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ПРИЙНЯТТЯ РІШЕНЬ НА ОСНОВІ ДАНИХ ДЛЯ ЗРОСТАННЯ IT-БІЗНЕСУ

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АНОТАЦІЯ *Сьогодні рішення, що ґрунтуються на даних, стають дедалі необхіднішими, якщо не суттєвими, у сучасному бізнес-світі. У цій статті багатогранне поняття прийняття рішень на основі даних (DDDM) в IT розглядається з точки зору теоретичних основ, прикладної спрямованості та потенційних переваг. Розглянуто необхыдны для дослыдження основи методів, керованих даними, описано, як використовувати технологічні інструменти для розробки та підтримки додатків, керованих даними, включаючи сховища даних, інтеграцію даних та аналіз даних. Особливий акцент робиться на організаційних змінах, необхідних для безперешкодного впровадження культури, керованої даними: зміна поведінки лідерства, підвищення кваліфікації співробітників та реінжиніринг бізнес-процесів. У статті також розглянуто різні проблеми впровадження DDDM, включаючи проблеми якості даних, проблеми інтеграції технологій та опір культурі змін. Аналіз демонструє, як компанії будь-якого розміру та сфер діяльності можуть використовувати аналітику даних для оптимізації бізнес-процесів, кращого управління клієнтами та стимулювання зростання продажів. В заключному розділі статті пыдсумовано ключові висновки дослідження, а також рекомендації для організацій, які прагнуть покращити свої аналітичні можливості в надії вижити в умовах дедалі більш цифрового конкурентного середовища.*
Ключові слова: *прийняття рішень на основі даних; бізнес-аналітика; аналітика даних; організаційна трансформація; управління IT*

DATA-DRIVEN DECISION MAKING FOR IT BUSINESS GROWTH

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ABSTRACT *Today the decisions that are underpinned by data are becoming more necessary, if not essential, in today's business world. In this article the multi-faceted notion of data-driven decision-making (DDDM) in IT is discussed in terms of theoretical foundations, an application focus, and potential benefits. The foundation of data-driven methods required for research is discussed, and how to use technology tools to develop and support data-driven applications, including data warehouses, data integration, and data analytics, is described. Special emphasis is placed on organizational change necessary for the seamless adoption of a data-driven culture: leadership behavior change, employee skillbuilding and business process re-engineering. The article also discusses the various DDDM implementation challenges, including data quality issues, technology integration issues, and change cultural resistance. The analysis demonstrates how companies of all sizes and domains can utilize data analytics to streamline business processes, manage customers better, and stimulate sales growth. We summarize the study's key findings in the final section of the paper, as well as recommendations for organizations in their quest to improve their analytics capacity in hopes of surviving in an increasingly digital competitive environment.*
Keywords*: data-driven decision making; business intelligence; data analytics; organizational transformation; IT management*

Introduction

The globally transforming industries pressurized by digital technologies significantly altered the nature of organization and competition. In this era, data has evolved to be one of the most important strategic assets for contemporary businesses, particularly the IT enterprises. Data-Driven Decision Making (DDDM) is a buzzword that describes a philosophical change that is occurring in the business world from old-fashioned, gut-based, decision making techniques to more quantitative, empirical, evidence-based, data-driven approaches. This change is an indication that there is an increasing awareness that in a climate of rising market turbulence and technological disruption, organizations can no longer afford to depend on historical precedent or the experience of senior executives to make critical business calls.

Several concurrent business and technological trends further underscore the value of DDDM. First, organizations are experiencing exponential increases in available data (commonly known as "big data"), which represents both opportunity and challenge for organizations. New industry projections estimate the global data sphere will expand to 186 zettabytes by 2025, with a compound annual growth rate of nearly 27% over 2020. This explosion of data, when tapped into effectively, can offer unparalleled visibility into customer

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behavior, operational effectiveness, and market factors [1].

Second, analytic tools have come a long way to enable organizations to analyze and interpret intricate sets of data. These days many business intelligence platforms, machine learning libraries, and data visualization tools have opened up access to advanced analytics capabilities that were once only within reach of large enterprises with substantial IT budgets. These technological advances have reduced the barriers to adoption of data-enabled methods and raised the competitive bar for data usage in all sectors of the economy.

The third is that the COVID-19 pandemic has served as a forcing function for digital acceleration, with companies being forced to scramble to adjust to such shocks as remote delivery of services, evolving consumer demand and impaired supply chains. This time of rapid transformation has underscored the importance of real-time data analytics and agile decision-making processes, and many organizations have reported that their abilities to react and predict with data were crucial in enabling them to effectively weather the storm.

Within the IT sector specifically, the adoption of DDDM practices has become particularly crucial due to several industry-specific factors. The rapid pace of technological innovation creates constant pressure to identify and capitalize on emerging opportunities while avoiding obsolete technologies. The project-based nature of much IT work requires precise estimation of timelines, resources, and costs. Additionally, the knowledge-intensive character of IT services means that human capital decisions - from hiring to professional development - can significantly impact organizational performance.

Despite these compelling reasons for adoption, many IT companies continue to struggle with implementing effective DDDM strategies. Common barriers include data silos within organizations, lack of analytical skills among employees, cultural resistance to data-centric approaches, and difficulties in integrating new analytical tools with legacy systems. Moreover, the sheer volume and variety of available data can lead to "analysis paralysis," where decision-makers become overwhelmed by information rather than empowered by it. All the problems for integrating DDDM are mentioned on Fig.1.

Theoretical Foundations of Data-Driven Decision Making

The notion of organizations embracing evidence-based decision making has roots in multiple academic disciplines and theoretical traditions. Its insight adds useful background in relation to current DDDM practices and it can also be used to explain why DDDM has becoming popular recently [2].

One of the early antecedents to the current form of DDDM is found in the scientific management school developed by Frederick Taylor in the early 1900s. Taylor's theory of systematic observation, measurement, and analysis of work performance created the concept of making management decisions based on reality, factors that can be quantified, rather than gut feelings and selective memory. Although Taylor's approach was first used in manufacturing, the broader case for cutting an empirical path has colored subsequent management theories in a variety of contexts. Quantitative techniques in business.

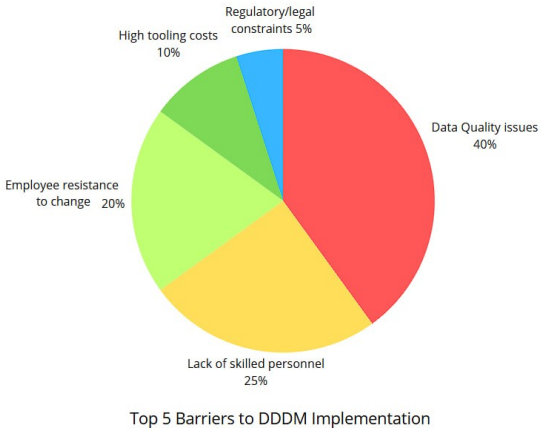

Fig. 1. – Top 5 obstacles for DDDM integration

During mid-20th century or development of operations research and management science and its application of quantitative approach to problems of decisions making in organization. These fields brought in advanced mathematical modeling techniques around optimization, forecasting, and resource allocation - many of which are still among the core of modern analytics practice. Herbert Simon's early studies of bounded rationality and satisficing behavior informed this work and emphasized the way decision processes can be enhanced through improved information and analysis. The concept of the quality management system began to emerge in the 1950s and the 1960s, notably with the work done by Feigenbaum. Feigenbaum's 1951 book, Quality Control: Principles, Practice, and Administration, emphasized the importance of quality control in the business world: The Quality Control Program, which calls for continuous measurement and action, was developed in 1949 by W. Edwards Deming. The Plan-Do-Check-Act cycle espoused by Deming has cemented the practice using performance data to guide iterative improvement in quality and productivity. The ideas were eventually refactored, re-tested, & further proven by Six Sigma methodology which brought about more heavy-weight statistical methods for process monitoring and improvement [3].

The business intelligence revolution that crystallized as its own industry sector in the 1990s was an important part of the evolution toward DDDM. Early provisions of BI systems have been centered around backward-looking reporting and descriptive analytics offerings managers the ability to have a historical snap

shot view of how an organization was performing. Though limited by today's standards, these systems were an important early step toward greater discipline in the use of data in decision-making. Thus, the theoretical landscape of DDDM has expanded further in the 21st century, shaped by a number of interrelated developments.

The revolution in big data has challenged traditional ideas of how data should be managed and analyzed – new methods are needed to cope with the scale, pace, and diversity of sources now available. "In parallel, machine learning and AI have made possible new categories of advanced predictive and prescriptive analytics, beyond the simple descriptive reporting that was once the standard, to actually prescribing the most optimal actions," Hayes said.

From the cognitive point of view, behavioral economics research has clarified how evidence-based methods can be used to counter decision biases. Daniel Kahneman and other work has shown that human judgement is easily swayed by systematic biases and heuristics that statistical thinking can mitigate. This study offers good theoretical support for DDDM as a promising solution to becoming better informed with decision results.

At an organizational level, theory, such as resource-based view (RBV), has put forward that the capacity of a firm to capture, analyze and act on data might be a valuable, rare, inimitable resource serving to support a competitive advantage. This theoretical approach contributes to explaining why some organizations are more successful in exploiting their data assets than others and emphasizes the need to build organizational capabilities in data analysis and data interpretation [4].

Adoption of DDDM practices in organizations can also be explained through the diffusion of innovations theory. This theory explains why some organizations adopt data-driven approaches earlier than others and provides insight into the key factors driving the decision to adopt, factors such as perceived benefits, compatibility and organizational readiness. With specific reference to IT firms, several other theoretical viewpoints are particularly applicable.

DDDM for IT business development demonstrates a shift from intuitive approaches to evidence-based strategic management and deep analytics [5]. In the modern era of digital transformation, DDDM is seen not just as a competitive advantage, but as a critical condition for business survival [5–7].

The technology acceptance model (TAM) sheds light on why IT professionals perceive and offer support for analytical tools, and sociotechnical systems theory offers guidelines for integrating technical systems with organizational structure and processes. This is where the dynamic capabilities framework can be useful as an aid for understanding how IT firms may apply data-based methods for sensing and responding to fast-paced changes in their markets. These combined theories will help to provide a strong conceptual framework for understanding the DDDM principles and practices in IT organizations. They show that evidence-based models aren't so much a set of technical tools as a holistic management mindset grounded in a tromp through some of the most influential literature in a variety of fields of inquiry. This dose of theoretical depth is why DDDM has been able to provide so much value across a wide variety of organizational contexts and why it is expected to become more important as technologies evolve.

The fundamental basis of DDDM is the transformation of raw data into knowledge through a hierarchy of levels of abstraction [5]. Researchers identify four key types of analytics that form the intellectual basis for decision-making:

1 Descriptive: analyzing historical data to understand past events [7].

2 Diagnostic: identifying cause-and-effect relationships and patterns [7].

3 Predictive: using statistical models and machine learning to predict future outcomes [7].

4 Prescriptive: suggesting specific actions based on predictive insights to optimize outcomes [7].

For effective implementation of DDDM, a powerful data storage and processing base is required. Current research emphasizes the role of modern database systems, such as RDBMS for structured data, NoSQL for the flexibility and scale of "big data", as well as NewSQL, which combine the best of both worlds [8].

Management accounting in IT companies is evolving towards creating an information field for monitoring costs and efficiency of business processes in real time [9]. The use of Process Mining methods allows for automated analysis of bottlenecks in the development (SDLC), marketing and technical support processes [9].

Research confirms the direct impact of analytics on the excellence of IT project management, in particular through the following indicators [9-10]:

- Return on investment (ROI): maximizing financial returns.
- Budget compliance: controlling cost overruns through predictive risk analytics.
- Resource utilization: optimizing the allocation of human and technical capacities.

Discussion of results

Enabling data-driven decision making in IT organizations, however, demands a strong technological backbone to serve different analytical needs. This infrastructure enables the collection, storage, processing, and visualization of data in ways that stimulate decisions making at all levels of an organization. The complexity and number of these structures may differ greatly between organizations and depending on the type of decision supported in particular [11].

At the simplest level, a DDDM system will need data acquisition and ingestion facilities. In the case of IT companies, data sources are often wide-ranging in nature

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and can involve such internal systems for us as project management tools, CRM (customer relationship management) platforms, version control systems, and help desk solutions. External sources could include market research reports, competitor studies, social media feeds, economic indicators and so on. Contemporary data ingestion pipelines need support for both structured data (e.g., records of databases) and unstructured data (e.g., text documents, images or log files), oftentimes in real time or near real time.

Data storage and handling is also another key element in the technological resources. Legacy relational database management systems (RDBMS) are still relevant for structured data workloads, but new data lakes and NoSQL systems have appeared for managing semi-structured datasets and unstructured data at scale. The decision of storage option is based on the volume, velocity, variety (3Vs of big data), and the kind of analysis that is needed. A lot of these organizations go with a hybrid approach, where you have different storage technologies based on use case, but still have mechanisms for data integration and consistency across the platforms.

Data processing and analytics functionalities are the backbone of the DDDM ecosystem. This level consists of ETL, or cleaning, transforming and integrating the data and exploratory, diagnostic, predictive, and prescriptive analytics engines. However, batch computation frameworks continue to be relevant for a large number of analytical workloads – the emergence of stream processing frameworks for gaining real-time insights has not nullified the importance of batch processing frameworks. The increasing deployment of “machine learning” and “artificial intelligence” methods has also massively extended the scope of what can be analyzed, supporting increasingly-complex pattern-recognition, anomaly detection and automated decision making.

On the user interface side of the DDDM infrastructure, we have business intelligence (BI) and data visualization tools. They do this by simplifying complex analytical work while also translating results into easier-to-understand dashboards, data stories, reports, and other visually oriented insight. Today, many BI tools are self-serve and more and more end users can do the exploration of data and even build their own visualization with little reliance or support from their IT departments. The story behind the data Beautiful charts and visualizations help you uncover insights that would go unnoticed in traditional tabular reports.

The technical implementation of these disparate pieces is problematic. Data integration middleware, APIs, and ETL pipelines play a wide role in the (smooth) flow of data between systems and the quality and consistency of the data throughout the analytical process. Data governance software helps administer metadata, enforce quality standards and maintain compliance with regulations such GDPR or CCPA.

In recent years, the infrastructure of DDDM has been significantly altered by cloud computing. Cloud-based analytics environments have several advantages over traditional on-premises capabilities, including improved scalability, lower initial costs and the ability to use state-of-the-art analytics functionalities without major skills investments to in-house teams. The big cloud providers have now complete analytics suites that connect storage, processing, and visualization together, with pre-built connectors and pre-configured machine learning models on top of all the common data sources.

Another significant trend in DDDM infrastructure is edge computing. As a result, we can perform data processing close to the source of the data generation (e.g., on IoT devices or local servers), saving the latency, bandwidth, and real-time decision-making in distributed environment. This is particularly true for IT companies creating or consuming edge applications and services.

Security and privacy guarantees should be part of the DDDM design of any infrastructure. Sensitive data are protected through encryption, access control and audit logging including anomaly detection. Privacy-preserving analytics methods, like differential privacy or homomorphic encryption, allow data to be analyzed for insights without revealing personal or sensitive details [12].

The technical deployment of DDDM is not fixed, but need be in a state of flux to meet business requirements and technology progress. DevOps practices have become popular with many organizations looking to automate the development, deployment, and support of their analytical systems. These approaches prioritize using automation, continuous integration/continuous delivery (CI/CD), and ensuring that data engineers, analysts, and business users work closely together.

In context of IT companies in particular, the DDDM infrastructure oftentimes should serve specialized use cases, such as software development analytics, IT operations monitoring or cybersecurity threat detection. These might be integrations with development tools, bespoke analysis algorithms, or an original approach to visualizing data the only way that makes sense to technical audiences. Let's not forget the human dimension of our DDDM infrastructure (Fig. 2). No matter how good the technological machinery it is doomed to fail without the correct training, documentation and support. Without user adoption strategies, the organization, the human capital, is handicapped, unable to effectively use the capabilities of the available technology.

When evaluating these infrastructure investments, IT organizations face the delicate task of balancing multiple but competing priorities, such as flexibility versus standardization, innovation versus stability, self-service versus governance. The ideal structure will be different for each individual company, depending on size, sector, or strategic goals. But there are some principles that tend to remain the same regardless of the organization: the infrastructure must be elastic enough to support growth, flexible enough to incorporate the latest technologies, and aligned with the company’s broader data strategy and business goals.

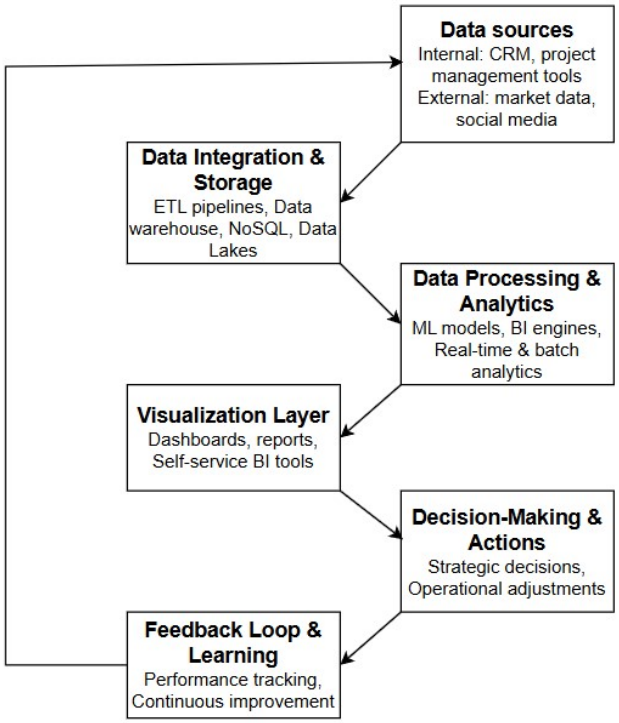

Fig. 2. – Infrastructure of DDDM

Conclusions

A comprehensive analysis of data-driven decision making (DDDM) in the IT sector provides critical insights that will enable us to connect theory, technology, and practical implementation. The synthesis of key findings can be summarized into practical recommendations for enterprises seeking to harness the power of data. The main statements include:

1) The shift from experience-based decisions to data-backed strategies is no longer optional for IT companies. (Fig. 2).

2) Companies adopting DDDM demonstrate 20-40% improvements in operational efficiency, risk mitigation, and customer satisfaction (based on case studies from Microsoft, Google, and mid-sized SaaS firms) (Fig. 1).

3) Documented results from DDDM adopters include:

• 30% faster project delivery (via predictive resource allocation).

• 25% higher customer retention (through personalized engagement).

• 15% cost reduction (by optimizing cloud spend and DevOps workflows).

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