Enhancing Decision-Making Through BI Automation

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Abstract. Every second, large volumes of data are generated which, if not properly interpreted, can lead to wrong decisions and undesirable consequences. Automating and optimising information processing enables faster handling and supports timely, informed decision-making. With the evolution of Business Intelligence tools, adopting data-driven solutions is essential for organisational competitiveness. This work tackles real-time management and analysis of strategic and operational industrial data through the design and development of the Unified Performance Metrics dashboard, which consolidates strategic information of internal business units via key metrics, and the improvement of the existing human resources dashboard. The system integrates a Power BI front-end with a Python- and SQL-based back-end for automation and the extract, transform, and load process. The dashboards were successfully evaluated, approved, and deployed. By automating strategic and operational analyses, the dashboards effectively replaced inefficient manual error-prone procedures, demonstrating clear operational advantages.

Keywords: Business intelligence, decision-making, dashboards, extract-transform-load, information management, metrics, Power BI, data automation workflow

1 Introduction

Global markets are evolving at unprecedented speed, requiring rapid decisions with significant consequences. To optimise decision-making, managers and administrators must access relevant, reliable, clear, and readily available information. Contemporary business environments generate vast volumes of data from Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) systems, intensifying the challenge of extracting actionable insights. Traditional approaches—such as spreadsheets and manual, time-intensive, error-prone processes—have become obsolete, paving the way for Business Intelligence

(BI). BI encompasses a suite of data-driven processes, technologies, and practices designed to support strategic decision-making.

The work was carried out at EFACEC, a company confronted with substantial challenges in the management and analysis of operational and strategic information, as key data remain fragmented, unprocessed, and present opportunities for further integration and enhancement. Consequently, there is a pressing need for a flexible tool that enables managers and administrators to efficiently extract insights and monitor key performance indicators. Such a solution must automate the entire information lifecycle—from ingestion to visualisation—enhancing internal efficiency and significantly improving team responsiveness.

The Unified Performance Metrics (UPM) solution comprises a set of interactive dashboards designed to consolidate diverse business information into a single, accessible platform. Their objective is to deliver real-time, clear, and detailed analytical data reflecting the performance of various business units. Given the sensitivity and strategic relevance of the data presented, access must be restricted to authorised managers and executives. To ensure seamless integration with the existing digital ecosystem, the dashboards must adhere to the organisation's visual identity and offer intuitive navigation, particularly considering the volume and complexity of data distributed across multiple views.

Following this introduction, Section 2 establishes the theoretical foundation by defining key concepts and methodologies and reviews illustrative works. Section 3 outlines the proposed solution, detailing the methodology, tools, requirements, data processing techniques, and architecture. Section 4 describes the improvement of the Timesheets Dashboard and the development of UPM. Section 5 presents the performed tests and discusses the results. Section 6 concludes by summarising key findings, evaluating objective fulfilment, highlighting contributions, identifying limitations, and recommending future work.

2 Background

Nowadays, organizations increasingly rely on BI to convert large and heterogeneous datasets into actionable insights. Modern BI systems integrate data processing with human-centred visualization techniques that enable both technical and non-technical users to interpret results effectively. Beyond infrastructure, the success of BI depends on effective communication of analytical outputs. Data visualization therefore acts not only as a presentation layer but as a cognitive bridge between data and decision-making, shaped by perceptual principles such as pre-attentive attributes, Gestalt grouping and design best practices.

BI comprises technologies and methodologies that transform raw data into insights that support strategic and operational decisions. Since its origins, BI has evolved into dynamic ecosystems integrated with Big Data and Artificial Intelligence (AI). In the Analytics 4.0 era, BI emphasizes real-time processing, automation, and AI-driven decision support [8,10]. Despite benefits like improved decision speed, efficiency, and risk management, BI adoption faces challenges such as data heterogeneity, quality assurance issues, skill gaps, and organizational resistance. Thus, effective BI initiatives rely on strong data governance and data literacy frameworks.

Analytical environments combine online transaction processing systems for operational transactions with online analytical processing systems and data warehouses for large-scale analytical processing. Such repositories are fed through Extract, Transform, Load (ETL) workflows that collect, clean, and integrate data from heterogeneous sources [9,5]. To support efficient querying, data warehouses use dimensional modelling with fact and dimension tables, organized into star, snowflake, or constellation schemas that balance performance and model complexity [7,12]. ETL provides a structured approach to integrating diverse data sources into consistent analytical environments. Extraction retrieves raw data from databases, systems, files, or application programming interfaces; transformation ensures cleaning, integration, reformatting, and aggregation; and loading transfers the processed data into a data warehouse optimized for performance. Dimensional modelling, using fact and dimension tables, underpins the organization of these refined data for analysis and reporting [15].

Data visualization translates complex datasets into intuitive visual formats that support understanding and analytical reasoning. Using charts, tables, and maps, it helps users detect patterns, trends, and anomalies. Its effectiveness relies on perceptual principles such as pre-attentive attributes, Gestalt laws, and best design practices that reduce cognitive load [2]. Cognitive science research, including Bayesian models, shows that perception is influenced by user expectations and biases, highlighting the need for visualization design that accounts for perceptual accuracy and cognitive limitations [3]. In this context, Power BI has been extensively explored to create interactive real-time dashboards by integrating data from multiple sources through a structured pipeline. The typical process begins with data extraction and transformation using Power Query, the Power BI ETL tool, and the M language, ensuring that the data are cleaned and shaped for analysis. The transformed data are then loaded into the Power BI data model, where the Data Analysis Expression (DAX) language is employed to create columns, measures, and aggregations. Finally, the processed data are visualised in dynamic dashboards, providing centralised real-time insights to support informed decision-making and operational efficiency. This is the case of the following illustrative applications:

Hospital Performance Atobatele et al. [1] review the integration of SQL-driven dashboards with Power BI visualisation models to support hospital strategic decision-making. This integration of SQL queries from multiple sources with Power BI can provide insights into hospital performance, resource utilisation, cost efficiency, and quality metrics, enabling real-time data analysis and identification of performance deviations and areas requiring intervention.

Manufacturing, Finance, Marketing and Supply Chain Das et al. [6] present a projection and forecasting solution for Atliq Hardware to enable data-driven decision-making. Data from multiple locations, covering sales, finance, marketing, and supply chain, are extracted via Power Query connected to SQL databases, transformed using DAX, and modelled into a snowflake schema.

The processed data feeds three Power BI dashboards, delivering real-time, centralised insights on the financial, marketing, and supply chain views.

Sales Marketing Gonçalves et al. [11] adopt the Vercellis methodology (analyse, design, plan, implement and control) and Power BI to support sales and marketing decision-making. The workflow extracts, processes, cleans, and transforms Excel data into visualisations. The study demonstrates the feasibility of creating an integrated data-warehouse-based system, enabling fast, concise, and easy-to-interpret analyses with real-time information updates.

Manufacturing Salvadorinho et al. [13] describe the development of a Power BI dashboard for a flush toilet manufacturer. IoT data from automated manufacturing cells are first exported to Excel for preliminary analysis and subsequently processed using Power Query. The workflow uses the M language for data transformation and applies DAX for calculations and aggregations within the data model, enabling real-time visualisation of the manufacturing cell status.

Agricultural Trade Sanabia-Lizarraga et al. [14] employ Power BI to bridge the gap between data analysis and business intelligence expertise within Mexico's Agro-Logistics Observatory. The goal is to develop an interactive dashboard to visualise and compare exports with imports and support business and academic decision-making. Following a step-by-step methodology, data are extracted from multiple sources using Power Query, modelled, and presented in a dashboard featuring newly tailored key performance indicators.

Table 1 compares these illustrative works with the proposed real-time decision-support visualisation tool for financial and industrial data, supported by open-source SQL queries and Python scripts as well as Power BI (PBI).

Table 1. Real-Time Decision-Support Dashboards Powered by Power BI (PBI).

Authorship	**Back-End**	**Front-End**	**Domain**	**Type**
Atobatele et al. [1]	SQL	PBI	Healthcare	Mixed
Das et al. [6]	SQL, Power Query, DAX	PBI	Industry	Proprietary
Gonçalves et al. [11]	Excel, Power Query, DAX	PBI	Marketing	Proprietary
Salvadorinho et al. [13]	Excel, Power Query	PBI	Industry	Proprietary
Sanabia-Lizarraga et al. [14]	Power Query, DAX	PBI	Agriculture	Proprietary
Current proposal	SQL, Python scripts, Power Query	PBI	Industry	Mixed

3 Method

The aim of the project is to support real-time decision-making by visualising operational and strategic data across domains such as finance, human resources, and production. Figure 1 provides an overview of the proposed method.

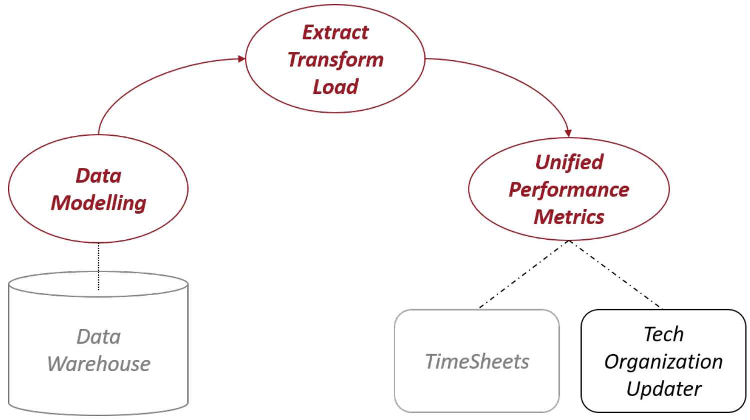

Fig. 1. Proposed BI automation pipeline.

All information is stored in a data warehouse with multiple tables of multi-modal data (numerical, categorical and documental). The functional specification, consolidating the information to be represented and outlining predefined requirements, defines three metric pages—Revenues, Gross Margin, and Product Line Team—and specifies a consistent layout with three equally sized zones for Filters, Big Numbers, and Detailed Numbers.

Regardless of content, data are segmented by Time (e.g., Year, Quarter, Month), Business Unit, Product Line, and Location. These dimensions are represented by dedicated tables linked to existing datasets describing the calendar, business units, product lines, and locations. In Power BI, relationships were established between the four dimension tables and the fact table to enable dynamic filtering within visualisations. Each analytical page adopts a star schema, with the fact table containing data specific to the corresponding metric. Based on this data model, the UPM visualization layer was designed to transform these analytical structures into interactive and visually coherent dashboards. As defined in the functional specification, the most suitable visualization types for each metric were preselected according to analytical goals.

At this stage, the focus shifted towards the customization and harmonization of visuals, ensuring that they were clear, intuitive, and aligned with effective data visualisation principles. Particular attention was paid to visual consistency across pages, achieved through standardized use of colours, typography, and visual hierarchies. The layout was designed to be balanced and responsive, allowing proper adaptation to different screen formats while preserving readability. Visual customization included careful adjustments to titles, legends, numeric formatting, and positioning, ensuring alignment with EFACEC's graphic identity and colour guidelines. Each page follows a common functional layout consisting of two primary zones: the Big Numbers Zone, which displays key indicators such as gauges, aggregated values, and target comparisons; and the Detailed Analysis Zone, which provides deeper insights through temporal, geographical, or categorical visualizations. This structure ensures that each dashboard offers both a high-level overview and detailed analytical depth, supporting strategic and operational decision-making simultaneously.

A significant design consideration was the definition of an appropriate colour scheme. Given the variety and quantity of data elements, the direct application of the institutional palette was insufficient to ensure clarity and distinction between metrics. Consequently, a complementary palette was developed to enhance readability and intuitive perception. Each page was assigned a distinct primary colour associated with its analytical meaning—for instance, green for Revenues, symbolizing financial inflow; gold for Gross Margin, emphasizing profitability; and dark purple and navy tones for Product Line Team, representing workforce metrics. Pages that compare actual and target values adopt a lighter tone of the main colour for the target, maintaining visual coherence while avoiding confusion. For time series and trend analysis, continuous lines represent actual values, whereas dashed lines indicate targets, improving distinction and interpretability. In more complex dashboards such as Gross Margin, additional colours were applied—red for incurred costs and orange for targets—maintaining balance and semantic clarity across visuals.

This combination of coherent layout, colour differentiation, and consistent design allows UPM to deliver a clear, intuitive, and visually appealing analytical environment. The resulting views facilitate interpretation and decision-making while reflecting commitment to analytical excellence and design consistency.

4 Development

This section presents the development of the implemented solution, which includes enhancing the Timesheets dashboard, implementing the TechOrganization Updater, and developing UPM—from Python-based ETL task automation to indicator consolidation through SQL.

Timesheets Dashboard was originally developed in Streamlit by the TECH-TEAM to provide insights on weekly hour allocation by project type, absences and employee availability. It includes filters by Business Unit (BU), employee classification, year and week, and presents the data through bar charts, doughnut charts, and tables. Data are processed through Python ETL scripts that extract and transform ERP information into SQLite. SQL queries aggregate the metrics displayed, and the system sends automated email alerts to BU directors when inconsistencies in time reporting occur. However, ETL-related issues compromised data reliability. The debugging process addressed a series of issues, namely the exclusion of active employees without recorded activity and the misidentification of active staff caused by flawed date comparisons. These fixes, based on complete logic and process redesign, ensured full and accurate coverage. New functionalities were introduced, including an authentication system to control access, a forecasting module to calculate and display planned hours, and an automated project classification mechanism to reduce manual input. Finally, the ETL process was extended to update the Projects, Employees, and Timesheets tables in the SQL Server, allowing integration with other analytical tools and future dashboards.

TechOrganization Updater was created to address inconsistency problems in TECHTEAM member data. The member records were maintained manually in Excel, relying on internal updates to reflect the current team composition. However, the absence of historical tracking—where records were deleted upon departure—prevented retrospective analysis. Updates were performed manually by comparing the Excel file with the structured Human Resources (HR) view, which includes each employee's last active reference month. This field enabled inference of the current team membership. To overcome the limitations of manual maintenance and ensure data reliability and historical tracking, a Python-based automated process was implemented. It compares current employee data from the HR view with active records in the TechOrganization table to detect entries and exits. New employees are added with relevant details, while departures are marked with a departure date set to the last day of the previous month. SQL Server replaces the Excel file as the primary data source, improving scalability, integrity, and query efficiency. In addition, all updates are logged in an Excel file for traceability. The HR view includes attributes such as Business Unit and supervisor, but omits internally defined fields like TechRole. To collect these, the management team receives an Excel form. Once completed, the script ingests the data and loads them into the database.

SQL Queries were developed to generate the fact tables that support the dashboards. Each query consolidates and structures data from multiple sources to produce fact tables aligned with the specific analytical needs of each dashboard. The `RevenuesvTarget` query creates the fact table for revenue monitoring by integrating sales records with target values and associating them with business units, product lines and geographic descriptors. It uses temporary tables to filter relevant business units and time periods and applies standardized joins to ensure alignment across sources. The `GrossMarginvTarget` query produces the fact table for gross margin analysis. It combines revenues, incurred costs and gross margin targets, applying the same mapping and filtering logic. The result is a consolidated structure with all metrics needed at the month, BU, destination and product line level. The `WorkedvAvailableHours` query builds the fact table for time-sheet analysis. It aggregates data on hours worked and available hours per employee and week—as provided for the Timesheets Dashboard—and restricts the dataset to the defined TECHTEAM members, as determined by the TechOrganization Updater, through a filtered join. A temporary table enables comparison between reported and available hours.

Unified Performance Metrics (UPM), which is the visualization layer of the solution, provides a structured environment to monitor key organizational indicators. Built in Power BI Desktop and published to the Power BI Service, they ensure accessible and centralized reporting for the Tech Organization and other stakeholders. Access control was enforced through Row-Level Security, with roles defined per Business Unit and permissions applied in the semantic model. Executive stakeholders retain full access, while BU directors are limited to their respective data. Filter synchronization across pages—based on year, BU, and product line—ensures analytic consistency and minimizes user interaction effort. The UPM dashboards cover four analytical domains: orders, revenues, gross margin and product line team. The Orders and Orders by Product Line dashboards (Figure 2) build on existing structures while integrating additional metrics such as open leads and quotes from another database. After integrating the new fact tables and defining relationships, the card visuals were configured with relative date filtering, and the drill-through pages enabled detailed comparisons by BU. Informational pages provide metadata on data sources and formulas. The Revenues dash-

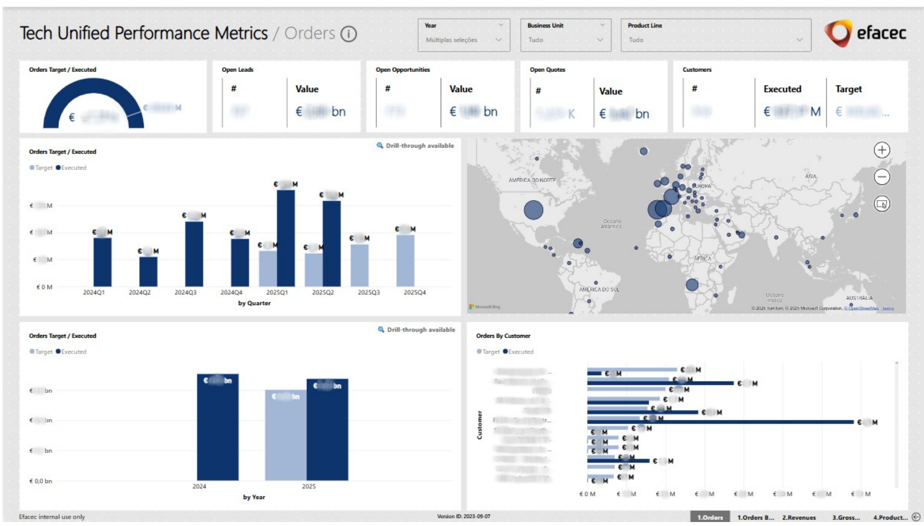

Fig. 2. Orders Dashboard (confidential data was hidden).

board follows the functional specifications, combining big-number indicators, gauges, bar and area charts, and geographic visuals. The executed and target values are displayed across time and product lines, complemented by a detailed page for segmented analysis. The Gross Margin dashboard mirrors this structure but incorporates revenues, incurred costs, and targets, along with mixed line–bar visualizations. Filters restrict data to the most recent closed month, and a complementary page provides breakdowns by BU, geography, cost structure, and incurred cost per unit. The Product Line Team page focuses on TECHTEAM human resources through the Full Time Equivalent (FTE) metric. It integrates data from the TechOrganization Updater and the

Timesheets Dashboard to ensure that only active employees with recorded hours are included. The page features big numbers and charts—FTE by TechRole, FTE Ratio by TechRole, and FTE by Product Line—with drill-down capabilities. An informational page documents formulas, definitions, and data connections. All dashboards maintain a consistent layout consisting of filters, big numbers, and detailed visuals. The visuals are supported by fact tables created during ETL and linked to their dimension tables, ensuring correct filtering, aggregation, and drill-through behaviour. Designed according to visualization effectiveness principles, the dashboards enhance readability, analytical efficiency, and decision-making through structured, centralized data presentation.

5 Tests and Results

Testing was essential to validate the solution, ensuring functional correctness, data integrity, and usability, as the dashboards support strategic decision-making. The evaluation covered three areas: functional testing, performance assessment and usability evaluation.

Functional Tests adopted a Pass/Fail approach to verify compliance with the defined requirements. The assessment included real-time data updates, access control, synchronized filtering, data validity, and alignment with company visualization standards. All tests were successful, confirming the correct implementation of the required features.

Performance Tests measured query latency, Power BI rendering times, and data volume handling. The queries for `RevenuesvTarget`, `GrossMarginvTarget`, and `WorkedvAvailableHours` fact tables were repeated ten times, with execution times collected via SQL Server statistics. The rendering times in the Power BI (PBI) Service were also recorded. Table 2 summarises the consistently satisfactory response times, demonstrating efficient scalability.

Table 2. Query performance results (average μ and standard deviation σ).

Metric	`RevenuesvTarget`[1] $\mu \pm \sigma$	`GrossMarginvTarget`[2] $\mu \pm \sigma$	`WorkedvAvailableHours`[3] $\mu \pm \sigma$
CPU Time (ms)	4684.50 ± 529.99	$19\,660.20 \pm 450.36$	84.50 ± 26.68
Elapsed Time (ms)	865.90 ± 79.83	3722.70 ± 1077.46	373.20 ± 26.68
Time PBI (ms)	229.90 ± 91.23	181.80 ± 32.33	196.50 ± 37.42
Volume PBI (kB)	9.30 ± 0.01	9.30 ± 0.00	9.30 ± 0.01

[1] The query returned 1995 six-column records, involving four tables.
[2] The query returned 3028 seven-column records, involving six tables.
[3] The query returned 40 437 nine-column records, involving three tables.

Usability was assessed using the System Usability Scale (SUS). SUS is a simple industry-validated instrument for benchmarking user-perceived usability, producing a global score from 0 to 100 by normalising and summing responses to a 10-item questionnaire rated on a five-point Likert scale [4]. Nine participants, including executives and BU-managers, completed predefined tasks before responding. The resulting average SUS score of 77.5 indicates good usability, confirming that the dashboards offer an intuitive and efficient interface for end users.

These results confirm that the UPM solution meets the initial goals: accurate functionality, robust performance, and high user acceptance, ensuring effective, secure, and timely insight delivery for organisational decision-makers.

6 Conclusion

This work developed an automated and optimized solution to support data-driven decision-making at EFACEC. The project started with a review of key concepts such as Business Intelligence, ETL processes, and dimensional modelling, followed by the implementation of automated data ingestion and transformation using Python and SQL. The processed data was then modelled in Power Query and visualized through Power BI dashboards, enabling the organization to monitor key metrics clearly and interactively.

All objectives were successfully met. Data integration from multiple systems was automated, processing accuracy improved, and dashboards were created to deliver real-time insights. The TechOrganization Updater additionally reduced manual work by keeping organizational records up to date, enhancing information accessibility and supporting faster, evidence-based decisions.

Some constraints arose, mainly related to restricted database permissions and inconsistent data sources. These issues were mitigated through close collaboration with the technical team and the implementation of data-cleaning and transformation mechanisms.

Future enhancements will focus on automated data validation, improved user feedback mechanisms, comprehensive technical documentation, and performance optimisation through stored procedures and DirectQuery.

The adopted design, development, and testing pipeline shows strong transferability as it relies on widely applicable practices supported by established research in data-quality assessment and dashboard design. As a result, organisations facing similar analytical or decision-support challenges can reuse this approach regardless of their specific domain, tools, or data environments.

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References

1. Atobatele, O.K., Ajayi, O.O., Hungbo, A.Q., Adeyemi, C.: Improving strategic health decision-making with SQL-driven dashboards and Power BI visualization models. International Scientific Refereed Research Journal 5(5), 291–313 (2022)
2. Barrera-Leon, L., Corno, F., de Russis, L.: Systematic variation of preattentive attributes to highlight relevant data in information visualization. In: 2020 24th International Conference Information Visualisation (IV). pp. 74–79 (Sep 2020)
3. Barrera-Leon, L., Corno, F., de Russis, L.: How the preattentive process is exploited in practical information visualization design: A review. International Journal of Human–Computer Interaction 39(4), 707–720 (2023)
4. Brooke, J.: SUS: A 'quick and dirty' usability scale. In: Jordan, P.W., Thomas, B., McClelland, I.L., Weerdmeester, B. (eds.) Usability evaluation in industry, chap. 21, pp. 189–194. Taylor and Francis, London, UK (1996), https://hell.meiert.org/core/pdf/sus.pdf
5. Chaudhuri, S., Dayal, U.: An overview of data warehousing and OLAP technology. SIGMOD Record 26(1), 65–74 (Mar 1997)
6. Das, S., Banerjee, K., Nath, S., Chatterjee, S.: Data visualization approach for business strategy recommendation using Power BI dashboard. International Journal of Latest Engineering Science 6(5) (2023)
7. Elmasri, R., Navathe, S.: Fundamentals of Database Systems Global Edition. Pearson Deutschland, 7th edn. (2016), https://elibrary.pearson.de/book/99.150005/9781292097626
8. Fernandes, F., Correia, J., Pontes, A.: Business intelligence: Trends and the impact of emerging technologies. In: 2023 18th Iberian Conference on Information Systems and Technologies (CISTI). pp. 1–6 (June 2023)
9. Ferraz, B.F.P.: Sistema de Gestão e Análise de Dados Para o Retalho de Produtos Óticos. Master's thesis, Instituto Superior de Engenharia do Porto, Rua Dr. António Benardino de Almeida, 431, 4249-015 Porto (2019), http://hdl.handle.net/10400.22/14853
10. Ferreira, M.I.C.d.M.A.: Business intelligence como suporte ao processo de tomada de decisão nas organizações. Master's thesis, Instituto Superior de Contabilidade e Administração do Porto, Rua Jaime Lopes Amorim, 4465-004 São Mamede de Infesta (2023), http://hdl.handle.net/10400.22/24563
11. Gonçalves, C.T., Gonçalves, M.J.A., Campante, M.I.: Developing integrated performance dashboards visualisations using power bi as a platform. Information 14(11) (2023)
12. Kimball, R., Ross, M.: The Data Warehouse Toolkit: The Complete Guide to Dimensional Modeling. Wiley (2011), https://books.google.pt/books?id=XoS2oy1IcB4C
13. Salvadorinho, J., Teixeira, L., Sousa Santos, B.: Storytelling with data in the context of Industry 4.0: A Power BI-based case study on the shop floor. In: Stephanidis, C., Salvendy, G., Wei, J., Yamamoto, S., Mori, H., Meiselwitz, G., Nah, F.F.H., Siau, K. (eds.) HCI International 2020 – Late Breaking Papers: Interaction, Knowledge and Social Media. pp. 641–651. Springer International Publishing, Cham (2020)
14. Sanabia-Lizarraga, K.G., Carballo-Mendívil, B., Arellano-González, A., Bueno-Solano, A.: Business intelligence for agricultural foreign trade: Design and application of Power BI dashboard. Sustainability 16(21) (2024)

15. Szilveszter, M., Molnár, G., Nagy, E.: Comparison of commercial and open source ETL tools. In: 2024 IEEE 11th International Conference on Computational Cybernetics and Cyber-Medical Systems (ICCC). pp. 37–42 (April 2024)