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**<u>Διπλωματική Εργασία</u>**

# Business Intelligence and Analytics Case Study in a Greek manufacturing company

**του**

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**Υποβλήθηκε ως απαιτούμενο για την απόκτηση του μεταπτυχιακού διπλώματος στην Αναλυτική των Επιχειρήσεων και Επιστήμη των Δεδομένων**

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This is dedicated to everyone who helped, supported, and challenged me.

***Abstract***

Corporate entities are approving ever greater investments in information technology tools designed to store and analyse the business data they possess. The field of Business Intelligence has significantly impacted the processes of decision making. The goal to convert the vast amount of collected data into information, knowledge and ultimately profit has rendered the role of reporting necessary. Such reporting insights are created by the tools of Business Intelligence and consist of presenting the results of a data analysing process in way that is relevant to the needs of the company. These analyses typically focus on the past performance but can also extend into the future. The present document aims to both present Business Intelligence as a field of study and perform an implementation of its techniques to create KPIs of a manufacturing company's critical processes. The tool used will be Power BI from Microsoft.

Business Intelligence (BI) originates on the MIS reporting systems of the 1970s and 1980s. The first example of BI within the literature can be found in the 1950s (Luhn, 1958). BI deals with the journey from data to information, then to decisions, and finally to actions (Sharda et al., 2018).

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# 1. Introduction

In the postindustrial era that modern businesses operate, the main driver for growth is information that exists both inside and outside the operating environment. Despite it being abundantly available, businesses and organizations struggle to root out signal from noise and thus to convert information to knowledge. Companies possess vast amounts of transactional data, the outcome of years of investments in ERP systems. Such systems have transformed the way businesses operate (Trieu, 2017). However, when there is too much information that has not been convert to actionable knowledge, a process known as information overload(Roetzel, 2019), they resort to other methods for decision making thereby increasing the risk for sub-optimal performance (Nonaka et al., 1996). The first step to enhance the performance is to establish a knowledge-based decision support system(Rouhani et al., 2016) as such methods have been shown to produce tangible results.

Business intelligence and analytics (BI&A) are data-centric approaches complementing data with a set of methodologies, processes, technologies, and tools to analyze and extract information from data (Lim et al., 2013). BI&A offers a way for businesses to examine their data to enhance decision-making, understand trends, and unearth valuable insights (Gürdür et al., 2019). It has evolved from data warehousing with a focus on static reporting focus on intelligence (Simmers, 2004). At the same time, it also shifts from a data transformation function into a function of information as the focal point of the current function of data transformation into intelligence. BI&A leverages software and services to transform data into actionable intelligence informing an organization's strategic and tactical business decisions. With BI&A, businesses can access and analyze data sets and present analytical findings in reports, summaries, dashboards, graphs, charts, and maps to provide users with detailed intelligence of the business's state. In short, BI&A is an information system supporting decision-making processes by helping organizations discover new knowledge, offer analysis solutions, ad hoc queries, reporting, and forecasting (Yoon et al., 2014). Globalization, the internationalization of markets, the knowledge economy, and e-commerce are some numerous challenges facing all organizations, regardless of size. If organizations will survive and be competitive in their new environment, they must use information systems (IS) and information technologies (IT) (PobaNzaou et al., 2008). Successful organizations are differentiated by their ability to make accurate, timely, and effective decisions at all levels to address their customers' preferences and priorities (Bose, 2009).

## 1.1. Motivation, Objective and Scope

Business intelligence and analytics have become essential components for organizations to make informed decisions based on data-driven insights. With the growth of big data, organizations are generating a massive amount of data every day, making it difficult to extract meaningful insights without using advanced analytics techniques. Therefore, the aim of this thesis is to investigate how business intelligence and analytics can be used to gain competitive advantage by analyzing a case study of a company operating in the manufacturing industry.

## 1.2. Motivation

The motivation for this study is the increasing importance of business intelligence and analytics in the modern business environment. In the manufacturing industry, for example, companies use business intelligence and analytics to gain insights into customer behavior, optimize supply chain management, and increase operational efficiency. However, there is limited research on how companies can use these techniques to gain a competitive advantage. Therefore, this study seeks to fill this research gap by exploring the use of business intelligence and analytics in a real-world manufacturing setting.

## 1.3. Objective

The main objective of this study is to analyze the use of business intelligence and analytics in a manufacturing company to gain competitive advantage. The specific objectives are:

- To identify the business intelligence and analytics techniques used by the company.
- To investigate how the company uses these techniques to gain insights into customer behavior.
- To analyze how the company uses these insights to optimize supply chain management and increase operational efficiency.
- To evaluate the effectiveness of the business intelligence and analytics techniques used by the company.

## 1.4. Research questions

The research questions that this study aims to answer are:

- What business intelligence and analytics techniques are used by the manufacturing company?
- How does the manufacturing company use these techniques to gain insights into customer behavior?
- How does the manufacturing company use these insights to optimize supply chain management and increase operational efficiency?
- How effective are the business intelligence and analytics techniques used by the manufacturing company?

## 1.5. Scope

This study focuses on a case study of a company operating in the manufacturing sector in Greece. The study will cover a period of three years from 2020 to 2022. The study will investigate the use of business intelligence and analytics techniques to capture key performance indicators that reflect on customer satisfaction, operational efficiency, and cost reduction efforts. The study will not investigate other sectors or industries.

The choice of a single case study provides an in-depth examination of the use of business intelligence and analytics techniques in a real-world setting. The two-year timeframe is sufficient to capture the changes and improvements made by the company with these techniques.

However, it is important to note that the findings of this study may not be generalizable to other manufacturing companies or industries. Therefore, the results of this study should be interpreted within the context of the specific case study and should not be extrapolated to other contexts without further investigation. Furthermore, the study will not investigate the technical aspects of implementing business intelligence and analytics techniques, as this is beyond the scope of the study.

## 1.6. Significance

This study is significant because it provides insights into the use of business intelligence and analytics techniques in the manufacturing industry. The findings of this study can help other manufacturing companies to optimize their operations, increase efficiency and gain a competitive advantage.

The motivation for this study is based on the increasing importance of business intelligence and analytics in the modern business environment. The amount of data generated by organizations is growing exponentially, and it is becoming more challenging to extract meaningful insights from the data without using advanced analytics techniques. In the manufacturing industry, companies use business intelligence and analytics to gain insights into customer behavior, optimize supply chain management, and increase operational efficiency. The use of these techniques can become a competitive advantage for organizations, enabling them to make informed decisions based on data-driven insights.

However, despite the increasing use of business intelligence and analytics in the manufacturing industry, there is limited research on how companies can use these techniques to gain a competitive advantage. This research gap highlights the need for a study that examines the use of business intelligence and analytics in a real-world manufacturing setting to understand how companies can leverage these techniques to gain a competitive advantage.

Therefore, the motivation for this study is to investigate how business intelligence and analytics can be used to gain a competitive advantage by analyzing a case study of a manufacturing company. By doing so, this study aims to provide insights into the effectiveness of these techniques in the manufacturing industry and contribute to the broader field of business intelligence and analytics. The findings of this study can help other manufacturing companies to optimize their operations, increase efficiency, and gain a competitive advantage in the market.

Additionally, the study seeks to assess the method, challenges, and particular obstacles to implementing a data driven business intelligence and analytics project in a company that has been traditionally slow to ingest new technologies and new methodologies.

Moreover, the study contributes to the broader field of business intelligence and analytics by demonstrating the effectiveness of these techniques in a real-world setting.

## 1.7. Methodology approach

Implementing Power BI in a manufacturing company requires a structured approach that ensures that the Power BI implementation meets the business requirements and provides valuable insights into the company's performance.

*Define the Objectives:*

The first step is to define the objectives of the Power BI case study implementation. This involves understanding the business requirements and identifying the key performance indicators (KPIs) that need to be monitored. The objectives in our case were the establishment of a metrics culture were departments and individuals can be measured according to hard facts (in addition to soft targets). The data collection for this study will involve a combination of primary and secondary data sources. The primary data sources will include interviews with key stakeholders involved in the implementation of the Power BI dashboard, observations of the implementation process, and the dashboard itself. The secondary data sources will include documents and records related to the implementation process, such as project plans and reports.

### *Data Gathering and Preparation:*

The second step is to gather and prepare the data required for the analysis. This involves identifying the data sources and collecting the data in a structured format. The data may be obtained from various sources, such as the company's ERP system, production systems, and external sources. The data also needs to be extracted, transformed and loaded to the analysis system.

The raw data reside in the various electronic systems of the company. These are an SQL server, SharePoint lists and excel files.

The SQL Server hosts the databases for the ERP, warehouse management and customer relationship management systems. Sharepoint and Microsoft365 in general hosts data for the marketing department. Custom SQL queries have been prepared that then deliver the relevant data to PowerBI. The SQL query that will be used for the procurement KPIs is mainly from a table that contains aggregate information per item and period. The data includes, sales quantity, turnover, cost of goods sold, purchase quantity, acquisition cost and valuation price along with item code and period code. The second query for the logistics department mainly uses the financial documents table. From there we get information about the date of the sales order along with customer name and code. We then use the delivery documents' date to calculate our KPIs. The third SQL query gathers third party transportation cost information from general ledger tables, first party transportation cost and then volume and revenue that are then used to calculate appropriate metrics.

All these systems are connected to PowerBI via relevant connectors.

### *Data Modeling:*

The third step is to create a data model in Power BI. This involves defining the relationships between the data sources and creating measures and calculated columns for the KPIs that need to be monitored.

*Dashboard Creation:*

The fourth step is to create the dashboards in Power BI. The dashboards should be designed to provide a quick and easy-to-understand overview of the KPIs. The dashboards should also be interactive, allowing the users to drill down into the details. Additionally, the dashboards need to be integrated into a familiar location that hosts all other reporting tools.

*User Training:*

The fifth step is to provide training to the users on how to use Power BI. The users should be familiarized with the dashboards and taught how to use the interactive features to explore the data in more detail. Another significant aspect of training was to get the uses and the top management to trust the metrics and lean on them to make decisions.

*Testing and Refinement:*

The sixth step is to test the dashboards and refine them based on the feedback received from the users. This involves identifying any issues with the data or the dashboards and making the necessary adjustments. This has been the case as evident in the following chapters. We used feedback to make the metrics more meaningful and trustworthy.

*Implementation and Deployment:*

The final step is to implement and deploy the Power BI dashboards. This involves integrating the dashboards into the company's systems and making them accessible to the users. The dashboards should be regularly updated with new data to ensure that the KPIs are being monitored effectively.

## 1.8. Research design

The research design for this study is a case study design. The case study design is suitable for exploring complex phenomena in real-life situations. The study will use a single-case design to investigate the implementation of a Power BI dashboard in a manufacturing company.

## 1.9. Sampling

The sampling strategy for this study will be purposive sampling. The sample will include key stakeholders involved in the implementation process, such as the project team, IT staff, and business users. The study will focus on these stakeholders to gain insight into the implementation process and the impact of the Power BI dashboard.

## 1.10. Ethical Considerations

This study will adhere to ethical guidelines for research involving archival data. The study will use only non-sensitive data, and the anonymity and confidentiality of the company and employees will be protected.

## 1.11. Limitations

The limitations of this study include the quasi-experimental design, which limits the generalizability of the findings. The study is also limited to the available archival data and may not capture all relevant variables. Finally, the study may be limited by the reliability and validity of the KPIs used in the study.

# 2. Business Intelligence (BI)

## 2.1. Definitions of Business Intelligence

BI's most important term is intelligence. It refers to the way information is assessed by an entity regarding its validity, suitability, and veracity. In essence it is the technologies to access, collect, and analyse the specific data that will improve the effectiveness of the business decisions making process. Therefore, an entity is required to have knowledge about numerous aspects of its internal and external environment such as suppliers, customers, competitors, stakeholders, and business processes to be both efficient and effective (Howson, 2008; Sharda et al., 2018).

BI's role is to locate the information that each organization considers important, and to present the parts that are useful for managerial decision support. BI may be a relatively new area for many businesses, however, the definition of BI (Luhn, 1958) was first provided more than 40 years ago. BI as a term encompasses different technologies and software platforms. It is described as "an approach to management that allows an organization to define what information is useful and relevant to its corporate decision making." (Negash and Gray, 2008; Vitt et al., 2002).

The main goal of BI is to provide interactive and real time data, information, and knowledge for all business stakeholders. The users of the BI platforms gain useful insights by examining past and current facts, situations, and performances. This enables more informed and ultimately better decisions.

## 2.2. Business Intelligence Development

In the 1960s, organizations began exploring the proliferation of computers by using software information systems (IS) to automate business operations (Arnott and Pervan, 2014) such as production. customer orders, pricing, payroll, and accounts payable. The need to use all the data that was created and stored by these transactional systems led to the development of Management Information Systems (MIS). The next step of this evolution was the emergence of Decision Support Systems (DSS) (Marakas, 2003). Next, Executive Information Systems (EIS)(Rainer Jr and Watson, 1995) are DSS with an emphasis on data (Leidner and Elam, 1993). At the same time, large organizations faced significant challenges analysing data from a multitude of sources, and this led to the emergence of Data Warehouses (DW) as a technological leap. A DW consists of several databases within a central repository (Cooper et al., 2000).

During this period, business process engineering (BPR) (Davenport, 1993) became a common issue for organizations and they sought to improve efficiency. A key topic of the literature was the transition from data to information and then knowledge via knowledge management systems (KMS) (Alavi and Leidner, 2001). This emerged from the need to capture organizational knowledge that would otherwise be lost due to redundancies proposed by the BPR initiatives (Newell et al., 2001).

After the proliferation of Data Warehouses, Business Intelligence (BI) and Business Analytics (BA) were introduced. BI systems are integrated systems that are linked to a data warehouse and provide data analysis (Davenport and Prusak, 1998). BI's main difference is their ability to seamlessly connect to and combine data from databases of different parts of the business. Businesses realized that all the reporting systems could be combined into one BI system, leading to readily available insights that should enable better decision making.

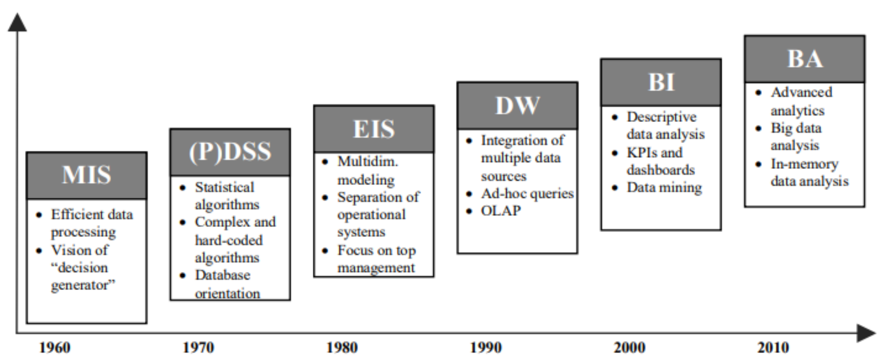


*Figure 1 The evolution of information systems designed to support decision-making*

(Chen et al., 2012)

### 2.3. Business Intelligence, Business Analytics, and Big Data.

The most recent step in the technological evolution of decision support technologies is the emergence of Business Intelligence (BI) and Business Analytics (BA) (Fink et al., 2017). Business Intelligence did not proliferate as a decision support methodology until the early 2000s (Arnott and Pervan, 2014). Later that decade, BA was introduced as an analytical tool that uses data, statistical analysis and predictive models (Davenport et al., 2010). The term business intelligence and analytics (BI&A) has been coined (Chen et al., 2012) to describe the way businesses harness the new technologies and improve the quality and speed of their decision-making process. This is achieved by improving both the velocity and quality of available information. Another adjacent field of study is big data analytics that describes massive, complex, and real-time data generated from emerging technologies like social media, smartphones, and internet of things (IoT) sensors (de Camargo Fiorini et al., 2018). Big data is understood based on the 3-V model (Klein et al., 2013) that described three dimensions of challenges in data growth: volume, velocity, and variety. Volume describes the amount of captured data. Velocity depicts the speed with which new data are being created. Variety represents the different sources and types of data.

### 2.4. BI&A Architecture

There are quite a few BI&A architectures that have been proposed (Watson and Wixom, 2007) that have significant differences. However, there are common components such as source data sources, data storage, and reporting tools. Typically, the architecture of BI&A solution consists of five layers. A data source layer, an Extract-Transform-Load (ETL) layer, a data warehouse (DW) layer, an end user layer, and a metadata layer (Ong et al., 2011).

The data source layer includes internal and external data sources. Internal data sources are data generated from business applications such as Material Resource Planning (MRP), Enterprise Resource Planning (ERP), Warehouse Management System (WMS), Customer Relationship System (CRM), and other applications. External data sources contribute data that are not produced inside the organization and typically the organization has no control of such as the weather, foreign currency rates, raw material price indexes, political developments, customer market research, country information, competitors etc.

The ETL layer is a process where data is extracted, transformed, and loaded for further analysis (Baars and Kemper, 2008). Extraction is the process of accessing data sources and selecting the data that are relevant (S et al., 2020). In the transformation phase the data are converted to uniform types (Ong et al., 2011). The loading phase deals with moving the data is loaded into the data warehouse.

The DW layer is a storage location that receives data from the previous steps and makes them available for analysis (El-Sappagh et al., 2011).

The end user layer refers to the different ways that the user can have at her/his disposal to view and analyse the data. These tools are typically used to query the data, create reports and dashboards and share them to the business users (Ong et al., 2011).

The metadata layer is used to store information about the data sources, the data transformations and the business rules and technical decisions that informed these choices (Davenport et al., 2010).

The typical BI&A architecture is shown in Figure 2.

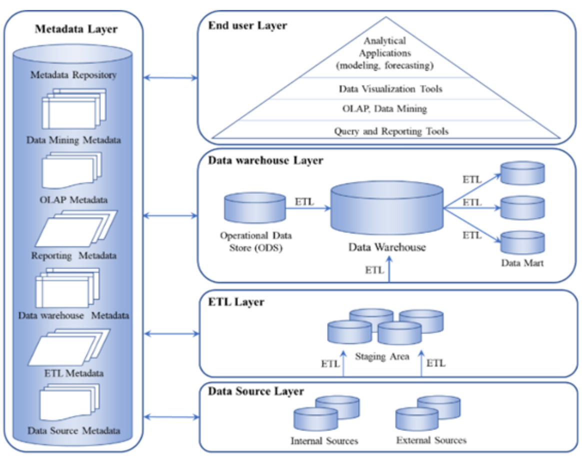


*Figure 2 BI&A Architecture (Ong et al, 2007)*

## 2.5. BI&A Evolution and Trends

BI&A systems allow, by accessing data stored in enterprise databases, organisations to search and analyze business data and thus improve decision-making and gain competitive advantages. The end goal is to realise the potential value of an organization's data resources (Elbashir et al., 2008).

The original BI&A solutions, or BI&A 1.0 focused on analyzing historical data to ascertain the current business status (Chen et al., 2012). A report typically includes data organized in rows and columns much like a spreadsheet. The proliferation of internet and the access to data previously unavailable to organizations led to the realization that only internal information was insufficient to make informed decisions. This led to a new evolution in BI&A systems that allowed organizations to complement their internal data with external to provide insights and speed up the time to decision. The data generated from external sources, like competitor prices, raw material indexes or public opinion, can be useful. This information provides a novel lens to identifying opportunities for market expansion and better serving customers. This evolution of BI&A during the proliferation of the internet, led to what has been described as BI&A 2.0 (Chen et al., 2012). Novel techniques such as web analytics, web scraping and data mining opens the possibility to access vast amount of data on company, industry, product, and customer on the web (Cheung and Li, 2012; Zorrilla and García-Saiz, 2013). During this era BI&A has begun being offered as software as a service (SaaS). This advancement lowered implementation costs and provided greater availability (Horakova, M. and Skalska, H., 2013) but not without risks (Rostek et al., 2012; Stjepić et al., 2021). Following the technological advancements BI&A began integrating data from mobile devices, radio-frequency identification, barcodes, and radio tags and other Internet of Things (IoT) devices. The mobile and sensor based content is the BI&A 3.0 (Chen et al., 2012; Stjepić et al., 2021). Studies on mobile BI&A have started to appear as the topic gained momentum (Moreno Saavedra and Bach, 2017; Tutunea, 2015).

## 2.6. BI&A Business Value Creation

BI&A systems aim to improve organizational performance while exposing weaknesses in business processes and competitive market placement (Williams and Williams, 2007) and therefore act as a driver for business value improvement. In the literature we can identify two main variations of business value: strategic and operational. Strategic value is created by supporting strategic objectives, like targeted research and development efforts assessing opportunities and threats and overall efficiency improvements, (Fink et al., 2017). Operational business value originates from internal processes, like shorter time to market, speedier order to delivery and more efficient purchase to pay processes. These in turn are translated into happier customers, more efficient operations and better overall results (Watson and Wixom, 2007).

The link between BI&A implementation and the creation of business value has not been fully identified (Elbashir et al., 2008; Moreno Saavedra and Bach, 2017). Two themes emerge for maximizing BI&A business value (Omar et al., 2019): shorter time to insight and pervasive use by the business end users. Consulting companies were quick to realise this opportunity and have begun offering relevant services for the implementation of BI&A platforms and tools (Mathrani and Mathrani, 2013; Namvar and Cybulski, 2014).

As with any project, technological or not, risk of failure exists, and consequently the intended benefits might not be fully realized (Bordeleau et al., 2020).

## 2.7. BI&A Adoption

BI&A literature is evidently increasing in the past two decades with an acceleration in the last years (Ain et al., 2019). Various studies have been conducted on the adoption of BI&A at a regional, country, and sectoral level.

Examples of recent regional studies include: (Puklavec et al., 2018) that researched Thailand, (Hartley and Seymour, 2011) study for South Afrika, Jordan from (Jaradat et al., 2022). We have a study for Greece that mainly focused on business intelligence via ERP systems by (Giotopoulos et al., 2017)

Of sectoral studies include: (Salisu et al., 2021) that researched the adoption in the healthcare industry, in the banking sector by ("An integrated model for determining business intelligence systems adoption and post-adoption benefits in banking sector," 2016), in the textile and apparel sector by (Ahmad et al., 2020). Some studies focus on small and medium enterprises such as (Giotopoulos et al., 2017; Puklavec et al., 2018; Stjepić et al., 2021).

Adoption can also be gauged by the total market value which follows the trend of the literature as seen in the figure below from ("Business Intelligence Software - Worldwide," n.d.).

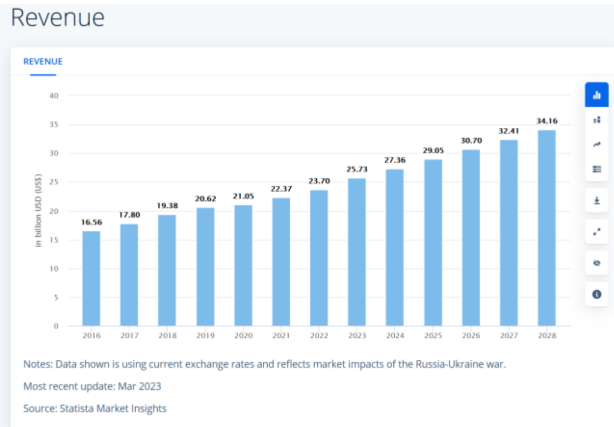


*Figure 3 Revenue in the BI Software market*

All the above factors point to the fact that as the years progress BI adoption is increasing as more than one marker makes evident.

## 2.8. BI&A Adoption factors

BI&A literature has identified three main factors that drive BI&A adoption: the strategic, technological, and people perspectives (Ain et al., 2019). The strategic perspective focuses on how aligned the implementation of a BI&A system with the strategic goals of the organisation is. This category includes factors like management support, competitive pressure, and organizational culture. The technological perspective deals with the quality of data and the readiness of the IT infrastructure (Kappelman et al., 2019). Lastly, the people perspective focuses on factors like IT competence and user involvement (Arizona State University et al., 2017).

# 3. Power BI

## 3.1. Self-service BI vs Data warehousing

The traditional way of implementing business intelligence systems was to use data warehouses. This suited larger companies that had the resources and knowhow to facilitate them. Today's proliferation of BI services such as Power BI Desktop has enabled end users to create reports on their own, thus creating the self-service BI methodology (Schuff et al., 2018). This is often the first step for SME's towards a fully-fledged BI strategy.

Data warehousing involves data extraction from the source, transformation and storing in a specialized repository. The data is then updated in batches and can be accessed for analysis in BI or other systems such as spreadsheets. Data warehouses hold historic data dating back several years as deemed necessary (Mohanty et al., 2013). A data warehouse's main goal is to serve as the single source of truth for the business (Alpar and Schulz, 2016).

On the other hand, in the self-service approach BI tools connect to the source systems directly, performing the same steps to make the data usable for analysis as in the data warehousing approach, while data itself reside in the BI solution. This has the benefit of connecting to only those data sources necessary for specific business case, is a faster and less expensive method of getting started with BI development. The drawback of this approach is that it does not scale (Mohanty et al., 2013): the more separate self-service BI analysis is conducted, steps such as data transformation must be repeated. Different users may connect to various sources and process data dissimilarly, leading to inconsistent analyses. Since each BI application stores the data locally, duplication and redundancy are unavoidable. Some BI solutions offer both models such as Power BI Desktop and the Power BI cloud service.

A third option that has emerged recently is the data lake (Llave, 2018). It is a collection of data in its raw unprocessed form. Data lakes main advantage is the capability to facilitate large and frequent volumes of unstructured data as generated in e.g., social media platforms. The data lake strategies can encompass SQL and NoSQL databases and online analytics processing (OLAP) and online transaction processing (OLTP) capabilities. Therefore, the data lake focuses on quick data retrieval and storage and aims to make data quickly available for analysis of data. Data transformation only occurs on where actually needed (Miloslavskaya and Tolstoy, 2016).

## 3.2. Extract, Transform, and Load

The first process when performing data analytics either from a DW or directly is to get to the source data and transform it commonly referred to as the Extract, Transform, and Load (ETL)(Jun et al., 2009) process. The first step is to connect to the data sources to extract the data. The next step is to transform the data into one common format. The ultimate step is to load the data into either the data warehouse or the local database in a self-service BI approach.

While using online transaction processing (OLTP) systems as data sources in BI solutions it is often needed to avoid extracting the data while the systems are operational. The reason is the need to maximise the availability while maintaining their stated level of service. One way to achieve this is to extract data in batches periodically as per the business requirements. One additional opportunity is to schedule the data extraction when the source system is underutilized (Rainardi, 2007).

Data transformation refers to manipulating the source data to fit the requirements while applying business logic. Most commonly, data is converted from one format to another but also combined, split, trimmed, cleaned and aggregated (Rainardi, 2007). Data analysts also gauge outlier values and may perform deletions or transformations. The successful completion of this step ensures that the BI system will receive high quality data.

The last step is to load the data into the target system. In the case of a self-service BI approach, there is no separate target system than the ETL one. The entire ETL process as a concept can be seen visualized in Figure 4 below, where the target system is a data warehouse and the data sources can be a Warehouse management system (WMS), a B2B website handling orders, a customer relationship management (CRM) system, an ERP system, or plain text files.

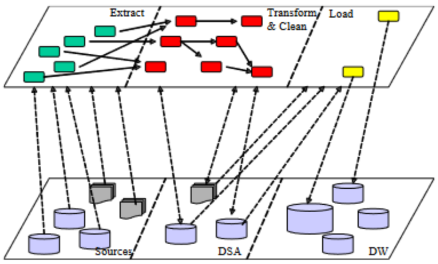


*Figure 4 ETL process*

(Vassiliadis et al., 2002)

## 3.3. Data model design

A common status after the ETL process is a selection of tables and query results from multiple sources that store data that are selectively related to each other. This implies certain assumptions about the real world where the data came from. In order to visualize this information, a model is required that is "an abstraction and reflection of the real world" (Ballard et al., 2012). By following the best practices in design techniques, common problems and challenges in data modeling can be minimized or altogether avoided (Ballard et al., 2012; Horakova, M. and Skalska, H., 2013).

### 3.3.1. Entity Relationship Model

In an entity/relationship (E/R) model data is stored inside tables that are related to each other while minimizing duplications i.e. being in a normalized state. The relationships are defined by using columns as keys that are common in related tables (Allen and Terry, 2006). A primary key uniquely identifies every row in the table. A foreign key in one table is a primary key in the related table (Clark, 2020).

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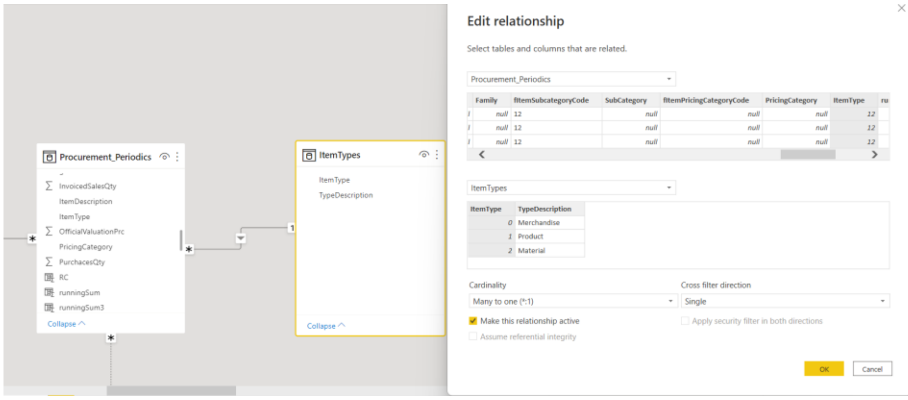



*figure 5 Many to one relationship between item type and procurement KPIs table*

For example, in figure 5 there is the ‘Procurement Periodics’ table that contains information about purchase order data aggregated per month, such as ‘Acquisition Cost’, ‘Official Valuation Price’, ‘Item code’, “Item type” and ‘Item ID’. The ‘Item type’ column in the ‘Procurement Periodics’ table is a foreign key referencing the primary key of the ‘ItemTypes’ table: ‘ItemType’.

By defining the relationship between these two columns, data from the ‘ItemTypes’ table can be linked to the data from the ‘Procurement Periodics’ table.

An additional aspect of relationships is their direction and cardinality. Direction refers to defining which table is the source and which is the target of the relationship. In the sample data model portrayed in figure 5, ‘Procurement Periodics’ is the source and the ‘ItemTypes’ table is the target of the relationship between them. So, each time we want to get more details about the item type in the ‘Procurement Periodics’ table , we refer to the ‘ItemTypes’ table. The cardinality of the relationship refers to the size of the set, i.e. how many items exist in each table. Three types of cardinality exist: one-to-one, one-to-many, and many-to-many. Referencing the sample data model in figure 5, the cardinality between the ‘Procurement Periodics’ and ‘ItemTypes’ tables is many-to-one: each Procurement Periodics row contains an item that has an item type that can be referenced uniquely. Thus, the ‘item type’ column can have duplicates in the ‘Procurement Periodics’ table but it must be unique in the

‘ItemTypes’ table. This is visible in the model diagram by an asterisk on the many side and an “1” on the one side as seen in figure 5.

In an E/R data model few redundant data are present as each table contains only the necessary data. This leads to performance benefits when inserting, updating, or deleting data. The disadvantage being slow relative performance when selecting data that must reference many tables (Ballard et al., 2012).

### 3.3.2. Dimensional modelling

Most real-world business intelligence solutions contain data form multiple tables that are interlinked in complex ways such as customers, items, suppliers, warehouses, etc. To meet the modern performance needs and simultaneously maintain data integrity, the dimensional schema model has been introduced, commonly referred to as the star schema. This model is most prevalent in DW applications and it refers to the kind of data each table contains and how the relationships between them are formed (Clark, 2020; Seamark and Martens, 2019). The star schema contains two kinds of table in the data model: fact tables and dimension tables. The fact tables contain all metrics that the business wants to track such as sales, quantity, cost, price. Dimension tables contain detail data for each fact table metric such as customer details, item detail, and country details. A sample star schema data model can be seen in figure 6 below.


*Figure 6 Star Schema*

(“Https://Docs.Microsoft.Com/En-Us/Power-Bi/Guidance/Star-Schema,” n.d.)

### 3.3.3. Granularity

Granularity refers to how specific or detailed the data source is. More granular data means that there are fewer details. For example, a sales table can have sales per item per order, i.e. multiple items per day, it can aggregate them per day i.e. one item per day. Some tables contain further aggregated data in the month or even year level. In the data model shown in figure 5, the 'Procurement Periodics' fact table is at the month level, which is not the lowest level of granularity available in this scenario. Increasing the level of granularity in this case would mean going up to year level by removing the monthly aggregations or removing the 'Item ID' field thereby getting information only on an item type level. Both decisions will greatly reduce the size of the data set. By examining the business requirements we can establish the optimal level of granularity while considering the reporting performance (Ferrari and Russo, 2017).

### 3.3.4. Data normalization and denormalization

Data normalization is a design technique that reduces redundancy in the data source. Theoretically all data of a model could exist in one table. This singular table would have columns that contained duplicate data. For example, a sales table would have a customer city column that would contain many times the same city as we expect different customers from the same city. Data normalization aims to fix this be separating data from a large table into smaller tables and then linking them together via relationships. In our example we would consider separating the customer details data into a second table that would then be linked back to our main table via a customer code column. There are different recipes to achieve this named normal form rules. For example, in the star schema data model presented in Figure 6, the 'Name' and 'details' information of the employee fulfilling the purchase order have been removed from the 'Purchase Orders' fact table and are instead found in the 'DimEmployee' table through the relationship formed between the 'Employee ID' fields of each table. The benefit of this is that the employee details are stored only once in our data model despite having multiple purchase order per employee. This action reduces our data model size and makes updating the employee details are simple as updating a single row in the employees dimensional table. (Köhler and Link, 2018). This is especially relevant on transactional databases where updates are frequent. On the other hand, data warehouses can sometimes benefit from denormalization where storing the attributes in the fact table instead of separating them into a dimension is beneficial because we need fewer separate tables in order to get to our information so minimizing the time needed to develop this information while expending disk space.

### 3.4. Microsoft Power BI

Microsoft Power BI is both a self-service BI that encompasses ETL and a standalone BI tool that accesses data stored in a data warehouse. Power BI Desktop provides easy connectivity to data sources. The main two methods of connecting are with a ‘DirectQuery’ data model that connects live to a data warehouse. This approach does not store data in the Power BI model but queries it on demand. The other method is an ‘Import’ data model, where data is stored from multiple sources in the model. This method allows to connect using SQL queries that mask the underlying database structure but also allows for greater flexibility. The full list of data connectors available in Power BI Desktop is listed in Table 1.

| | |
|---|---|
| File data sources | Excel Workbook, Text/CSV, XML, JSON, Folder, PDF, Parquet, SharePoint folder |
| Database data sources | SQL Server database, Access database, SQL Server Analysis Services database, Oracle database, IBM Db2 database, IBM Informix database (Beta), IBM Netezza, MySQL database, PostgreSQL database, Sybase database, Teradata database, SAP HANA database, SAP Business Warehouse Application Server, SAP Business Warehouse Message Server, Amazon Redshift, Impala, Google BigQuery, Vertica, Snowflake, Essbase, Actian (Beta), Amazon Athena, BI Connector, Data Virtuality LDW, Denodo, Dremio Software, Dremio Cloud (Beta), Exasol, Indexima, InterSystems IRIS (Beta), Jethro |

| | |
|---|---|
| | (Beta), Kyligence, Linkar PICK Style / MultiValue Databases (Beta), MariaDB, MarkLogic, TIBCO(R) Data Virtualization, AtScale cubes |
| Power Platform data sources | Power BI datasets, Power BI dataflows, Common Data Service (Legacy), Dataverse, Dataflows |
| Azure data sources | Azure SQL Database, Azure Synapse Analytics SQL, Azure Analysis Services database, Azure Database for PostgreSQL, Azure Blob Storage, Azure Table Storage, Azure Cosmos DB, Azure Data Explorer (Kusto), Azure Data Lake Storage Gen2, Azure Data Lake Storage Gen1, Azure HDInsight (HDFS), Azure HDInsight Spark, HDInsight Interactive Query, Azure Synapse Analytics workspace (Beta), Azure Time Series Insights (Beta), Azure Cost Management, Azure Databricks |
| Online Services data sources | SharePoint Online List, Microsoft Exchange Online, Dynamics 365 (online), Dynamics 365 (Dataverse), Dynamics NAV, Dynamics 365 Business Central, Dynamics 365 Business Central (on-premises), Azure DevOps (Boards only), Azure DevOps Server (Boards only), Salesforce Objects, Salesforce Reports, Google Analytics, Adobe Analytics, appFigures (Beta), Data.World - Get Dataset (Beta), GitHub (Beta), LinkedIn Sales Navigator (Beta), Marketo (Beta), |

| | |
|---|---|
| | Mixpanel (Beta), Planview Enterprise One - PRM (Beta), QuickBooks Online (Beta), Smartsheet, SparkPost (Beta), SweetIQ (Beta), Planview Enterprise One - CTM (Beta), Twilio (Beta), Zendesk (Beta), Asana (Beta), Assemble Views, Automation Anywhere, Automy Data Analytics (Beta), Dynamics 365 Customer Insights (Beta), Emigo Data Source, Entersoft Business Suite (Beta), eWay-CRM, FactSet Analytics, Palantir Foundry, Hexagon PPM Smart API, Industrial App Store, Intune Data Warehouse (Beta), Projectplace for Power BI, Product Insights (beta), Quick Base, SoftOne BI (beta), Spigit (Beta), TeamDesk (Beta), Webtrends Analytics (Beta), Witivio (Beta), Workplace Analytics (Beta), Zoho Creator (Beta), Digital Construction Works Insights (Beta) |
| Other data sources | Web, SharePoint list, OData Feed, Active Directory, Microsoft Exchange, Hadoop File (HDFS), Spark, Hive LLAP, R script, Python script, ODBC, OLE DB, Acterys : Model Automation & Planning (Beta), Anaplan Connector v1.0 (Beta), Solver, Bloomberg Data and Analytics, Cherwell (Beta), Cognite Data Fusion, Delta Sharing, EQuIS (Beta), FHIR, Google Sheets (Beta), Information Grid (Beta), Jamf Pro (Beta), Kognitwin, MicroStrategy for Power BI, |

| | |
|---|---|
| | Paxata, QubolePresto (Beta), Roamler (Beta), SIS-CC SDMX (Beta), Shortcuts Business Insights (Beta), Siteimprove, SumTotal, SurveyMonkey (Beta), Microsoft Teams Personal Analytics (Beta), Tenforce (Smart)List, Usercube (Beta), Vena, Vessel Insight, Zucchetti HR Infinity (Beta), BQE Core, MicroStrategy for Power BI, Starburst Enterprise, Amazon OpenSearch Service (Beta), OpenSearch Project (Beta), Blank Query |

*Table 1 PowerBI data sources (microsoft.com)*

The Power BI Desktop's Query Editor tool enables the ETL process steps via an easy graphical user interface or users can opt to take advantage of the Power Query M formula language found in the Advanced Editor (Lachev and Price, 2018).

### 3.5. The data model in the finished BI solution

While designing the solution two plans were considered. The first one included a consolidation of the data in an on premises Microsoft SQL Server data warehouse by implementing a custom ETL process. The advantage of this approach is that it would enable us to build a single location for all data and power BI would connect to it live. The second option was to follow the self-service BI approach in which connections to the data would be initiated from Power BI Desktop. The decision was made to follow the latter approach as it would be easier to maintain and troubleshoot and would also minimize the time to build the solution. The report containing the dashboards and the data model are in fact several Power BI file (*.pbix file format). The distribution is done via a special teams channel that has a tab that contains the PowerBI pbix file.


*Figure 7 PowerBI delivery to users via teams*

The source data for the completed BI solution is extracted from different systems: Entersoft ERP using custom SQL queries, SharePoint lists and excel files. The data model it forms consists of 14 facts and 11 dimensions, as well as 6 other entities that contain no data but are used to organize the DAX measures containing the KPI calculations. The data model is designed according to a star schema, in that there are no relationships between dimensions.

# 4. KPI implementation using PowerBI case study

## 4.1. The case study company

The case study will be done in a company that the writer is an employee of. The company is based in Greece and specializes in the production and distribution of construction chemicals and materials. They offer a wide range of products for various applications in the construction industry, such as waterproofing systems, adhesives, tile grouts, insulating materials, paints, and more. They also operate internationally, with subsidiaries and representatives in different countries. It has developed integrated solutions for both large and small construction projects through its wide portfolio of more than 350 high-quality products falling into the following 8 product categories:

- Waterproofing
- External Thermal Insulation
- Paints & Surface Protection
- Tile & Natural Stone Installation
- Concrete Admixtures & Repair Products
- Masonry Construction & Repair
- Industrial floorings
- Microcement Coatings & Decorative Floorings

## 4.2. KPIs status and the need for digitalisation

For the purposes of improving the organizational performance in the company that we examine, a project was started to capture the process, methods and tools that were used to create and monitor the Key Performance Indicators (KPIs). An initial finding was that, over the time, the information and quantity of data concerning the KPIs have accumulated to a great extent but at the same time have been collected and archived in unsafe and unreliable Excel files, which could be opened, modified, saved, and uploaded without the guarantee of confidentiality, concurrency, and absence of data corruption. Furthermore, given the nature of editable excel files, there was confusion regarding the process of updating and then viewing the KPIs. It was not clear when a specific file containing data was ready to be viewed while free from errors and data defects. Another issue identified is the number of files used, which are numerous and often contain redundant or duplicate information: in fact, a lot of data is duplicated and available in two or more files, causing a redundancy of information and once again increasing the probability of errors and lack of coherence between the data. To initiate the digitalization process, a massive work of mapping of all these files has been necessary, to understand where all the information came from, who was responsible for entering each data, how the values were calculated, based on which formulas and through which calculations.

### 4.3. KPIs per department

The initial analysis by the responsible department of the company formulated several metrics to be tracked per department.

| Department | Objective | KPI | Measures |
|---|---|---|---|
| **Production** | operations efficiency inventory management cash flow JIT | Inventory Days | The time that finished goods remain in stock until sold |
| | | Inventory Value | The average value of inventory on our warehouses |
| | | nonconformity index (production only) | Total number of con conformities at production of liquids |
| | | MRP Success Factor | Deviation between production planning and the actual production |

| | | | |
|---|---|---|---|
| | | Total Productivity | Productivity according to measurements in 3 production lines |
| | | Production Delays | Total production delay in hours |
| **Maintenance** | Work efficiency Costs and spending Work order management | Maintenance cost | Cost of maintenance and related consumables in relation to the total production quantities |
| | | Malfunction completion index | Average time to restore malfunctions |
| | | Malfunction index | Total hours of production halts due to malfunctions in relation to the total production hours |
| **Logistics** | operational efficiency Cost | On time delivery | Percentage of order delivered on time |
| | | Additional order rate | Number of additional orders after each original order |
| | | Transportation Costs | Cost of transportation in relation to the revenue |
| **Quality Control** | Process Improvement | Nonconformity index | Number of quality checks that were deemed nonconformities |

| | | | |
|---|---|---|---|
| | Effectiveness Reduction of errors | Returns index | Number of returns or complaints |
| | | Process improvement index | Number of complaints or returns due to inefficient procedures |
| **Procurement** | Operational Efficiency Cash flow Profit | Days of inventory | Time that raw materials, products, and consumables stay in inventory |
| | | purchase order cycle time | Average time of purchase order completion |
| | | Procurement ROI | Return of investment resulted from purchase price differences |
| | | Current inventory in value | Average value of raw materials and products |
| **IT** | Operational Efficiency Flexibility Communication | Office 365 Index | Microsoft365 usage index over time |
| | | Average Handle Time | Average time to complete incoming requests |
| **Marketing** | Engagement brand awareness | Social Media Traffic | Facebook, LinkedIn, Instagram followers |
| | loyalty brand awareness Engagement | Website Traffic | Corporate website visitors number |

| | | | |
|---|---|---|---|
| | operational efficiency | Completion indicator | Average time to task completion |
| | operational efficiency branding | Completion indicator for fixed equipment on stores | Average time to complete task to install promotional fixed assets at selling points |
| **HR** | improving employees’ skills reduce staff turn over | Training Cost | Total training cost in euros |
| | | Employee Training | Percentage of employees that received trainings in relation to total number of employees |
| | | Employee Turnover Rate | Employees turnover in relation to total number of employees |
| | | Training hours | Total and average employee training hours |
| **Technical Applications** | Operational Efficiency | Seminars Index | Number of seminars |
| | | Trained people index | Number of trainees |
| | | Technical Applications Index | Number of Technical Applications |

| | | | |
|---|---|---|---|
| **R&D** | Profit Speed Competitiveness Employees Effectiveness | New products index | Time required to complete a new product vs budgeted time |
| | | Replacement of raw materials index | Percentage of approvals of requests to replace raw materials |
| | | | |
| | | | |
| **Technical Support** | operations efficiency customer satisfaction | Average Response time | Average time to respond to calls |
| | | Total number of Calls | Total number of Calls per agent |
| | | Average Resolution Time | Average Resolution Time per agent |
| | | Maximum resolution Time | Maximum resolution Time per agent |

Table 2 KPIs index

Table 2 KPIs index contains the complete list of the KPIs that are to be included in the system. However, due to budgetary and time constraints, the management decided to implement initially the KPIs for the Marketing, Procurement, R&D and Logistics departments. This would also serve as a proof of concept, minimizing the risk and ensuring greater focus.

### 4.3.1. Data model and visual design

The approach that was used to create the metrics in PowerBI was to proceed with each department KPIs one by one. Additionally, we would create specific SQL queries to fetch data at the necessary granularity and as properly formatted as possible. For example, we will exclude cancelled sales order at the SQL query level without having to perform this action during the ETL process. One further need that arose was that of having date tables that contain only date related data. These dimension tables will be used to reference the relevant dates from the data tables at any granularity level (e.g. day, month, year). They will allow for time intelligence calculations when creating reports that require precise date information. One further need was to have two date tables linked between them and at the same time to the same data table. This will allow to have two separate slicers that filter information. E.g. to display at different columns this vs last year performance.

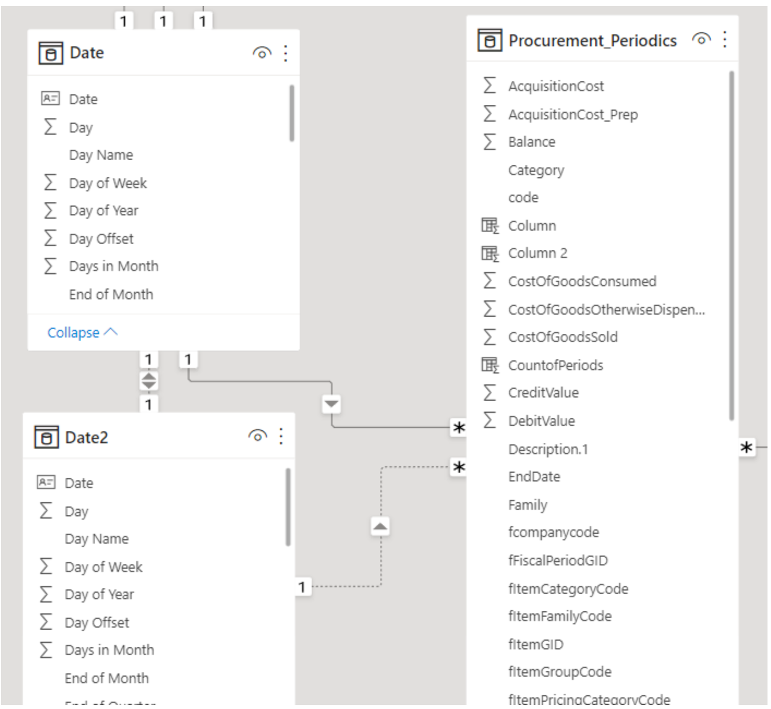



*Figure 8 Two date tables*

### 4.3.2. Marketing KPIs

The Marketing department uses a Microsoft Planner board to manage incoming tasks. This board servers as the first data table for the operational efficiency indicator. The board looks like Figure 9 below. The picture has been blurred for confidentiality reasons. Since PowerBI does not connect directly to planner boards,

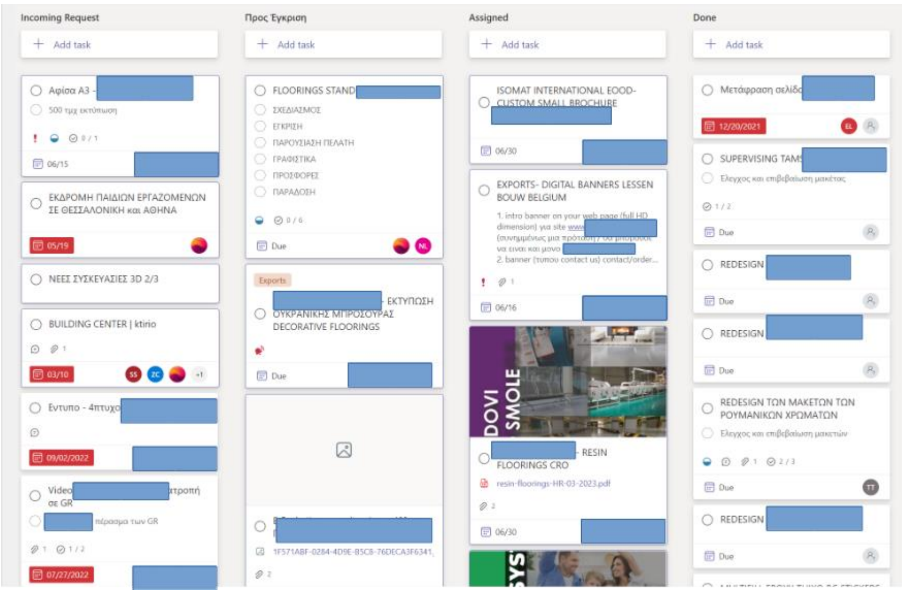



*Figure 9 Marketing tasks board*

We export the board as an excel file in pre-defined intervals and we load this excel file into powerBI.

The excel file contains the following data:

| Task ID | UniqueID |
|---|---|
| Task Name | Text column that has the name of the task |
| Bucket Name | List containing the values: Incomning Task, Under approval, Assigned, Done |
| Progress | List containing the values: Not started, in progress, Completed |
| Priority | List containing the values: Low, Medium, High, Urgent. |
| Assigned To | Contains person objects |
| Created By | Contains a single person |
| Created Date | Datetime |
| Start Date | Datetime that the manager decides |
| Due Date | Datetime that the manager decides |
| Late | Boolean based on the current date vs due data |
| Completed Date | Datetime of the completion date |
| Completed By | Contains a single person that completed the task |
| Description | Large text |
| Completed Checklist Items | List containing the completed items |
| Checklist Items | List containing items to be completed |
| Labels | Custom labels showing the company that the task applies to. In our case the companies subsidiaries |

*Table 3 Marketing Tasks schema*

After loading the file, we perform some transformation steps mostly related to the date time locale. We also create two calculate columns that contain the completed-created metric as seen on Figure 10.

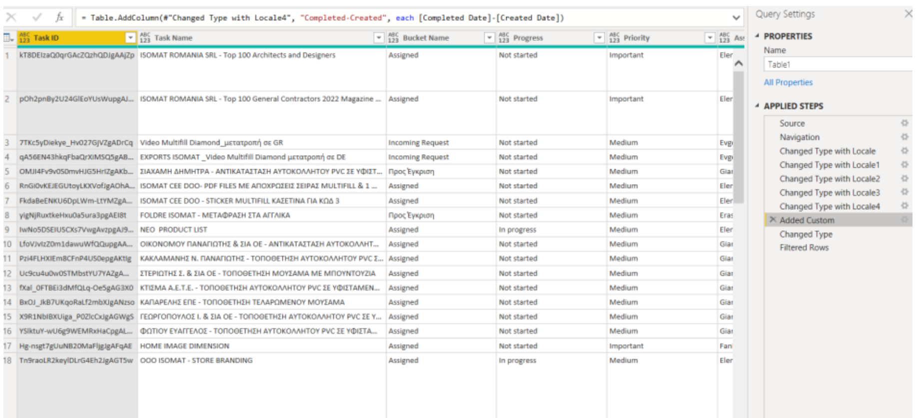


*Figure 10 marketing tasks transformation step*

After the transformation, the team began to implement the KPI metric, utilizing appropriate figures.

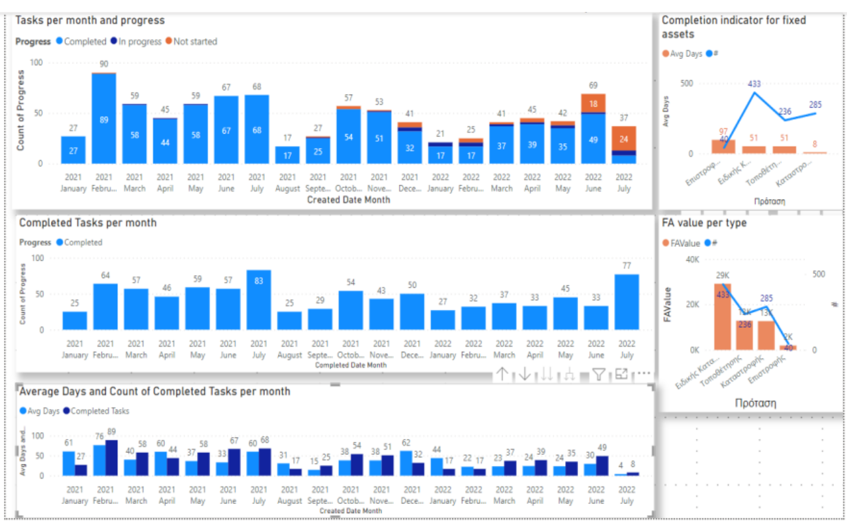


*Figure 11 PowerBI Marketing metrics*

Figure 11 is the PowerBI page that contains the metrics. The top left chart contains the number of tasks created per month and their current progress status. The left middle chart contains the number of completed tasks per month irrespective of their created month date. The bottom left chart displays the average number of days that were needed to complete a task and the count of completed tasks per month.

In our example, In June 2022 we have completed forty-nine tasks. Seven of them started on June and 42 on July. The average days for completion were thirty as seen in the highlighted parts below in Figure 12.

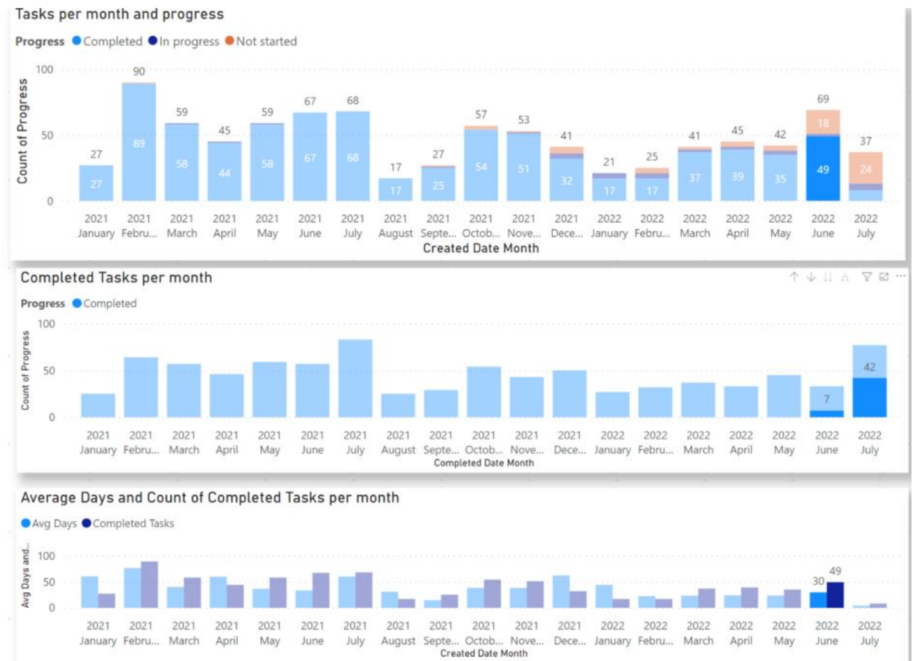



*Figure 12 Marketing Tasks Example*

A different question is when the fifty tasks that were completed started and the average days of completion. This can be answered by clicking in December 2021 in the second figure as seen below.

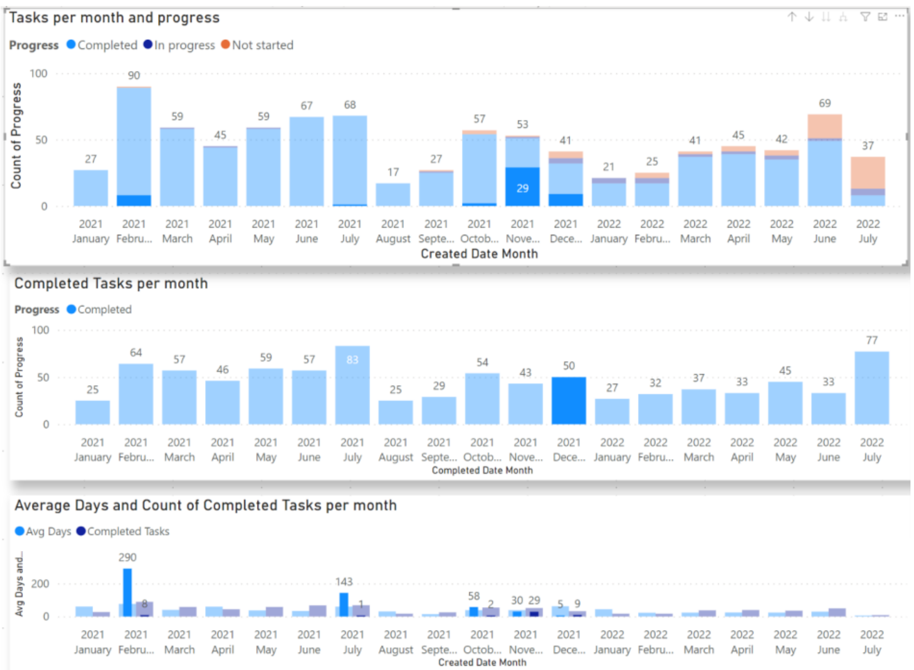



*Figure 13 Marketing Tasks 2nd example*

In order to track the operational efficiency branding KPI , we have created a custom power apps application (shown in Figure 15 ) to submit and manage requests regarding signage fixed assets in customers. This application uses a SharePoint list (shown in Figure 14) as its data source and provides a way for salespersons to submit an application.

*Figure 14 SharePoint list example row*

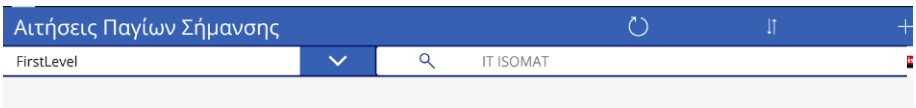



*Figure 15 PowerApps app*

In the PowerApps application, the users can check the status of their applications, they can search clients by filtering their name as seen in Figure 16. After selecting the customer, certain data are being prefilled in the application screen such as customer address, category, revenue for the last 3 years, existing signage and competitor information. The user is then to select the application category between (new installation, removal, custom installation and notification of destruction). The next step is to select the type and subtype of the item to be installed along with quantity and place of installation. All selections act as filter for the next ones. One example might be to select a new installation. This enables a subset of types that can be installed. For example, a banner that can only be installed in 1x2 meters or 2x3 meters subtype. The final touch is that we are keeping a counter of how many attachments are being uploaded since there must be at least one.


*Figure 16 PowerApps select customer screen*

After the application is submitted, a power automate flow is executed that applies the business process order with several steps containing approvals as seen below in Figure 17.

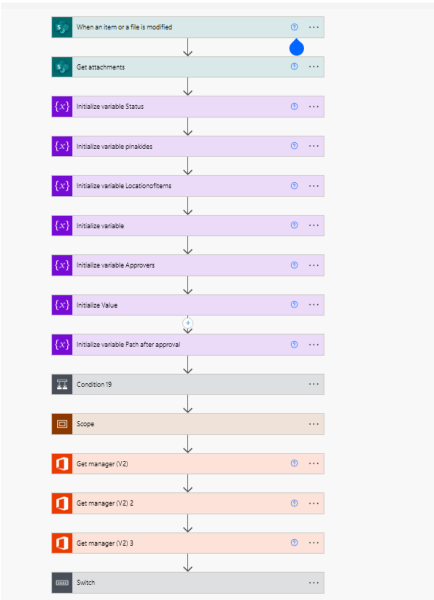



*Figure 17 Signage Flow*

The top right figure in Figure 12 displays the average days to completion per request category and the total number of requests per category. The bottom right figure displays the total value of the fixed assets and their total number per category.

The last of the powerBI reports that were created (shown in Figure 18) uses an excel file as a source to keep track of the social applications activities of the companies in the group.

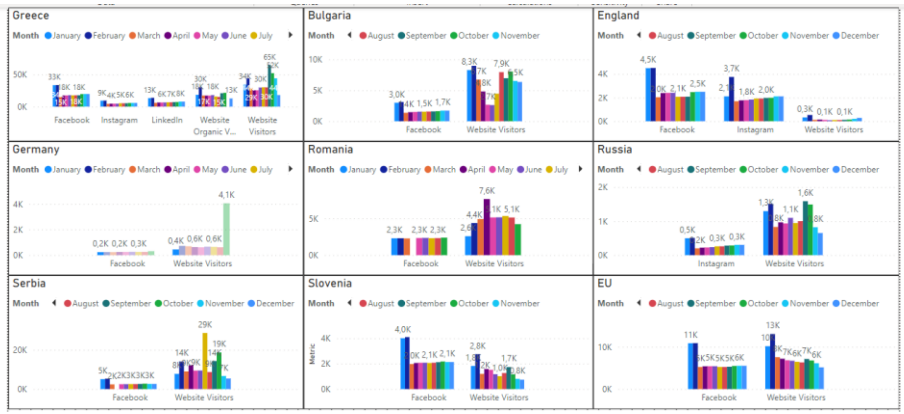
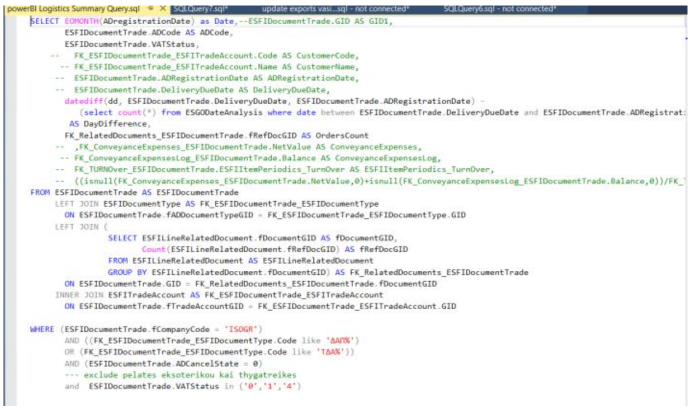



*Figure 18 Social Metrics*

### 4.3.3. Logistics KPIs

The performance of the logistics department is of great importance for evaluating and improving the level of service that the company offers. The data source of this is the company's ERP and four metrics have been designed.

As depicted in the figure below, there are 4 main SQL queries that capture the data related to the own transportation cost, third party cost, turnover per month and the number of deliveries per order and each line's difference from the actual delivery day to the programmed delivery date.



powerBI Logistics Summary Query.sql   SQLQuery7.sql*   update exports vasi...sql - not connected*   SQLQuery6.sql - not connected*

```sql
SELECT EOMONTH(ADregistrationDate) as Date,--ESFIDocumentTrade.GID AS GID1,
        ESFIDocumentTrade.ADCode AS ADCode,
        ESFIDocumentTrade.VATStatus,
    --   FK_ESFIDocumentTrade_ESFITradeAccount.Code AS CustomerCode,
     -- FK_ESFIDocumentTrade_ESFITradeAccount.Name AS CustomerName,
    --  ESFIDocumentTrade.ADRegistrationDate AS ADRegistrationDate,
    --  ESFIDocumentTrade.DeliveryDueDate AS DeliveryDueDate,
      datediff(dd, ESFIDocumentTrade.DeliveryDueDate, ESFIDocumentTrade.ADRegistrationDate) -
         (select count(*) from ESGODateAnalysis where date between ESFIDocumentTrade.DeliveryDueDate and ESFIDocumentTrade.ADRegistrat
       AS DayDifference,
      FK_RelatedDocuments_ESFIDocumentTrade.fRefDocGID AS OrdersCount
    --  ,FK_ConveyanceExpenses_ESFIDocumentTrade.NetValue AS ConveyanceExpenses,
     -- FK_ConveyanceExpensesLog_ESFIDocumentTrade.Balance AS ConveyanceExpensesLog,
    --  FK_TURNOver_ESFIDocumentTrade.ESFIItemPeriodics_TurnOver AS ESFIItemPeriodics_TurnOver,
    --  ((isnull(FK_ConveyanceExpenses_ESFIDocumentTrade.NetValue,0)+isnull(FK_ConveyanceExpensesLog_ESFIDocumentTrade.Balance,0))/FK_
FROM ESFIDocumentTrade AS ESFIDocumentTrade
    LEFT JOIN ESFIDocumentType AS FK_ESFIDocumentTrade_ESFIDocumentType
      ON ESFIDocumentTrade.fADDocumentTypeGID = FK_ESFIDocumentTrade_ESFIDocumentType.GID
    LEFT JOIN (
              SELECT ESFILineRelatedDocument.fDocumentGID AS fDocumentGID,
                     Count(ESFILineRelatedDocument.fRefDocGID) AS fRefDocGID
              FROM ESFILineRelatedDocument AS ESFILineRelatedDocument
              GROUP BY ESFILineRelatedDocument.fDocumentGID) AS FK_RelatedDocuments_ESFIDocumentTrade
      ON ESFIDocumentTrade.GID = FK_RelatedDocuments_ESFIDocumentTrade.fDocumentGID
    INNER JOIN ESFITradeAccount AS FK_ESFIDocumentTrade_ESFITradeAccount
      ON ESFIDocumentTrade.fTradeAccountGID = FK_ESFIDocumentTrade_ESFITradeAccount.GID

WHERE (ESFIDocumentTrade.fCompanyCode = 'ISOGR')
      AND ((FK_ESFIDocumentTrade_ESFIDocumentType.Code like 'ΔΑΠ%')
      OR (FK_ESFIDocumentTrade_ESFIDocumentType.Code like 'ΤΔΑ%'))
      AND (ESFIDocumentTrade.ADCancelState = 0)
      --- exclude pelates eksoterikou kai thygatreikes
      and  ESFIDocumentTrade.VATStatus in ('0','1','4')
```

*Figure 19 Logistics cost SQL query*

More specifically, the query that calculates the own transportation cost, uses a SQL table that aggregates the net value of the documents that contain own transportation costs such as fuel, service and repairs, traffic tolls, etc since 2019 that have not been cancelled. This information is 5649 lines since 2019 and is then aggregated per month via a suitable GROUP BY SQL function.

The third-party transportation cost query is more simple since it just a sum of the debit minus the credit of the general ledger account 64.00.03.0024. This amounts to 17.234 rows that are then totaled via the familiar GROUP By function to a value per month.

The turnover per month query uses the SQL table ESFIItemPeriodics that contains data per document, item and document item line. These documents are what we generally call as invoices. The total number of lines are over 6 million and we aggregate the turnover column per month for our reporting needs.

The final query deals with the days of difference calculation between the programmed and the actual delivery date of the goods sold. This is achieved by the formula "datediff(dd, ESFIDocumentTrade.DeliveryDueDate, ESFIDocumentTrade.ADRegistrationDate) - (select count(*) from ESGODateAnalysis where date between

ESFIDocumentTrade.DeliveryDueDate and ESFIDocumentTrade.ADRegistrationDate and IsWorkingDate=0" that also does not take into account weekends.

The output of the query is the following table that contains 390.000 rows.

| | Date | ADCode | VATStatus | DayDifference | OrdersCount |
|---|---|---|---|---|---|
| 1 | 2016-06-30 | ΤΔΑ-Κ-08355 | 0 | -1 | 2 |
| 2 | 2022-04-30 | ΤΔΑ-Κ-114582 | 0 | 0 | 2 |
| 3 | 2019-12-31 | ΤΔΑ-Α-75089 | 0 | 1 | 3 |
| 4 | 2022-05-31 | ΤΔΑ-Κ-116844 | 0 | 1 | 1 |
| 5 | 2018-04-30 | ΔΑΠ-Κ-36369 | 0 | -1 | 1 |
| 6 | 2016-02-29 | ΤΔΑ-Κ-01024 | 0 | -1 | 1 |

*Table 4 Days of difference query output*

This information is fed into the PowerBI dashboard as is and the aggregations are done on the report level,

On the PowerBI dashboard we have created the following figures.

The first one is the time to deliver metric. This uses the per order line agreed delivery date as compared to the actual delivery date. Figure 20 charts the evolution across the time axis. This KPI excludes exports because they have a set shipping date that is not amenable to changes due to hard limits such as ships, international trucks and trains embarking. For the domestic customers, the ERP has a set rule that promises next day delivery for customers that place an order until 12am. However, this has the limitation that it assumes a successful and timely credit check pass of the order. Oftentimes, the credit department does not discharge an order before 12am, so making it incorrect to assume that the logistics department is to blame for the broken promise of next day delivery. This highlights a crucial aspect that must be considered when designing KPIs with a departmental focus, in that most enterprise processes are cross departmental. In this case, it is the company that is failing the promise of next day delivery and not the logistics department. As such, considering the time that the order has been credit check cleared to calculate the business rule of next day delivery has been proposed to rectify this. Another business reason for delivery delays is failure to produce or procure on time. This fact does not permit the logistics department to meet its goal and must be considered. Currently, since it is difficult to account for this fact, it has been suggested that it will be dealt with at a later stage.

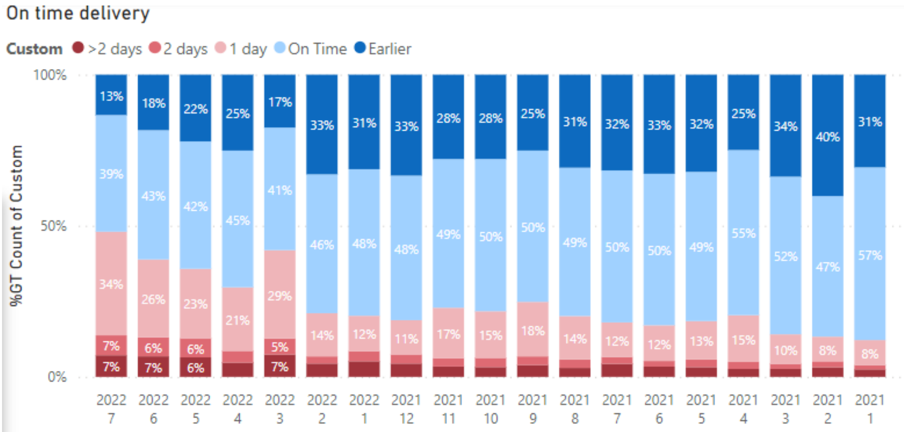



*Figure 20 On time delivery chart*

The second metric has to do with the average cost by quarter and year as compared to the turnover. We can observe the discrepancy that happens on years end due to the end of year credit notes that are being issues to the customers. To calculate the transportation, cost we used a specific SQL query that summarizes the results as detailed in Figure 19. This cost is calculated as a sum of our cost as captured in a specific general ledger account, the third part cost as captured by invoice registrations by third parties and the total cost for drivers divided by 12 using this calculated column formula "= Table.AddColumn(#"Renamed Columns", "DriversCost", each 332552.08/12)".

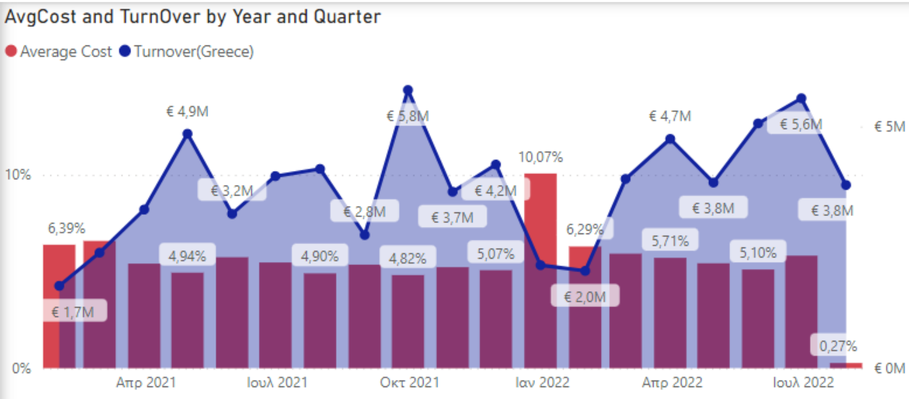
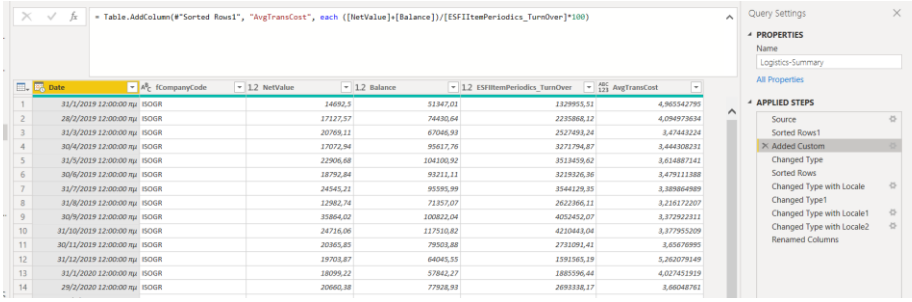



*Figure 21 Average cost and turnover*

After the import, on the transformation step the main addition is a calculated column of the average transportation cost as seen in Figure 22.




| | Date | fCompanyCode | NetValue | Balance | ESFIItemPeriodics_TurnOver | AvgTransCost |
|---|---|---|---|---|---|---|
| 1 | 31/1/2019 12:00:00 πμ | ISOGR | 14692,5 | 51347,01 | 1329955,51 | 4,965542795 |
| 2 | 28/2/2019 12:00:00 πμ | ISOGR | 17127,57 | 74430,64 | 2235868,12 | 4,094973634 |
| 3 | 31/3/2019 12:00:00 πμ | ISOGR | 20769,11 | 67046,93 | 2527493,24 | 3,47443224 |
| 4 | 30/4/2019 12:00:00 πμ | ISOGR | 17072,94 | 95617,76 | 3271794,87 | 3,444308231 |
| 5 | 31/5/2019 12:00:00 πμ | ISOGR | 22906,68 | 104100,92 | 3513459,62 | 3,614887141 |
| 6 | 30/6/2019 12:00:00 πμ | ISOGR | 18792,84 | 93211,11 | 3219326,36 | 3,479111388 |
| 7 | 31/7/2019 12:00:00 πμ | ISOGR | 24545,21 | 95595,99 | 3544129,35 | 3,389864989 |
| 8 | 31/8/2019 12:00:00 πμ | ISOGR | 12982,74 | 71357,07 | 2622366,11 | 3,216172207 |
| 9 | 30/9/2019 12:00:00 πμ | ISOGR | 35864,02 | 100822,04 | 4052452,07 | 3,372922311 |
| 10 | 31/10/2019 12:00:00 πμ | ISOGR | 24716,06 | 117510,82 | 4210443,04 | 3,377955209 |
| 11 | 30/11/2019 12:00:00 πμ | ISOGR | 20365,85 | 79503,88 | 2731091,41 | 3,65676995 |
| 12 | 31/12/2019 12:00:00 πμ | ISOGR | 19703,87 | 64045,55 | 1591565,19 | 5,262079149 |
| 13 | 31/1/2020 12:00:00 πμ | ISOGR | 18099,22 | 57842,27 | 1885596,44 | 4,027451919 |
| 14 | 29/2/2020 12:00:00 πμ | ISOGR | 20660,38 | 77928,93 | 2693338,17 | 3,66048761 |

*Figure 22 Average transportation cost*

Additionally, we have created a date table that we linked to all other data sources to have proper date hierarchy on the visuals.

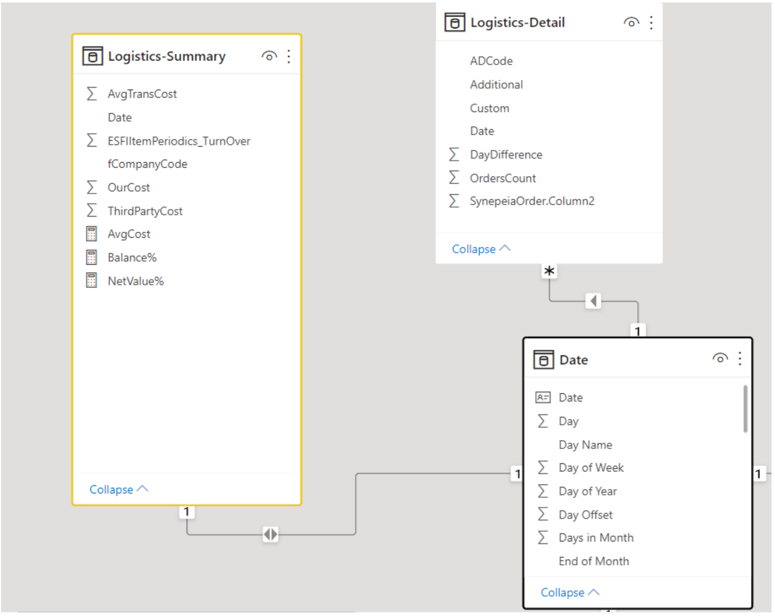



*Figure 23 Date data table*

Upon examining this metric, the team decided that comparing cost to revenue was not fully correct due to being skewed by seasonal postings such as yearly revenue-based credit notes and by nominal increases in product prices. So, it was proposed that a secondary metric would be created that would compare cost to quantity as seen below.

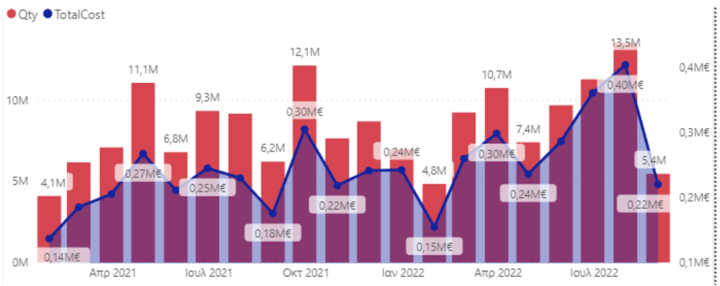



*Figure 24 Cost vs Quantity*

The next visual in Figure 25 displays our cost and third-party transportation cost in relation to the quantity distributed. This KPI is important because it allows the company to keep track of the delivery costs though certain caveats must be considered. The metric is considering only the cost that are being posted in a specific general ledger account that captures fuel, service, and other related costs. Because the ERP system does not contain salary cost per cost center for drivers, we taken it at a yearly level and divided by 12 (months) to alleviate the skewness caused by seasonal salary expenses like that constitute the $13^{th}$ and $14^{th}$ salary that are being handed in Spring, Summer, and Winter. On the quantity part, the KPI considers only quantity transported in the domestic market and not exports to clients or intra-company sales to subsidiaries. This is because they are paying directly for the transportation cost of the goods whereas exports clients pay the cost themselves. changes in revenue or item prices. The formulas used are OurCost% = DIVIDE((Sum('Logistics-Summary'[OurCost])+sum('Logistics-Summary'[DriversCost])),SUM('Logistics-Summary'[Qty])) that calculates our cost in relation to quantity moved. The other formula

ThirdPartyCost% = DIVIDE(Sum('Logistics-Summary'[ThirdPartyCost]),SUM('Logistics-Summary'[Qty])) calculates the third party cost in relation to quantity moved.

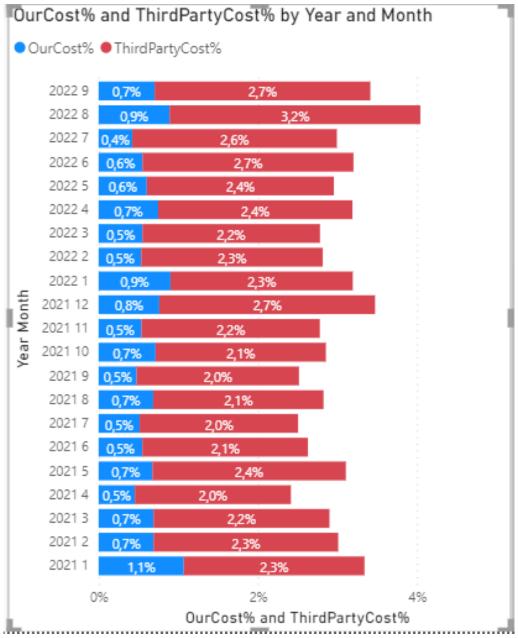



*Figure 25 First- and third-party transportation cost*

The x axis of this visual is the date hierarchy containing only year and month. The schema of this visual is displayed below with a 1:1 relationship between the data column of the main table and the date column of the date table.

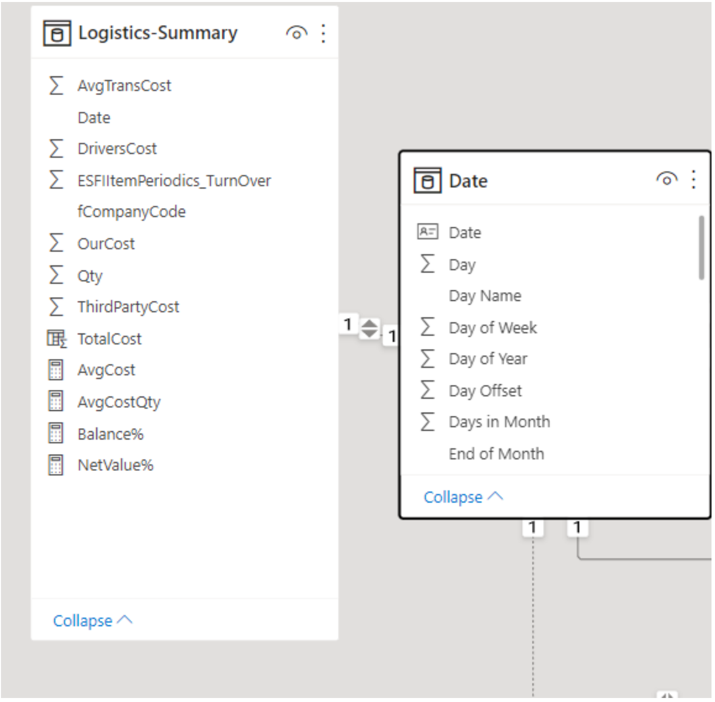



*Figure 26 Our and third party cost % data model*

The last metric has to do with the amount of additional order that are being inserted in the system in relation to an existing one. This is a valuable metric because it allows us to measure the efficiency of the ordering process. Currently, the process is as follows: The customer places an order, this order is credit checked and priced. Then, the order places a reservation in the system and then it is transferred to the warehouse management system where it is released for picking and subsequently packing and loading. The final step is to create the delivery note. In this step, all different picking and packing orders are combined to one delivery note. So, the KPI count the amount of packing orders that constitutes one delivery note and treats this number as additional orders.

There are multiple reasons why a customer may place multiple orders per day. One main reason is that there are production delays so some ordered items must be exchanged with others. Another reason is that when they are placing the order, they are below certain limits that entitle them to additional discounts or other perks like free transportation.

Upon observation we have identified some cases where for some customer we issue several delivery notes per day. This is due to business reasons such as the need to send certain product categories separately. The impact on the KPI is under investigation and it will be dealt with at a later stage.

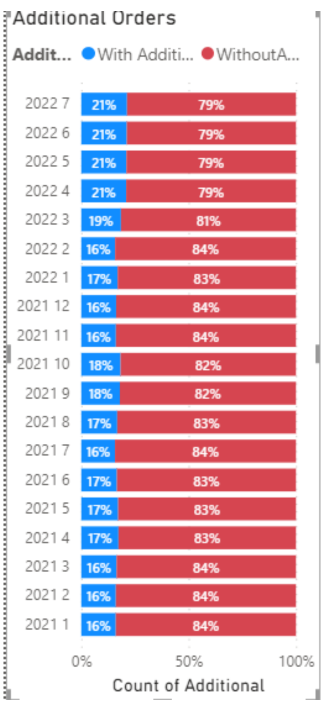



*Figure 27 Additional Orders*

For this table we used a specific SQL query detailed below in Figure 28

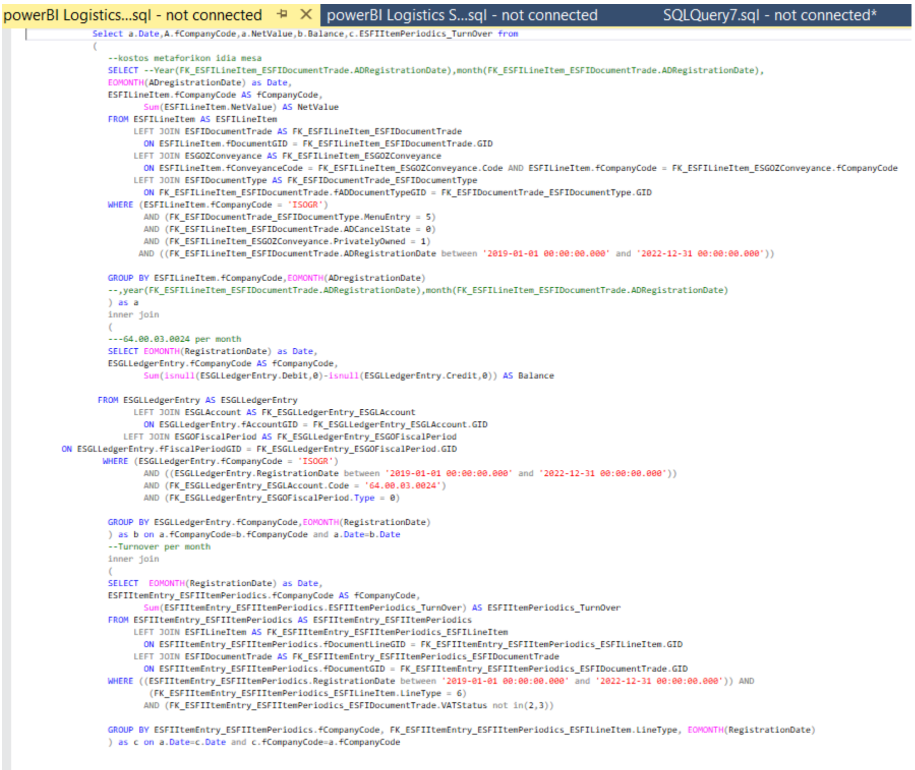



*Figure 28 Additional Orders SQL query*

### 4.3.4. Procurement KPIs

For the procurement department we created an SQL query that would fetch all the necessary data as seen in Figure 29.

*Figure 29 Procurement SQL Query*

The query itself is 116 lines of code indicating the complexity of calculating the metrics.

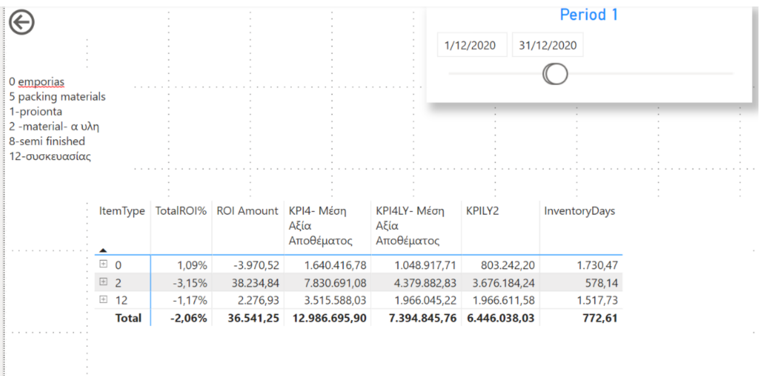
The results of the query are 425.000 lines that contain the item code, the period, the sales quantity, the turnover, the cost of goods sold value, the purchases quantity, the acquisition cost, the cost of goods that are consumed, the official valuation price that is calculated by the ERP, the balance of the item, and the item's category, subcategory, group, type and pricing category. These columns will be used in the PowerBI report to calculate the required metrics.

| | fItemGID | Description | fFiscalPeriodGID | EndDate | SalesQty | TurnOver | InvoicedSalesQty | DebitValue | CreditValue | CostOfG |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2358895A-567A-48E0-8880-0009DDE938A1 | 02 - ΦΕΒ 2022 | 3B953C62-7392-431F-BC5C-18DC566D7659 | 2022-02-28 00:00:00.000 | 171.0000000000 | 914.0000000000 | 166.5000000000 | 0.0000000000 | 735.8400000000 | 730.17C |
| 2 | 2358895A-567A-48E0-8880-0009DDE938A1 | 13 - ΚΛΕΙΣΙΜΑΤΟΣ 2020 | 88D27CD7-3C79-4446-99DA-1AE9463887F9 | 2020-12-31 00:00:00.000 | 0.0000000000 | 0.0000000000 | 0.0000000000 | 0.0800000000 | 0.0600000000 | 0.0000C |
| 3 | 2358895A-567A-48E0-8880-0009DDE938A1 | 08 - ΑΥΓ 2019 | DFE87714-52E2-4118-BF1C-49ABF008872A | 2019-08-31 00:00:00.000 | 267.7500000000 | 1495.7400000000 | 258.7500000000 | 0.0000000000 | 819.7600000000 | 818.84C |
| 4 | 2358895A-567A-48E0-8880-0009DDE938A1 | 05 - ΜΑΪ 2020 | F2C9C8B1-3203-462E-B93B-55F9B2D86DC4 | 2020-05-31 00:00:00.000 | 733.5000000000 | 4099.0700000000 | 688.5000000000 | 0.0000000000 | 2471.6700000000 | 2471.67 |
| 5 | 2358895A-567A-48E0-8880-0009DDE938A1 | 04 - ΑΠΡ 2018 | CD556DAA-9411-45F1-9F9A-585512DDAB56 | 2018-04-30 00:00:00.000 | 453.0000000000 | 2396.1600000000 | 408.7500000000 | 0.0000000000 | 1349.6100000000 | 1345.6C |
| 6 | 2358895A-567A-48E0-8880-0009DDE938A1 | 09 - ΣΕΠ 2020 | 08E0E66D-718B-48F3-B32A-5AD988053CB4 | 2020-09-30 00:00:00.000 | 399.0000000000 | 2361.8000000000 | 415.5000000000 | 12129.9600000000 | 1507.6900000000 | 1491.59 |
| 7 | 2358895A-567A-48E0-8880-0009DDE938A1 | 11 - ΝΟΕ 2015 | AC2C5531-60D7-41D6-B1D5-6F1B9457C0D8 | 2015-11-30 00:00:00.000 | 162.7500000000 | 925.6300000000 | 162.7500000000 | 0.0000000000 | 0.0000000000 | 474.66C |
| 8 | 2358895A-567A-48E0-8880-0009DDE938A1 | 00 - ΑΠΟΓΡΑΦΗΣ 2017 | 5073A619-EE52-4C9D-B027-7C84D9C3388A | 2017-01-01 00:00:00.000 | 0.0000000000 | 0.0000000000 | 0.0000000000 | 468.5500000000 | 0.0000000000 | 0.0000C |
| 9 | 2358895A-567A-48E0-8880-0009DDE938A1 | 12 - ΔΕΚ 2022 | AB25D9C2-4722-4213-9278-9980949087D4 | 2022-12-31 00:00:00.000 | 126.0000000000 | 440.3500000000 | 126.0000000000 | 277.1900000000 | 556.5400000000 | 552.54C |
| 10 | 2358895A-567A-48E0-8880-0009DDE938A1 | 04 - ΑΠΡ 2021 | 2284B049-963F-418F-9211-9D03094A0CCE | 2021-04-30 00:00:00.000 | 405.7500000000 | 2520.0800000000 | 468.7500000000 | 0.0000000000 | 1758.6400000000 | 1754.16 |
| 11 | 2358895A-567A-48E0-8880-0009DDE938A1 | 07 - ΙΟΥΛ 2021 | 3F3C83F6-C13F-45EC-81A3-D3CBDAF02066 | 2021-07-31 00:00:00.000 | 344.2500000000 | 1997.6400000000 | 362.2500000000 | 1363.6300000000 | 1287.2900000000 | 1355.64 |
| 12 | 2358895A-567A-48E0-8880-0009DDE938A1 | 07 - ΙΟΥΛ 2020 | FBB59D12-DC92-4DAC-A08F-11DB8BD7EAC2 | 2020-07-31 00:00:00.000 | 603.7500000000 | 3531.8400000000 | 599.2500000000 | 0.0000000000 | 2151.2500000000 | 2151.25 |
| 13 | 2358895A-567A-48E0-8880-0009DDE938A1 | 10 - ΟΚΤ 2020 | EB0742CA-8D9A-43CF-BE33-213CA6A2E80F | 2020-10-31 00:00:00.000 | 472.5000000000 | 2566.1400000000 | 468.0000000000 | 0.0000000000 | 1682.4200000000 | 1680.05 |
| 14 | 2358895A-567A-48E0-8880-0009DDE938A1 | 03 - ΜΑΡ 2022 | A28EA900-E682-45F3-9248-2FF209B64D08 | 2022-03-31 00:00:00.000 | 185.2500000000 | 1050.2500000000 | 189.7500000000 | 0.0000000000 | 832.1000000000 | 832.10C |
| 15 | 2358895A-567A-48E0-8880-0009DDE938A1 | 00 - ΑΠΟΓΡΑΦΗΣ 2019 | 55B4ED27-A97E-4CB2-9792-643353254860 | 2019-01-01 00:00:00.000 | 0.0000000000 | 0.0000000000 | 0.0000000000 | 945.5600000000 | 0.0000000000 | 0.0000C |

*Table 5 Items periodics data for procurement KPIs*

On the transformation phase, the one major addition was the calculation of sales consumption metric using the formula SalesConsumption=cost of goods sold+cost of goods consumed + cost of goods otherwise dispensed.

While designing the report a matrix visualization was chosen to depict the KPIs per item and item category as seen in the work in progress Figure 30.




| ItemType | TotalROI% | ROI Amount | KPI4- Μέση Αξία Αποθέματος | KPI4LY- Μέση Αξία Αποθέματος | KPILY2 | InventoryDays |
|---|---|---|---|---|---|---|
| 0 | 1,09% | -3.970,52 | 1.640.416,78 | 1.048.917,71 | 803.242,20 | 1.730,47 |
| 2 | -3,15% | 38.234,84 | 7.830.691,08 | 4.379.882,83 | 3.676.184,24 | 578,14 |
| 12 | -1,17% | 2.276,93 | 3.515.588,03 | 1.966.045,22 | 1.966.611,58 | 1.517,73 |
| **Total** | **-2,06%** | **36.541,25** | **12.986.695,90** | **7.394.845,76** | **6.446.038,03** | **772,61** |

*Figure 30 Procurement KPIs matrix*

The KPI metrics are the following measures:

```
1. TotalROI% = -DIVIDE([ROI Amount],SUMX(Procurement_Periodics,Procurement_Periodics[AcquisitionCost]))
2. ROI Amount = sumx(VALUES(Procurement_Periodics[ItemDescription]),[ROI])
3. KPI4- Μέση Αξία Αποθέματος = SUM(Procurement_Periodics[runningSum])/[Periods]
4. KPI4LY- Μέση Αξία Αποθέματος = CALCULATE( SUM(Procurement_Periodics[runningSum])/[PeriodsLY] ,ALL('Date'), USERELATIONSHIP('Date'[Date],Date2[Date]) )
5. KPILY2 = CALCULATE([KPI4- Μέση Αξία Αποθέματος],SAMEPERIODLASTYEAR('Date'[Date]))
6. InventoryDays = divide([KPI4- Μέση Αξία Αποθέματος],sum(Procurement_Periodics[SalesConsumption]),0)*365
```

1. The first KPI TotalROI% is dividing the ROI Amount measure over the sum of the Acquisiyion Cost for each item.
   1.1. The ROI Amount is calculated by as "`ROI Amount = sumx(VALUES(Procurement_Periodics[ItemDescription]),[ROI])`".

1.2. The Acquisition Cost denotes the cost to replenish one quantity of each item, i.e. the purchase or production cost per unit. This is a value that is being calculated by the ERP system.

2. The ROI Amount has been described above

3. The KPI4- Μέση Αξία Αποθέματος is translated as mean inventory value and is the division of the value of each item over the number of periods that we are taking into account.

   3.1. The RunningSum is calculated as below

```
runningSum = CALCULATE(sum(Procurement_Periodics[Balance])
,filter(Procurement_Periodics,
Procurement_Periodics[fItemGID]=EARLIER(Procurement_Periodics[fItemGID])
&&Procurement_Periodics[Year]=EARLIER(Procurement_Periodics[Year])
&&Procurement_Periodics[EndDate]<=EARLIER(Procurement_Periodics[EndDate])))
```

   3.2. Periods is calculated as “Periods = CALCULATE(DISTINCTCOUNT('Date'[Month]))”

4. The KPI4LY is the same KPI as the one above but only for the same period of last year. It is worth mentioning the the KPI4LY metric was designed two times using different formulas. At first a second date slicer was introduced that allowed the calculation using a different period than the KPI4 metric. After gaining additional knowledge on the DAX formulas of PowerBI, the KPI4LY2 measure was designed that used the very useful sameperiodlastyear formula to achieve the same result.

   4.1. The formula to produce this KPI is

```
KPI4LY- Μέση Αξία Αποθέματος = CALCULATE(
SUM(Procurement_Periodics[runningSum])/[PeriodsLY]

,ALL('Date'),
USERELATIONSHIP('Date'[Date],Date2[Date]))
```

   4.2.

   4.3. runningSum = CALCULATE(sum(Procurement_Periodics[Balance])

The ROI is calculated as “ROI = IFERROR( ([ValuationPrice]-[ValuationPriceLY])/[ValuationPriceLY]*SUMx(Procurement_Periodics,Procurement_Periodics[AcquisitionCost]),0)”

## 5. Conclusion

Business intelligence (BI) is an essential tool for any business, regardless of its size and industry. It provides valuable insights into the business's performance, enabling the management to make informed decisions. BI helps businesses to identify patterns, trends, and relationships in their data, which can be used to optimize their operations and improve their profitability.

The Power BI case study on the manufacturing company provided valuable insights into the company's performance, which can be used to make data-driven decisions. The analysis identified areas of improvement, such as inventory management and supplier diversification, which can help the company improve its performance and reduce risks.

In particular, the following picture has been the subject of discussion to identify the reasons for the increase of the delay in customer orders in the summer of 2022. After a few workshops several actions have been proposed including staffing the warehouse in Attiki, monitoring the causes of the delays monthly in order to be proactive and suggesting alterations in the agreements with logistics companies.

The same was identified in January 2023 for the warehouse in Attiki. This had a different cause due to it being relocated from Central Greece to Attiki.

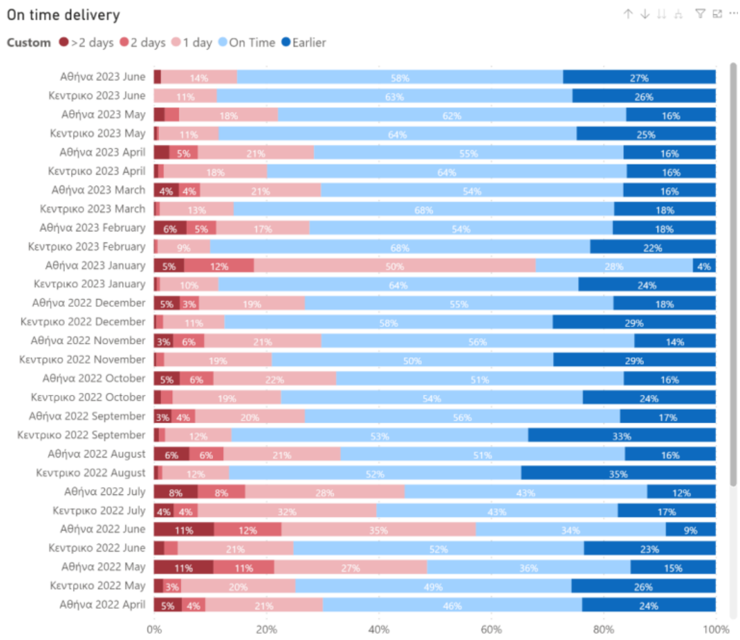



*Figure 31 On time delivery KPI discussion*

The project also revealed that there is a trove of useful data that are waiting to be brought to attention by similar future projects. The analysis provided by Power BI allowed the company to identify patterns and trends in their data, enabling them to optimize their operations and improve their performance.

We must not fail to mention that these cases need continuous investment, monitoring, and control to verify the metrics and ensure they are prompt, accurate and reflect the truth. Stakeholders, especially when pressed, are seeking ways to undermine the legitimacy of any such project and an oversight or error carries risk. Secondly, unless these metrics are being monitored and evaluated constantly, people tend to ignore them unless there is a specific reason, thus losing the opportunity of small gradual improvements while acting and not being proactive.

In any case, business analytics tools are essential for any business looking to make data-driven decisions. PowerBI, is user-friendly, interactive, and enables businesses to gain insights into their data quickly and efficiently.

In conclusion, the Power BI case study on the manufacturing company demonstrated the importance of business intelligence and Power BI as a tool for making data-driven decisions. The analysis provided by Power BI allowed the company to identify areas of improvement and optimize their operations, improving their performance and reducing risks. BI intelligence tools such as PowerBI are a necessity for any business looking to gain insights into their data and make informed decisions.

## Bibliography:


Ahmad, S., Miskon, S., Alabdan, R., Tlili, I., 2020. Exploration of Influential Determinants for the Adoption of Business Intelligence System in the Textile and Apparel Industry. Sustainability 12, 7674. https://doi.org/10.3390/su12187674

Ain, N., Vaia, G., DeLone, W.H., Waheed, M., 2019. Two decades of research on business intelligence system adoption, utilization and success – A systematic literature review. Decis. Support Syst. 125, 113113. https://doi.org/10.1016/j.dss.2019.113113

Alavi, M., Leidner, D.E., 2001. Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. MIS Q. 25, 107. https://doi.org/10.2307/3250961

Allen, S.L., Terry, E., 2006. Beginning relational data modeling. Apress.

Alpar, P., Schulz, M., 2016. Self-service business intelligence. Bus. Inf. Syst. Eng. 58, 151–155.

An integrated model for determining business intelligence systems adoption and post-adoption benefits in banking sector, 2016. . J. Adm. Bus. Stud. 2. https://doi.org/10.20474/jabs-2.2.4

Arizona State University, Kulkarni, U., Robles-Flores, J., Universidad ESAN, Popovič, A., University of Ljubljana, 2017. Business Intelligence Capability: The Effect of Top Management and the Mediating Roles of User Participation and Analytical Decision Making Orientation. J. Assoc. Inf. Syst. 18, 516–541. https://doi.org/10.17705/1jais.00462

Arnott, D., Pervan, G., 2014. A Critical Analysis of Decision Support Systems Research Revisited: The Rise of Design Science. J. Inf. Technol. 29, 269–293. https://doi.org/10.1057/jit.2014.16

Baars, H., Kemper, H.-G., 2008. Management Support with Structured and Unstructured Data—An Integrated Business Intelligence Framework. Inf. Syst. Manag. 25, 132–148. https://doi.org/10.1080/10580530801941058

Ballard, C., Farrell, D.M., Gupta, A., Mazuela, C., Vohnik, S., 2012. Dimensional Modeling: In a Business Intelligence Environment. IBM Redbooks.

Bordeleau, F.-E., Mosconi, E., de Santa-Eulalia, L.A., 2020. Business intelligence and analytics value creation in Industry 4.0: a multiple case study in manufacturing medium enterprises. Prod. Plan. Control 31, 173–185. https://doi.org/10.1080/09537287.2019.1631458

Business Intelligence Software - Worldwide, n.d. URL https://www.statista.com/outlook/tmo/software/enterprise-software/business-intelligence-software/worldwide

Chen, Chiang, Storey, 2012. Business Intelligence and Analytics: From Big Data to Big Impact. MIS Q. 36, 1165. https://doi.org/10.2307/41703503

Cheung, C.F., Li, F.L., 2012. A quantitative correlation coefficient mining method for business intelligence in small and medium enterprises of trading business. Expert Syst. Appl. 39, 6279–6291. https://doi.org/10.1016/j.eswa.2011.10.021

Clark, D., 2020. Importing Data into Power BI Desktop, in: Clark, D. (Ed.), Beginning Microsoft Power BI: A Practical Guide to Self-Service Data Analytics. Apress, Berkeley, CA, pp. 21–46. https://doi.org/10.1007/978-1-4842-5620-6_2

Cooper, B.L., Watson, H.J., Wixom, B.H., Goodhue, D.L., 2000. Data Warehousing Supports Corporate Strategy at First American Corporation. MIS Q. 24, 547. https://doi.org/10.2307/3250947

Davenport, T.H., 1993. Process innovation: reengineering work through information technology. Harvard Business School Press, Boston, Mass.

Davenport, T.H., Harris, J.G., Morison, R., 2010. Analytics at work: smarter decisions, better results. Harvard Business Press, Boston, Mass.

Davenport, T.H., Prusak, L., 1998. Working knowledge: how organizations manage what they know. Harvard Business School Press, Boston, Mass.

de Camargo Fiorini, P., Roman Pais Seles, B.M., Chiappetta Jabbour, C.J., Barberio Mariano, E., de Sousa Jabbour, A.B.L., 2018. Management theory and big data literature: From a review to a research agenda. Int. J. Inf. Manag. 43, 112–129. https://doi.org/10.1016/j.ijinfomgt.2018.07.005

Elbashir, M.Z., Collier, P.A., Davern, M.J., 2008. Measuring the effects of business intelligence systems: The relationship between business process and organizational performance. Int. J. Account. Inf. Syst. 9, 135–153. https://doi.org/10.1016/j.accinf.2008.03.001

El-Sappagh, S.H.A., Hendawi, A.M.A., El Bastawissy, A.H., 2011. A proposed model for data warehouse ETL processes. J. King Saud Univ. - Comput. Inf. Sci. 23, 91–104. https://doi.org/10.1016/j.jksuci.2011.05.005

Ferrari, A., Russo, M., 2017. Analyzing Data with Power BI and Power Pivot for Excel. Microsoft Press.

Fink, L., Yogev, N., Even, A., 2017. Business intelligence and organizational learning: An empirical investigation of value creation processes. Inf. Manage. 54, 38–56. https://doi.org/10.1016/j.im.2016.03.009

Giotopoulos, I., Kontolaimou, A., Korra, E., Tsakanikas, A., 2017. What drives ICT adoption by SMEs? Evidence from a large-scale survey in Greece. J. Bus. Res. 81, 60–69. https://doi.org/10.1016/j.jbusres.2017.08.007

Hartley, K., Seymour, L.F., 2011. Towards a framework for the adoption of business intelligence in public sector organisations: the case of South Africa, in: Proceedings of the South African Institute of Computer Scientists and Information Technologists Conference on Knowledge, Innovation and Leadership in a Diverse, Multidisciplinary Environment. Presented at the SAICSIT '11: South African Institute of Computer Scientists and Information Technologists Conference, ACM, Cape Town South Africa, pp. 116–122. https://doi.org/10.1145/2072221.2072235

Horakova, M., Skalska, H., 2013. Business intelligence and implementation in a small enterprise. J. Syst. Integr. 4, 50–61.

Howson, C., 2008. Successful business intelligence: secrets to making BI a killer app. McGraw-Hill, New York.

Jaradat, Z., Al-Dmour, A., Alshurafat, H., Al-Hazaima, H., Al Shbail, M.O., 2022. Factors influencing business intelligence adoption: evidence from Jordan. J. Decis. Syst. 1–21. https://doi.org/10.1080/12460125.2022.2094531

Jun, T., Kai, C., Yu, F., Gang, T., 2009. The research & application of ETL tool in business intelligence project. Presented at the 2009 International Forum on Information Technology and Applications, IEEE, pp. 620–623.

Kappelman, L., Johnson, V., Torres, R., Maurer, C., McLean, E., 2019. A study of information systems issues, practices, and leadership in Europe. Eur. J. Inf. Syst. 28, 26–42. https://doi.org/10.1080/0960085X.2018.1497929
Klein, D., Tran-Gia, P., Hartmann, M., 2013. Big Data. Inform.-Spektrum 36, 319–323. https://doi.org/10.1007/s00287-013-0702-3
Köhler, H., Link, S., 2018. SQL schema design: foundations, normal forms, and normalization. Inf. Syst. 76, 88–113.
Lachev, T., Price, E., 2018. Applied Microsoft Power BI Bring your data to life! Prologika Press.
Leidner, D.E., Elam, J.J., 1993. Executive Information Systems: Their Impact on Executive Decision Making. J. Manag. Inf. Syst. 10, 139–155. https://doi.org/10.1080/07421222.1993.11518014
Llave, M.R., 2018. Data lakes in business intelligence: reporting from the trenches. Procedia Comput. Sci. 138, 516–524.
Luhn, H.P., 1958. A Business Intelligence System. IBM J. Res. Dev. 2, 314–319. https://doi.org/10.1147/rd.24.0314
Marakas, G.M., 2003. Decision support systems in the 21st century. Prentice Hall Upper Saddle River.
Mathrani, S., Mathrani, A., 2013. Understanding the Transformation Process Success Factors in Enterprise System Implementations: An IT Professional's Perspective. Int. J. Hum. Cap. Inf. Technol. Prof. 4, 9–21. https://doi.org/10.4018/jhcitp.2013010102
Miloslavskaya, N., Tolstoy, A., 2016. Big Data, Fast Data and Data Lake Concepts. Procedia Comput. Sci. 88, 300–305. https://doi.org/10.1016/j.procs.2016.07.439
Mohanty, S., Jagadeesh, M., Srivatsa, H., 2013. Big data imperatives: Enterprise 'Big Data'warehouse,'BI'implementations and analytics. Apress.
Moreno Saavedra, M.S., Bach, C., 2017. Factors to Determine Business Intelligence Implementation in Organizations. Eur. J. Eng. Res. Sci. 2, 1. https://doi.org/10.24018/ejers.2017.2.12.527
Namvar, M., Cybulski, J., 2014. BI-based organizations: A sensemaking perspective.
Negash, S., Gray, P., 2008. Business Intelligence, in: Handbook on Decision Support Systems 2. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 175–193. https://doi.org/10.1007/978-3-540-48716-6_9
Newell, S., Pan, S.L., Galliers, R.D., Huang, J.C., 2001. The Myth of the Boundaryless Organization. Commun. ACM 44, 74–76. https://doi.org/10.1145/501317.501350
Nonaka, I., Umemoto, K., Senoo, D., 1996. From information processing to knowledge creation: A Paradigm shift in business management. Technol. Soc. 18, 203–218. https://doi.org/10.1016/0160-791X(96)00001-2
Omar, Y.M., Minoufekr, M., Plapper, P., 2019. Business analytics in manufacturing: Current trends, challenges and pathway to market leadership. Oper. Res. Perspect. 6, 100127. https://doi.org/10.1016/j.orp.2019.100127
Ong, I., Siew, P., Wong, S., 2011. A Five-Layered Business Intelligence Architecture. Commun. IBIMA 1–11. https://doi.org/10.5171/2011.695619
Puklavec, B., Oliveira, T., Popovič, A., 2018. Understanding the determinants of business intelligence system adoption stages: An empirical study of SMEs. Ind. Manag. Data Syst. 118, 236–261. https://doi.org/10.1108/IMDS-05-2017-0170
Rainardi, V., 2007. Building a Data Warehouse: With Examples in SQL Server.

Rainer Jr, R.K., Watson, H.J., 1995. The keys to executive information system success. J. Manag. Inf. Syst. 12, 83–98.
Roetzel, P.G., 2019. Information overload in the information age: a review of the literature from business administration, business psychology, and related disciplines with a bibliometric approach and framework development. Bus. Res. 12, 479–522. https://doi.org/10.1007/s40685-018-0069-z
Rostek, K., Wiśniewski, M., Kucharska, A., 2012. Cloud Business Intelligence for Smes Consortium. Found. Manag. 4, 105–122. https://doi.org/10.2478/fman-2013-0006
Rouhani, S., Ashrafi, A., Zare Ravasan, A., Afshari, S., 2016. The impact model of business intelligence on decision support and organizational benefits. J. Enterp. Inf. Manag. 29, 19–50. https://doi.org/10.1108/JEIM-12-2014-0126
S, G., Rajesh Dhanani, K., Pankaj Doshi, P., 2020. DATA ANALYSIS AND ETL TOOLS IN BUSINESS INTELLIGENCE. Int. Res. J. Comput. Sci. 07, 127–132. https://doi.org/10.26562/irjcs.2020.v0705.007
Salisu, I., Bin Mohd Sappri, M., Bin Omar, M.F., 2021. The adoption of business intelligence systems in small and medium enterprises in the healthcare sector: A systematic literature review. Cogent Bus. Manag. 8, 1935663. https://doi.org/10.1080/23311975.2021.1935663
Schuff, D., Corral, K., St Louis, R.D., Schymik, G., 2018. Enabling self-service BI: A methodology and a case study for a model management warehouse. Inf. Syst. Front. 20, 275–288.
Seamark, P., Martens, T., 2019. Data Modeling, in: Pro DAX with Power BI. Springer, pp. 21–53.
Sharda, R., Delen, D., Turban, E., 2018. Business intelligence, analytics, and data science: a managerial perspective, Fourth edition, global edition. ed. Pearson, Harlow, England London New York Boston San Francisco Toronto Sydney.
Stjepić, A.-M., Pejić Bach, M., Bosilj Vukšić, V., 2021. Exploring Risks in the Adoption of Business Intelligence in SMEs Using the TOE Framework. J. Risk Financ. Manag. 14, 58. https://doi.org/10.3390/jrfm14020058
Trieu, V.-H., 2017. Getting value from Business Intelligence systems: A review and research agenda. Decis. Support Syst. 93, 111–124. https://doi.org/10.1016/j.dss.2016.09.019
Tutunea, M.F., 2015. Business Intelligence Solutions for Mobile Devices – An Overview. Procedia Econ. Finance 27, 160–169. https://doi.org/10.1016/S2212-5671(15)00985-5
Vassiliadis, P., Simitsis, A., Skiadopoulos, S., 2002. Conceptual modeling for ETL processes, in: Proceedings of the 5th ACM International Workshop on Data Warehousing and OLAP. Presented at the CIKM02: Eleventh ACM International Conference on Information and Knowledge Management, ACM, McLean Virginia USA, pp. 14–21. https://doi.org/10.1145/583890.583893
Vitt, E., Luckevich, M., Misner, S., 2002. Business intelligence: making better decisions faster. Microsoft Press, Redmond, Wash.
Watson, H.J., Wixom, B.H., 2007. The Current State of Business Intelligence. Computer 40, 96–99. https://doi.org/10.1109/MC.2007.331
Williams, S., Williams, N., 2007. The business value of business intelligence, in: The Profit Impact of Business Intelligence. Elsevier, pp. 1–24. https://doi.org/10.1016/B978-012372499-1/50002-8

Zorrilla, M., García-Saiz, D., 2013. A service oriented architecture to provide data mining services for non-expert data miners. Decis. Support Syst. 55, 399–411. https://doi.org/10.1016/j.dss.2012.05.045