusing on Key Performance Indicators relating to the financial situation and accommodation to define the preferences of tourists. Blagojević et al. (2020) used the public open data of the Republic of Serbia to analyse tourists in the last decade. Power BI was used to overview different types of touristic activities by Serbian regions and helped to identify the key factors which could lead to an increase in tourist visits and revenue.

Although with less frequency, BI solutions have also been applied to cultural tourism. In their research, de Mooij et al. (2022) searched for patterns that might be applied to data from archives, museums, and other institutions that deal with cultural property. They highlighted three interconnected problems—query formulation, source selection, and data source alignment—that researchers may run into while querying such distributed data sources. To tackle these issues, the authors presented a multiagent architecture and presented about a prototype implementation of the design using multiple technologies. Sarti et al. (2022) concentrated primarily on the technical material collection, classification, and divulgation that led to the creation of a large open-source technical database, which

1 https://www.tripadvisor.com

2 https://www.powerbi.com

supported the work of conservators, restorers, and researchers for preserving our Cultural Heritage in response to the challenges encountered in the digitization of photographic and filmic material. Origlia et al. (2021) organize information on cultural heritage from Wikidata, Wikipedia, and Flickr into a unified, application-oriented resource that is arranged as a graph database. The authors proposed its use as a common benchmark for technological applications designed to support the effective management of cultural resources. They also discussed the potential use of this resource to perform multiple source analyses targeting the particular case of cultural tourism on a national scale.

Based on the above literature review, the implementation of BI seldomly focused on cultural tourism or helping preserve cultural heritage. Therefore, this paper is to demonstrate a BI solution focusing on data warehousing and data visualization for a public company that manages ticket sales to support the team to quickly monitor the business.

3. METHODOLOGY

In this section, we describe the available data and detail the most important methodological decisions applied to optimize the original PSML database for data analysis.

3.1. DATA

PSML provided historical transaction data comprising the years 2017, 2018 and 2019. The data was made available in a relational database backup document that was restored using SQL Server Management Studio[3] (SSMS). On first analysis, the database contained 159 tables with 1389 columns, mostly business-related tables such as tickets, events and locations that were mixed with other tables regarding logs, security roles and empty tables. Figure 3.1 shows the relational diagram of the original database.

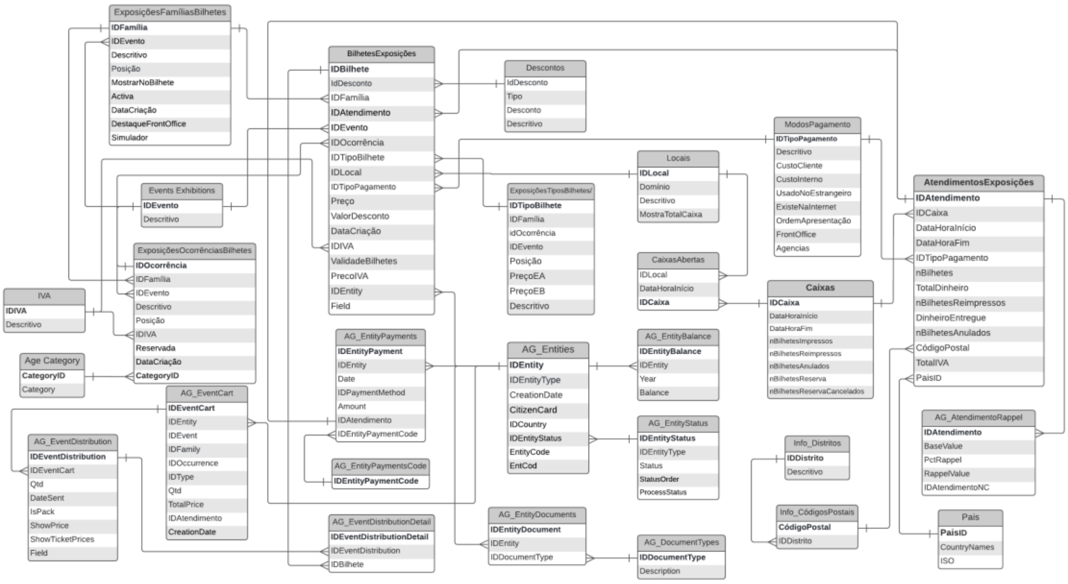

Figure 3.1 – The relational diagram of the original PSML database

We first checked the objects and their data quality by querying them in SSMS. As a result, we performed an initial cleansing process, in which tables that were not relevant to answer the needs regarding the core business of ticket sales management were removed. This removal process also included empty and log tables since they were unrelated to the core business and could not be combined into the expected model. Figure 3.2 shows the relational diagram of the cleaned database.

3 https://docs.microsoft.com/en-us/sql/ssms/sql-server-management-studio-ssms?view=sql-server-ver16

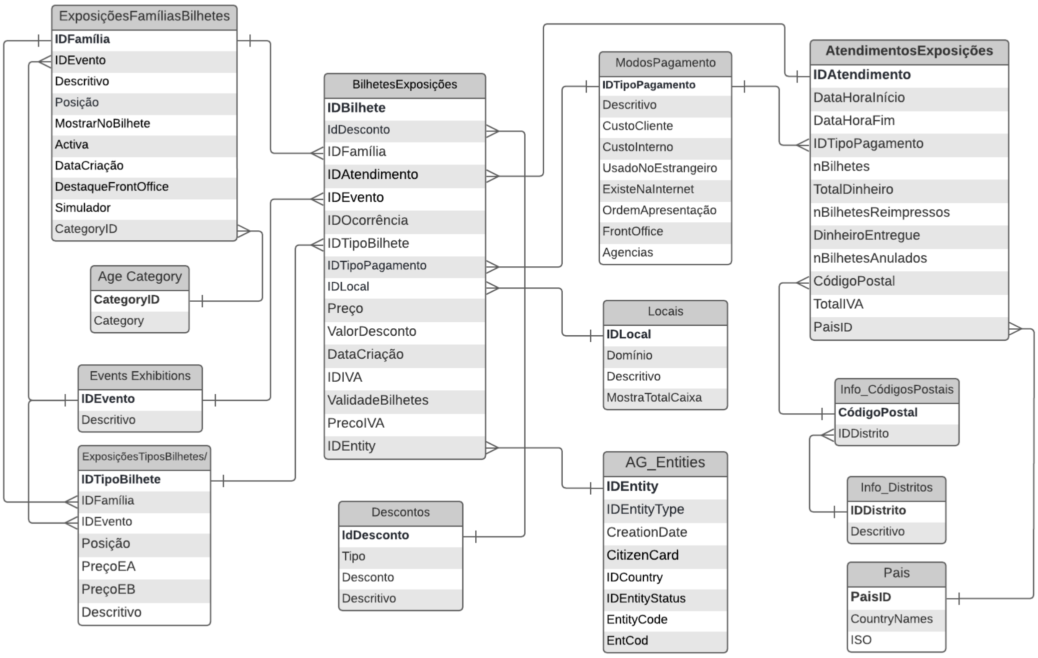

Figure 3.2 – The relational diagram of the cleaned PSML database

3.2. DATAWAREHOUSE DESIGN

In this work, we resort to Moody and Kortink's (2000) method for developing dimensional models, from relational models in four steps: Classify Entities, Identify Hierarchies, Produce Dimensional Models, and Evaluation and Refinement.

3.2.1. Step 1: Classify Entities

The first step consists in dividing the entities (tables) into three categories – Transaction, Component and Classification. Transaction entities keep track or measure the specifics of certain business occurrences and events. The two transaction entities identified in the model were "Exhibition Tickets" and "Exhibition Service". Component entities are directly linked to a Transaction entity via a one-to-many relationship and give context to the business events. We identified 8 component entities: "Discounts", "Membership", "Ticket Events", "Ticket Services", "Ticket Types", "Payment Types" and "Postal code". Finally, Classification entities are directly linked to component entities, but only indirectly linked to Transaction entities, and are used to further classify them. Two (2) Classification entities were identified: "Districts" and "Age Category". The model with the entities classified is shown in Figure 3.3.

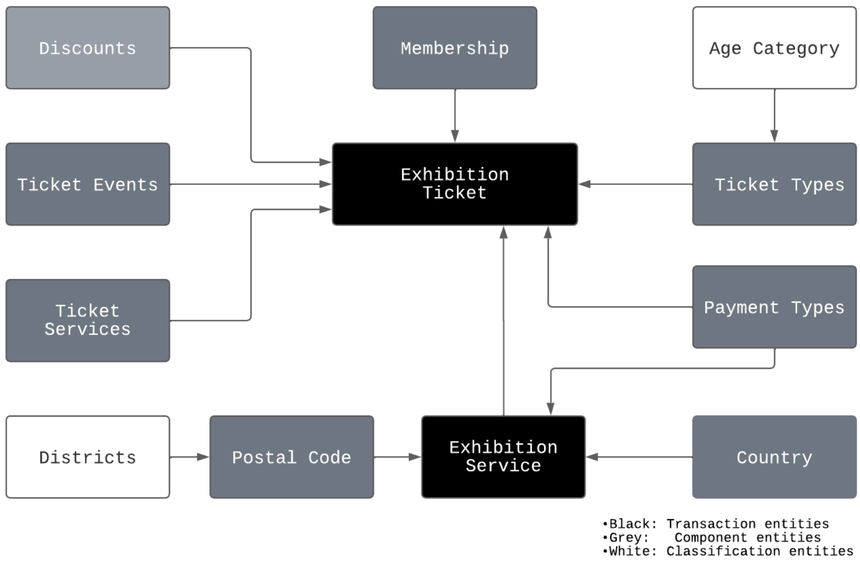

Figure 3.3 - Entity classification model of PSML

3.2.2. Step 2: Identify Hierarchies

In the second step, we defined the hierarchical structure underlying the entities' relationships which are suggested by the one-to-many relations existing in the database structure. A hierarchy is called maximal if it cannot be extended upwards or downwards by including another entity. In total, there were 9 maximal hierarchies in the model:

- Districts > Postal Code > Exhibition Service > Exhibition Ticket
- Discounts > Exhibition Ticket
- Ticket Events > Exhibition Ticket
- Ticket Service > Exhibition Ticket
- Country > Exhibition Service > Exhibition Ticket
- Membership > Exhibition Ticket
- Age Category > Ticket Types > Exhibition Ticket
- Payment Types > Exhibition Ticket
- Payment Types > Exhibition Services > Exhibition Ticket

3.2.3. Step 3: Produce Dimensional Models

In the third step, we generated a preliminary dimensional model by collapsing the hierarchies identified in step 2. In this process, higher-level entities can be combined into lower-level entities within one hierarchy (from left to right). Figure 3.4 shows the entity "District" collapsed into "Postal code", and Figure 3.5 the entity "Age Category" collapsed into "Ticket Types".

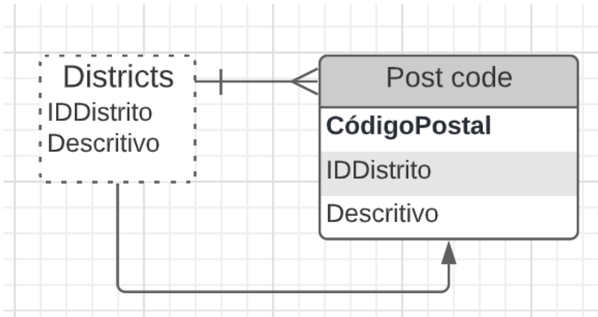

Figure 3.4 - District Entity "collapsed" into Postal code

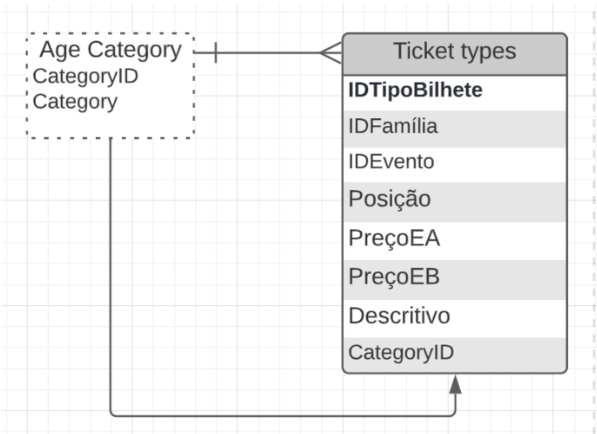

Figure 3.5 - Age Category Entity "collapsed" into Ticket Types

3.2.4. Step 4: Evaluation and Refinement

Hierarchies were collapsed until the component entities' level and an initial Star Schema design was reached, containing two (2) fact tables: "Exhibition Ticket" and "Exhibition Service"; and six (6) dimension tables: "Postal Code", "Ticket Service", "Ticket Event", "Ticket Type", "Membership" and "Payment Types". These tables were related through a one-to-many relationship. Moreover, the fact table "Exhibition Service", which shared a relationship with "Exhibition Ticket", was collapsed into the latter to reduce model complexity and facilitate comparison between related facts. The "Exhibition Service" table collected a large amount of ticketing information, which included the number of tickets purchased by the customer, the total amount, and geographic information. The two tables were merged into a fact table called "Fact Ticket". Furthermore, the dimensions of "Ticket Event", "Ticket Service" and "Ticket Type" were considered conceptually related, as they describe information regarding the types of the ticket. As a result, they were merged into a single dimension table "Ticket Type", as shown in figure 3.6.

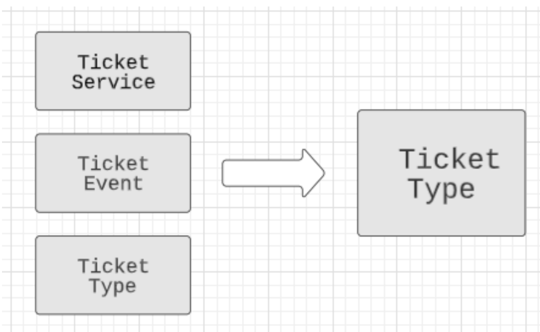

Figure 3.6 - Combining dimensions of Ticket Type

3.3. Extract, Transform and Load

The transactional data for the period between 2017 and 2019 was acquired from the SQL server database and loaded to Power BI[4]. All the necessary model transformations were applied through the Power Query editor (creating a date table, removing duplicates, removing unnecessary columns, merging columns, joining tables, etc.). Finally, tables and column names were changed to English and renamed according to a dimensional model nomenclature. The final model is shown in figure 3.7 and contains one fact table “Fact Ticket” and seven dimension tables: “Dim Country”, “Dim Location”, “Dim Payment Type”, Dim Membership”, “Dim Date”, “Dim Discount Type” and “Dim Ticket Type”-

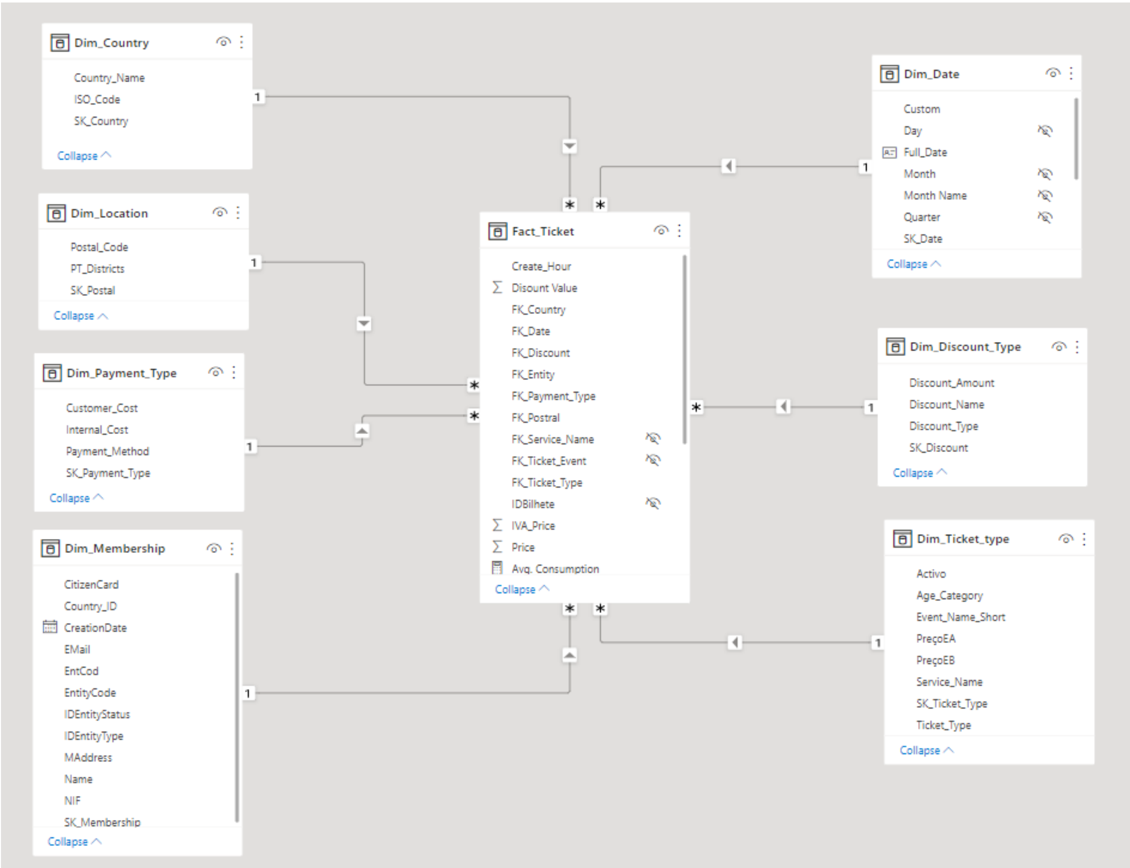

Figure 3.7 - The implemented dimensional model for PSML

4 https://powerbi.microsoft.com

4. RESULTS

After defining the dimensional model for PSML solution, we proceeded to develop insightful data visualizations for the process of ticket management. These visualizations were compiled in three dashboards – “Overall Performance”, “Attraction Insights” and “Customer Segmentation” – each pertaining to a different perspective of the business. This section details the results of the data visualization work carried out in Power BI.

4.1. Overall Performance Dashboard

The first dashboard (illustrated in figure 4.1) provides an overall view of the company’s performance. It allows the PSML team to monitor sales performance from several points of perspective, namely gross sales, net sales, discount values, ticket amount, tax paid and average consumption. The totals for each perspective are displayed in a card format in the header of the dashboard.

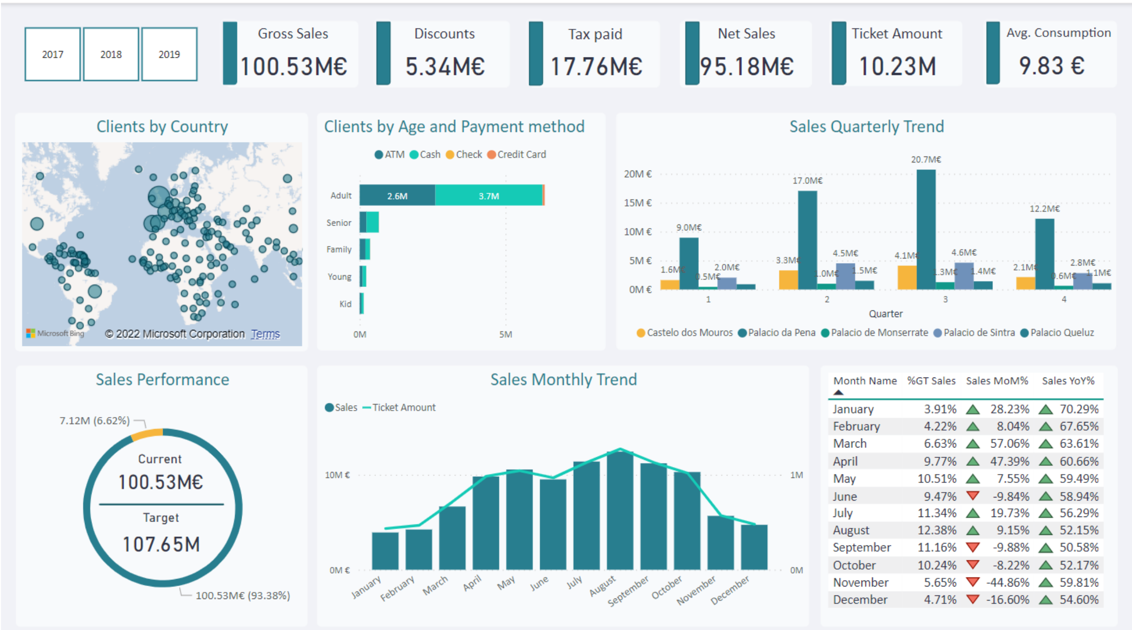

Figure 4.1 - Company performance dashboard

Looking at each visual, on the top left, it is displayed a map showing the distribution of PSML clients geographically. Most clients come from Europe, being the top three (3) countries in terms of client origin are the United Kingdom (UK) (1.9 million clients), Portugal (1.3 million clients) and France (1.1 million clients). Outside of Europe, Brazil is the country where most clients come from, with 0.8 million clients.

On the top centre, next to the map, a stacked bar chart shows the age distribution of customers and the preferred payment method for each age category. The majority of the clients fall into the adult category and, overall, cash is the preferred payment method (3.7 million clients), followed closely by ATM (2.6 million), whereas other payment methods are residual.

In another column chart (top right), the quarterly sales trend is displayed in a clustered column chart for the different types of cultural locations. *Palácio da Pena* has sales values significantly higher than other sights for all quarters. Not surprisingly, due to the influence of the summer season, the third quarter is the one with higher total sales, with 20.7 million.

On the bottom left, a yearly sales indicator of performance is displayed in a donut chart. A percentage number shows the remaining proportion of the target for the three-year period. Currently, the target value used in this chart is merely indicative, since we do not have access to the actual sales target defined by PSML. Nonetheless, the real values can be easily incorporated allowing for the company to understand the gap to sales targets more directly.

To measure the monthly behaviour of gross sales and ticket amount, we designed a line and clustered column chart. As well, a table was created showing the weight of each month in the total sales and displaying a comparison to the previous month and the same month last year, showing the percentage differences. Again, we note that summer months achieve higher values of sales and clients. Overall, March is the month that has the higher increase in percentage of sales compared to the previous month (57%), which means that sales tend to duplicate from February to March. On the opposite end, sales tend to decrease almost by half from October to November.

All these visuals can be filtered to show data for a specific year by pressing one of the options in the year filter, on the top left corner. Figure 4.2 displays an example of the dashboard filtered for 2019.

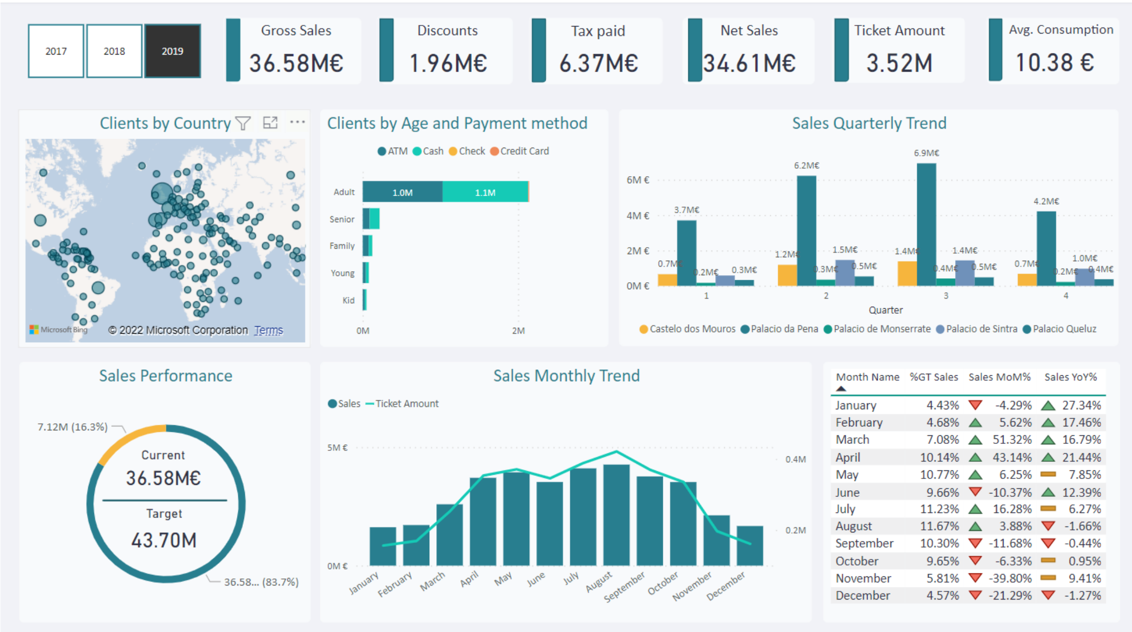

Figure 4.2 - Company performance dashboard filtered for 2019

This is the year with more sales, with 36.6 million euros, followed by 2018 and 2017, with 33.9 million and 30.0 million euros, respectively. Hence, there is a clear pattern of the continual increase in sales (as well as ticket amount) during these three years. Moreover, the user can also select a field from one visual and filter other visuals to display only the data for that field. As an example, in figure 4.3 we filter the entire dashboard to show only data for UK clients in 2019, by pressing the country's bubble on the map. In this case, one can see for example, that the month with more sales was October, instead of August.

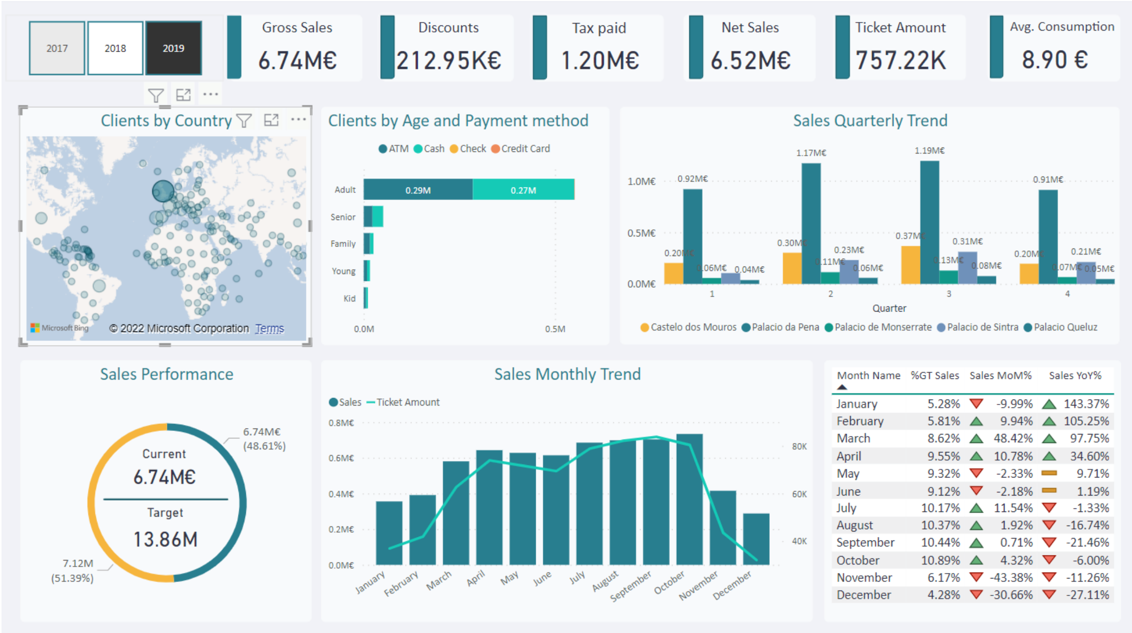

Figure 4.3 - Company performance dashboard filtered for UK clients in 2019

4.2. Attraction Insights Dashboard

The second dashboard focuses on the ticket metrics for the different cultural attractions managed by PSML. For this purpose, a filter was added at the top of the page that allows the user to select the attraction to be analysed. Figure 4.4 displays the dashboard filtered for *Palácio da Pena*.

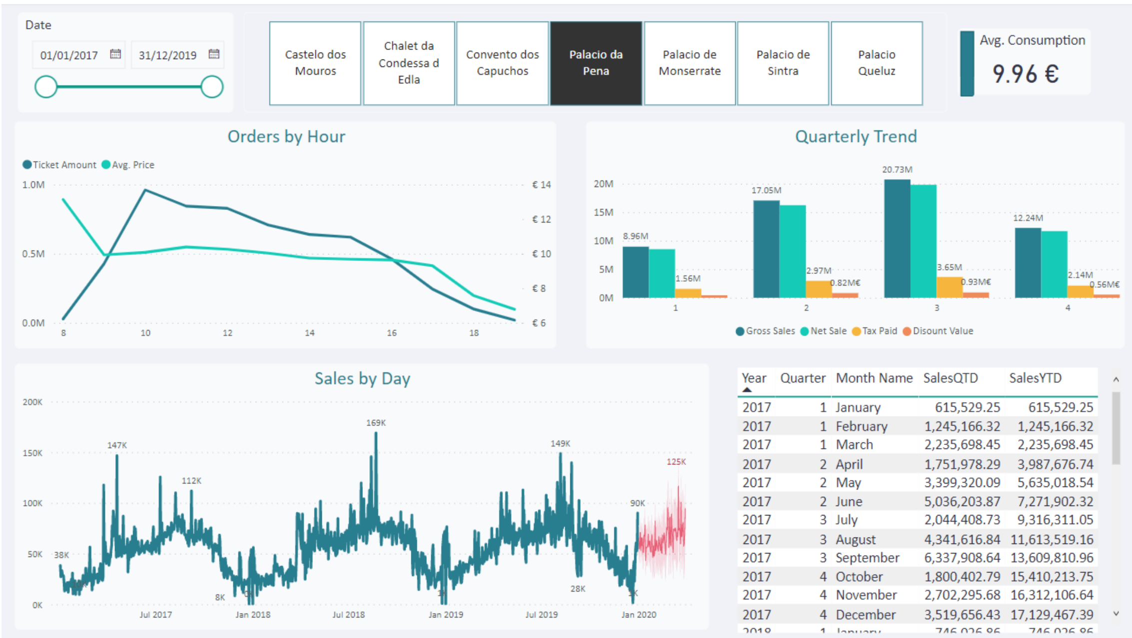

Figure 4.4 - Attraction Insights Dashboard filtered for *Palácio da Pena*

On the top left, a double-line chart displays the number of tickets sold and the average price per hour (limited by opening and closing hours), being the period between 10 am and 12am the one with more tickets sold, while the opening time (8 am) displays the higher values of average price. This may have to do with the fact that in the early morning period, visitors are adults without family that do not get any discount. This visual can assist the company in analysing customers' time regularity and consumption habits on purchasing tickets.

This page also displays the quarterly trend for each metric and the quarter-to-date and year-to-date sales values, through a clustered column chart and a table, respectively. On the left side we can see a line chart that displays the sales evolution across the timeframe considered. It directly shows data fluctuations over a large time range, based on which sales teams can quickly find outliers among historical data and spot commercial possibilities. This visual confirms the high seasonality of PSML business. To help predict sales trends and support planning for future strategies, a forecasting (red line) was performed on the daily sales for each attraction. The forecast can easily be updated to accommodate new data for 2022 and on.

4.3. Customer Segmentation Dashboard

Lastly, the Customer Segmentation dashboard (shown in figure 4.5) displays information that can be used for the PSML team to monitor the most critical customer features and it is divided into several charts.

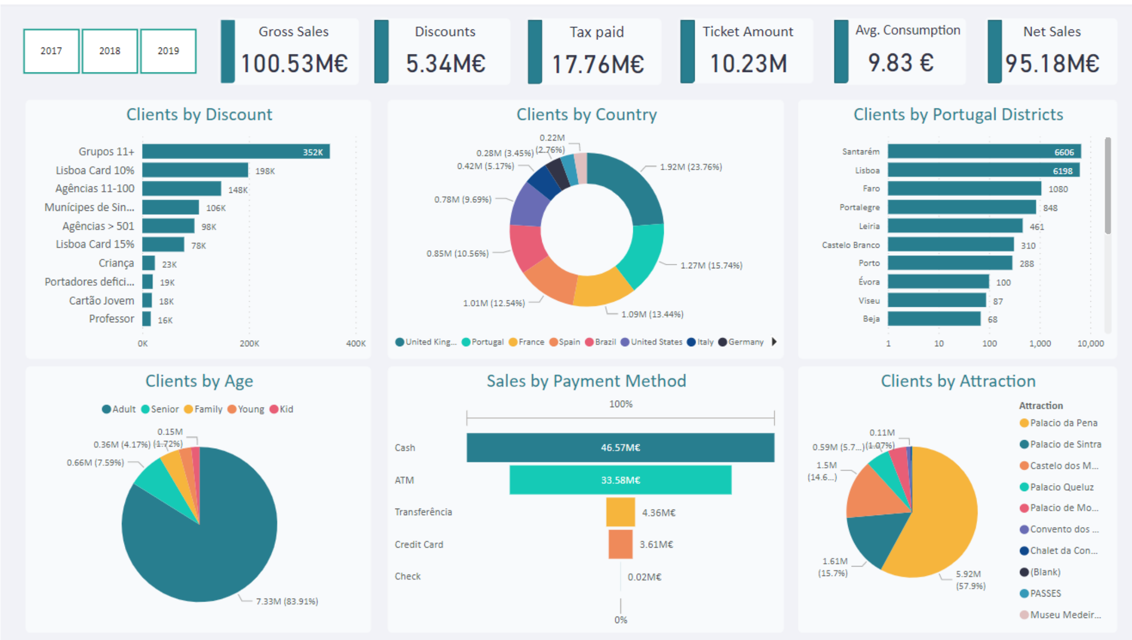

Figure 4.5 - Customer Segmentation Dashboard

One piece of information that can be extracted from the customers' transaction data is the discounts applied in ticket sales. The bar chart shows on the top left show the customer amount for the ten most used discounts. "Grupos 11+", which stands for groups with more than eleven members is the discount type through which more clients buy tickets (352K clients). The client's preferred payment method, the age distribution of clients, preferred attractions and their country of origin are presented more specifically in this dashboard. With the year slicer and drill-down of visuals, the detailed performance can be observed more easily.

In addition, the district distribution for Portuguese customers is displayed through a stacked bar chart (top right side of the page). The two most common Portuguese districts of origin are Santarém and Lisboa. We must note that this field (district) presents a significative quantity of null values, which can make the data displayed here less credible. Nonetheless, with the correct data available, geographic information will allow PSML to learn the performance of different countries or regions in detail, which, combined with other attribute information of customers in the dashboard, can help the team during decision making processes for perspectives such as regional sales, advertising strategy and customer services.

5. CONCLUSIONS

In this work, we developed a Business Intelligence solution for PSML with the objective of supporting the decision-making process for ticket sales management. First, we analysed and cleaned their transactional database, keeping only the relevant fields for the scope of our analysis. Moreover, we designed a new data model that served as the bases for the development of dashboards for three different business perspectives. These dashboards are analysed to describe the most important trends found in the data. This solution allows the company to measure business performance indicators to assist in decision making and support the development of business strategies that directly contribute to the efficiency of ticket sales management and indirectly contribute to the development of business strategies that integrate smart and sustainable tourism practices and cultural heritage preservation for the company. Likewise, our work demonstrates the potentiality of Business intelligence solutions in tourism and provides a general methodology that can be carried out in similar contexts to support tourism ticket sales services. These results need to be complemented with dashboard user guides so that new users can understand and operate the dashboard. The work is limited by the lack of more information in the database such as the membership details, advertising channels of clients, and inside traffic count of each location. For future work, researchers can add other measures and visuals to the dashboard to provide analyse in a wider perspective. Locations and entrances inside the park could also be taken into consideration with the analyse of the customer behaviour. The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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