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FUNCTIONING OF PREDICTIVE ANALYTICS IN BUSINESS

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Purpose: The goal of the paper is to analyze the main features, benefits and problems with the predictive 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: Predictive analytics is a powerful tool that leverages historical data and statistical models to forecast future outcomes and behaviors. It enables organizations to gain valuable insights, make informed decisions, and drive business growth. By analyzing patterns, correlations, and trends in data, predictive analytics can uncover hidden relationships and provide a deeper understanding of business processes, customer behavior, market trends, and other important factors. The benefits of predictive analytics are numerous. It enables organizations to forecast and predict future events, leading to proactive decision-making and the ability to anticipate trends and outcomes. It enhances decision-making processes, improves resource allocation, and provides enhanced customer insights. Predictive analytics also helps in risk mitigation, fraud detection, optimization of operations and pricing, product development, and marketing effectiveness. By leveraging these benefits, organizations can gain a competitive advantage and achieve sustainable success.
Originality/value: Detailed analysis of all subjects related to the problems connected with the predictive analytics.

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

Category of the paper: literature review.

1. Introduction

Predictive analytics is an advanced analytical discipline that utilizes historical data, statistical algorithms, and machine learning techniques to forecast future events, behaviors, and trends. It goes beyond diagnostic analytics, which focuses on understanding past events, by providing insights into what is likely to happen in the future. Predictive analytics enables organizations to make proactive, data-driven decisions, anticipate outcomes, identify opportunities, and mitigate risks.

Predictive analytics is a powerful tool that enables organizations to anticipate future outcomes, behaviors, and trends. By leveraging historical data and sophisticated algorithms, organizations can make proactive decisions, identify opportunities, and mitigate risks. Predictive analytics has a wide range of applications across industries and domains, and its adoption can lead to enhanced operational efficiency, improved customer experiences, and increased competitiveness. To fully harness its benefits, organizations need to invest in data quality, develop robust models, and foster a data-driven culture.

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

2. Predictive analytics - definitions

At its core, predictive analytics leverages historical data to build models that can predict future outcomes or behaviors. These models are trained using various statistical and machine learning techniques, such as regression analysis, decision trees, neural networks, and clustering algorithms. By analyzing patterns, correlations, and trends in historical data, these models can make accurate predictions and generate valuable insights (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).

One of the key advantages of predictive analytics is its ability to identify hidden patterns and relationships that may not be apparent through traditional data analysis methods. It can uncover complex interactions between multiple variables and reveal the factors that contribute to specific outcomes. This empowers organizations to gain a deeper understanding of their business processes, customer behavior, market trends, and other important factors that drive success (Hurwitz et al., 2015).

Predictive analytics refers to the practice of using historical data, statistical modeling techniques, and machine learning algorithms to make predictions and forecasts about future events, behaviors, or outcomes. It involves analyzing patterns, correlations, and trends in the data to identify predictive patterns and develop models that can anticipate future scenarios (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 process of predictive analytics typically involves several steps, including data collection, data cleaning and preprocessing, model selection, model training and validation, and applying the model to new data for making predictions (Patanjali, 2018; Nourani, 2021; Sharma et al., 2020). Predictive analytics leverages various statistical and machine learning techniques such as regression analysis, decision trees, neural networks, clustering algorithms, and more.

The goal of predictive analytics is to uncover hidden insights and relationships in the data that may not be apparent through traditional analysis methods. By understanding these patterns and trends, organizations can make informed decisions, develop strategies, optimize operations, and gain a competitive advantage (Cam et al., 2021).

Predictive analytics finds applications across diverse industries and domains. In finance, it helps detect fraudulent transactions, predict credit risks, and optimize investment strategies (Greasley, 2019). In marketing, it enables personalized targeting, customer segmentation, and churn prediction. In healthcare, predictive analytics can aid in early disease detection, treatment optimization, and resource allocation. It also supports supply chain optimization, demand forecasting, predictive maintenance, and risk management in manufacturing and logistics (Jonek-Kowalska, Wolniak, 2021, 2022; Jonek-Kowalska et al., 2022; Kordel, Wolniak, 2021, 2023; Rosak-Szyrocka et al., 2023; Gajdzik et al., 2023, Orzeł, Wolniak, 2021, 2022; Ponomarenko et al., 2016; Stawiarska et al., 2020, 2021; Stecuła, Wolniak, 2022; Olkiewicz et al., 2021).

Implementing predictive analytics involves several stages. First, organizations need to define the problem they want to solve and identify the relevant data sources. They then collect, clean, and preprocess the data to ensure its quality and reliability. Next, they select the appropriate predictive models and algorithms based on the nature of the problem and the available data. The models are trained using historical data and validated to assess their accuracy and performance (Hurwitz et al., 2015; Lawton, 2019; Charles et al., 2023; Scappini, 2016; Peter et al., 2023).

Once the predictive models are built and validated, they can be applied to new data to make predictions and generate insights. Organizations can use these insights to make informed decisions, develop strategies, optimize operations, and gain a competitive edge. It is important to note that predictive analytics is an iterative process, requiring continuous monitoring and refinement of models as new data becomes available and the business landscape evolves.

However, predictive analytics also faces certain challenges. Data quality and availability issues, inadequate or biased data, and the need for skilled data scientists and analysts are common hurdles. Additionally, ethical concerns related to privacy, security, and the potential for discriminatory outcomes should be carefully addressed.

There are following steeps of predictive analytics implementation:

- Define the requirements. Understand the business problem you're trying to solve. Is it managing inventory? Reducing fraud? Predicting sales? Generating questions about the problem and listing them in order of importance is a good start. Collaborating with a statistician at this stage can help form metrics for measuring success. A business user or subject matter expert generally takes charge of this first step.

- Explore the data. Here, you'll want to loop in a statistician or data analyst or both. The job is to identify the data that informs the problem you're trying to solve and the goal. Consider the relevancy, suitability, quality and cleanliness of the data.
- Validate the results. Performance of the model can change over time due to shifts in customer preferences or the business climate, or unforeseen events such as a pandemic. Thresholds for updating models vary, requiring the joint expertise of a business user and a data scientist in this step.

Below in table 1 there is a comparison table highlighting the differences between diagnostic analytics and predictive analytics:

Table 1.
Comparison of diagnostic analytics and predictive analytics

Aspect	Diagnostic Analytics	Predictive Analytics
Objective	Understand past events and their causes. The primary objective of diagnostic analytics is to understand why a certain event or outcome occurred in the past. It focuses on analyzing historical data to identify the root causes or factors that contributed to a particular result.	Forecast future events and behaviors. The main objective of predictive analytics is to make predictions and forecasts about future events or outcomes. It utilizes historical data and statistical modeling techniques to identify patterns and trends that can be used to anticipate future scenarios.
Focus	Historical data analysis. It focuses on understanding the past and gaining insights into historical events or outcomes. It is often used for post-event analysis, troubleshooting, and identifying opportunities for improvement.	Future data analysis. It focuses on future outcomes and aims to provide actionable insights for proactive decision-making. It helps organizations anticipate future scenarios, mitigate risks, optimize operations, and gain a competitive advantage.
Purpose	Identify root causes, patterns, and correlations in past events.	Make predictions, anticipate outcomes, and identify trends.
Data Usage	Analyze historical data.	Analyze historical data and apply it to new data.
Timeframe	Analysis of past events. It focuses on analyzing historical data to understand past events, trends, and patterns. It looks backward and explains what happened in the past.	Forecasting future events. It focuses on analyzing historical data to make predictions and forecasts about future events, behaviors, or outcomes. It looks forward and tries to anticipate what will happen in the future.
Analytical Techniques	Statistical analysis, data mining, data visualization. It typically involves retrospective analysis and seeks to answer questions such as "What happened?", "Why did it happen?", and "What were the contributing factors?" It often uses techniques such as data mining, root cause analysis, and exploratory data analysis to uncover insights from historical data.	Statistical modeling, machine learning algorithms. It involves analyzing historical data to build models that can make predictions about future events. It uses statistical modeling, machine learning algorithms, and data mining techniques to identify patterns and relationships in the data and make forecasts.
Decision-Making	Provides insights for informed decision-making based on past events.	Supports proactive decision-making by anticipating future outcomes.
Benefits	Performance improvement, risk mitigation, enhanced customer insights, process optimization, resource allocation.	Proactive decision-making, opportunity identification, risk mitigation, resource optimization.

Cont. table 1.

Limitations/ Challenges	Time-intensive, limited real-time insights, data quality and availability issues, lack of predictive capabilities, complexity of analysis.	Data quality and availability issues, need for skilled data scientists, ethical considerations.
Examples	Analyzing sales data to identify factors influencing revenue decline.	Predicting customer churn, forecasting sales demand.
Applications	Business intelligence, healthcare, finance, marketing, manufacturing, logistics.	Finance, marketing, healthcare, supply chain, maintenance, risk management.

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

3. Benefits and problems of predictive analytics usage

Predictive analytics empowers organizations to make proactive decisions, anticipate future trends, mitigate risks, optimize operations, and drive business growth. By leveraging the benefits of predictive analytics, organizations can gain a competitive advantage and make data-driven decisions that lead to improved outcomes and success.

On the basis of literature analysis following benefits of predictive analytics can be formulated (Hwang et al., 2017; Hurwitz et al., 2015; Lawton, 2019; Charles et al., 2023; Scappini, 2016; Peter et al., 2023; Tucci, 2022).

- Forecasting and prediction: Predictive analytics enables organizations to forecast future outcomes and events based on historical data and statistical models. By analyzing patterns, trends, and correlations in the data, predictive analytics can provide insights into future customer behavior, market trends, demand patterns, and other relevant factors. This helps organizations make more accurate predictions and forecasts, supporting proactive decision-making.
- Improved decision-making: This type of analytics provides organizations with data-driven insights that enhance decision-making processes. By leveraging predictive models, organizations can make informed decisions based on anticipated outcomes. This allows them to identify opportunities, mitigate risks, optimize resource allocation, and develop effective strategies for business growth.
- Enhanced customer insights: Type of analytics described in the paper helps organizations gain a deeper understanding of their customers' preferences, needs, and behaviors. By analyzing customer data, organizations can identify patterns and trends that enable them to personalize offerings, target specific customer segments, and improve customer experiences. This leads to increased customer satisfaction, loyalty, and retention.

- Risk mitigation and fraud detection: Predictive analytics is effective in identifying and mitigating risks. By analyzing historical data and patterns, organizations can identify potential risks, fraudulent activities, or anomalies that require attention. This enables organizations to take proactive measures to prevent fraud, minimize losses, and strengthen their risk management strategies.
- Optimization of operations and resources: Predictive analytics helps organizations optimize their operations and resource allocation. By analyzing data on resource utilization, demand patterns, and production processes, organizations can identify areas of inefficiency, anticipate demand fluctuations, and optimize their supply chain. This leads to improved operational efficiency, cost savings, and better utilization of resources.
- Product development and innovation: This analytics aids organizations in developing new products and services. By analyzing market trends, customer feedback, and historical data, organizations can identify emerging needs, gaps in the market, and potential areas for innovation. This helps organizations stay ahead of the competition and develop products that align with customer preferences and market demands.
- Improved marketing effectiveness: Predictive analytics enhances marketing effectiveness by enabling organizations to target the right audience with the right message at the right time. By analyzing customer data, organizations can segment their customer base, identify the most promising prospects, and personalize marketing campaigns. This leads to higher conversion rates, improved marketing ROI, and increased customer engagement.
- Optimization of pricing and revenue management: Predictive analytics helps organizations optimize their pricing strategies and revenue management. By analyzing historical sales data, market conditions, and customer behavior, organizations can determine optimal pricing levels, identify pricing trends, and implement dynamic pricing strategies. This allows organizations to maximize revenue, increase profitability, and maintain a competitive edge.
- It automates decision-making, reducing manual work.
- It speeds complex approval processes, enabling faster time to value.
- It enables faster response to changing market conditions, for example, automating stock trades faster than humans can.
- It improves resilience to fast-changing circumstances, helping enterprises, for example ride out supply chain disruptions.
- It operationalizes predictive analytics insights, increasing the value of existing analytics.

Predictive analytics empowers organizations to make data-driven decisions, optimize operations, enhance customer experiences, mitigate risks, and drive business growth (Sharma et al., 2020; Wolniak, 2013, 2016; Hys, Wolniak, 2018). By leveraging the power of predictive analytics, organizations can gain a competitive advantage, capitalize on emerging opportunities, and achieve sustainable success in today's dynamic business landscape.

Below are some of the key disadvantages and problems associated with the usage of predictive analytics (Hwang et al., 2017; Hurwitz et al., 2015; Lawton, 2019; Charles et al., 2023; Scappini, 2016; Peter et al., 2023):

- Anticipating Future Trends and Outcomes: Predictive analytics leverages historical data and statistical models to forecast future events, trends, and outcomes. By analyzing patterns and correlations, organizations can gain insights into customer behavior, market trends, demand fluctuations, and other factors that impact their business. This enables proactive decision-making and allows organizations to stay ahead of the competition by anticipating and preparing for future changes.
- Enhanced Decision-Making: This type of analytics provides valuable insights that support informed decision-making. By using predictive models and algorithms, organizations can make data-driven decisions based on the likelihood of specific outcomes. This minimizes guesswork and subjective judgment, leading to more accurate and reliable decisions across various business functions such as marketing, finance, operations, and human resources.
- Improved Resource Allocation: Predictive analytics helps organizations optimize resource allocation by identifying areas where resources can be allocated most effectively. By analyzing data on customer preferences, market trends, and resource utilization, organizations can allocate their budget, workforce, and other resources in a way that maximizes efficiency and productivity. This leads to cost savings, improved operational performance, and better utilization of available resources.
- Enhanced Customer Insights: The type of analytics described in the paper enables organizations to gain a deeper understanding of their customers. By analyzing customer data, including past purchases, preferences, browsing behavior, and demographics, organizations can generate customer profiles and segmentation. This helps in personalizing marketing efforts, improving customer experiences, and tailoring products or services to meet specific customer needs. Ultimately, this leads to increased customer satisfaction, loyalty, and retention.
- Risk Mitigation and Fraud Detection: Predictive analytics is effective in identifying potential risks and detecting fraudulent activities. By analyzing historical data and patterns, organizations can identify anomalies, unusual behaviors, or potential fraud instances. This helps organizations take proactive measures to mitigate risks, prevent fraud, and protect their assets and reputation. Predictive analytics also supports effective risk management by identifying potential areas of concern and enabling organizations to develop strategies to minimize risks.

- Optimization of Operations: Predictive analytics helps organizations optimize their operational processes. By analyzing data on production, supply chain, inventory levels, and demand patterns, organizations can identify inefficiencies, streamline operations, and improve overall productivity. Predictive analytics also assists in identifying maintenance needs, equipment failures, and potential downtime, enabling organizations to take preventive measures and minimize disruptions.
- Marketing Campaign Optimization: This type of analytics plays a crucial role in optimizing marketing campaigns. By analyzing customer data, organizations can identify the most effective channels, messages, and timing for their marketing efforts. This enables organizations to target the right audience with personalized campaigns, resulting in higher conversion rates, improved return on investment (ROI), and overall marketing effectiveness.
- Innovating Product Development: Predictive analytics supports product development and innovation by identifying market trends, customer preferences, and emerging needs. By analyzing data on customer feedback, market research, and competitor analysis, organizations can identify new product opportunities, improve existing products, and align their offerings with market demands. This helps organizations stay competitive, drive innovation, and capture new market segments.

4. Example of descriptive analytics usage in business

Predictive analytics has numerous applications in various areas of business, enabling organizations to make data-driven decisions, anticipate future outcomes, and gain a competitive edge (Hwang et al., 2017; Hurwitz et al., 2015; Lawton, 2019; Charles et al., 2023; Scappini, 2016; Peter et al., 2023). Predictive analytics can analyze historical sales data, market trends, customer behavior, and other relevant factors to forecast future sales and demand patterns. This helps businesses optimize inventory levels, plan production or procurement activities, and allocate resources effectively to meet customer demand.

By analyzing customer data, such as purchase history, interactions, and demographics, predictive analytics can identify customers who are at risk of churning or ending their relationship with the business. This allows organizations to take proactive measures, such as targeted marketing campaigns or personalized retention strategies, to retain valuable customers and reduce churn rates. Predictive analytics can be used to detect fraudulent activities by analyzing patterns, anomalies, and historical data. By applying machine learning algorithms to transactional data, businesses can identify suspicious behavior, flag potentially fraudulent transactions, and minimize financial losses due to fraud (Cam et al., 2021).

Predictive analytics can help businesses assess and manage various types of risks. For example, in the insurance industry, predictive models can be used to assess the likelihood of insurance claims, estimate potential losses, and determine appropriate premium rates. In financial institutions, predictive analytics can analyze market trends, customer data, and economic indicators to forecast credit risks and make informed lending decisions (Peter et al., 2023).

Predictive analytics can optimize supply chain operations by forecasting demand, optimizing inventory levels, and improving logistics and distribution processes. By analyzing historical data, market trends, and external factors like weather patterns, businesses can anticipate demand fluctuations, identify potential supply chain disruptions, and make informed decisions to enhance efficiency and minimize costs. Predictive analytics can assist businesses in optimizing pricing strategies by analyzing factors such as customer behavior, market conditions, competitor pricing, and product attributes. By leveraging predictive models, businesses can identify optimal price points, determine price elasticity, and develop dynamic pricing strategies to maximize revenue and profitability (Hurwitz et al., 2015).

Predictive analytics can analyze customer data, demographics, preferences, and past campaign performance to optimize marketing efforts. By predicting customer responses and behavior, businesses can personalize marketing campaigns, target specific customer segments, allocate marketing budgets effectively, and improve campaign ROI. This type of analytics can help organizations identify top-performing candidates, assess their fit with job requirements, and predict their likelihood of success within the company. By analyzing data from resumes, assessments, performance reviews, and employee demographics, businesses can make informed hiring decisions and develop strategies for talent retention and development.

Predictive analytics can be utilized in quality management to improve processes, identify potential issues, and enhance overall product or service quality. These are just a few examples of how predictive analytics can be applied in quality management. By leveraging predictive analytics techniques and technologies, organizations can proactively identify quality issues, optimize processes, and continuously improve the overall quality of their products or services.

Below are some of examples of usage of predictive analytics in quality management (Hwang et al., 2017; Hurwitz et al., 2015; Lawton, 2019; Charles et al., 2023; Scappini, 2016; Peter et al., 2023):

- Predictive analytics can be employed to forecast the likelihood of defects or quality issues in manufacturing processes. By analyzing historical data on product defects, process parameters, and environmental factors, organizations can develop models that predict the probability of defects occurring during production. This enables proactive measures to be taken, such as adjusting process parameters, implementing preventive maintenance, or enhancing quality control practices to minimize defects and improve product quality.

- Predictive analytics can help evaluate and predict the performance of suppliers in terms of quality. By analyzing supplier data, including delivery times, product quality, and customer feedback, organizations can develop models that predict the likelihood of supplier-related quality issues. This enables organizations to make informed decisions when selecting suppliers, negotiate contracts based on predicted performance, and proactively address potential quality issues by working closely with suppliers.
- Predictive analytics can be used to analyze customer complaints and identify patterns or trends that may indicate potential quality issues. By analyzing data such as customer feedback, product reviews, and support tickets, organizations can develop models that predict the likelihood of future complaints or identify areas where quality improvements are needed. This enables organizations to take corrective actions, improve product design, address common customer pain points, and enhance overall customer satisfaction.
- This type of analytics can be employed to optimize equipment maintenance and reduce equipment failure rates. By analyzing sensor data, historical maintenance records, and environmental conditions, organizations can develop models that predict the likelihood of equipment failures or breakdowns. This enables organizations to implement proactive maintenance strategies, schedule maintenance activities based on predicted failure probabilities, and minimize unplanned downtime. By addressing maintenance needs in advance, organizations can ensure optimal equipment performance, reduce production interruptions, and improve overall product quality.
- Predictive analytics can be utilized to optimize manufacturing or service processes and improve quality outcomes. By analyzing process data, organizations can identify variables or factors that significantly impact product quality. Predictive models can then be developed to forecast the impact of process changes or adjustments on product quality. This enables organizations to optimize process parameters, identify the optimal process conditions for achieving desired quality levels, and continuously improve the quality of their products or services.
- Also predictive analytics can be employed to develop early warning systems that alert organizations to potential quality issues before they occur. By monitoring real-time data from various sources, such as production lines, quality control checkpoints, or customer feedback channels, organizations can develop predictive models that identify early indicators of quality issues. This enables organizations to take proactive measures, such as implementing corrective actions, conducting root cause analyses, or initiating preventive measures to avoid quality problems and ensure consistent product or service quality.

5. Conclusion

In conclusion, predictive analytics is a powerful tool that leverages historical data and statistical models to forecast future outcomes and behaviors. It enables organizations to gain valuable insights, make informed decisions, and drive business growth. By analyzing patterns, correlations, and trends in data, predictive analytics can uncover hidden relationships and provide a deeper understanding of business processes, customer behavior, market trends, and other important factors.

The benefits of predictive analytics are numerous. It enables organizations to forecast and predict future events, leading to proactive decision-making and the ability to anticipate trends and outcomes. It enhances decision-making processes, improves resource allocation, and provides enhanced customer insights. Predictive analytics also helps in risk mitigation, fraud detection, optimization of operations and pricing, product development, and marketing effectiveness. By leveraging these benefits, organizations can gain a competitive advantage and achieve sustainable success.

However, there are challenges associated with predictive analytics. Data quality and availability issues, biased data, and the need for skilled data scientists and analysts are common hurdles. Ethical concerns related to privacy, security, and potential discriminatory outcomes should also be carefully addressed.

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