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Chapter 1: Foundations of Modern Enterprise Intelligence Systems

1.1. Introduction

Intelligence is vital for an enterprise's success. Without it, an organization is adrift. Enterprise Intelligence systems provide the data, information, knowledge, and wisdom necessary for effective and long-term asset value management. These systems foster decision-making, planning, control, learning, and accountability across all aspects of the enterprise.

Advances in systems and information technologies create the necessary conditions for enhancing business Intelligence capabilities and supporting new paradigms. These include a data-driven focus aimed at collecting, storing, processing, analyzing, and displaying information and knowledge; improving the quality and reliability of information and knowledge; enacting the necessary formal controls; bridging physical and digital worlds; and gathering and managing enterprise data provenance information. Towards these ends, core areas should be addressed: methods and techniques for controlling data and information quality; analyses of corporate and external data for supporting strategic, tactical, and operational decision-making; semantic and knowledge management technologies; Intelligent infrastructure and operations; and Intelligence-oriented Cloud-computing services.

1.1.1. Background and Significance

Enterprise intelligence systems collect data from multiple sources and transform it into information that decision makers can use to make better decisions during the planning, execution, and improvement of business processes. Companies apply business intelligence to identify opportunities and examine operational problems. Intelligence can be augmented by analytics. Descriptive analytics analyzes historical data to better understand how something happened. Diagnostic analytics examines the reasons behind past success or failure. Predictive analytics uses historical data to make forecasts. Prescriptive analytics recommends one or more courses of action. Advanced analytics may also introduce artificial intelligence, machine learning, and other scientific methods. Therefore, there is a need for platforms to provide business intelligence and supporting facilities, such as analytics, information retrieval, natural language processing, or natural language generation. However, these systems require data quality and data governance to turn data into information.

Enterprise intelligence systems assist organizations in risk management, compliance, customer relationship management, marketing, and sales, among other applications. Bad decisions lead to great losses for companies. Research investigation indicates how enterprise decisions have become more complex and important. Examples such as Blockbuster's lack of response to Netflix and Kodak's failure to recognize the potential of the digital camera show that failure to make sensible decisions leads to decline. These examples reveal the importance of understanding how to transform data into information to improve decision making. Enterprise decisions are classified into strategy, operations, and tactical levels. Understanding why such decisions have become important.

Fig 1.1: Foundations of Modern Enterprise Intelligence Systems

1.1.2. Research design

In the 21st century, the emergence of the signal-processing paradigm of computer science has led to substantial improvements in machine perception tasks through the application of data-driven artificial-intelligence algorithms, resulting in unprecedented deep-learning performance success stories over closed, controlled testing datasets. However, the realm of decision-making engines has not benefitted as much from these same algorithms, and companies still rely heavily on statistics and simulation-based data analytics and risk management techniques supported by architectures that have not changed in several decades. The existing decision-support- and operations-optimization systems enabled by these architectures are generally characterized as Business Intelligence (BI) systems, which are based on conventional database-centric enterprise data. The information produced by BI systems suffers from two main quality problems—garbage in/garbage out problems and the "ineffectively used" paradox—both of which can be resolved with proper Data Governance and Quality management.

Although the years 2020–2030 are characterized by a shift from Data-Management-centric Business Intelligence systems to more "holistic" Intelligent-Enterprise Data-Management systems that broaden the Enterprise Intelligence perspective and consider "digital business" from Data Governance, Data Quality, Data Pipelines, Intelligent Decision Support Operations, Analytics, Semantic Data, and Advanced Information-Retrieval Capabilities perspectives, the high operational cost of Internet giants encourages investment in Analytics-Operation Process Automation and orchestration of the companies' PaaS offerings. Such an architecture is called an Event-Driven Architecture. The entire Digital Business of Internet giants consists of a collection of components, each developing its own Digital Business using a PaaS (Integration PaaS, Analytics PaaS, Inference PaaS), and integrating them by means of Event-Driven Architecture. Such a shift, viewed from Society, Technology, Architecture, and Intelligence Perspectives, moves Data-centric Systems into the Signal Processing paradigm.

1.2. Conceptual Frameworks for Enterprise Intelligence

Two conceptual frameworks shed light on enterprise intelligence systems: the progression from data through information and knowledge to corporate wisdom and monitor the construction of system architectures. Data, derived from measurement, is not useful per se; it gains significance when put into context as information. Information eventually becomes knowledge when it is appropriately processed and learned. Corporations desire knowledge because it enables better business decisions and moves them toward corporate wisdom. Wisdom cannot be obtained through methods or models; instead, “wisdom has to come from within,” requiring reflection and experience-dominated heuristics.

Some architectures for electronic intelligence support intelligence processes better than others. Monolithic applications provide powerful, productive solutions to many intelligence processes but create islands of automation. Service-oriented architectures control the islands but require excessive effort for program development. Event-driven architectures capture business events and allow near-real-time analysis for decision support, business process reengineering, business monitoring, and alerting.

1.2.1. Data, Information, Knowledge, and Wisdom in a Corporate Context

Data, Information, Knowledge, and Wisdom (DIKW) are often depicted as a hierarchical model. Data are the raw building blocks of information, the facts and figures with no context. Information is data given context, like events providing business intelligence or identifying patterns of customer sentiment, in which case the data come from tweets and reviews and the context the analysis of the emotional load of the words used. Information leads to knowledge, an understanding of how the world works, sometimes described as knowing what to do when the next event occurs. The highest conceptual category contains the complete understanding required to run a business successfully, so that the required actions unfold automatically and more-or-less-every time have a successful outcome, thus minimizing risk. In a sense the DIKW structure describes a rainwater collection reservoir. Water from the sky is collected without any treatment, and it is stored in the reservoir. Before someone drinks the water, it needs to be filtered, so that pollutants make it safe for ingestion, and then treated before the water is safe for human consumption. In a business context DIKW behaves more like a swimming pool.

In a swimming pool water arrives clean and is treated before someone swims in it. The treated water then sits idle, except for some evaporation and sludge that requires periodical cleaning and treatment, until it is used. Even then the actual usage doesn't change the main features of the water: its temperature, salinity, chlorination, among others. Likewise, in a global business some events/conditions only affect one part, and thus require actions on one or some isolated parts of the organization, without altering the rest; and thus knowledge is only required in one or some specific areas. If the collected data are complete and up-to-date, that is, data governance is functioning perfectly, and if the steward roles are observed, then the DIKW hierarchy is used by enterprise business intelligence without failure. However, knowledge generation could be more efficient using some help.

1.2.2. Architectural Paradigms: Monolithic, Service-Oriented, and Event-Driven Systems

Corporate information systems can be understood as systems of record serving business operations, advisory systems providing business intelligence, and applications supporting decision-making. Business Operations Systems involve transactions, records of business events and activities that happens in a simple transaction-centric level. It provides a reliable wiring and plumbing of transaction processing and reporting. Advisor Systems includes Corporate Performance Management (CPM), Business Intelligence (BI) and Enterprise Reporting. They provide descriptive, diagnostic and simple predictive analytics capabilities.

Decision Support Systems are applications aimed at optimizing business processes, events (e.g. costs, revenues) and results (profits). Their structure typically reflects the internal (activity-based) structure of the business.

1.3. Data Governance and Quality for Reliable Intelligence

The usage of data to generate intelligence must be coupled with effective data governance and management to maintain the reliability of the information generated. Data stewardship, supported by the establishment of metadata management practices and processes, as well as the specification of data quality rules and controls, is essential to ensure that the data used in the intelligence generation processes is reliably accurate.

Fig 1.2: Data Governance and Quality for Reliable Intelligence

Data stewardship partitions the responsibility for the ownership and control of data assets within the organisation among individuals within the business, usually mapping to specific data domains or data categories. Data stewardship roles are focused on the availability and usability of data assets and their associated metadata, rather than the technical implementation surrounding a dataset, which is managed through traditional IT governance processes. Data steward roles typically encompass data domain steward (the owner of the data), operational steward (the day-to-day steward of the data), and accreditation steward (responsible for endorsing the decisions of other stewards) roles.

Established metadata management practices support an understanding of the definition, origin (through lineage), reliability (through quality rules) and appropriateness for use (through annotations such as business glossaries, taxonomies and ontologies) for data assets across the organisation. Enterprise metadata management solutions contain the specialised metadata required to describe the semantic meaning of data assets – such as business glossaries defining business terms; taxonomies that classify and organise files, documents and communication; and the semantic models that provide the semantic basis for services that manipulate or query unstructured data.

1.3.1. Data Stewardship and Stewardship Roles

Data stewardship—including stewardship frameworks and associated roles—is a fundamental aspect of enterprise data governance and necessary to ensure the quality and reliability of enterprise data. Data stewards are responsible for the quality and fitness-for-use of data resources and work toward meeting compliance requirements. Typically, data stewards operate under the authority of the data owner and are responsible for deciding how the data can be used within the established guidelines. In some companies, data owners and stewards may be distinct roles. The stewards are supported in their responsibilities by data custodians, who are responsible for the implementation of the systems and processes that support the data and compliance requirements. In some companies, data steward roles may be fulfilled by back-office partners, such as data governance or architecture specialists, who define policies and standards. Data stewardship also includes the stewardship of key metadata, especially business glossaries and taxonomies that support a common understanding of data terms and concepts. In this context, data stewards are responsible for obtaining the correct definitions and use cases for data categories that appear in reports or are otherwise made available to users.

Stewardship can be deployed at multiple levels in the organization—corporate, departmental, and local. Corporate roles are responsible for data on a companywide dimension, departmental roles for data pertaining to a functional area or department of the corporation, and local roles for data pertaining to one organization unit or business account. Often, local stewardship is not established unless the data require special attention or a minimal number of users want to improve the data quality. Companywide efforts tend to be resource-intensive. In some organizations, the oversight of cross-department data is assigned to one department, usually the corporate IT group. Because such control group may not have ownership or operational authority, the full participation of the departments is required to maintain the data at a high level of quality and relevance.

1.3.2. Metadata Management and Provenance

In many cases, explicit definitions, business glossaries, and knowledge management are not enough to ensure that the semantics of the data are understood properly, and that data product users correctly interpret the values. It remains crucial for intelligence service providers to manage metadata associated with existing facts, summaries, models, and decision processes. Metadata about data users will indicate if a data product was used correctly, or if a misunderstanding occurred. Determining why a data product failed is essential in order to learn from mistakes, and can also help in detecting potential issues that may arise in the future. For a given set of data, it must be possible to answer questions, such as what the organization can conclude or infer from it; what combines or summarizes the data; what models have been built on it, by whom, when, and with what predictive performance; and for which of the model's features is a lesson learned available.

The data provenance of any intelligence service constitutes a rich set of metadata, which can be classified into four categories: who did what, composition, sharing, and quality. "Who did what" refers to user activity with facts, visualizations, data products, and domain-specific guiding data. It answers questions such as who was the last user of a fact or a fact set, who checked a fact, and who created the summary. The composition category identifies users who combined data or models, and tracks how the combinations were achieved. Sharing-related metadata specify what data and models have been shared with which users, whether the sharing was timely, and which other users have missed the sharing opportunity. Finally, the quality category provides metadata associated with quality controls or quality assessments of models, alerts the community about probable low-quality models, and points out models that have not undergone quality checks.

1.4. Analytics Capabilities and Methodologies

The use of business intelligence models for competitive advantage and performance improvement demonstrates the importance of the analytics capabilities of an organization. Analytics can be defined as methodologies for data analysis, including the data collected, the tools for analysis, and the results obtained. It combines and employs data management, statistical methods, and predictive modelling to identify patterns and determine future behavior.

Analytics can be classified into four categories, although there is much overlap among the techniques used in each area. Descriptive analytics examines historical data to gain insight into past events of business performance. It is the most widely used analytics capability and includes the forms of data mining and data visualization that enable the generation of reports. Diagnostic analytics revolves around identifying the factors affecting performance; it uses a broad range techniques from trend analysis to more advanced methods, such as decision trees and regression analysis for discovering the relationships between the variables. Predictive analytics anticipates future behavior through a variety of techniques, including predictive modelling, forecasting, and pattern matching. The data used may be generated internally or obtained from third-party sources. Prescriptive analytics goes a step further by using predictive models to make recommendations to decision-makers about the actions that are most appropriate for achieving a particular outcome.

1.4.1. Descriptive, Diagnostic, Predictive, and Prescriptive Analytics

Business organizations deal with a wealth of data and, like other forms of information represented in a BI system, it must be analyzed and transformed into useful intelligence in order to provide value. Enterprise Analytical Capability answers the question: “What is happening inside the organization?” through descriptive analytics. Furthermore, through diagnostic analytics, it makes able to scrutinize the reasons behind what has been happening. In turn, predictive analytics enable the business to ask “What will happen if things stay the same?”, while prescriptive analytics examines “What should I do?” by making use of all enterprise BI information, intelligence from advanced analytics, business rules, and heuristics.

Fig 1.3: Descriptive, Diagnostic, Predictive, and Prescriptive Analytics

Each one of these analytical dimensions relies on different types of techniques. Descriptive analyses summarize and analyze historical behavior of what is being monitored through classical statistical methods (mean, trends, correlation factors, etc.) and techniques such as dashboards and scorecards. Such techniques outline what is happening. Diagnostic analyses go one step further by identifying hidden patterns and anomalous behavior using primarily exploratory statistical methods such as outlier detection, clustering analysis, factor and principal component analysis, etc. Predictive analyses identify patterns that suggest how the future will behave based on what has happened in the past and employ classical statistical techniques such as regression models, data mining techniques such as neural networks and decision trees, or multivariate time series analysis. Finally, prescriptive analyses are usually heuristic-based and make use of rules or simulation to suggest which action to take given a certain set of criteria.

1.4.2. Advanced Analytics Techniques: Statistical Methods and ML

Descriptive, diagnostic, and predictive analytics identified the intelligence capabilities of modern enterprise data ecosystems, in conjunction with the advanced analytics methodologies deriving from the knowledge domains of statistics and machine learning (ML). These domains embrace the array of compute algorithms and related quantification models, as well as computational logic derived from ancient philosophy and computer science, pursuing the rendering and association of variable signatures and behaviours in an explicit or latent pattern schema supporting the augmentation and augmentation of intelligence. Such quantification models are usually executed using software libraries that encapsulate the exhaustive calculus of artificially intelligent systems designed to depict or emulate the intelligence of humans, organise and govern multiple variables within a small number of classifications, predict multiple behaviours based upon previous history and experience, and assist human intelligence via intelligent chat dialogues.

Traditional classification methods—such as logistic regression for binary-class classification, multinomial regression for multinomial classification, ordinary least-squares (OLS) regression for numeric prediction, and Cox's regression for survival-time analysis—are all ML methods based on a relatively simple linearised model. However, when a large number of measured and computed variables are difficult to condense into independent-variable signatures, and complex non-linear or non-monotonic behaviours must be classified or predicted, a breadth of machine-learning (ML) classification methods can be applied. Some of these ML methods construct models with an ensemble or majority-vote strategy, combining a large number of single models that all use a subset of the available variables and classifies using a database of previously described associations. Such methods usually perform well in establishing classification patterns or predicting future behaviours in unknown populations.

1.5. Enterprise Information Retrieval and Knowledge Management

In an enterprise context, information retrieval (IR) encompasses all strategies and techniques aimed at locating data and documents relevant to a specified need. Within modern organizations, these are often non-structured or semi-structured documents—e.g., Word documents, PowerPoint presentations, email messages, and PDF files—stored in file systems, Sharepoint repositories, or as repositories in collaboration tools such as Microsoft Teams. Dedicated IR systems enable searching through indexed content based on keyword-based queries, although the emergence of Generative AI technologies gives rise to a new wave of chat-like, conversational interfaces, even for document nationalization tasks.

Enterprise retrieval systems go beyond basic search capabilities by explicitly capturing the meaning of information. These systems can determine synonyms or similar terms, enabling retrieval answers that do not rely on exact words or phrases staged, but that spring from multiple sources. Since access to sensitive information may be restricted by security labels such as clearance level, information retrieval technology also includes security policies that permit only authorized users to access specific documents or classes of documents. Advanced IR systems may also incorporate Graph Database approaches to represent the meaning of concepts or entities connected to a search. These systems must cover a wide spectrum of information assets, including Linked Data available on the Web and in partner sites—whether on-premises or in the cloud.

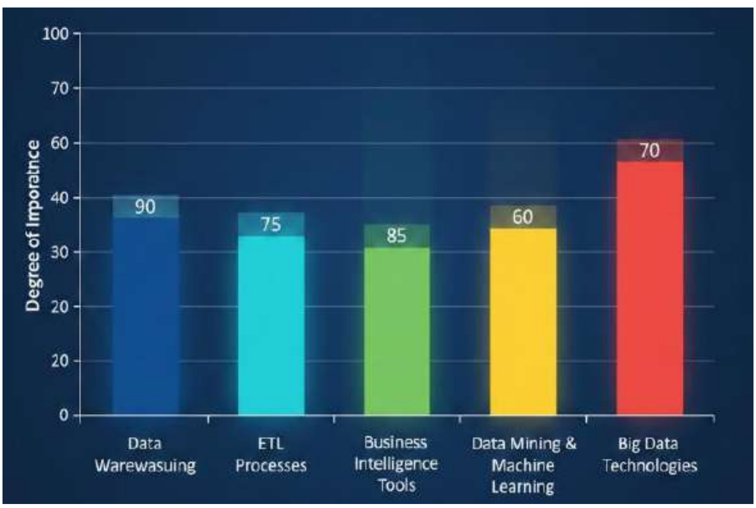

Fig 1.4: Foundations of Modern Enterprise Intelligence Systems

1.5.1. Semantic Technologies and Ontologies

Modern enterprises operate in a complex and rapidly changing environment where the products, markets, and businesses of tomorrow are often unknown. As the evolution of social and business networks, open data sources, and open-source solutions has made such a climate of uncertainty widespread, the combination of classical business Intelligence mechanisms and techniques with advanced capabilities such as predictive and event-driven operation is increasingly required. However, the enterprise's initiative with respect to such techniques is often impulsive and not completely thought out. Although an analytics capability is put in place, Event-Driven Architecture concepts are not properly understood nor correctly applied. The same can be said for Data Governance, Data Quality, and Enterprise Search, which indeed were part of the business Intelligence Area of Interest and have been extensively explored for a long time. Data Pipelines, together with orchestration and automation, are other concepts and technologies of critical importance to business Intelligence.

For building a truly intelligent enterprise, reliability, maintainability, and security are still largely to be solved or properly addressed. Often, the solutions set up by the companies merely obey the necessity of satisfying the “mandatory” requirements of reliability, maintainability, and accessibility. Replacing a system or a component due to malfunctions may be a costly price to pay when involving the support of an external supplier. Cloud-based solutions may substantially reduce such costs, but they should still be properly planned. Many companies just take advantage of “platform-as-a-service” solutions, without worrying about the technologies and architectures hidden behind the services they use. An enterprise that has acquired a certain level of expertise in the area should plan to set up its own infrastructure, where costs would remain under control and the system tailored on the company needs.

1.5.2. Business Glossaries and Taxonomies

A business glossary defines domain-specific business terms crucial to an organization, clarifying their context and use in business processes. It references descriptions drawn from authoritative sources whenever possible, corresponding to terms in an associated data model. Business glossaries serve as the data stewards’ key information asset during data stewarding activities and enable consistent use of business terms for outside-the-organization information exchanges such as business-to-business (B2B) messaging standards.

Business taxonomies categorize up to several thousand business concepts and their economic characteristics, supporting cross-organizational analysis for key performance indicators (KPIs) and business-to-business information exchanges. Taxonomies typically conform to a few, not many, recognized industry or common-domain standards. Business taxonomies differ from information technology–oriented taxonomies (or folksonomies)—informal taxonomiesthe business glossaries use to categorize instances of business concepts for easier information-retrieval access. Both types have similar structures, and the same software tool can manage both. The two taxonomies can also couple to search-based information-retrieval systems and business intelligence analysis.

1.6. Intelligence Infrastructure and Operations

The operations of enterprise intelligence systems underpin the generation and distribution of the intelligence required for effective decision-making. Intelligence systems allow any company activity requiring the deployment of sophisticated data science capabilities, such as predictive analytics or machine learning, to be executed. Data pipelines are established to retrieve information from various source systems as and when it becomes available, subject to rules governing the quality of that data. The pipelines multiply the data across any of the functions within the business as required, and data flows can also be orchestrated to enable the efficient execution of complex business processes. Automation is increasingly leveraged to take decisions without human intervention, provided that the available data is sufficiently rich to support such actions. Process automation, monitoring and triggering are also standard capabilities in service-oriented and event-driven systems, where work activities are generated dynamically.

Enterprise intelligence systems can be implemented using on-premises infrastructure maintained by the organisation or deployed in a platform-as-a-service environment by an external specialist. Cloud-based offerings allow an organisation to consume the services on an as-needed basis without the requirement to purchase and maintain expensive infrastructure for limited periods of time. Nevertheless, data privacy, security, internal control and regulatory issues must be carefully addressed in these environments, particularly when the deployed analytics capabilities access personal data or support customer-facing interfaces. The deployment of proper data governance and quality management frameworks ensures that enterprise intelligence systems deliver a consistent level of business value, independent of the technical architecture used to operate the associated data processing activities.

1.6.1. Data Pipelines, Orchestration, and Automation

In common usage within information technology (IT), a pipeline is a series of processing components that cooperate to transfer data along with various stages of transformation to produce one or more output sets that collectively form some end product. In the enterprise information intelligence context, this can broadly be interpreted to apply to any processing of data that operates in an established manner, typically in an automated fashion and often incrementally, such as accumulating daily sales statistics for subsequent later reporting. The term data pipeline can be used to refer to ETL processes that include transformation within the system, although the narrower extract-load pipeline is also widely used. Pipelines that primarily aggregate lower-level, frequent changes are generally known as data feeds.

Texture provides enterprise intelligence services with data contained in enterprise storage systems—including data lakes and warehouses—as well as third-party API sources. Transfer involves preparing, moving, validating, and possibly transforming the relevant data using any available processing services operated by Texture and supporting systems. Transmission can also include injecting content of local sources such as MES systems, code-scanning tools, or system logs into Texture repositories. Support for pipelines is provided via data-flow-oriented APIs for organizing, executing, monitoring, and validating pipelines; auto-registering data sources with API abstraction layers for iterative development; and relevant telemetry and debugging capability.

1.6.2. Platform-as-a-Service versus On-Premises Deployments

The Intelligence Infrastructure and Operations section's treatment of infrastructure-as-a-service offerings pertinent to enterprise data analytics recognizes cloud provider implementations promoting application security and support. A more granular choice is platform-as-a-service, which enables service provisioning at higher abstraction levels involving hardware and operating system virtualization as well as runtime stack, application software framework, and middleware hosting.

Enterprise information technology may be regarded as a monolithic environment, consisting of three sub-environments—the development, testing, and operational environments—constituted likewise. Vendors of enterprise information technology apply rigorous systems engineering discipline to the product life cycle, supporting the construction of an enterprise integrated operational environment, civil in nature and characterized by empirical expertise, with data quality and reliability ensured. Such supplier investments are explicitly recognized. However, with platform-as-a-service solutions made available by cloud service providers, operations of such integrated environments ought to be regarded as strategic cost in the operating budget of an employing enterprise. Application analytics service level agreements entered with service providers ought to provide comfort in this matter.

On-premises enterprise information technology may further be regarded as infrastructure-as-a-service provisioning devoted to information processing. As such, it embodies great fiscal liquidation or mortgage commitment and offers low replication expenses for inexpensive data processing. Inexpensive processing is rarely confronted with unpredictable demand and consequently typically does not require emergency capacity planning. Large on-premises deployments, however, unless aesthetically structured substantiate association and government cynicism by providing too-rich-and-comfortable infrastructure-to-render-with-complaint arguments.

1.7. Conclusion

Intelligence supports a corporation's mission by enabling correct decisions and solid action plans. An intelligence system encompasses all participants, products, and information-technology landscapes that deliver information to support decision-making for all business processes at all levels. Such systems comprise the entire data-management environment, from data governance for ensuring data quality to technologies, tools, and techniques for data movement, analytics, information retrieval, and aggregation for knowledge invention.

Corporate-intelligence activities start in a factory for intelligence production. The environment of creation includes data sources, technologies, tools, infrastructure, and processes. Only when raw material flows in freely and quality is absolutely under control can quality information and later knowledge flow out smoothly. The factory is then ready to operate and work toward meeting end-user requirements for descriptive, diagnostic, predictive, and prescriptive analysis. With that in place, accurate reports can be produced, followed by reports that contain recommended future actions, and finally early warnings and forecasts. The factory for intelligence production can be viewed as a vertically integrated corporate intelligence platform developed in-house or offered as a platform-as-a-service by a cloud provider. Platforms are becoming popular because they allow companies to focus on the development of analytics capabilities and advanced methods rather than data integration and information retrieval.

1.7.1. Future Trends

Distributed intelligence, whereby analytics capabilities, predictive and analytical models, dashboards, and reports are created closer to the business domains by data scientists embedded in such domains, is growing within organizations. These new capabilities, combined with the need for richer product offerings, faster turnaround to meet changing customer demands, and enhanced customer experience based on contextual and personalized products and services, require greater adoption of event-driven architecture by enterprise data and analytics functions. Event-driven systems embed computation into events narrated by streams of temporal data and associated actions. Enterprise processes, applications, enterprise systems interiors, business clouds, partnered and customer channels, and the external world are instrumented to create an event cloud. Events emerging from and entering this cloud are sourced, consumed, and processed typically in real time.

Organizations continue to enhance their enterprise intelligent ecosystem control rooms in the form of enterprise private clouds. These clouds centralize control over data, governance, stewardship, tooling, portals, and AI services for use by local cloud intelligent business services that provide both intelligence and analytics capabilities. Telemetry is applied to IT operations with the emergence of AIOps, applying machine and statistical learning methods to IT operations to automate themselves. A similar concept of AIBizOps applies the same techniques to intelligence and analytics business operations. Intelligence and analytics activities, along with enterprise support functions, receive continuous R&D investments to leverage the cloud-native approach for assuring future readiness.

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