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THE BASIS OF PROSPECTIVE ANALYTICS IN BUSINESS

Radosław WOLNIAK[1*], Wies GREBSKI[2]

[1] Silesian University of Technology, Organization and Management Department, Economics and Informatics Institute; rwolniak@polsl.pl, ORCID: 0000-0003-0317-9811
[2] Penn State Hazletonne, Pennsylvania State University; wxg3@psu.edu, ORCID: 0000-0002-4684-7608
* Correspondence author

Purpose: The goal of the paper is to analyze the main features, benefits and problems with the prospective 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: Prescriptive analytics aims to assist businesses in making informed decisions that optimize desired outcomes or minimize undesired ones. It goes beyond predicting future outcomes and provides recommendations on the best actions to achieve desired goals while considering potential risks and uncertainties. Prescriptive analytics finds applications in various domains such as supply chain management, financial planning, healthcare, marketing, and operations management. It empowers businesses to make data-driven decisions, optimize resource allocation, enhance efficiency, and gain a competitive advantage. Considered the highest level of analytics, prescriptive analytics combines historical data, real-time information, optimization techniques, and decision models to generate actionable recommendations.
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, predictive analytics.

Category of the paper: literature review.

1. Introduction

Prescriptive analytics is a branch of advanced analytics that focuses on providing recommendations or actions to take based on the analysis of available data. It goes beyond descriptive and predictive analytics by not only answering the question of "what is likely to happen?" but also offering insights on "what should be done about it?".

Prescriptive analytics utilizes various techniques such as mathematical modeling, optimization algorithms, machine learning, and simulation to evaluate different possible scenarios and recommend the best course of action. It takes into account multiple factors, including historical data, real-time data, constraints, and objectives, to provide decision-makers with actionable insights.

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

2. Prospective analytics - definitions

The goal of prescriptive analytics is to help businesses and organizations make informed decisions that maximize desired outcomes or minimize undesired ones. It helps in solving complex problems and optimizing processes by considering different variables and potential trade-offs. Rather than simply predicting outcomes, prescriptive analytics suggests the best actions to achieve desired goals, taking into account potential risks and uncertainties. (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).

Prescriptive analytics can be applied in various domains, such as supply chain management, financial planning, healthcare, marketing, and operations management (Patanjali, 2018; Nourani, 2021, Sharma et al., 2020). It enables businesses to make data-driven decisions, optimize resource allocation, improve efficiency, and gain a competitive advantage in today's complex and dynamic business environment. Prescriptive analytics empowers decision-makers by providing them with actionable recommendations based on thorough analysis, allowing them to make informed choices and achieve better outcomes (Wolniak, 2016; Czerwińska-Lubszczyk et al., 2022; Drozd, Wolniak, 2021; Gajdzik, Wolniak, 2021, 2022; Gębczyńska, Wolniak, 2018, 2023; Grabowska et al., 2019, 2020, 2021).

Prescriptive analytics is often considered the highest level of analytics because it not only provides insights into what is likely to happen in the future (predictive analytics) but also suggests the best course of action to achieve a desired outcome. It combines the power of historical data, real-time information, optimization techniques, and decision models to generate actionable recommendations (Hurwitz et al., 2015).

Prescriptive analytics can address a wide range of business problems, including supply chain optimization, resource allocation, pricing strategies, risk management, marketing campaign optimization, fraud detection, and healthcare treatment recommendations (Cam et al., 2021). It empowers organizations to make data-driven decisions, optimize processes, improve efficiency, reduce costs, and achieve their business goals (Wolniak, Sułkowski, 2015, 2016;

Wolniak, Grebski, 2018; Wolniak et al., 2019, 2020; Wolniak, Habek, 2015, 2016; Wolniak, Skotnicka, 2011; Wolniak, Jonek-Kowalska, 2021, 2022).

By leveraging prescriptive analytics, businesses can gain a competitive advantage, enhance customer satisfaction, and drive innovation (Hwang et al., 2017). It enables them to move beyond reactive decision-making and embrace proactive, forward-looking strategies that are based on a deep understanding of data and analytics (Greasley, 2019).

The process of prescriptive analytics typically involves several steps Hurwitz et al., 2015; Lawton, 2019; Charles et al., 2023, Scappini, 2016; Peter et al., 2023):

- Data Collection: Relevant data from various sources is collected, including historical data, real-time data, external data feeds, and contextual information. This data forms the foundation for analysis and decision-making.
- Data Analysis: Advanced analytical techniques, such as statistical analysis, machine learning, and data mining, are applied to the collected data to identify patterns, correlations, and trends. This analysis helps in understanding the relationships between different variables and uncovering insights.
- Predictive Modeling: Predictive models are built using the analyzed data to forecast future outcomes or events. These models use statistical algorithms or machine learning algorithms to make predictions based on historical patterns and trends.
- Optimization and Simulation: Optimization algorithms and simulation techniques are employed to evaluate different scenarios and determine the best course of action. Optimization takes into account various constraints, objectives, and trade-offs to find the optimal solution that maximizes desired outcomes or minimizes undesired ones.
- Decision Support: The results of the analysis and optimization are presented to decision-makers in a user-friendly format, often through interactive dashboards or reports. These outputs provide actionable insights and recommendations that help decision-makers understand the potential consequences of different choices.
- Implementation and Monitoring: Once a decision is made based on the prescriptive analytics insights, it is implemented in the real-world context. Monitoring and feedback mechanisms are put in place to assess the impact of the decision and refine the models and algorithms based on new data and insights.

Below in table 1 there is a comparison table highlighting the differences between predictive analytics and prospective analytics.

Table 1.
Comparison of predictive analytics and prospective analytics

Aspect	Predictive Analytics	Prescriptive Analytics
Objective	Predict future outcomes or events based on historical data and patterns.	Provide recommendations on the best course of action to achieve a desired outcome.
Focus	What is likely to happen?	What should be done about it?
Key Outputs	Predictive models, forecasts, insights on future trends.	Actionable recommendations, optimized solutions, decision support.
Techniques	Statistical analysis, machine learning, data mining, forecasting models.	Mathematical modeling, optimization algorithms, simulation, decision models.
Usage	Helps in understanding trends, identifying patterns, and making informed predictions.	Enables decision-makers to make data-driven decisions, optimize processes, and achieve desired outcomes.
Example	Predicting customer churn, forecasting sales, fraud detection.	Optimizing supply chain, resource allocation, pricing strategies.
Timeframe	Focuses on the future based on historical data.	Focuses on the future and suggests specific actions based on analysis and optimization.
Decision-making	Provides insights to support decision-making.	Provides actionable recommendations to guide decision-making.
Integration	Can be integrated into various systems and processes to enhance decision-making.	Requires integration into decision support systems and organizational workflows.
Data Requirements	Relies on historical and real-time data to make predictions.	Relies on historical and real-time data, as well as contextual information, to make recommendations.
Limitations	Predictions are probabilistic and subject to uncertainties.	Recommendations may be influenced by assumptions, constraints, and limitations of the models.

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 prospective analytics usage

Prescriptive analytics empowers organizations to make better decisions, optimize processes, mitigate risks, allocate resources efficiently, and gain a competitive advantage. It enables organizations to leverage data and insights to achieve desired outcomes and drive success in a rapidly changing business landscape.

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).

- Informed Decision-Making: Prescriptive analytics provides decision-makers with actionable insights and recommendations. It goes beyond simply predicting outcomes and offers guidance on the best course of action to achieve desired outcomes. This enables organizations to make more informed decisions, considering various factors and potential trade-offs.

- Optimization and Efficiency: This type of analytics utilizes mathematical modeling and optimization algorithms to evaluate different scenarios and identify the most optimal solutions. By considering constraints, objectives, and resource allocation, organizations can optimize processes, minimize costs, maximize efficiency, and improve overall performance.
- Real-Time Adaptability: Prescriptive analytics can incorporate real-time data and continuously adapt to changing conditions. This enables organizations to respond promptly to dynamic environments and make real-time decisions based on the most up-to-date information. It supports agile decision-making and helps organizations stay competitive in rapidly evolving markets.
- Risk Mitigation: Describe in the paper type of analytics takes into account potential risks and uncertainties when recommending actions. By simulating different scenarios and evaluating the impact of different decisions, organizations can proactively identify risks, assess their potential consequences, and make risk-informed decisions. This helps in mitigating risks and minimizing the negative impact of uncertain events.
- Resource Optimization: Prescriptive analytics helps optimize the allocation of resources, whether it's workforce, inventory, budget, or equipment. By analyzing historical data, demand patterns, and other relevant factors, organizations can efficiently allocate resources to meet demand, reduce waste, and improve overall resource utilization.
- Competitive Advantage: By leveraging prescriptive analytics, organizations can gain a competitive edge in the market. It enables them to make data-driven decisions, optimize processes, and identify innovative strategies. Prescriptive analytics helps organizations stay ahead of their competitors by enabling them to make more accurate predictions, better allocate resources, and make informed choices.
- Enhanced Customer Experience: The usage of proscriptive analytics enables organizations to tailor their products, services, and experiences to individual customer needs. By analyzing customer data and preferences, organizations can make personalized recommendations, improve customer satisfaction, and enhance the overall customer experience.
- Continuous Improvement: Prescriptive analytics is an iterative process that allows organizations to continuously refine and improve their decision-making. By monitoring the outcomes of decisions made based on prescriptive analytics, organizations can collect feedback, identify areas for improvement, and refine their models and algorithms. This iterative approach ensures ongoing optimization and improvement.
- 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.

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):

- Uncertainty and Assumptions: Predictive analytics relies on historical data and statistical models to make predictions about the future. However, the accuracy of these predictions is inherently limited by uncertainties and assumptions. Factors such as changing market dynamics, unforeseen events, or data quality issues can affect the reliability of predictions.
- Data Limitations: Predictive analytics heavily relies on the availability and quality of data. Businesses may face challenges in obtaining relevant and comprehensive data sets, especially if data is scattered across multiple systems or if there are data privacy and security concerns. Incomplete or inaccurate data can negatively impact the accuracy and effectiveness of predictive models.
- Complex Implementation: Implementing predictive analytics solutions can be complex and resource-intensive. It requires expertise in data science, statistical modeling, and machine learning. Organizations need to invest in skilled personnel, appropriate technologies, and robust infrastructure to effectively implement and maintain predictive analytics capabilities.
- Interpretation and Communication: Predictive analytics outputs often require interpretation and context to be effectively understood and utilized. Decision-makers may not have the necessary statistical knowledge or expertise to interpret the predictions accurately. Communicating the insights and recommendations derived from predictive analytics to non-technical stakeholders can be challenging, potentially leading to misinterpretation or resistance to change.
- Overreliance on Historical Data: Predictive models are built based on historical data, assuming that the future will behave similarly to the past. However, market dynamics, consumer behavior, and other external factors can change rapidly, rendering historical patterns less relevant or reliable. Relying solely on historical data without considering emerging trends and evolving customer preferences can limit the accuracy and applicability of predictions.

- Ethical and Privacy Concerns: The use of predictive analytics raises ethical and privacy concerns, particularly when dealing with personal or sensitive data. Predictive models may inadvertently introduce bias or discriminatory outcomes if they are built on biased or incomplete data. Organizations must ensure proper data governance, transparency, and fairness in the predictive analytics processes to mitigate these risks.
- Implementation Challenges: Deploying predictive analytics solutions within an organization can face challenges related to integration with existing systems and processes. Organizations may encounter resistance to change or difficulties in aligning the predictive analytics outputs with existing decision-making frameworks. Ensuring a smooth integration and adoption of predictive analytics capabilities requires effective change management and organizational buy-in.

Despite these challenges, organizations can address many of these disadvantages through careful planning, data quality assurance, continuous model validation, and effective communication and training. It is essential to recognize the limitations and actively manage them to maximize the value and impact of predictive analytics in business decision-making (Sharma et al., 2020; Wolniak, 2013, 2016; Hys, Wolniak, 2018).

4. Example of predictive analytics usage in business

Predictive analytics is extensively used in businesses across different industries to make informed decisions. It involves analyzing historical data and patterns to predict future outcomes and trends. This information is valuable for organizations in multiple ways: One common application is customer analytics. By examining customer behavior, preferences, and buying patterns, businesses can anticipate future actions. This allows for effective customer segmentation, identifying potential churn, and personalizing marketing campaigns and product recommendations (Cam et al., 2021).

Sales forecasting is another important use of predictive analytics. By analyzing past sales data and considering market trends, businesses can make accurate predictions about future sales. This helps with optimizing inventory, production, and resource allocation to meet demand and improve sales performance. Risk assessment is crucial for businesses, and predictive analytics aids in this area. It helps identify potential risks such as fraudulent activities, credit defaults, and insurance claim fraud. By analyzing patterns and anomalies in data, organizations can detect and prevent financial losses (Hwang et al., 2017; Hurwitz et al., 2015; Lawton, 2019; Charles et al., 2023; Scappini, 2016; Peter et al., 2023).

Supply chain optimization is also enhanced through predictive analytics. By forecasting demand, evaluating supplier performance, and optimizing inventory levels, businesses can streamline their supply chain operations. This leads to cost reduction, minimization of stockouts, and improved logistics processes. Quality control is another area where predictive analytics plays a role. By analyzing data from manufacturing processes and historical quality metrics, organizations can identify patterns contributing to defects or variations. This enables them to take corrective actions and improve product quality (Peter et al., 2023).

Predictive analytics aids in maintenance and asset management as well. By analyzing sensor data, maintenance logs, and historical performance, organizations can predict equipment failures, optimize maintenance schedules, and minimize downtime. This improves operational efficiency and reduces costs. In marketing and advertising, predictive analytics helps optimize campaigns and spending. By analyzing customer data, demographics, and online behavior, businesses can identify effective channels, messaging, and targeting strategies, maximizing their return on marketing investments (Hurwitz et al., 2015).

Human resources benefit from predictive analytics as well. It assists in talent acquisition, workforce planning, and employee retention efforts. By analyzing employee data, performance metrics, and external factors, organizations can identify high-performing candidates, predict attrition risks, and implement strategies to improve employee engagement and retention. Financial analysis benefits from predictive analytics in financial forecasting, portfolio management, and risk assessment. It helps predict market trends, optimize investment portfolios, and assess credit risks.

Lastly, in healthcare, predictive analytics aids in medical diagnosis, patient risk assessment, and disease prevention. By analyzing patient data, medical records, and clinical research, it helps identify health risks, improve patient outcomes, and optimize healthcare resource allocation. These applications highlight how predictive analytics enables businesses to gain valuable insights, optimize processes, and make data-driven decisions across various domains.

Predictive analytics is increasingly utilized in quality management to enhance product quality, identify potential issues, and optimize quality control processes. Predictive analytics supports quality management by providing insights, enabling proactive decision-making, and optimizing processes to ensure consistent product quality and customer satisfaction.

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 analyze historical quality data, manufacturing parameters, and other relevant variables to predict the likelihood of defects in products or processes. By identifying patterns and factors that contribute to defects, businesses can take proactive measures to prevent quality issues and improve product quality.

- Predictive analytics helps identify the root causes of quality problems by analyzing data from various sources, including production logs, sensor data, and historical quality data. It can identify correlations and patterns that contribute to quality deviations, enabling organizations to address the underlying causes and implement corrective actions.
- This type of analytics aids in failure analysis by examining historical data on product failures or breakdowns. By analyzing factors such as operating conditions, usage patterns, and maintenance records, businesses can predict failure probabilities and take preventive measures to reduce failures and improve reliability.
- Predictive analytics can analyze warranty claim data, customer feedback, and other relevant information to identify potential quality issues or failure patterns. By detecting emerging trends or patterns, organizations can proactively address these issues, improve product quality, and reduce warranty claims.
- Type of analytics described in the paper helps assess and monitor the quality performance of suppliers. By analyzing supplier data, historical quality records, and other relevant factors, businesses can identify high-risk suppliers and predict their quality performance. This enables organizations to take corrective actions or make informed decisions when selecting or managing suppliers.
- Predictive analytics can optimize manufacturing processes to improve quality. By analyzing process data, sensor readings, and historical quality metrics, organizations can identify process parameters or conditions that significantly impact product quality. This allows for process adjustments or optimization to maintain consistent quality levels and reduce variations.
- Predictive analytics can be used to develop early warning systems for quality deviations or failures. By continuously monitoring real-time process data, organizations can detect anomalies or deviations from expected quality standards. This enables timely intervention and preventive actions to mitigate quality issues before they escalate.
- This type of analytics assists in optimizing resource allocation for quality control activities. By analyzing historical quality data, defect patterns, and process variability, organizations can prioritize quality inspections or allocate resources to critical process steps or products that are more likely to have quality issues.

5. Conclusion

The goal of prescriptive analytics is to help businesses make informed decisions that maximize desired outcomes or minimize undesired ones. It goes beyond predicting future outcomes and suggests the best actions to achieve desired goals, considering potential risks and uncertainties. Prescriptive analytics finds applications in various domains such as supply chain management, financial planning, healthcare, marketing, and operations management. It enables businesses to make data-driven decisions, optimize resource allocation, improve efficiency, and gain a competitive advantage. Prescriptive analytics is considered the highest level of analytics as it combines historical data, real-time information, optimization techniques, and decision models to generate actionable recommendations.

The implementation process typically involves data collection, analysis, predictive modeling, optimization, decision support, implementation, and monitoring. By leveraging prescriptive analytics, businesses can enhance customer satisfaction, drive innovation, and move beyond reactive decision-making to proactive, forward-looking strategies based on a deep understanding of data and analytics. However, there are some challenges associated with predictive analytics, including uncertainty, data limitations, complex implementation, interpretation and communication, overreliance on historical data, ethical and privacy concerns, and implementation challenges. These challenges can be mitigated through careful planning, data quality assurance, continuous validation, and effective change management. Despite these challenges, the benefits of prescriptive analytics outweigh the disadvantages, making it a valuable tool for businesses to make better decisions and achieve their desired outcomes.

In conclusion, predictive analytics is a valuable tool utilized by businesses across various industries to make informed decisions. It involves analyzing historical data and patterns to predict future outcomes and trends, providing organizations with valuable insights and opportunities for optimization. Predictive analytics finds widespread application in customer analytics, sales forecasting, risk assessment, supply chain optimization, quality control, maintenance and asset management, marketing and advertising, human resources, financial analysis, and healthcare.

In the domain of quality management, predictive analytics plays a crucial role in enhancing product quality, identifying potential issues, and optimizing quality control processes. By analyzing historical quality data, manufacturing parameters, and relevant variables, organizations can predict the likelihood of defects and take proactive measures to prevent quality issues. It helps identify root causes of quality problems, facilitates failure analysis, detects emerging quality issues, assesses and monitors supplier quality performance, optimizes manufacturing processes, develops early warning systems, and optimizes resource allocation for quality control activities.

The applications of predictive analytics in quality management contribute to consistent product quality, improved customer satisfaction, and streamlined quality control processes. By leveraging predictive analytics, organizations can gain valuable insights, make proactive decisions, and ensure the delivery of high-quality products to meet customer expectations.

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