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THE FLEXIBLE SYSTEM SUPPORTING INDUSTRIAL ANALYTICS

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Purpose: The aim of this article is to analyze and assess the possibilities of building and implementing flexible Business Intelligence systems for modern industrial analytics.
Design/methodology/approach: The article presents a project of a system supporting multi-criteria analysis of production processes. The project included analytical work, the development of a prototype (data warehouse, OLAP server application, user interface), and its verification. The conclusions provide an assessment of selected technical solutions implemented in the prototype, as well as an evaluation of the expected software flexibility.
Findings: The flexibility of the system prototype was validated through pilot studies conducted in a large furniture manufacturing company. The experiment confirmed the feasibility of creating new analytical objects within a spreadsheet environment equipped with active connections to the OLAP server. The implementation process included software installation and configuration, training sessions for industrial analysts and development work carried out in the form of workshops. The development work was carried out by industrial analysts without the involvement of IT specialists.
Research limitations/implications: Due to the experimental nature of the project, the selection of appropriate techniques for industrial data visualization was deliberately omitted during the prototype implementation process. Future research will focus on evaluating the functionality, ergonomics and flexibility of the data visualization system.
Practical implications: The results of the experiment can be practically used for the designing and implementation of BI systems in the industrial sector. The flexibility of BI software will enable a reduction in costs associated with its maintenance and development, which will contribute to the popularization of this technology in the market economy.
Social implications: Data analysis using BI technologies can be a significant element in the process of implementing new research programs in the area of human-centric production management, in line with the Industry 5.0 perspective.
Originality/value: The article addresses the issues related to the design, implementation and development of specialized systems supporting industrial data analysis. It is intended for analysts, architects, and designers of Business Intelligence class systems.
Keywords: industrial analytics, software flexibility, Business Intelligence.
Category of the paper: Research paper.

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1. Introduction

Business Intelligence systems are a collection of tools, technologies and software components used to integrate heterogeneous data sets, analyze them and publish insights to support economic decision-making processes (Wixom, Watson, 2010, p. 14). These systems are applied in various areas of economic, institutional and social activities. They have found numerous applications, including in healthcare (Basile, 2023), pharmaceuticals (Belghith, 2024), banking (Mohammed, 2024), industry (Wolniak, 2023), logistics (Seddigh, 2023), energy (Wang, 2024) and education (Hmoud, 2023).

In manufacturing enterprises, Business Intelligence systems can be effectively used to analyze production profitability. This includes direct costs (e.g., materials, infrastructure, labor, transportation, subcontracting) as well as indirect costs (e.g., administration, machine maintenance, factory hall renovations). In line with the principles of Industry 5.0, these analyses should also take into account factors related to workplace conditions and space, occupational safety, machine operation, environmental impact, and sustainable manufacturing (Adel, 2022; Bordeleau, 2020; Grabowska, 2022; Sever, 2024).

The aim of this article is to analyze and assess the possibilities of building and implementing flexible Business Intelligence systems for modern industrial analytics.

Flexibility is understood as the ability to create new multidimensional analytical objects (controlling models, reports, indicators) without the need to modify data structures or source code. These analyses will be conducted in real time based on current technological and manufacturing data.

The research process begins with a synthetic literature review covering selected topics in Business Intelligence software design. Next, the experiment is discussed, which involved developing a system prototype. The mission of this system is the multi-criteria analysis and evaluation of production processes. The project resulted in the development of a software prototype and its verification in a manufacturing company in the furniture industry.

2. Characteristics of Business Intelligence Systems

The core components of Business Intelligence systems include a data warehouse, OLAP (Online Analytical Processing) tools for processing multidimensional data structures and software that supports data visualization (Figure 1).

In the classical approach, designing a data warehouse structure involves specifying data tables, attributes, and reference connections. A data warehouse consists of two main elements: fact tables and dimension tables. Fact tables store quantitative data related to the enterprise's activities, while dimension tables serve as reference entities defining the context for future analyses and simulation studies. For example, a fact table may contain historical sales data for product batches, whereas dimension tables would store analytical attributes such as product structure, sales region, customer profile, distribution network and time period. The data warehouse model is designed based on the star schema principle. At the center of the star schema is the fact table, which holds individual business transactions. Dimension tables extend radially from the fact table and contain descriptive data related to the analysis subject. Advanced variations of the star schema include the snowflake schema and the fact constellation schema. The snowflake schema allows for the representation of hierarchical dimensions.

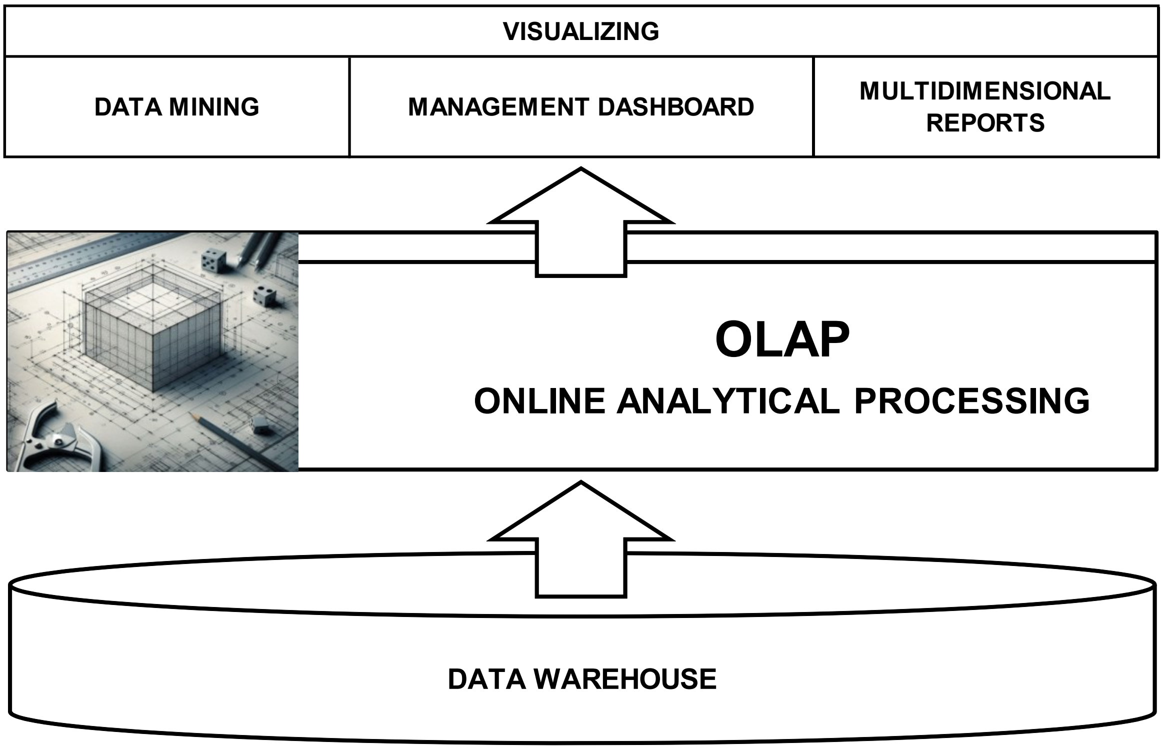

Figure 1. Architecture of a Business Analytics Support System.

Source: Author.

OLAP technology is used to implement multidimensional data structures and optimize the processing of large analytical datasets. A key element of OLAP technology is the data cube, which enables efficient multidimensional analysis.

The design of the user interface in analytical systems differs significantly from that of transactional systems. In transactional systems, the graphical user interface (GUI) is structured functionally, thematically and hierarchically, allowing access to forms through a central application menu.

In Business Intelligence systems, the choice of data presentation method depends on the needs of individual user groups.

For example, management dashboards can be effectively used to present summarized information on cost structures, including areas such as production, logistics, payroll and the maintenance of machinery and industrial facilities. These tools feature a consistent, clear interface with an intuitive navigation and control system.

Industrial analysts should be provided with tools that support the design of interactive summaries and reports, as well as spreadsheets enhanced with pivot table functionality.

Meanwhile, statisticians and econometricians will require Data Mining tools to support simulation studies, the construction of optimization models and the development of machine learning algorithms.

3. Experiment description

The project aimed to conduct analytical work in a large manufacturing company in the furniture industry, implement a prototype and assess the system's flexibility through a pilot deployment.

3.1. Research assumptions

A key assumption was that a system supporting multi-criteria analysis of industrial data should be flexible, meaning it should allow for the reconfiguration of reports, dashboards and other visual elements. The process of introducing changes should be driven by the continuous redefinition of functional requirements, the declaration of new reporting needs and the evolution of methods, techniques and tools for measuring key financial, production and social indicators.

Therefore, all development work should be carried out using predefined administrative consoles, eliminating the need for modifications to data structures or the reconstruction of software objects.

3.2. Research questions

Reconfiguring the visual elements of the user interface is a relatively simple task that does not require the involvement of specialists in databases, data warehousing or software engineering.

However, some fundamental issues remain to be resolved:

Will the reconstruction of analytical objects necessitate changes to the data warehouse or modifications to OLAP multidimensional data processing technology?

What functional, architectural and application assumptions should be adopted to ensure that inevitable requirement changes do not lead to weeks of costly development work?

Should the concept of flexibility in Business Intelligence tools be considered exclusively in relation to GUI applications?

Answering these questions requires an in-depth analysis of the methods, techniques and tools used in analytical system implementations, as well as the execution of a scientific experiment.

3.3. Experiment organization

The experiment involved developing a prototype and evaluating the feasibility of flexible modifications to multidimensional analytical reports without the need for time-consuming and costly programming work. It included analytical work in a large furniture manufacturing company, prototype development and an assessment of the validity of new functional requirements. These new requirements were identified over six months following the system's implementation (Figure 2).

At the outset, the functional requirements and data source specifications were identified. These requirements included:

- users' informational needs regarding the creation of multidimensional reports,
- expectations for improving strategic decision-making using a set of technical, economic and social indicators,
- preferences for the presentation and visualization of historical data.

The requirement specification was developed based on interviews with specialists in production, quality, safety and workplace environment, as well as an analysis of job documentation.

In Business Intelligence systems, an essential part of analytical work is defining data sources. Operational data may be stored in relational, hierarchical and object databases, as well as in text, binary, graphical (bitmaps, vector graphics) and multimedia files. Therefore, the experiment analyzed data from existing ERP (SAP-ERP), MES (Wonderware MES 4.0) and HRM (Oracle) systems, as well as semi-structured files from specialized safety management software.

The analytical data architecture design included: logical design of the data warehouse (data schema, fact tables, dimension tables, reference connections), implementation of a central data warehouse, designing the data migration process.

In detail, the data migration project involved: analyzing the data schema in source systems, examining table structures, files and data attributes, constructing transformation rules to support data conversion, developing monitoring mechanisms for data flow processes, implementing quality control procedures to ensure data integrity. The data migration process is undoubtedly a broader and more complex task compared to the relatively simple operation of data import. In practice, data import consists of sequential operations of loading data from previously prepared flat files (e.g. MS Excel spreadsheets) into the table structures of the information system.

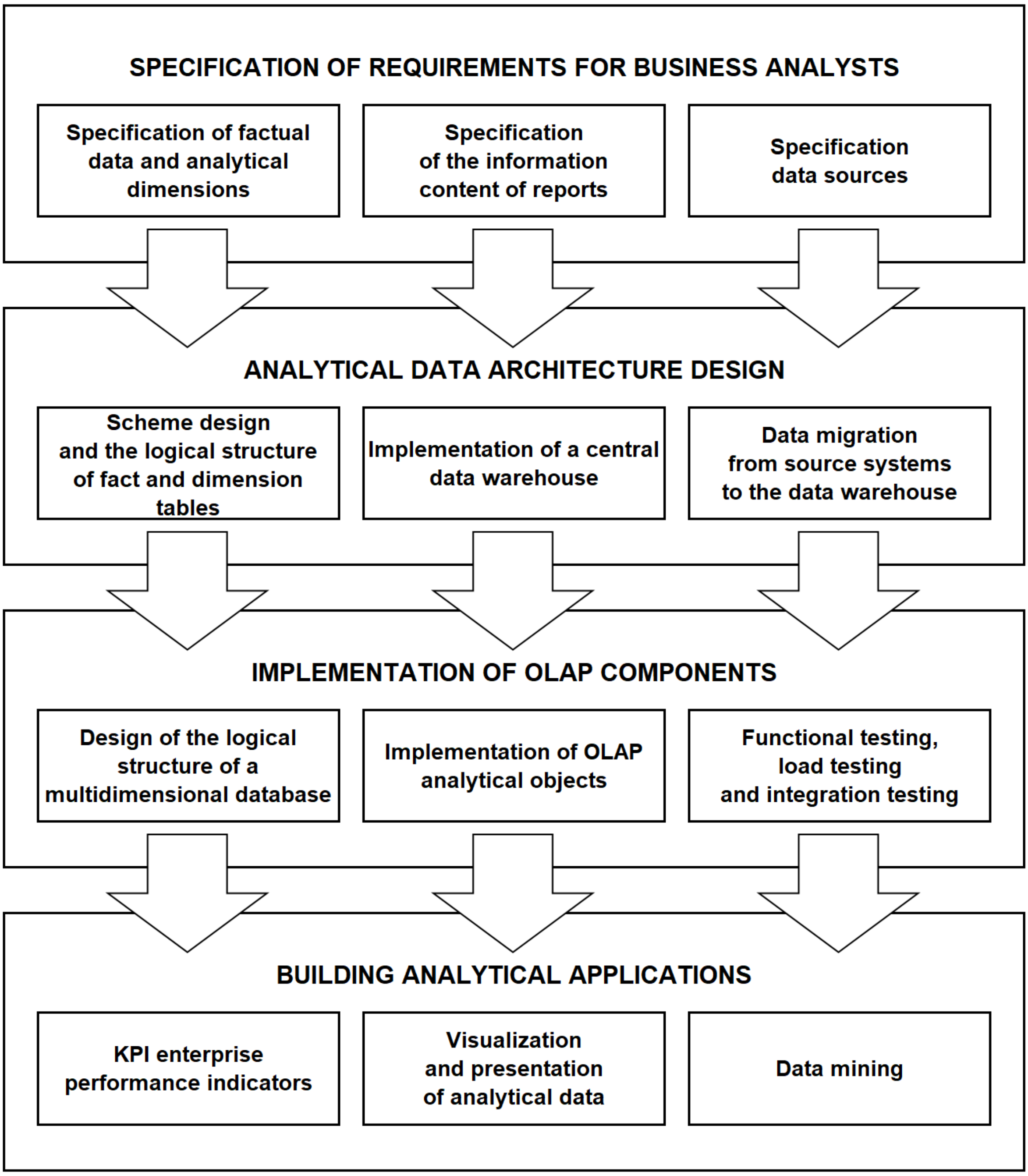

Figure 2. Experiment scheme.

Source: Author.

In the designed industrial analytics support system, the data migration process was the most time-consuming and costly phase of the project. This was not merely due to the data transfer time between heterogeneous sources and the central data warehouse, but rather the complexity of analyzing database structures in source systems. A major challenge was addressing issues arising from the use of inconsistent column names to represent analogous attributes of business objects, as well as differing data formats and types. Another significant problem was the non-uniform length of character strings in equivalent data fields.

The tasks related to the implementation of OLAP components included the design of the logical structure of the multidimensional database, the creation of new analytical objects (including informational dimensions, algorithms and calculation formulas), as well as the construction of KPI indicators. It should be noted that multidimensional databases include both source data and aggregated data. Therefore, the data migration process from the data warehouse to the multidimensional data cubes involved replicating operational data and calculating aggregates, statistics and other elements relevant to the computational efficiency of the analytical system.

The final stage of prototype development involved designing the graphical user interface (GUI) framework.

The prototype underwent a series of functional, performance and acceptance tests. Over the next six months, consultation sessions were conducted with users to evaluate: information content, quality and usability of analytical reports and KPIs. Based on this feedback, new requirements for the structure of reports and dashboards were formulated. Additionally, an assessment was conducted to determine whether these requirements could be implemented without modifying connection pools or reconstructing program objects.

4. Discussion of experiment results

4.1. Evaluation of the software prototype

The experiment involved the construction of a prototype system supporting industrial analytics. The software prototype was developed using a three-tier architecture (data warehouse, OLAP, user interface).

For the implementation of the data warehouse, a snowflake schema was applied. This solution enables the creation of dimension hierarchies. For example, a dimension hierarchy can illustrate the process of technical product assembly (hierarchical structure: product → subassembly → component → part). It is important to note that the dimension tables contain normalized data, including reference attributes. During the design process of the data warehouse, various groups of factual data can be described using the same informational dimensions. These dimensions are shared across different fact tables.

In turn, OLAP technology was applied to implement multidimensional data structures and optimize the processing of large analytical data sets.

According to the author, a key research problem in analytical data management is the division of operations between the data warehouse subsystem and the separate subsystem for processing multidimensional data cubes.

As previously mentioned, the design of the data warehouse structure may include a defined set of relatively autonomous fact tables and a set of shared dimension tables. This approach is characterized by flexibility – new fact tables and dimension tables can be created as the company's informational needs evolve. Conducting multiple experimental simulations and economic analyses typically leads to the formulation of new research questions. This, in turn, requires verifying initial assumptions and requirements, redefining the structure of multidimensional reports and modifying diagnostic indicators. Naturally, these changes may require the introduction of appropriate modifications to the structure of data sources, fact tables and dimension tables.

Considering the implementation of a multidimensional OLAP database as a solution closely tied to a previously developed and deployed central data warehouse, one may ask:

Is the need to build new analytical objects in the multidimensional database layer a result of potential oversights (errors) made during the creation of the central data warehouse?

Let us examine this issue using the example of the "time" dimension. In a data warehouse, fact tables contain timestamps for individual business transactions (e.g., invoice issue date, payment transaction date, production order completion date, etc.). Typically, the central data warehouse does not store a separate table structure representing the hierarchy of the "time" dimension. Considering data normalization principles, this approach can be deemed correct. In a two-dimensional tabular system, it is also difficult to identify practical use cases for such a redundant structure. The use of standard SQL queries allows for the construction of clauses that filter records based on a specified time range, e.g. "2024-06-01 – 2024-09-20". The query can be formulated using a typical "date" field in the fact table. Thus, from the perspective of working within a two-dimensional relational data model, a redundant table structure illustrating the "time" dimension is unnecessary.

In the context of implementing a multidimensional model, this issue must be considered differently. The hierarchical "time" dimension (e.g., structure: year, quarter, month) is one of the fundamental dimensions used in business analytics. Its construction should be carried out during the development of the multidimensional database. The structure of the new dimension and the processed analytical data will be managed on the server side of the OLAP analytical application. Metadata defining the logical schema of the analytical cube, the structure of informational dimensions and reference relationships will be stored as XML scripts in the data repository.

Of course, during the construction of the multidimensional OLAP database, it is also possible to extend the central data warehouse with elements related to handling the "time" dimension. In detail, this process requires creating appropriate data tables and T-SQL scripts. These scripts will be responsible for periodically updating the content of dimension tables based on new fact data. This solution introduces elements of transactional processing into the data warehouse architecture, which is fundamentally at odds with the concept of a data warehouse as a repository for historical data archiving.

Based on the conducted experiment, it can be concluded that achieving high flexibility in designing and reconfiguring data cubes requires the prior implementation of a central data warehouse. The recommended approach is to use the snowflake schema model. Furthermore, a critical success factor is the proper handling of periodic data loading from source systems into the central data warehouse.

As a supplementary remark, if the data warehouse layer is omitted in the development of a Business Intelligence system, the need for manually creating analytical structures in the multidimensional database layer will arise. Source data will be inserted directly into analytical structures, increasing the risk of errors and reducing system efficiency. These data will be duplicated across multiple data cubes, reducing model clarity and increasing redundancy. In general, this solution will be characterized by high failure rates resulting from inevitable changes in the system configuration and changes in the structure of data resources. For example, system reconfiguration will involve: changes in the pool of connections to external data sources, changes in protocol configurations, network address modifications and changes in the system of accounts, roles, and permissions. These changes are a logical consequence of the updates and development of source systems, which serve as the 'data providers' for the industrial analytics system.

4.2. Evaluation of the pilot implementation

As part of the pilot implementation, it was verified whether the set of multidimensional analytical reports developed within the project met the actual needs of the users. In particular, it was examined whether these reports required increased data granularity, the introduction of new analytical dimensions, as well as modifications to data structures and processing logic within the OLAP layer.

Based on the results of the analytical work, the system prototype was implemented with twenty-four reports evaluating production profitability. The profitability analysis covered direct costs related to manufacturing, industrial technologies, quality, machinery, infrastructure (buildings, factory halls), maintenance, production personnel, workplace safety, shipping and transportation. In the pilot study, indirect costs such as administration, marketing and research & development were deliberately omitted. It was assumed that these costs would be included in subsequent versions of the system prototype.

The process of creating analytical reports utilized the pivot table mechanism, which is typically an integral component of spreadsheet applications. Architecturally, pivot tables serve as an interface for presenting data retrieved from the OLAP analytical server and for further analysis, including charts, macro definitions, and the construction of technical, economic and social indicators.

The pilot study involved workshops with industrial analysts and managerial staff. Using pivot tables and active connections to the OLAP server, the process of redefining analytical reports included: transposing rows and columns, filtering data, rotating row and column labels, hiding data subsets, grouping and applying standard statistical, logical, database functions. The modified reports were saved as spreadsheet files with active connections to the OLAP server.

Workshops were held 2-3 times per week, during which dozens of new analytical reports were developed based on existing report templates. This approach proved to be highly flexible, as creating new analytical reports from previously developed templates did not require modifications to the OLAP structures. Industrial analysts acquired the necessary skills after completing a three-hour training session on pivot table usage.

5. Summary

The pilot study revealed that it is not possible to develop a complete and comprehensive specification of functional requirements at the initial stage of the project. Working with a predefined set of multidimensional reports serves as an inspiration for creating additional analyses, summaries and indicators. This leads to the conclusion that a Business Intelligence system should be characterized by flexibility – the ability to modify and expand analytical objects without requiring changes to data structures or source code.

The development of an analytical system using a three-tier architecture enables the creation of scalable solutions for modern industry. The key advantage of this approach is flexibility – the ability to generate new multidimensional reports without modifying data structures or software objects. The flexibility of the system prototype was validated through pilot studies conducted in a large furniture manufacturing company. The experiment confirmed that new analytical objects could be created within a spreadsheet environment equipped with active connections to an OLAP server. These development tasks were carried out by industrial analysts without the involvement of IT specialists.

Based on the conducted experiment, it can be boldly concluded that achieving the intended flexibility of a system supporting industrial analytics requires prior analytical and technical work. A key element is the construction of a central data warehouse. The execution of these tasks is undoubtedly a complex and time-consuming endeavor, which may be perceived as a potential limitation of the proposed solution.

It is also worth noting that the use of pivot tables allowed for a swift and efficient verification of the prototype's core functionality, as well as further development efforts. Naturally, the final version of the industrial analytics support system should be equipped with an advanced data visualization system. In this regard, the implementation of management dashboards should be considered. Future research will focus on evaluating the functionality, usability and flexibility of industrial data visualization systems.

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