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THE FIVE STAGES OF BUSINESS ANALYTICS

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Purpose: The goal of the paper is to analyze the main features, benefits and problems with the business analytics usage.
Design/methodology/approach: Critical literature analysis. Analysis of international literature from main databases and polish literature and legal acts connecting with researched topic.
Findings: The paper explores the main concepts of business analytics, including descriptive, real-time, diagnostic, predictive, and prescriptive analytics. Each stage of development builds upon the previous one, addressing specific needs in data analysis and decision-making. The paper also presents a detailed comparison of the five types of business analytics, showcasing their unique characteristics, techniques, and applications. Understanding these differences helps organizations select the appropriate analytics type to suit their requirements and drive success. As technology and data processing capabilities advance, business analytics continues to evolve. Embracing the power of data and analytics grants organizations a competitive advantage, unlocking opportunities and driving innovation. Integrating analytics into decision-making processes is essential for thriving in a data-driven world, ensuring sustained growth and success in an ever-changing marketplace.
Originality/value: Detailed analysis of all subjects related to the problems connected with the prospective analytics.

Keywords: Industry 4.0; diagnostic analytics, business analytics, data analysis.

Category of the paper: literature review.

1. Introduction

Business analytics is the practice of utilizing data analysis and statistical methods to gain valuable insights and make informed business decisions. It involves the exploration, examination, interpretation, and visualization of data from various sources to identify trends, patterns, and correlations that can drive strategic planning and operational improvements

(Wolniak, 2016; Czerwińska-Lubszczyk et al., 2022; Drozd, Wolniak, 2021; Gajdzik, Wolniak, 2021, 2022; Gębczyńska, Wolniak, 2018, 2023; Grabowska et al., 2019, 2020, 2021).

The main objective of business analytics is to extract meaningful and actionable information from data, enabling organizations to make data-driven decisions, optimize processes, enhance efficiency, and gain a competitive edge. By leveraging historical and real-time data, businesses can better understand their operations, customer behavior, market trends, and other critical factors that influence their performance.

The goal of the paper is to analyze the main features, benefits and problems with the business analytics usage.

2. Business analytics – main concepts

Business analytics is the systematic application of statistical and quantitative methods to explore and interpret data, providing valuable insights that aid in making data-driven decisions to improve business performance and achieve strategic goals (Hurwitz et al., 2015). Business analytics also refers to the process of analyzing data from various sources using statistical and computational techniques to uncover patterns, trends, and correlations (Sułkowski, Wolniak, 2015, 2016, 2018; Wolniak, Skotnicka-Zasadzień, 2008, 2010, 2014, 2018, 2019, 2022; Wolniak, 2011, 2013, 2014, 2016, 2017, 2018, 2019, 2020, 2021, 2022; Gajdzik, Wolniak, 2023; Wolniak, 2013, 2016; Hys, Wolniak, 2018). The insights gained from this analysis help organizations make informed decisions and optimize their operations for greater efficiency and competitiveness.

Business analytics empowers organizations to transform raw data into valuable knowledge, enabling them to make data-driven decisions that positively impact their overall performance and success.

Business analytics plays a crucial role in aiding decision-makers to (Cam et al., 2021):

- Identify opportunities for growth and improvement.
- Optimize operational efficiency and resource allocation.
- Understand customer behavior and preferences.
- Mitigate risks and identify potential threats.
- Monitor and evaluate the performance of various initiatives and strategies.

We can divide business analytics into five following stages (Hwang et al.; Hurwitz et al., 2015; Lawton, 2019; Charles et al., 2023; Scappini, 2016; Peter et al., 2023):

- Descriptive analytics involves the examination and interpretation of historical data to gain insights into past performance and understand what has happened in a business. This type of analytics focuses on summarizing and presenting data in a meaningful way, often using data visualization tools like charts, graphs, and dashboards to provide a clear and concise overview of key performance indicators (KPIs) and trends.
- Real-time analytics, also known as streaming analytics or instant analytics, is the process of analyzing data as it is generated or received, without any delay. It enables organizations to monitor and respond to events, transactions, and data streams in real time. This type of analytics is especially useful in dynamic and time-sensitive environments, such as financial markets, supply chain management, and online customer interactions.
- Diagnostic analytics goes beyond descriptive analytics by seeking to understand why certain events or patterns occurred in the data. It involves analyzing historical data to identify the root causes of specific outcomes or anomalies. By investigating past performance and understanding contributing factors, businesses can gain insights into how to improve processes and avoid potential issues in the future.
- Predictive analytics involves the use of historical data and statistical algorithms to make predictions about future events or outcomes. By identifying patterns and relationships in the data, predictive analytics helps organizations anticipate potential scenarios and trends. This enables them to proactively plan and make more informed decisions, such as predicting customer behavior, demand for products, or financial performance.
- Prescriptive analytics takes data analysis to the next level by recommending specific actions to optimize outcomes based on the insights gained from descriptive, diagnostic, and predictive analytics. It uses advanced algorithms and decision models to determine the best course of action under different circumstances. Prescriptive analytics provides actionable recommendations that guide decision-makers in maximizing efficiency, minimizing risks, and achieving strategic objectives.

3. Evolution of business analytics

Descriptive analytics, as the initial stage of business analytics, focused on examining historical data to summarize past performance and identify trends. Organizations relied on batch processing and traditional data analysis methods to gain insights from historical datasets. However, as the pace of business and the need for faster decision-making increased, a new demand emerged for real-time insights.

The evolution to real-time analytics was driven by advancements in technology and data processing capabilities. Organizations began to adopt technologies like stream processing and complex event processing (CEP) to analyze data as it was generated or received in real-time. This shift allowed them to monitor events, transactions, and data streams as they happened, enabling immediate responses to emerging trends or critical situations.

Real-time analytics became essential in industries where timeliness and quick reactions were critical, such as financial markets, online retail, and fraud detection. With the ability to process and analyze data in real-time, organizations gained a competitive advantage, as they could identify opportunities and respond to threats faster than their competitors (Sharma et al., 2020).

The transition from descriptive analytics to real-time analytics was driven by the recognition that historical insights alone were insufficient to keep up with the rapidly changing business landscape. Organizations realized the need to leverage the power of real-time data to make more informed and agile decisions, ultimately leading to the evolution of business analytics to the next stage of development (Hwang et al., 2017; Hurwitz et al., 2015; Lawton, 2019; Charles et al., 2023; Scappini, 2016; Peter et al., 2023).

As organizations began leveraging real-time analytics to gain immediate insights, they recognized the need to go beyond simply reacting to events and delved deeper into understanding the underlying causes of specific outcomes. This realization led to the evolution from real-time analytics to diagnostic analytics (Peter et al., 2023).

With real-time analytics in place, organizations could quickly identify anomalies and emerging trends. However, the next logical step was to investigate the reasons behind these patterns. Diagnostic analytics emerged as the stage where historical data was thoroughly analyzed to identify root causes, contributing factors, and correlations. By performing drill-down analyses, root cause analysis, and other investigative techniques, organizations could pinpoint the factors that led to specific events or performance outcomes. Diagnostic analytics provided a deeper understanding of the relationships between different variables and helped identify potential bottlenecks or inefficiencies in processes.

The evolution to diagnostic analytics represented a shift from reactive decision-making to a more proactive approach. By understanding the underlying causes of both positive and negative outcomes, organizations could take corrective actions, optimize processes, and make data-driven improvements to their operations (Hurwitz et al., 2015).

Building on the insights gained from diagnostic analytics, organizations sought to move from understanding past events to anticipating future scenarios. The evolution from diagnostic analytics to predictive analytics was driven by the desire to leverage historical data and patterns to make informed predictions. With the historical data already analyzed during the diagnostic stage, organizations had the groundwork to develop predictive models. Advanced statistical algorithms, machine learning techniques, and time series forecasting were employed to identify patterns and relationships in the data that could be used to forecast future trends.

Predictive analytics enabled organizations to anticipate potential outcomes, market trends, customer behavior, and demand for products or services. This forward-looking approach allowed businesses to proactively plan and allocate resources, optimize inventory management, and strategize marketing campaigns based on anticipated changes in the market. The shift to predictive analytics empowered organizations to move beyond reactive and proactive decision-making to predictive decision-making. Armed with data-driven predictions, they could be better prepared for the future and adapt their strategies to potential changes, thereby gaining a competitive edge in their respective industries.

The transition from predictive analytics to prescriptive analytics marks the final and most advanced stage in the evolution of business analytics. While predictive analytics focused on forecasting future outcomes, organizations recognized the need to take it a step further and move from predicting what might happen to determining the best course of action to achieve desired outcomes. This shift led to the development of prescriptive analytics (Jonek-Kowalska, Wolniak, 2021, 2022; Jonek-Kowalska et al., 2022; Kordel, Wolniak, 2021; Orzeł, Wolniak, 2021, 2022, 2023; Rosak-Szyrocka et al., 2023; Gajdzik et al., 2023; Ponomarenko et al., 2016; Stawiarska et al., 2020, 2021; Stecuła, Wolniak, 2022; Olkiewicz et al., 2021).

Prescriptive analytics builds upon the insights gained from descriptive, real-time, diagnostic, and predictive analytics to recommend specific actions or decisions to optimize results. By using optimization models, decision trees, simulation techniques, and machine learning algorithms, organizations could evaluate various scenarios and potential outcomes (Hwang et al., 2017).

Prescriptive analytics considers multiple variables, constraints, and objectives to arrive at the best possible course of action. It enables decision-makers to weigh the potential risks and rewards of different strategies and make well-informed choices based on data-driven insights. With prescriptive analytics, organizations can answer questions such as "What should we do?" and "How can we achieve our goals most effectively?" It empowers businesses to optimize their resources, streamline processes, maximize profitability, and make strategic decisions that align with their long-term objectives (Greasley, 2019).

In practice, prescriptive analytics finds applications in complex decision-making processes, such as supply chain optimization, resource allocation, pricing strategies, and personalized recommendations in e-commerce. For instance, prescriptive analytics can recommend the most cost-efficient distribution routes for a logistics company or suggest personalized product offers based on individual customer preferences. Prescriptive analytics represents the pinnacle of data-driven decision-making, enabling organizations to gain a competitive advantage by making precise, well-informed choices in a dynamic and rapidly changing business landscape. By fully embracing prescriptive analytics, businesses can optimize their operations, enhance customer experiences, and position themselves for sustained success in the ever-evolving marketplace (Wolniak, Sułkowski, 2015, 2016; Wolniak, Grebski, 2018; Wolniak et al., 2019, 2020; Wolniak, Habek, 2015, 2016; Wolniak, Skotnicka, 2011; Wolniak, Jonek-Kowalska, 2021; 2022).

4. Comparison of business analytics types

In table 3, we compare five types of business analytics: Descriptive Analytics, Real-time Analytics, Diagnostic Analytics, Predictive Analytics, and Prescriptive Analytics. Each type is described based on its definition, focus, time perspective, purpose, techniques/models used, and application examples.

Descriptive Analytics involves the examination and interpretation of historical data to gain valuable insights into past performance and understand what has happened in a business or operational context. By summarizing data, identifying patterns, and presenting key performance indicators and trends, descriptive analytics offers a clear and concise overview of historical events, enabling stakeholders to comprehend past outcomes and assess the effectiveness of their strategies and initiatives.

In contrast, Real-time Analytics focuses on the analysis of data as it is generated or received, without any delay. This dynamic approach allows organizations to monitor and respond to events, transactions, and data streams in real-time. By leveraging complex event processing and stream processing techniques, real-time analytics empowers decision-makers to promptly detect emerging trends, identify anomalies, and react swiftly to changing market conditions or critical situations.

Table 1.
Comparison of five types of business analytics

Factor	Descriptive Analytics	Real-time Analytics	Diagnostic Analytics	Predictive Analytics	Prescriptive Analytics
Definition	Examination and interpretation of historical data.	Analysis of data as it is generated or received, without delay.	Understanding the reasons behind past events or patterns.	Using historical data and statistical algorithms to predict future outcomes.	Recommending specific actions to optimize outcomes.
Focus	Past performance and trends.	Immediate events and streams.	Root causes of outcomes.	Future trends and possibilities.	Best course of action.
Time Perspective	Historical data.	Real-time data.	Historical data.	Future predictions.	Future predictions.
Purpose	Summarize data, identify patterns, and provide a clear overview of key performance indicators and trends.	Monitor and respond to events in real-time, enabling quick decision-making in dynamic and time-sensitive contexts.	Investigate past performance to identify the factors that contributed to specific outcomes or anomalies.	Anticipate potential scenarios and trends, allowing proactive planning and decision-making.	Provide actionable advice based on insights gained from other types of analytics to achieve desired objectives.

Cont. table 1.

Techniques/ Models	Data visualization, reporting, descriptive statistics.	Stream processing, complex event processing (CEP).	Drill-down analysis, root cause analysis.	Regression analysis, time series forecasting, machine learning models.	Optimization models, decision trees, simulation models.
Application Examples	Monthly sales reports, customer segmentation, website traffic analysis.	Fraud detection, stock market analysis, real-time website monitoring.	Customer churn analysis, identifying reasons for a decrease in sales.	Demand forecasting, predictive maintenance, stock price prediction.	Supply chain optimization, resource allocation, dynamic pricing strategies.
Data Sources	Structured and unstructured data from various sources.	Diverse data streams, sensors, social media, etc.	Structured and unstructured historical data.	Historical data from various sources.	Data from various sources, integrated and processed for analysis.
Decision-Making Impact	Informative insights for informed decision-making.	Immediate insights for real-time decision-making.	Identifying areas for improvement and optimization.	Anticipate risks and opportunities for better strategic planning.	Guiding optimal decisions to achieve desired outcomes.
Data Volume and Velocity	Handling larger historical datasets.	Handling real-time data streams, fast processing.	Working with historical data with varying volume.	Managing large datasets for future predictions.	Handling data to recommend decisions for future outcomes.
Industry Applications	Applicable across various industries.	Various industries and sectors.	Widely used in diverse business sectors.	Commonly used across industries for predictive insights.	Applied in various industries for decision optimization.
Data Integration	Data integrated from multiple sources for analysis.	Real-time data integration for immediate insights.	Data integration for analyzing historical performance.	Data integration for historical data analysis.	Integration of data to derive actionable recommendations.
Time Horizon	Historical view of performance over a specific period.	Immediate view of ongoing events and their impact.	Historical view to understand past performance.	Future-oriented view for forecasting long-term outcomes.	Future-oriented view for determining optimal actions.
Data Exploration	Understanding past trends and performance patterns.	Identifying emerging trends and anomalies in real-time.	Exploring historical data for potential insights.	Uncovering hidden patterns and relationships in data.	Evaluating potential scenarios for decision-making.
Implementation Complexity	Typically less complex due to historical data analysis.	May require sophisticated real-time data processing.	Can be complex, depending on the factors being analyzed.	Requires advanced statistical modeling and machine learning.	Involves complex optimization algorithms and simulations.

Cont. table 1.

Data Storage	Can be stored in databases, data warehouses, or spreadsheets.	Real-time data may be stored in memory or temporary storage.	Stored in databases or data warehouses for historical analysis.	Stored in databases or data warehouses for modeling.	Utilizes databases or specialized models to store recommended actions.
Data Visualization	Charts, graphs, and reports to summarize historical data.	Real-time dashboards and visualiza-tions for ongoing events.	Visual representations to explain past performance patterns.	Visualizations to display predictive outcomes and trends.	Visualizations to present recommended actions and their impacts.

Source: Authors own work on the basis of: (Hurwitz et al., 2015; Lawton, 2019; Charles et al., 2023, Scappini, 2016, Peter et al., 2023).

Diagnostic Analytics goes beyond descriptive analytics by seeking to understand why certain events or patterns occurred in the data. It involves in-depth analysis of historical data to identify the root causes of specific outcomes or issues. By investigating past performance and uncovering contributing factors, diagnostic analytics provides crucial insights that enable organizations to gain a deeper understanding of their operations and identify areas for improvement or optimization.

Predictive Analytics harnesses historical data and applies statistical algorithms, machine learning models, and data mining techniques to predict future outcomes and trends. By identifying patterns and relationships in the data, predictive analytics allows organizations to anticipate potential scenarios and make data-driven decisions for better planning and resource allocation. This forward-looking approach empowers businesses to proactively address challenges and seize opportunities.

Prescriptive Analytics represents the pinnacle of data-driven decision-making. Building upon descriptive, diagnostic, and predictive analytics, prescriptive analytics provides actionable recommendations and guidance on the best course of action under different circumstances. By utilizing optimization models, decision trees, and simulation techniques, prescriptive analytics assists decision-makers in optimizing resources, mitigating risks, and achieving strategic objectives with precision and effectiveness.

By analyzing and understanding the distinct characteristics of each type of business analytics, organizations can effectively leverage data to gain actionable insights, improve operational efficiency, enhance customer experiences, and stay ahead in an increasingly data-driven and competitive landscape. The wide range of analytical techniques and approaches available empowers businesses to unlock the full potential of their data and make more informed, strategic decisions that drive success and growth.

5. Conclusion

Throughout this paper, we have explored the main concepts of business analytics, including descriptive, real-time, diagnostic, predictive, and prescriptive analytics. Each stage of development builds upon the previous one, addressing specific needs and challenges in data analysis and decision-making.

Descriptive analytics serves as the foundation, offering a historical perspective on performance and trends. As the need for real-time insights emerged, organizations transitioned to real-time analytics, enabling swift responses to dynamic events. Recognizing the importance of understanding the underlying reasons behind outcomes, the evolution continued to diagnostic analytics, providing deeper insights into root causes.

Predictive analytics emerged as a response to the demand for future-oriented decision-making. By leveraging historical data and advanced algorithms, organizations could anticipate trends and scenarios, thereby enabling proactive planning and strategic decision-making. The ultimate stage of prescriptive analytics recommends specific actions to optimize outcomes, synthesizing insights from previous analytics stages. Prescriptive analytics empowers decision-makers to make precise, well-informed choices, driving efficiency and achieving strategic objectives.

In this paper, we also presented a detailed comparison of the five types of business analytics across various factors. Each type possesses unique characteristics, techniques, and applications that cater to diverse business needs. By understanding these differences, organizations can select the appropriate analytics type to suit their specific requirements and drive success in their respective industries.

Business analytics continues to evolve with advancements in technology and data processing capabilities. As organizations harness the power of data and analytics, they gain a competitive advantage, unlock hidden opportunities, and drive innovation. The integration of business analytics into decision-making processes is crucial for organizations seeking to thrive in a data-driven world, paving the way for sustained growth and success in an ever-evolving marketplace.

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