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Chapter 1: Foundations of Operational Intelligence Engineering

1.1. Introduction

Operational intelligence engineering enables evidence-based decision making by the systematic processing of data from various sources, leading to information relevant to individual, team, or organizational decisions. Although still in its infancy, operational intelligence engineering has the potential to advance decision making in any dynamic situation conducive to data-driven support, including finance, healthcare, disaster management, humanitarian negotiation, and climate response. Operational intelligence engineering focuses on designing appropriate architectures, solutions, methods, and tools. To that end, it defines the elements and generic high-level processes for operational intelligence and captures requirements for operational intelligence systems.

Systematic, comprehensive use of data for decision making requires careful requirements engineering to capture needs, metrics, constraints, and success criteria. Modeling, simulation, and scenario planning enable exploration of the problem space, identification of possible data sources, assessment of the ability to derive the needed information, and detection of knowledge gaps. A lack of data does not preclude a solution—transformation of high-level requirements into a data model, integration into the required format, and population from semantically aligned storages, text, or knowledge bases can lead to sufficient derived information. Proceeding in the opposite direction by identifying gaps between available information and what is needed and by establishing a research program for the creation of that intelligence is equally valid.

1.1.1. Overview of Operational Intelligence Engineering

Operational intelligence engineering is concerned with the enabling technology for operational intelligence solutions: the software and hardware that accomplishes the transformation of data into decision support for human or machine actors in an operational context. The aim of this research is to establish a coherent, comprehensive foundation for the field. What does it mean to “engineer” an operational intelligence solution? What questions must be asked, and answered, to enable successful delivery? What constitutes an operational intelligence solution? What is the definition, domain, objective, structure, and essential concepts? What are the core concerns, boundaries, stakeholders, and ethical implications? Structuring operational intelligence engineering as a specific area of study will allow for a more focused and insightful exploration of these and other related questions, and for an eventual proposal of an associated reference work.

Operational intelligence is delivered by an operational intelligence solution. Operational intelligence solutions differ from business intelligence solutions mainly in their response to imposed timing constraints. The nature of these constraints renders practically all decision-relevant data of interest to an operational intelligence solution, and decision-relevant information is therefore the primary product. Solutions consist of a combination of standardized information-processing functions executed along an information-processing pipeline or through a well-defined sequence of processing steps. Solutions share operational context in two ways: they support the decision-making of actors—human or machine—within that context, and they exploit data unique to that context. The required technology forms an operational intelligence engineering solution.

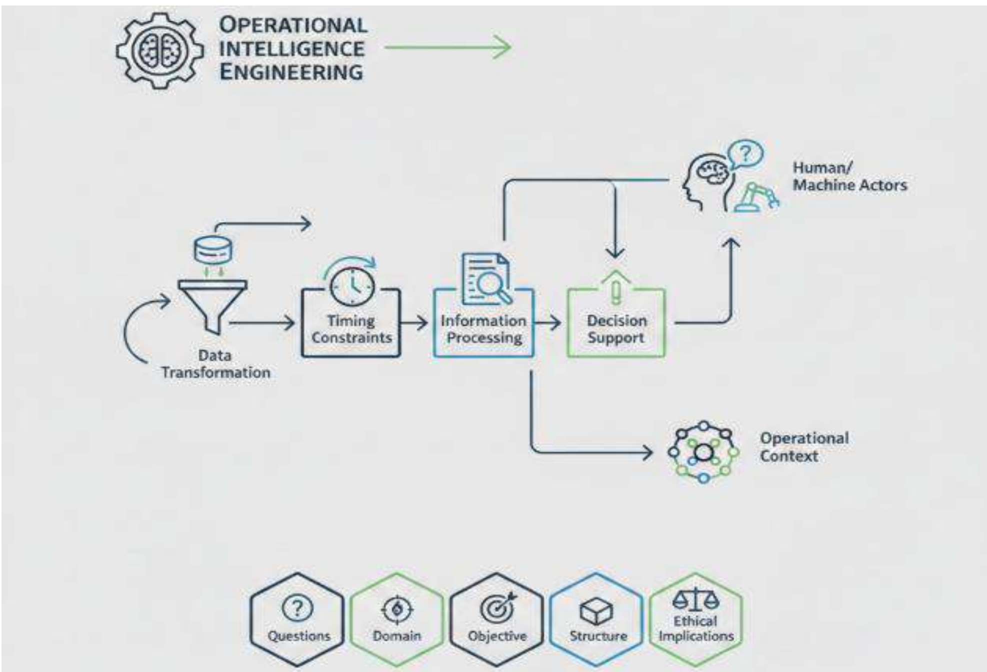

Fig 1.1: Foundations of Operational Intelligence Engineering: A Framework for Time-Constrained Decision Support Systems

1.2. Definition and Scope of Operational Intelligence Engineering

Operational intelligence engineering defines and delimits a domain concerned with the engineering of intelligent processes that support (operational) decision-making. It includes the analysis of all aspects of these processes: their concept, design, implementation, operation, management and continuous improvement. The interest of scholars and practitioners alike lies in the formulation of methods, frameworks and tools that systematically define and govern these processes and provide the stage for both standard and innovative knowledge extraction.

A domain engineering area is a specialized definition engineering domain that produces and maintains the knowledge needed to support decision-making processes for the requirements and architecture definition of a narrow group of specialized systems. These, in turn, represent the execution environment for systems from the original domain engine process. Applying these ideas in an operational intelligence context leads to a specific framework solution for an operational intelligence engineering process dealing with the operational intelligence requirements of an organization. It considers the whole organization that loans and utilizes information to support operational decisions—across any level, function and department—as its reason to exist. The ultimate goal is to formulate and improve a systematic approach to defining the requirements of operational intelligence systems across all their life cycle stages. Hence, practitioners become more systematic, repeatable, accessible and discoverable when acting as modelers, analyzers, designers or engineers.

1.2.1. Understanding the Role of Data in Operational Intelligence

Data quality, provenance, representation, and data value are the key aspects to consider from the perspective of decision cycle integration in operational intelligence. Data are the chosen material for operational-intelligence engineering. Good-quality data that faithfully represent the target phenomenon, area, or domain through the different phases and moments of the intelligence cycle provide useful information for decision-making. In particular, it is decision relevance and perception of the decision-making audience that define, respectively, the accessibility and usefulness, and thus the value, of the information produced. All other factors being equal, the higher the quality and fidelity of the data, the more fitting the produced information is to underpin decision-making. It is in this direction that data governance development must move: toward the identification of key properties for data quality and of rules and practices that ensure that data fall within the expected ranges.

Operational-intelligence engineering is the systematic acknowledgment of the information and knowledge production process. The main objective is generating actionable insights from the primary information-processing pipelines. For a particular item of information to lead to the production of knowledge, it must integrate with pre-existing knowledge in the knowledge-at-hand pool of the decision-making audience, producing an understanding of the world (actuality knowledge) or an understanding of the future state and its implications (expected future proposition knowledge). The extraction of particular and aggregate pieces of knowledge improves the quality of acted-on decisions. A knowledge-extraction pipeline, the linkage to occasional-scenario modeling and simulation, and the strategic-study framework constitute a comprehensive approach to supporting the decision life cycle.

1.3. Theoretical Foundations

Three interlinked aspects support the theory of operational intelligence engineering. Data is treated as a material for intelligence—such natural resources must exhibit sufficient quality, provenance, and representational power to underpin actionable decisions for business-oriented end users. Information processing is regarded as actionable insight generation—an intelligence unit extracts knowledge by exploiting Traditional and Contemporary Intelligence Models. Decision models and cycles provide operational context for these developments. Together, these concepts articulate the intelligent decision support sought by operational intelligence engineering.

Data as a Material for Intelligence

Raw Intelligence is treated here as natural resource material gathered from a region of activity. These data must satisfy intelligence end users by being sufficiently timely, accurate, complete, and concise; adhering to source provenance; providing a suitable representation; and being of sufficient value. The specific forms and flavors of data quality, provenance, representation, and value are essential components in fulfilling the needs of business-oriented intelligence users. Data quality reflects the design and management quality of layer BZs in a maritime disaster. Data provenance arises from the performance of layer AlXs and the maintenance of SLM specifications, while data representation quality is defined by the thoroughness of regional ontology specification and the semantic alignment of layer AmTSs.

Timeliness grows from efficient data pipeline design and the precision of tempo TL-measures. The natural need for the Big Data triad—volume, variety, and velocity—releases holders of the numerous Other Intelligence Mission data sources from the tyranny of traffic light reporting systems. Rather, it enables the timely aggregation of many Big Data Natural Resources for analysis in wider analytical thrusts. Finally, the value of data hinges on the intelligence end users' ability to act on the information at the time it is presented.

1.3.1. Data as a Material for Intelligence

Data quality affects intelligence engineering, directly impacting operational decisions and supporting enterprise risk management. As seen in C-MAX, critical requirements can be defined and quantified, allowing data constraints and quality measures to be established. Provenance and historical context provide insight into a set of data's quality characteristics, and operational analytics can augment quality assessments with real-time decision relevance. Cost and effort constraints should balance strategic decisions on local, distributed, or cloud execution, aligning locations with processes, policies, and laws.

All forms of information must be correctly aligned with the enterprise's data landscape, reflecting the involved parties' operational context, objectives, culture, time frame, and risk profile. This includes a schema that accurately conveys the involved elements, models of their statistical and dynamic properties, and deployable models. The deployment mode must align with the decision support cycle and priority of the information, with coherency and proven value supporting the selected model. Information must be timely, trustworthy, pertinent to the decision, accessible while meeting protection constraints, cost-effective, and deliverable via a user-friendly process. Similarly, sentiment expressed in social media can be relevant for classifying transactions, assessing models, and improving solutions, demanding a suitable representation.

Acting in accordance with their risk profile, stakeholders must acknowledge that both risk and opportunity involve uncertainty. Recognising this enables such considerations to inform decisions about providing capabilities for detecting, predicting, acting on, or capitalising on disruptive events. Indeed, the primary purpose of both risk and opportunity management is to increase the probability of making the right decision in a given set of circumstances. As Graham Waller explains: 'A fundamental principle of a well-designed decision-support system is to abstract away the noise from the data, allowing only that part of the evidence that significantly enhances predictability to surface.'

1.3.2. Information Processing and Decision Support

Decision-making defines intelligence arms and, ultimately, enhances survival chances. Once a business or operational question is framed, subsequent investigation aims at finding the appropriate answer. Usually this process is called knowledge management. As applied to operational intelligence, however, it must be multidimensional and distributed. Data flow in and out of analytic services; some are recursive and stable, while others are ephemeral and ad hoc. Knowledge generation relies on history and context.

The intelligence cycle starts with the production or collection of information (an issue well known to information theory and relevant to the quality of the intelligence material). Returning to the business question, if the flow of information is able to yield an answer, it must undergo one or more of the following processes to provide the final outcome:

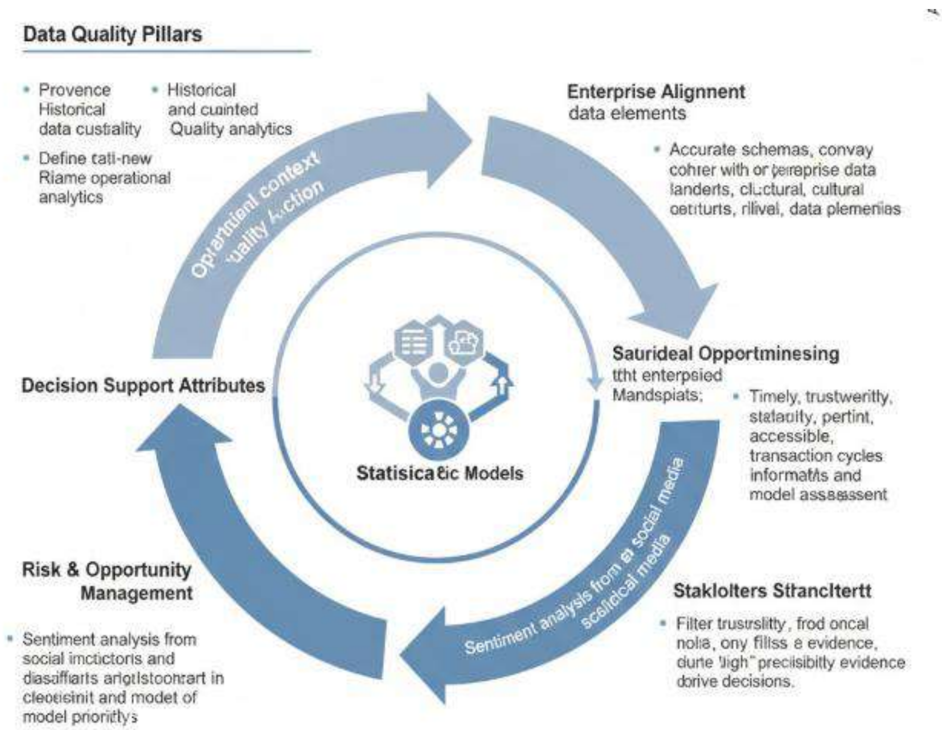

Fig 1.2: Precision intelligence Engineering: A Context-Aware Framework for Aligning Data Quality with Enterprise Risk and Opportunity Management

- First, different types of processors operate on raw data to generate information. The processes may involve any combination of standard processing, advanced or predictive analytics, automated machine learning, and artificial intelligence—be it stochastic or deterministic. The model itself may be executed as a service.

- Second, basemaps and overlays are generated: this includes geospatial translation (if necessary), as well as added context, such as sector-related information.

1.4. Architectural Principles

Standardizing Decision Support for Interoperability, Auditability, and Governance Operational-intelligence engineering establishes a set of architectural blueprints for decision-support solutions that conform to recognized principles and practice community disciplines. Specialized roles and well-defined interfaces afford interoperability among the components in a decision-support ecosystem. Such an ecosystem can be built to support multiple forms of operational intelligence for different domains by assembling appropriate component implementations for the corresponding requirements. The reference architecture serves dual purposes: it can be used descriptively to analyze existing solutions as well as prescriptively to guide new solutions. Specification of principles and a reference architecture facilitates systematic discovery of the required engineering technology.

The role-based standardization applies key architectural concepts of enterprise architecture and service-oriented architecture to decision support. Consequently, these blueprints establish control points for auditing data mission and for monitoring data missile. Potential mission-impacting modifiable sources can be identified, developer access can be limited to specified parts of the solution, and unauthorized change can be detected. Such auditing capabilities enable governance bodies to oversee operational-intelligence engineering decisions and operation; for example, by periodically checking a decision-support solution for alignment with approved-maintenance responsibilities.

1.4.1. Reference Architectures for Operational Intelligence

Standardized reference architectures are important for any area of engineering. They provide a common language that assists both communication and interoperability, facilitating the deployment of best practices and lessons learned in other projects. In the case of operational intelligence, a standardized multi-layer operational intelligence reference architecture provides a common language for the integration of the important components that enable operational intelligence. These are data endpoints that supply different and complementary types of data for the analysis and decision-support process (historical, real-time, predictive, prescriptive). Well-established reference architectures are widely cited in the literature to define the different data endpoints that supply the historical, real-time, predictive and prescriptive information for digital twins and digital thread. Enterprise and federated-level reference architectures are also defined for a wide range of domains. These architectures are complemented by operational intelligence reference architectures that organize other data endpoints with operationally focused modeling capabilities. The model abstraction layer defines models that are operationally focused and the simulation layer provides the framework for both transition and operational readiness testing.

The collection of all these reference architectures enables layered engineering of all data endpoints with the same properties still constitutes an important factor for consistency and privacy, together with the establishment of asymmetric and federated access for all the data generated and consumed. Moreover, the existence of external black-box or white-box predictive analytics models may allow the substitution of the complete analytics engine when such prediction models are more efficient or the usage of those models is mandatory by law. Non-traditional analogies or relations have been attempted to establish between the accreditation process of a flight envelope and the successful execution of the modeling layer and the analytics engine. Non-functional properties are also widely used and established in systems engineering in the validation of safety, security, privacy, and operational readiness of the fully aligned system.

1.4.2. Data Ingestion, Integration, and Fusion

Operational Intelligence Engineering encompasses a multitude of heterogeneous data sources, which are then rendered suitable for action-oriented and decision-centric purposes. Suppliers typically provide clean and well-structured data; aggregators (such as the New York Times and Reuters) concentrate various collections; sensor networks and monitoring systems provide high-velocity streams; while social networks open the gates to innumerable connected persons and events. As such a multitude of data sources cannot be handled with a monolithic structure, operational intelligence engineering relies on the ETL (Extract–Transform–Load) paradigm for traditional data warehousing, on the ELT paradigm for cloud-based data lakes, and on streaming directly from the sources for real-time operational dashboards.

The initial operational intelligence engineering pipeline merges, aligns, and combines the relevant subsets of both structured and unstructured data using dedicated schemas. Semantic alignment methods use background knowledge representation—including ontologies, thesauri, and lexicons—to represent content and context information, integrate results across modalities, and therefore enable fusion. The final step benefits from sophisticated sensor fusion techniques, such as Kalman filters for time series, Particle filters for non-linear and non-Gaussian data, and the Dempster-Shafer theory of evidence for information coming from different, non-cooperative, sources. Such methods enable redundancy reduction while maintaining the maximal amount of information.

1.5. Methodologies and Life Cycle

Operational Intelligence Engineering encapsulates the knowledge-producing activities needed to support managerial decision making and planning with data, information, and knowledge. Stakeholders can have distinctive needs and perspectives on how their requirements are represented. Operational Intelligence Requirements Engineering captures these by identifying core business objectives or needs; quantifying and qualifying functional and non-functional requirements; determining success or business impact metrics; and specifying resource, time, and concurrency constraints.

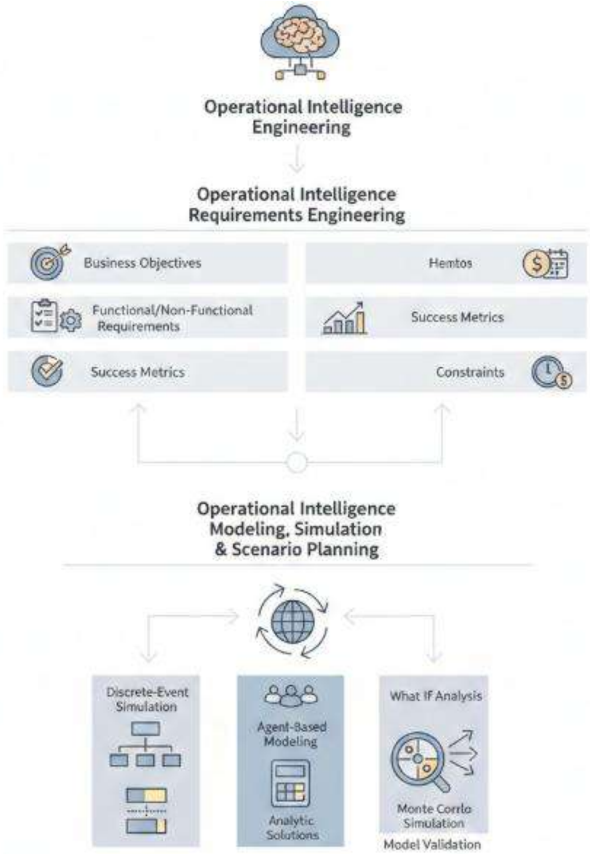

Fig 1.3: Operational Intelligence Engineering: A Requirements-Driven Framework for Stochastic Modeling and Strategic Scenario Planning

Operational Intelligence Modeling, Simulation, and Scenario Planning provide a means of investigating medium and long-term operational outcomes and inform tactical planning. Uncertainty necessitates abstraction from some of the operational details; these abstractions can be captured as models. Several types of simulation approaches can be employed, ranging from fully-fledged discrete-event simulation through agent-based modeling to analytic close-form solutions. Once the structure of dynamic business models is developed, they can be validated using techniques such as Monte Carlo Simulation and What If Analysis.

1.5.1. Requirements Engineering for Operational Intelligence

In operational intelligence engineering, requirements engineering aims to capture and agree on the following aspects of the required operational intelligence: what stakeholders wish to understand, analyze, and support with operational intelligence decision support; how they measure, benchmark, and assess the needed intelligence; what the key timelines are; which constraints—such as laws, regulations, ethics, policies, and corporate governance—apply; and how success of the supported activity will be validated and demonstrated. In the context of operational intelligence, these requirements pertain to intelligence that informs operational, tactical, or near-time decision making, supporting activities such as vertical and horizontal operations in the context of business activity and verticals—tasks such as financial and corporate planning, budgeting and forecasting. Requirements for intelligence that directly influences long-term strategy have different time frames and different forms of more classical strategic decision support.

Requirements for operational intelligence engineering, then, identify success criteria for a decision-support pipeline that run on a database with the necessary data quality for intelligence in a decision-making support capability area that is sufficient for human or automated decision making in the short term. In the presence of such requirements, a modeling, simulation, and scenario-planning methodology provides a way of both validating and demonstrating the achievement of the requirements. Supporting operational decision making is seldom the most trivial aspect of a business and requires a well-supported decision-support pipeline, model, methodology, and data-basis set of physical, logical, and semantic models—together with a trusted analytics engine, reliable analytics methods, machine intelligence models—both classic and machine-learning-based—and physical and logical control over machine-learning models and processes.

1.5.2. Modeling, Simulation, and Scenario Planning

Operational Intelligence Engineering can benefit from the modeling of systems and their operational environments: from the design phase and during their operational life-cycle, engineers, operators, stakeholders, and other parties that systematically interact with the systems or their environment can create, review, validate, refine and execute simulation scenarios to assess the impact of changes and estimate the associated effects.

Despite the utility of these activities, considerable knowledge and system expertise are required for their successful completion. The modeling of systems, of their operational environment, and of the interactions between them is one of the most valuable contributions of Information Engineering to Operational Intelligence Engineering. Information Engineering defines models, in particular abstraction models, to support not only the conceptualization and representation of information elements but also the specification and communication of clear models of what is to be achieved, and how it is to be achieved. Simulation is the Art of modeling a system that evolves in time. It allows the investigation of the system behavior according to different hypotheses regarding its dynamics not necessarily aimed at using the model to reproduce the system behavior in a specific instance; indeed, validation of the model constitutes a key step. What-if analysis considers variations in experimentally controlled values, leading to an uncertainty set of values.

1.6. Technologies and Tools

Operational Intelligence engineering draws on technology solutions from related areas, the appropriate combination depending on context and requirements. The most relevant technologies for immediate inclusion are: data platforms, covering the range of structured data storage options including lakes, warehouses and lakehouses; analytics engines that provide query capabilities, whether conventional, statistical, machine-learning, or general artificial intelligence; operational-support tools that make data-derived knowledge actionable; and dashboards that curate analytics into consumable views. Other technology categories, such as geospatial viewers or natural-language processing engines, are not explored explicitly but are equally relevant. 6.1. Data Platforms and Storage Solutions Data platforms are technology ecosystems that ingest, store, and serve data. The area of operational-intelligence engineering most closely related to operational data platforms is big-data engineering, which addresses platform scalability, data management, and operational-process governance requirements. Beyond volume, the platform-scaling requirements are driven by the operational-intelligence architectural model, as the architecture separates ingest from analytics, thus decentralizing demand for data-storage access. The main types of platform area operational-data lakes, operational-data warehouses, and hybrid lakehouse platforms. An operational-data lake is based on open object-storage technology and stores data at its processing-agnostic atomic level, sacrificing conventional database abstraction for improved scalability. Operational-data lakes are typically used with an extract-transform-load process, where data is cleansed, enriched, and structured into a data-mart schema before analysis. An operational-data warehouse stores data in a structured form and supports a schema-on-write process, where data is cleansed, enriched, and structured before the write operation. A lakehouse provides the scalability of an operational data lake, but batches data into structure, thus supporting a schema-on-read process. Ideally, operational-data-platform evolution should lead to the creation of standardized operational-data-lake and operational-data-lakehouse platforms. In addition to these three main types ofplatform, large multinational organizations should also adopt decentralized operational-data-schemas defined in tooling and process that govern how distributed teams create, sync, access, and manage schemas in common module collections. These schemas contain the schema definitions and metadata description used by the governance tooling to maintain security across scaled shared access.

1.6.1. Data Platforms and Storage Solutions

Data platforms serve as the bedrock of operational intelligence, offering convenient data storage and access. Precise specification for data storage is paramount. At minimum, it should: accommodate present and likely future data volume; support affordable access for genuine needs (especially by analytics engines); and enable recovery of recent lost data without excessive expense. Notably, damage from electronic failure, application programming errors, or vandalism usually comes to the operators' attention soon enough for action.

Data must be distinguished from information. Information is valued chiefly not for its own sake but rather for the actionable insights it makes available, enabling operations to be conducted and supported more effectively. Consequently, companies may profit if they can foresee how information is to be employed, not just how data is to be gathered. If all potential uses of information can be envisaged, then the corresponding data quality, representational adherence, and metadata capture can also be defined. Predictive models can thus direct data, information, and, eventually knowledge management.

A plethora of data platforms exists, but three families—data lakes, data warehouses, and data lakehouses—are especially worthy of attention. Data lakes permit storage of any data; a data warehouse imposes a specific structure; a data lakehouse seeks to combine the advantages of both while avoiding their disadvantages. Optimizing data storage and access for relevance-preserving decision-support processes requires assessing the trade-offs associated with these and other approaches.

1.6.2. Analytics Engines and Machine Intelligence

Analytics enable organizations to experiment, profile, investigate, discover, share, and present intelligence models, insights, and other products. They process data—normally substances—in order to provide answers, information, and more intelligence-related materials for particular problems. Three classes of analytics address decision-support problems: descriptive analytics that examine past events and facilitate decisions, predictive analytics that assess the likelihood of future events and assist in preparing for them, and prescriptive analytics that suggest policies to obtain desirable results while minimizing undesired ones. Various types of intelligence models can be created via analytics engines, including statistical models, information-theoretic models, machine-learning models, and simulation-based models. Each type has its strengths and weaknesses, which influence the choice of analytics engine.

Analytics products derive their utility and value from being employed for a purpose. Changes in environment, requirements, or objectives typically necessitate the design and deployment of new products. Governance issues therefore focus on establishing reusable templates (e.g., for descriptive reporting) and product deployment within a controlled process that enables suitable planning, quality assurance, and invocation. Answering the same or similar What-If? questions with different versions of the same model assists governance and reduces operational overhead. The design and preparation of these types of products are therefore separately examined in the chapters on analytical modeling and machine intelligence, respectively.

1.7. Conclusion

Operational intelligence engineering is an emerging area centered on using vast data collections to derive insights that support managerial decisions and other organizational activities. Focused on operational processes—production, logistics, transportation, sales, service, and support—these insights serve organizations by optimizing processes, enhancing product/service quality, improving legal compliance, and informing competitive strategies. The objective of this paper series is to define the field, identify its theoretical foundation, outline its reference architecture, and propose a life cycle methodology. Knowledge gaps within the domain—including leading approaches to requirements engineering, modeling, simulation, analytics, and enrichment—form the basis for a future research agenda.

Inspection of these topics yields an integrated view of operational intelligence as an engineering discipline. Its success hinges on a broad understanding of the problem domain, the decision-makers' objectives, and the salient concepts that govern the processes in focus. The broader set of stakeholders then capture and formalize their states, constraints, metrics, and performance measures. Based on these preparations, OGGM modeling tools and what-if analysis are employed to generate scenarios—process-specific, abstracted, idealized representations—that open the gate to data platforms, analytics tools, and machine intelligence.

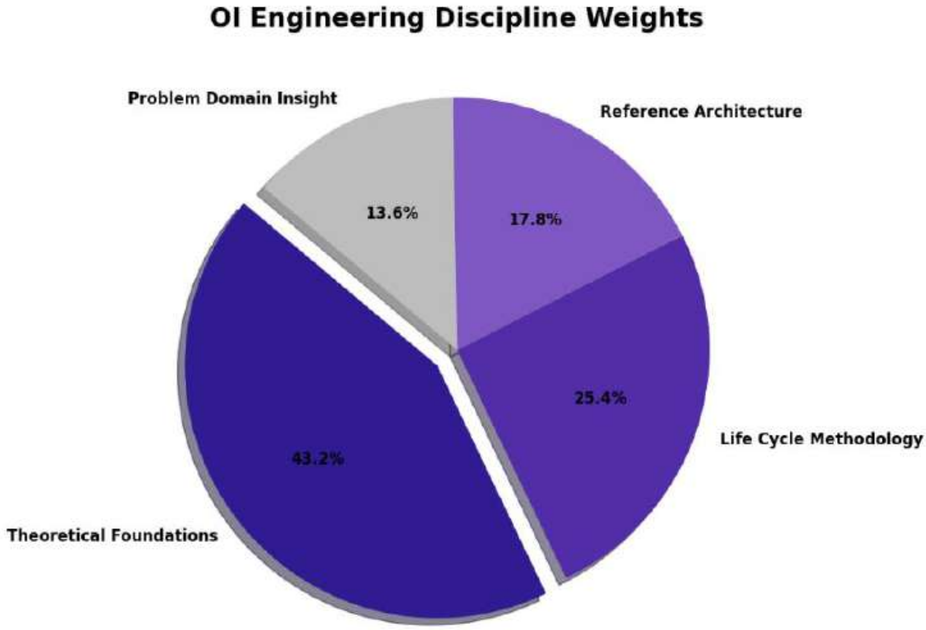

Fig 1.4: OI Engineering Discipline Weights

1.7.1. Final Thoughts and Future Directions in Operational Intelligence Engineering

As presented, operational intelligence engineering addresses the definition, the fundamental concepts of data and information, architectural principles, methodologies, technologies, and tools. However, some aspects have been left unattended or emerged only partially, but warrant deeper study. Therefore, the following questions arise: what has been left out of the current foundations of operational-intelligence engineering? What aspects have been only partially approached, and what additional research is warranted? Seven directions for future research on operational-intelligence engineering would contribute to filling the missing gaps. First, the quality, provenance, representation, and finally the value of the data used in the analysis process of real-world problems have not been discussed. Historically, quality has played a fundamental role in cross-disciplinary works such as data-integration literature, for virtual-data-integration becomes impossible when the same semantic concepts are described across data sources by syntactically (and semantically) different structural elements. Data-provenance description has also traditionally received attention, usually for identifying the sources of data at a fine granularity and allowing the detection of inconsistencies when cross-checking against external knowledge.

Second, models of how information is processed into decision-relevant knowledge with due level of abstraction have been proposed but only partially defined—particularly by omitting main phases of information analysis, like what-if or counter-factual decision-support analyses and testing, or scenario planning and simulation—that provide an additional level of confidence in the expected behavior of the system being acted on. Third, standardized reference architectures with regard to the operational-intelligence-engineering life cycle coordination and consolidation of commonly agreed and accepted (or at least usable) architectural representations for operational intelligence engineering do not exist yet. Such representations would comprise layers, roles, and distinct points of data flow, and play a fundamental role in the expected ability to support the automatic generation of coordinated, interconnected, and interoperating intelligence-analytical agent systems in the operation of a closed-loop decision-support system with feedback control and adaptive-middleware solutions. Failure to define such standardized representations poses grave threats to the effectiveness of these full-scale real-world automation systems—indeed, without due understanding and control of the intelligence-building effort, there exists the possibility of producing primarily "any" intelligence.

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