Augmented Business Intelligence: A Multi-Criteria Approach

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ABSTRACT

This study examines enhanced Business Intelligence (A-BI) solutions that incorporate advanced simulation and predictive analytics to improve decision-making processes. We highlight the limitations of conventional BI infrastructures focused on data warehousing in forecasting and scenario modeling. We offer a multi-criteria evaluation methodology utilizing the Analytic Hierarchy Process (AHP) to evaluate A-BI solutions based on essential criteria: what-if scenarios, forecasting, and machine learning capabilities. Our analysis designates SAP Analytics Cloud as the most efficient solution for adding simulation features. This study presents a systematic approach for choosing BI systems that correspond with contemporary corporate requirements for agility, interaction, and strategic insight.

Keywords : *Augmented Business intelligence; Artificial intelligence; Digitalization; Data analytics; Process analytics; Machine learning; Simualtion; Deep learning;*

1. INTRODUCTION

Business Intelligence (BI) refers to a collection of processes, methodologies, and technology solutions intended to gather, centralize, process, and retrieve data from diverse sources, with the objective of generating high-value strategic information. This data, frequently dispersed and unstructured in its original state, is consolidated in a data warehouse, where it is converted and analyzed to reveal previously obscured insights (Bany Mohammed et al., 2024).

The Business Intelligence notion evolves from the decision support systems established in the 1960s. Nonetheless, the phrase "Business Intelligence" was officially established by Howard Dresner, a researcher at the Gartner Group, in 1989. The concept, originally centered on enhancing organizational management, swiftly transformed into a crucial technological element in the formulation of decision-making processes.

Data warehousing is the basis for most business intelligence solutions that use traditional architecture. This process involves taking data out of transactional or operational systems, changing it, and then putting it into a data warehouse (Ain et al., 2019). This architecture lets you organize and combine data so that end users can use dashboards, automated reports, or interactive visualizations to better understand it.

The best thing about this architecture is that it gives you a consistent and reliable view of the company's past business activities, which makes it easier to make decisions based on facts from the past. But it does have some problems, especially when it comes to making predictions and forecasts. Traditional BI isn't very good at predicting how a choice will affect a business or an entity in the future. Because of this limitation, decision-making systems need to be more flexible and able to see things coming. This can be done by using more advanced methods like predictive analytics and artificial intelligence.

New ways of doing business intelligence have been created to meet businesses' growing needs for speed and accuracy because traditional methods have their limits. Real-Time BI has been a big step forward among these (Freudenreich et al., 2013). Unlike conventional architecture, which relies on periodic data extractions, Real-Time BI lets you see data flows as they happen. This ability to constantly look at and analyze data gives decision-makers a quick picture of how the business is doing, which helps them respond more quickly to unexpected events, problems, or strategic opportunities.

AI and ML have also changed the BI environment significantly (Tavera Romero et al., 2021). We now call it Augmented BI. It's a new kind of smart system that can not only look at old data but also guess what will happen in the future and tell you what to do. These systems can automatically look at data, find complicated patterns, make suggestions that are specific to each person, and act out different situations. This link changes BI from a simple decision-making tool into a real engine of proactive intelligence that makes businesses work better.

Augmented Analytics is changing Business Intelligence by adding AI, ML, and natural language processing (NLP) to traditional analytics methods (Marques et al., 2024). This integration makes it easier to analyze data automatically, speeds up the process of gaining insights, and makes decisions more quickly. AI-driven data governance is an important part that automatically improves compliance, security, and data integrity. AutoML and NLP-powered insights let anyone, no matter how tech-savvy, build models and interact with data through conversational queries. This makes data more accessible to businesses of all sizes.

Furthermore, augmented analytics improves business intelligence tools by utilizing AI-driven visuals and intelligent dashboards that provide automated, context-sensitive reporting. It modernizes data processing with enhanced ETL and seamless data integration, facilitating the efficient transformation and consolidation of various data sources (Alghamdi & Al-Baity, 2022). AI-optimized data lakes and warehouses automate storage administration, enhancing scalability and performance. Ultimately, intelligent data pipelines and orchestration optimize workflows and guarantee effective data transfer and transformation, enhancing the responsiveness and adaptability of analytics systems to business requirements.

With this in mind, we chose an augmented Business Intelligence system that can satisfy today's expectations for analysis, performance, and interactivity. The objective is to implement a solution that incorporates the conventional architectural principles of Business Intelligence—specifically data storage, processing, and retrieval—while enhancing it with sophisticated predictive analytics and simulation functionalities. This solution would facilitate comprehensive analysis of extensive data sets while providing end-users with an intuitive interface, enabling dashboard navigation, dynamic visualization of key performance indicators (KPIs), and scenario simulation to predict the effects of specific decisions on the overall business. This method seeks to enhance decision-making agility, data transparency, and strategic alignment across the organization.

The remainder of this publication is structured as follows: section 2 provides the literature evaluation, section 3 outlines the adopted technique, and section 4 shows the achieved results. The effort ultimately culminates in a summary and suggestions.

2. LITERATURE REVIEW

2.1. Academic review

The scientific literature emphasizes various methodologies for assessing and selecting BI solutions, whether open source or proprietary, tailored to the distinct requirements of organizations, especially SMEs, the healthcare sector, or data-intensive contexts such as security systems or big data.

A significant study released in 2012, (Tutunea & Rus, 2012), examines open-source solutions for small and medium-sized organizations. The author assesses tools based on their development environment and their functional and operational capabilities. Actuate BIRT (Business Intelligence and Reporting Tools) is recognized as a viable solution, merging an intuitive interface with sophisticated reporting functionalities designed for SMEs.

A comparison assessment issued in (Ben Rabia & Bellabdaoui, 2022) evaluates proprietary tools (Tableau, QlikView, and Power BI) using an analytical framework that encompasses factors like data management, analytical content development, results distribution, and IT infrastructure support. The study concludes that Microsoft Power BI is distinguished by its user-friendliness, seamless interaction with the Microsoft ecosystem, and dynamic visualization features.

The research conducted by (Brandão et al., 2016), examines open-source solutions within healthcare systems. The primary criteria are user-friendliness, data processing management, and administrative functionalities. Pentaho BI was chosen for its user-friendly graphical interface and superior analytical processing capabilities.

A comparative examination of proprietary BI solutions performed in 2013 (CORE.ac.uk) emphasizes factors like development infrastructure, data analysis, scorecards, visualization, and mobile integration. The study indicates that MicroStrategy provides a comprehensive, integrated platform that addresses the analytical requirements of major companies.

The Pramanik et al. (2017) study on open source BI tools for criminal data analysis (Semantic Scholar) assesses particular criteria including report and dashboard production, OLAP, ETL, data mining, cross-platform compatibility, and fault tolerance. The Apache Hadoop tool is noted for its capacity to process huge volumes of distributed data with reliability and scalability.

The topic of predictive modeling and "what-if" simulations is examined in Golfarelli & Rizzi, (2009) article, What-if Simulation Modeling in Business Intelligence, which suggests a coherent framework for depicting intricate decision-making situations. The research emphasizes the significance of hierarchical decomposition, standardization, and ergonomics in sophisticated business intelligence systems.

Dell'Aquila et al. (2008) provides a comprehensive overview of BI solutions, both open source and commercial, across three primary dimensions: information delivery, source integration, and analytical capabilities. MicroStrategy once again emerges as a prominent authority in the domain of professional business intelligence solutions.

2.2. Contribution

Our research builds on previous work and introduces a new point of view called "Augmented Business Intelligence: a Multi-Criteria Approach." This approach aims to fix the problems with traditional selection methods. We contributed by using an integrated multi-criteria methodology that makes it easier to compare and evaluate Augmented Business Intelligence solutions based on technical, functional, and strategic factors.

We integrate traditional aspects, like analytical capabilities, performance indicator visualization, integration ease, and infrastructure compatibility, with advanced criteria related to artificial intelligence, "what-if" scenario simulation, and user experience (Popovič et al., 2012). The objective is to present a robust evaluation framework tailored to the needs of contemporary enterprises seeking to implement scalable, interactive, and predictive business intelligence solutions.

Our methodology is to enhance the selection of BI solutions based on both their technical efficacy and their supplementary value in strategic decision-making, underpinned by an intuitive interface, modular architecture, and real-time simulation functionalities.

3. RESEARCH METHODOLOGY

The Analytic Hierarchy Process (AHP) is a multi-criteria decision-making methodology established by Thomas L. Saaty in the 1970s (Emrouznejad & Marra, 2017). It allows us to organize a complex issue into a multi-tiered hierarchy, ranging from the overarching objective to the criteria and sub-criteria, culminating in the many choices to be assessed. This deconstruction enhances analysis by clarifying the choice criteria and their interrelations, which is especially beneficial when the criteria encompass both quantitative and qualitative aspects. The Analytic Hierarchy Process (AHP) relies on pairwise comparisons across elements at the same level, facilitating the evaluation of their relative significance through a standardized preference scale.

The AHP methodological procedure commences with the establishment of the decision hierarchy, succeeded by paired evaluations of criteria and subsequently of alternatives (Sadiq & Tesfamariam, 2009). The comparisons are synthesized through mathematical techniques, particularly eigenvector analysis, to ascertain numerical weights that indicate the relative significance of each criterion and the prioritization of alternatives. An essential benefit of this method is the capacity to verify the consistency of the expressed judgments, so ensuring the dependability of the results. AHP is extensively utilized across several domains to facilitate strategic decision-making, particularly in the selection of technology solutions, project management, or the evaluation of alternatives (Figure 1).

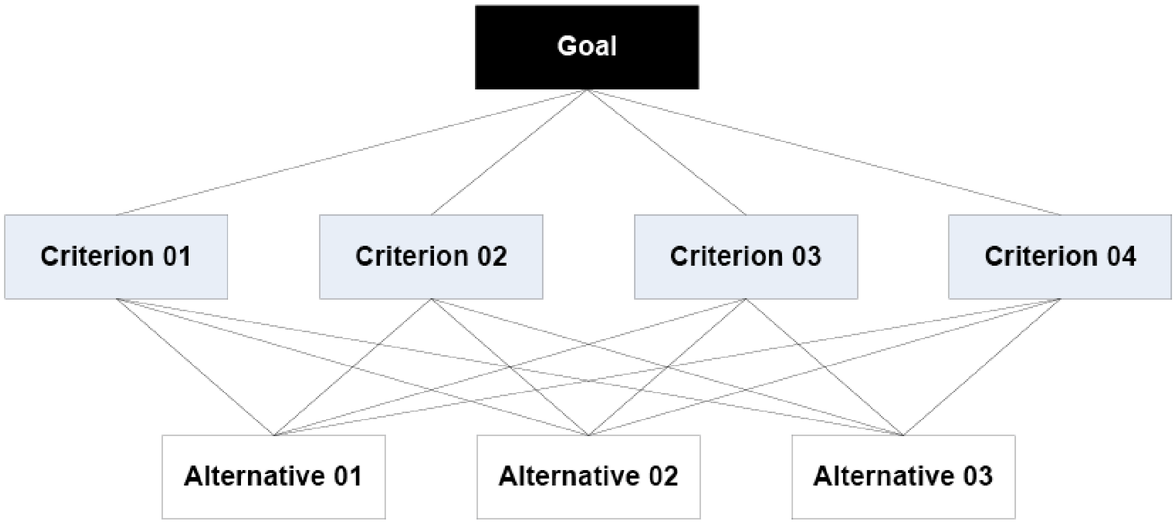

Figure 1: AHP architecture

In our AHP-based methodology, we have identified three primary criteria for assessing augmented business intelligence solutions: what-if scenarios, forecasting, and machine learning. These criteria were selected as they significantly and relevantly represent the capability of tools to incorporate advanced simulation and predictive analytic features, which are important to contemporary business expectations about informed decision-making (Figure 2).

The "what-if" scenarios criterion pertains to the capacity of BI systems to allow users to investigate various hypotheses and assess the possible effects of alternative actions, hence providing a robust method for modeling future scenarios and predicting strategic outcomes. Forecasting evaluates the capacity of instruments to produce predictions through the examination of past trends, essential for anticipatory resource planning and management. Ultimately, machine learning assesses the amalgamation of sophisticated algorithms that can learn from data, identify intricate patterns, and perpetually enhance the precision of analyses and recommendations. Collectively, these three criteria establish a robust foundation for evaluating the maturity of simulation components in BI solutions, thereby facilitating an educated selection tailored to the contemporary requirements of enterprises.

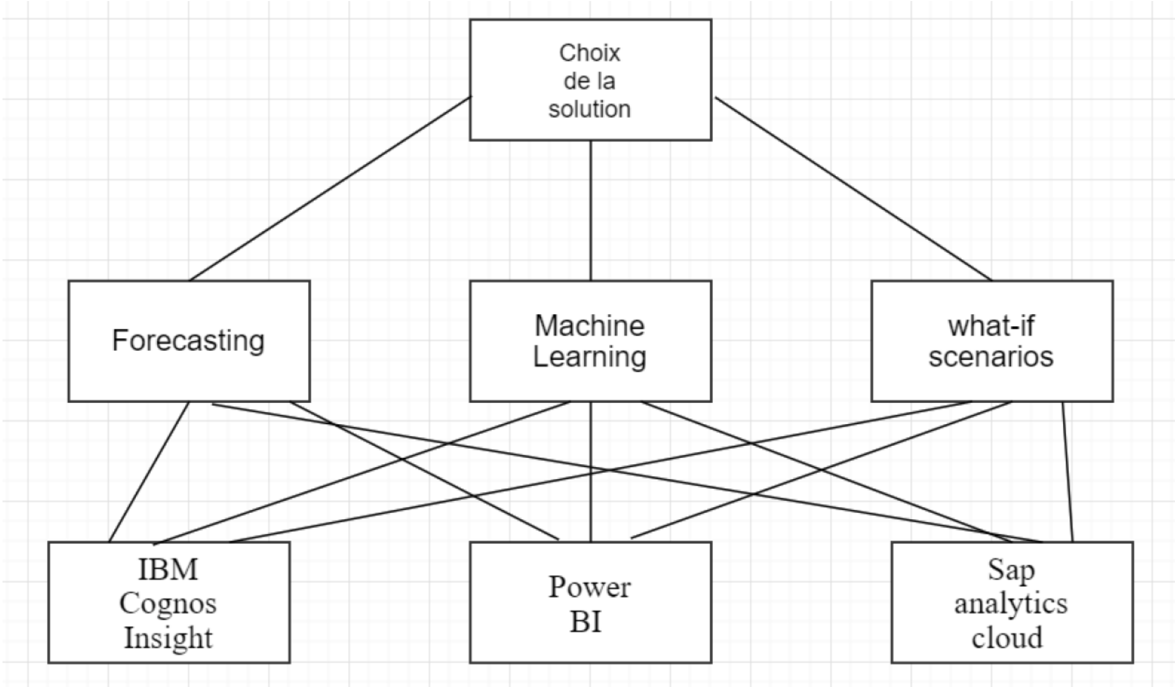

Figure 2: Building the hierarchy.

4. RESULT AND DISCUSSION

In the AHP technique, every non-leaf node in the hierarchy undergoes pairwise comparisons among its subordinate criteria or alternatives (Kašpar et al., 2025). This mechanism converts the decision-maker's qualitative evaluation of the relative significance of each criterion or option into numeric values, within the precise context of the decision at hand. Specifically, for each pair of kid criteria, the decision-maker articulates a preference based on a predetermined scale, so creating a binary comparison matrix (Szczypińska & Piotrowski, 2009).

To standardize these evaluations and guarantee their consistency, we employ Saaty's comparison scale, which spans from 1 (equal importance) to 9 (extreme preference). This scale enables the transformation of subjective preferences into numerical values for the calculation of relative weights. The created matrices are further analyzed using particular mathematical techniques, such as the eigenvector approach, to derive the weighted priority of each criterion or option (Figure 3).

	Forecasting	Machine Learning	What-if Scenarios
Forecasting	1	5	0,33333333
Machine Learning	0,2	1	0,2
What-if Scenarios	3	5	1

Figure 3: Generation of binary comparison matrices..

We assessed three criteria: what-if scenarios, forecasting, and machine learning. Following careful consideration and contingent upon the problem's nature, we opted to prioritize the “what-if scenarios” criterion over “forecasting,” thereby emphasizing the significance of simulating various hypotheses and their effects in the decision-making process. This preference illustrates the enhanced utility of simulation in predicting the outcomes of several options.

Furthermore, we significantly preferred the "what-if scenarios" and "forecasting" criteria to the "machine learning" criterion. This conclusion arises from the observation that, while machine learning offers sophisticated predictive analysis capabilities, it is regarded as less directly associated with the dynamic simulation aspect that we aim to emphasize in our evaluation approach. Nonetheless, we acknowledge its supplementary function and increasing significance in contemporary business intelligence solutions (Figure 4).

	Forcasting	Machine Learning	what-if Scenarios
Forcasting	1	5	0,333333333
Machine Learning	0,2	1	0,2
What-if Scenarios	3	5	1
Sum	4,2	11	1,533333333

	Forcasting	Machine Learning	what-if Scenarios	Weights
Forcasting	0,238095238	0,454545455	0,217391304	0,303343999
Machine Learning	0,047619048	0,090909091	0,130434783	0,089654307
what-if Scenarios	0,714285714	0,454545455	0,652173913	0,607001694
Sum	4,2	11	1,533333333	1

	Weights
Forcasting	0,303343999
Machine Learning	0,089654307
what-if Scenarios	0,607001694

Figure 4: Determining relative weights

This prioritization of criteria, grounded on precise and carefully quantified assessments, ensures a transparent and consistent review that directs the selection process of enhanced Business Intelligence tools according to priorities aligned with the stated specific needs.

	Forcasting	Machine Learning	what-if Scenarios
IBM Cognos Insight	1	3	4
Power BI	4	4	4
Sap analytics cloud	5	5	5
Sum	10	12	13

	Forcasting	Machine Learning	Simulation Scenarios
IBM Cognos Insight	0,1	0,25	0,307692308
Power BI	0,4	0,333333333	0,307692308
Sap analytics cloud	0,5	0,416666667	0,384615385
Sum	10	12	13

	Score
IBM Cognos Insight	0,239517729
Power BI	0,337992121
Sap analytics cloud	0,422490151

Figure 5: Generation of final alternative weights

Through the implementation of the AHP technique, considering the provided criteria, we have determined that SAP Analytics Cloud is the Business Intelligence solution that most proficiently incorporates functions related to the simulation component.

5. CONCLUSION

This study concentrated on Business Intelligence solutions, specifically highlighting advanced simulation and predictive analytic capabilities, which are crucial for facilitating strategic decision-making in contemporary enterprises. By conducting a comprehensive literature review and employing a multi-criteria analysis utilizing the AHP technique, we identified and prioritized critical criteria, including "what-if" scenarios, forecasting, and machine learning.

The stringent implementation of this methodology allowed us to establish that SAP Analytics Cloud is the most efficient solution for integrating the simulation component, hence fulfilling the specified objectives. This methodical methodology provides a clear decision-making framework, customized for organizations seeking to implement augmented Business Intelligence solutions.

To enhance this research, it is advisable to broaden the study to encompass additional criteria, particularly by incorporating elements related to data security, solution scalability, and user experience. Moreover, practical experimentation with these technologies in a real-world situation would significantly enhance our ability to evaluate their operational and strategic effects beyond theoretical parameters.

CONFLICTS OF INTEREST

All authors declare that they have no conflicts of interest.

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