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Chapter 6: Predictive Analytics for Strategic and Operational Decision-Making

6.1. Introduction

Predictive analytics encompasses techniques and tools to analyze current and historical data, detect patterns, and model relationships for predicting future values and outcomes. In its various forms, it is used throughout organizations to understand customer preferences, forecast demand for products and services, anticipate equipment failure, schedule maintenance, allocate resources, and make investment and pricing decisions. Strategic decisions typically support the long-term direction of the organization, and usually require an assessment of the uncertainty associated with possible future states of the world. Predictive analytics acts as an integral part of this process by providing forecasts of uncertain events and anticipating the effect of strategic decisions on these uncertainties.

Decision-making is inherently a process governed by the best choice and whenever several alternatives exist, one of them must be chosen based on certain factors, which influences the behaviour, performance and requirement of an organization. Predictive analytics is also utilized in an operational framework for either day-to-day managerial issues of the organization or for a short-term planning horizon. It identifies the probable future demand for varying products or services of an organization with a short span of time and all attempts are made to meet the anticipated future demand in the most economical way possible.

6.1.1. Background and Significance

Predictive analytics for strategic and operational decision-making leads to informed choices. Analysis and forecasting support decisions at all organizational levels, though adoption rates—especially by middle managers—are low compared to self-service metrics. Integration into corporate strategy, addressing uncertainty, and facilitating demand planning are key issues, as are method appropriateness, underpinnings of success, adoption challenges, and modelling-paradigm evolution. Stakeholders include decision-makers and data consumers, sources comprise comprehensive, reliable historical data, and applicability spans all business sectors.

Organizations exploit data to build trusted, accurate models for critical decisions. Increasing model success fosters integration of predictive analytics into the strategic planning lifecycle, enabling simulation and aggregation of all-choice scenarios and uncertainty and risk assessment. Predictive models help with complex short-term decisions, from inventory to capital resources, providing timely estimates of stock levels, required maintenance, and production quotas. For factors such as product recovery and resumes, demand forecasts are indispensable for both creation and customer-satisfaction fulfilment, with successful prediction lowering inventory holding, shipping, and supply risks. Yet empirical studies indicate that such models, though conceptually attractive, are seldom executed by operational executives.

Fig 6.1: Predictive Analytics for Strategic and Operational Decision-Making

6.1.2. Research design

Using a mixed-method approach, the investigation encompasses a structured literature review, conceptual framework development, scientific publication, and reflective guidance for practitioners. The literature review synthesizes fundamental predictive analytics concepts, defines predictive modeling as a technology for strategic and operational decision-making, assesses its objectives, and identifies corresponding hypothesis-driven research questions. Corporate strategy development and operational decision-making scenarios are then examined in depth.

The design also includes a proof-of-concept predictive model for forecasting litigation count at the U.S. International Trade Commission, which illustrates predictive analytics in action and highlights evaluation considerations. Broadly, these elements constitute a preliminary, theoretical foundation for developing – and subsequently implementing or operating – predictive models within an organization. The ongoing research work extends this foundation to cover the full predictive modeling process, from data preparation and feature engineering through model selection and evaluation. Subsequent sections outline the background and significance of predictive analytics, spell out the research problem, and elaborate on the proposal structure.

6.2. Foundations of Predictive Analytics

Although data-driven decisions have been in practice since the emergence of modern management concepts in the 1980s, the analytics tools available to management practitioners lagged behind. Recent developments in data storage, processing, and modeling allow organizations to extract insights from extensive sets of structured and unstructured data with great precision. These insights affect not only the operational side but also the strategic side of management decision-making. Hence, organizations at different levels of maturity adopt descriptive analytics for operational decision-making, conducted primarily through demand forecasting and inventory optimization; and invest in demand prediction capabilities to empower a range of corporate strategy decisions, such as corporate scenario planning, portfolio resource allocation under uncertainty, and competitive positioning.

Data are often defined as a collection of numeric and non-numeric facts, but data are not the sole ingredient for building successful predictive analytics programs. A supervised predictive analytic model requires a data set with target values and a set of features that surface patterns in the data and explain the variation in the target values. These features contribute to achieving prediction. They are functions that assign attributes to a data point captured in the records. Feature values are numeric and character attributes of that data point. The target value is usually a number, but the target can also be character values in classification problems.

6.2.1. Data, Features, and Quality

Data constitutes the foundation of predictive models. However, the adage "garbage in, garbage out" remains relevant in analytical contexts. Propagating low-quality, unfit, or erroneous data across the analytic process not only produces worthless models but also distracts stakeholders, increases wear and tear on technology and people, and often contributes to product failures. Therefore, attention to data features, quality, and preprocessing is essential.

Data features include the input variables in relation to the respective prediction targets. Data quality can be measured in a multitude of ways, and therefore the definitions of "good" and "bad" data often differ between stakeholders.

6.2.2. Modeling Paradigms and Algorithms

Predictive models fall into three categories: descriptive, predictive, and prescriptive. Descriptive models generate insights from historical data (e.g., market basket analysis, clustering). Predictive models augment managerial judgment with forecasts of future developments that cannot be directly controlled (e.g., demand forecasts) or take the form of predicted probabilities (e.g., likelihood of credit default). Prescriptive models complement forecasting by evaluating how a response variable (e.g., profit) will vary with decisions that managers can take (e.g., advertising spend). Well-designed strategic and operational decision processes formalize and combine forecasting and prescriptive models.

A broad classes of predictive models can be identified: regression, classification, time series, and machine learning/AI. Regression models are employed in continuous-valued prediction and classification models in categorical prediction. Both classes of model can be estimated using a standard framework, although different loss functions are applied to training error. Time series models are specialized to exploit temporal structure in the data and incorporate a richer set of explanatory variables. Machine learning and AI algorithms generalize beyond the classical modeling frameworks to accommodate advanced data types (e.g., images, text) and large numbers of predictors. While these models can provide substantial predictive accuracy improvements, benefit is offset by potential discontinuities and loss of interpretability, particularly for single predictions from deep neural networks.

6.2.3. Evaluation and Validation

Evaluation and Validation

Established evaluation metrics provide a standard of performance by which predictive models can be validated against some known criterion. When prediction serves prescriptive analytics, it is useful to begin such evaluation with the rules of the underlying decisions. Such rules can be used to set targets for prediction, validation schemes, and out-of-sample testing. Common metrics are considered for the various modeling paradigms; when predictive accuracy is a primary goal, it is important to take additional steps to avoid overfitting. Quantitative predictive models—especially non-parametric models, such as traditional machine-learning models or deep-learning neural networks—can be difficult for humans to interpret, and when algorithmic decisions can have substantial social impact, interpretable models are preferable.

Prediction serves many different forms of modeling and not all of those require the same accuracy. In descriptive modeling, the objective is to identify and measure the structure and relationships in the data, adequacy is more important than predictive accuracy. The same is true for risk considerations related pandemic or adversary attack. Verification considers both expected loss and the variance of that loss; it seeks a model that minimizes expected loss.

6.3. Strategic Decision-Making with Predictive Analytics

An essential group of decisions relate to the long-term direction of the business and the allocation of resources over long time horizons. These choices are made in the context of a business strategy that defines the company's long-term positioning; guides significant initiatives such as mergers, acquisitions, and joint ventures; and articulates an overall approach to addressing uncertainty and risk. Because of their scope and resource requirements, strategic decisions cannot be supported fully by predictive models. Predictive analytics contributes to strategic choices in three ways.

Fig 6.2: Strategic Decision-Making with Predictive Analytics

Scenario planning, testing the integration of forecasts into the strategic plan, and analyzing how uncertainty and risk affect strategic alternatives. A second area of long-term strategic concern is how to set the portfolio of investments or the allocation of resources to support day-to-day operations under uncertainty. A third area is the company's position with respect to the competitive forces at play in an industry and the timing of new market entries.

6.3.1. Scenario Planning and Forecasting for Strategy

Successful companies prepare for the unpredictable nature and uncertain trajectory of the future by using scenario planning. Scenario planning involves creating plausible and internally consistent descriptions of the future by combining various uncertain exogenous variables. Strategic forecasts of the environment, industry, and market development are then integrated into the selected scenarios. Although these scenarios are neither predictions nor forecasts, they provide a testbed for decision-making under uncertainty. Risks from strategic decisions are formally assessed and identified in terms of the driving forces, in contrast to a conventional systematic but unrealistic evaluation of risks of corporate strategy, where uncertainty is viewed in terms of the probability density function of the future development of the main uncertainties.

The incorporation of critical uncertainties into the decision-making process makes it possible to assess how specific developments, say, a more aggressive behaviour by a competitor or a downturn in the world economy, would affect performance relative to other choices. Various forecasting models are usually deployed to provide assessments of future developments of, for example, technology and markets. A range of forecasting techniques, both qualitative and quantitative, is therefore required.

6.3.2. Portfolio and Resource Allocation under Uncertainty

Portfolio management and resource allocation decisions govern the allocation of scarce resources across diverse opportunities, products, projects, and initiatives. Resources are allocated based on expected returns and associated risks; however, uncertainty surrounding both expectations and possible ramifications must be considered. Predictive models assist in quantifying expected returns through decision trees, Monte Carlo simulations, and credible intervals on returns. Similarly, the predictive model's framework can form the basis of resource allocations under uncertainty via the automation of portfolio-level trade-offs, optimization under constraints, and rule-based decision-making. Such approaches can effectively allocate resources across new product development pipelines, marketing portfolios, and strategic initiation priorities.

Portfolio allocation embraces the up-start of several related but separate initiatives within a limited timeframe, while resource allocation involves the pinpointing and deploying of key individuals or groups on key initiatives regardless of the incoming demand for new product introductions. Both types of decisions are highly complex, yet that complexity arises not merely due to the trade-offs that must be made, but also because a wide range of outcomes exists with different probability distributions. Predictive models inform the returns for each initiative, but the shape of the corresponding probability distribution remains crucial. Portfolio and resource allocation decisions tackle the uncertainty using more sophisticated decision rules—rules, in fact, that many companies adopt successfully.

6.3.3. Competitive Positioning and Market Entry Decisions

Competitive positioning drives company profit. Therefore, predictive analytics can offer valuable insight about schedule investments, assessing key success factors, and optimizing customer value. Modelling market competition enables assessment of competitor signals, barriers to entry, selecting optimal timing, and evaluating new venture viability. Strategic forecasting by Allen and Linda P. B. Appel, ex-CEO and ex-MBA director of MGI, respectively, is crucial to a firm's long-term success. Testing corporate decisions and choices ensures dynamic alignment and adjustment of operational plans with knowledge of future business environments.

The sources of predictive input can be classified into two groups: indirect signals (from customers, suppliers, financial institutions, or other outside sources) and direct signals (from firms within the same industry). One of the most relevant areas of predictive analytics in strategic positioning is assessing the barriers to entry. Firstly, barriers are key success factors, and the general rule states that the higher the entry barriers, the higher the profits. Secondly, it matters less if a firm is in a concentrated market or a fragmented one—the real issue is the degree of barriers. When barriers are low, stable players face the constant threat of new entrants with a profit potential that deeply risks astounding the industry players with low price and high service levels.

6.4. Operational Decision-Making with Predictive Analytics

Outcome-driven predictive analytics help decision-making in all three operational domains. Demand forecasting models match demand with supply, optimize inventory levels, minimize stockouts, and specify service-level targets. Maintenance and reliability analytics predict asset failures, determine preventive maintenance schedules, and maximize productive uptime at minimal cost. Capacity planning and scheduling balance available capacity with expected demand, apply queuing models to identify difficult bottlenecks, and manage service quality.

Demands on goods and services vary with season, economy, competition, and life cycle. Forecasting methods incorporate discrete and continuous variables. Stockouts not only generate lost sales but also diminish service reputation; forecasting methods should target service levels as well as forecast accuracy. Forecasts determine policies for replenishment, maintenance, staffing, and logistics.

Optimal Trade-off: Predictive analytics delivers tremendous potential to balance optimization and different forms of downtime in maintenance operations. Predictive techniques identify when an asset is likely to fail so that maintenance is not performed too early or too late. Satisfactory implementation prevents the need for run-to-fail systems, and bang for buck improves reliability-centered maintenance planning.

Capacity planning relates the sustainable service level to expected future demand, and residual capacity is ideally allocated to avoid the need for service denials at places and times.

6.4.1. Demand Forecasting and Inventory Optimization

Demand forecasting is the prediction of the next period's demand volume within a specified time horizon, with the resolution of the forecast being either calendar or product-specific. Volatility is often inherent to demand, and if an organization cannot eliminate that variability, it must take steps to reduce the negative consequences for its bottom line. One of its main tools is inventory management, which aims to strike the right balance between supply and demand. Having too much inventory can lead to high holding costs, theft, spoilage, and obsolete inventory; having too little can lead to stockouts and customer dissatisfaction. To manage these opposing forces, organizations define service-level targets that balance the costs of what they are trying to minimize. Together with demand forecasts, these targets lead to replenishment policies for inventory and specifications for the associated supply chain policies.

Demand forecasts can therefore range from simple to highly complex. For example, simple seasonal indices may use multipliers to modulate a recent average demand to get a seasonal forecast. Stationary time-series models, which assume that the time series is stationary at the moment of forecast preparation, require statistical tests. More elaborate decomposition models can use seasonal factors, trends, and cycles. Demand for a group of items may be forecasted explicitly as the sum of the demand for individual items, which are forecasted using component time-series forecast methods. Alternatively, the group can be modeled as a combination of the cross-sectional average and the remaining component effects, such as those from time, training, and error.

6.4.2. Maintenance and Reliability Analytics

Predictive maintenance leverages data analysis tools and techniques to predict equipment failures, risk duration, and failure timing. These predictions can facilitate timely inspection and enable preventive maintenance activities, using spare parts already in stock and avoiding unplanned breakdowns. Consequently, downtime and operating costs can be reduced while equipment reliability is maintained. To ensure these reliability improvements, cost-related decision support systems need to take affected equipment downtime into account. Predictive maintenance heralds a significant transformation of maintenance activities from calendar-based preventive methods toward reliability-centred maintenance, condition-based maintenance, and ultimately towards risk-based maintenance depending on demand.

Reliability analytics feature several layers. The first aims to predict failure mode timing based on production or operation time, continuous process conditions, and on-line sensed data like vibration and thermal profiles. Based on the predicted time of failure, the next layer schedules unavoidable maintenance and inspection work to minimize impact on overall system reliability. Finally, the predicted operation condition of the equipment being maintained is utilized for decision making, enabling a more reliable maintenance strategy and better trade-offs between maintenance and stock cost.

6.4.3. Capacity Planning and Scheduling

Capacity planning links forecasted demand to a firm's operational capabilities. A mismatch leads to lost sales or unnecessary costs. Predictive analytics address both concerns. Demand exceeding capacity can be detected and investigated, with increased demand triggering investment. Where capacity exceeds demand, queuing or optimization models help allocate scarce resources to reduce wait times and costs.

Capacity management guides the allocation of limited production resources, such as personnel, facilities, equipment, and capital. Action is often needed far in advance and must consider competing priorities. For example, if a factory can produce three different products but can run only one at a time, demand forecasting can help signal the product mix. In a distribution centre, trucks may be the limiting factor, making queuing models useful for scheduling deliveries to minimize wait times.

Where capacity is not fully utilized, costs can be reduced by carefully matching the use of resources to demand. Predictive analytics can identify periods of low expected demand for resources that are costly to retain. The level and timing of maintenance and repairs can also be informed by predictions of failure, taking both expense and risk of stockouts into account.

6.5. Data Governance, Ethics, and Risk Management

Data governance comprises all roles, responsibilities, and processes that ensure the effective and efficient use of data within an organization to achieve its goals. It safeguards data against misuse and abuse and mitigates data-related risks. Data Quality Assurance (DQA) processes are integral to the overall data governance ecosystem. They ensure that data meet quality standards and adhere to established policies and procedures throughout their lifecycle, from creation through use, archival, and deletion. DQA entails managing the quality of data throughout its lifecycle, the assessment of data quality issues, and the rectification of noncompliant data. In regulatory environments, data lineage demonstrates compliance with regulations that require organizations to retain data in an unaltered form. A comprehensive data governance framework can validate and enforce corporate data stewardship standards that promote trusted data sources. It can define roles and responsibilities that highlight accountability for the collection, validation, updating, and use of data, making clear who is responsible for compliance with quality assurance processes.

Fig 6.3: Data Governance, Ethics, and Risk Management

Fairness, accountability, and transparency (FAT) have emerged as central themes in the ethical governance of AI systems. The AI Bias Management Toolkit lays out FAT concerns related to predictive models. Fairness explores whether a model's outcomes are free from bias, Accountability assesses whether decision-makers assume responsibility for decisions, and Transparency questions whether the rationale behind the model's predictions is readily understood. Bias relates to the discriminatory impact of AI model decisions on specific user groupings. Evaluation of prediction bias places focus on the effects of a model's decisions on protected groups. Explainability concerns relate to the degree of user understanding of a model's outputs. It is based on the premise that users will place more trust in a model that is easier to interpret. Regulatory compliance addresses adherence to the EU General Data Protection Regulation, which requires organizations to provide information on, gain consent for, and restrict access to personal data.

6.5.1. Data Stewardship and Quality Assurance

Data stewardship encompasses a broad range of activities, including establishing and maintaining processes for validating, cleansing, and enriching data, ensuring that the metadata remains current, documenting decision-making around data, designing the datamart for ease of use, governing secure access, defining permissible use cases, and providing a conduit for error reporting. These tasks require the involvement of many parties, but someone must assume overall responsibility. The lack of these practices can lead to low quality and trustworthiness of data-driven decisions, and, hence, ultimately prevent the successful delivery of business outcomes.

Data quality assurance processes should define the frequency for routine validation, cleansing, and enrichment of the data, detail who executes the processes, outline how to perform them, and document decision-making. Data lineage that tracks data from its source to the decision is also valuable for quality assurance because it enables the root causes of errors to be identified for rectification. Additionally, users should know who is responsible for the data and how to obtain clarification. This accountability framework functions similarly to a responsibility assignment matrix in project management.

6.5.2. Fairness, Accountability, Transparency, and Privacy

Despite the considerable potential of immersive technologies, their adoption in the tourism and travel industry is still in its nascent stages. Organisational readiness is a crucial factor for successful implementation. Readiness can be understood as the degree to which an organisation is capable of performing the change required to introduce a given innovation. Thus, specific qualities, both managerial and organisational, need to be identified that facilitate the incorporation of these technologies. Following a systematic review of the field, nine facilitators to the introduction of immersive systems in tourism were identified: top management support, digital orientation, change management, social responsibility, external support, market-oriented strategic focus, environmental orientation, active/experiential business strategy, and knowledge management. A qualitative study involving industry professionals was then conducted to deepen and extend the understanding of these facilitators; it resulted in the development of a model of organisational readiness specifically tailored for decision-making involving virtual or augmented reality. Potential barriers to adoption seem to be related to a lack of knowledge about virtual or augmented reality, the immaturity of supply in such technologies, inadequate technical support and concerns about a low return on investment.

Growing concern for ethical issues in society and the increasing weight of continuous communication through mass media is pushing companies to be increasingly sensitive to social responsibility issues. Social responsibility is defined as the disjunction between what the company says in its declarations and what it really does in practice. A socially responsible company is not only concerned with its own interest but also takes into account the impact of its choices on society, the environment and the rest of its stakeholders. In a market oriented towards customer satisfaction, consumers have begun to punish failure of companies in adopting socially and environmentally responsible behaviour. Consumers are not only interested in quality and price but also in other factors such as concern for the environment, equality in treatment and other social responsibility actions carried out by the company.

6.5.3. Risk and Compliance Considerations

Risk management and data governance are crucial for successful predictive analytics programs. Regulatory and risk considerations vary by industry and geography, and mapping compliance requirements is an essential first step. Subsequent risk assessments should identify relevant threats, their mitigation, and prioritization.

Existing theories posit a relationship between effective data governance and analytics success, making data governance and risk oversight important. Analysis of past data breaches highlights key failure causes, which offers lessons for compliance and supervision strategies. Specific risk assessment frameworks are tailored for predictive models, and frameworks for responsible AI support business AI adoption with proactive risk mitigation plans.

Governance and monitoring of predictive analytics models remain challenging in practice. Risks such as algorithmic bias—where training data amplify existing inequalities—are gaining scrutiny and require model monitoring to ensure compliance with fairness, accountability, and transparency principles. Regulations may force companies to explain critical model decisions; approaches for generating fair and explainable models are actively explored.

6.6. Implementation Considerations and Case Studies

Implementation considerations ensure that organizations are fully prepared to capture the benefits of predictive analytics. Organizational readiness influences the likelihood of success by assessing past experience with change, alignment of stakeholders and decision makers, and whether the benefits are evident to users. A well-defined change management process considers the human impact of a predictive initiative and identifies potential sources of resistance. Guidelines for stakeholder engagement clarify how groups external to the analytics team should be involved at different stages of the project. Pathways to adoption describe how predictive insights will be implemented in business processes.

The technology stack encompasses the hardware, software, and technology infrastructure supporting the organization's analytics capabilities. A data and analytics platform enables purchase, storage, integration, exploration, and consumption of data. Data platforms and predictive modeling toolkits support model development, testing, and deployment. Integrated decision-support solutions connect predictive algorithms with BI and visualization tools along the analytics lifecycle.

Real-world case studies of predictive analytics programs yield transferable lessons. Success factors include presence of an organizational champion, development of a prototype to showcase use-case feasibility, reliance on external expertise for model development and evaluation, and assurance of stakeholder involvement and buy-in. Pitfalls include failure to adequately consider use-case background and requirements, rushing into implementation without engaging stakeholders and ensuring readiness for change, overestimating accuracy, and neglecting human-machine collaboration.

6.6.1. Organizational Readiness and Change Management

Implementation of predictive analytics must consider the state of the organization's change readiness. The adoption of predictive analytics requires significant organizational change, including changes in technology, people, processes, and business practices. The degree of organizational readiness for each of these four change dimensions influences the scope, pace, and success of implementation across almost all change initiatives. Different human and organizational factors influence change readiness; for instance, willingness to change stems from perceived need, belief in the benefits of change, and satisfaction with current practices.

Organizational change is generally substantive and systemic, often disrupting the social structure and culture of the organization. The degree of disruptive change demands ongoing monitoring, communication, and support, as well as addressal of change resistance. Incorporating stakeholder perspectives early, nurturing participation, minimizing disruption, and developing change capabilities enhance success. An early signature of credibility from executives and regular communication of progress also foster an environment favorable to change. Predictive-analytics implementation extends beyond established practices into areas where people hold strong views and are concerned about the potential impact on their functions. Consequently, message consistency, frequent user engagement, and sensitive handling of complaints and concerns remain essential throughout implementation.

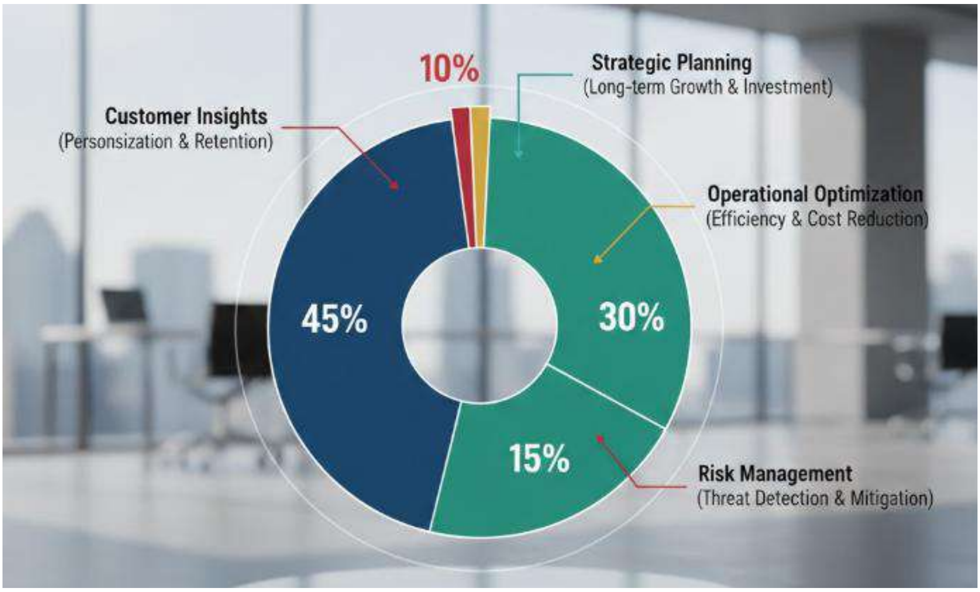

Fig 6.4: Predictive Analytics for Strategic and Operational Decision-Making

6.6.2. Technology Stack and Best Practices

During the past two decades, the wealth of digital data generated in business operations and the advances in data storage and processing technologies have enabled organizations to tap this data for analytical insights. The focus of the analytics landscape—often depicted as layered pyramid—has gradually shifted from descriptive analytics, which addresses historical performance with historical data, toward predictive and prescriptive analytics that answer "what is likely to happen?" and "what should we do?" questions. Predictive analytics identifies likely future outcomes based on historical relationships by means of statistical modeling and machine learning techniques. Predictive models can serve as inputs for prescriptive analytics, which optimize decision variables according to certain criteria. New wave of AI technologies, along with well-established forecasting methods, are increasingly being applied to a wide range of business problems. These developments present significant opportunities for improving strategic and operational decision-making for firms.

However, predictive analytics also entails significant challenges, as acknowledged by recent literature reviews. Developing trusted and reliable predictive models for critical business decisions requires sound methodological foundations, data governance guidelines, competent talent, and appropriate technology and tooling within the organization's analytics ecosystem. These aspects are particularly crucial when deploying predictive analytics at scale. Although organizations typically have a technology stack that enables descriptive analytics, scaling predictive-model development and deployment quite often introduces gaps associated with data quality, data science competency, tool availability, model proliferation, and out-of-service models.

6.6.3. Case Studies: Successful Predictive Analytics Programs

A cadre of companies have harnessed predictive analytics to fuel their success stories. Accenture implements predictive maintenance analytics for its physical assets, developing demand models that capture location-specific patterns for different asset classes and using them to inform maintenance scheduling. Predictive models power ticket forecasting for Major League Baseball, informing real-time pricing decisions that adjust to sales patterns. Netflix leverages a delicate balance of predictive and prescriptive models to fine-tune content acquisition, production, and recommendation, leading to astounding growth and subscriber retention. First Union targets its ATM network for maintenance and cash replenishment. Coal mining companies mostly use predictive analytics to assess asset failure risk and schedule maintenance. painwant predicts surgeon performance and intervention results, providing a foundation to help patients make informed choices and enabling hospitals to arrange joint surgeries with the best overall performance because of minimal risks.

Such cases spotlight success factors and pitfalls in predictive analytics deployment. One common enabler is management buy-in, appendage of competent data scientists to a strong business function, use of easy-to-explain solutions optimally integrated in business processes, and a focus on solving the most pressing and exigent questions.

6.7. Conclusion

Predictive analytics is applied to forecasting future outcomes and events based on operational, environmental, and market data. Strategic choices with long-term consequences can be made more robust through scenario planning and forecast integration with corporate strategy. Portfolios can be constructed and resources allocated under uncertainty to trade off profitability, risk, and market pressure. Competitive positioning and market-entry decisions can be evaluated by analyzing competitor signals, barriers to entry, and timing considerations. At the operational level, predictive analytics facilitates demand forecasting, inventory optimization, maintenance scheduling, and capacity planning.

Synthesizing existing research, providing empirical evidence, and applying predictive modeling involved three stages: defining an analytical data repository for a specific organization; assessing a process of strategic decision-making and identifying aspects that would benefit from formal prediction; and identifying operational-level decisions that could be informed by predictive modeling. Results can inform strategic and operational decision-making in a variety of organizations. Supporting the data preparation and feature engineering aspects of predictive analytics programs, making predictions that answer strategic or operational decision questions, and assessing whether such analyses are required are roles for practitioners who lack analytics expertise.

6.7.1. Emerging Trends

Prediction: Implementation of predictive analytics using big data encourages valuable new predictions in hotels and metropolitan police forces, beyond traditional finance, marketing, and supply chain domains. Recognition of the unreliability of standard models has resulted in broader application of machine-learning methods. Predictability of unstructured data has led to its combination with structured data to create more context-sensitive models. Increasing mastery of natural language processing has enabled analysting of consumers' sentiments about products and brands. An understanding of how and when brands and products differ in consumers' attitudes toward ensuring fairness in pricing has accelerated integration of machine-learning activities into production—trading?—systems. Use of crowd-sourcing and consultative services to validate knowledge and models has become increasingly prevalent, enabling analytics programs to ensure that predictions are plausible and interpretable. Cloud-computing resources have improved accessibility of modeling capabilities and intensified competition across a range of organizational types. Increasing real-time availability of predictions has facilitated both private- and public-sector responsiveness to opportunities, threats, and adverse events..

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