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Chapter 2: Architectural Patterns for Enterprise Knowledge Platforms

2.1. Introduction

Knowledge-driven businesses must align organizational practices with life-long learning. Knowledge needs are partially met through enterprise search and knowledge bases; however, they fall short in quality, completeness, and relevance. Despite the technology-enabling trend of knowledge management, the underlying architecture remains ambiguous. An enterprise knowledge platform is a system-of-systems that meets current and future knowledge needs for multiple user roles. Architectural patterns identify solutions to recurring problems; those highlight the layers of technology and functions necessary to realize these capabilities.

Knowledge-driven businesses distinguish themselves through innovation, service improvement, and continuous customer-engagement. Organizational practices are supported by technological platforms that acquire, structure, connect, integrate, and share mission-critical data in real time. Unlike marketing, sales, or business-development platforms that are organized around external engagement, the focus of knowledge-driven businesses is learning—internal learning from disparate, often unstructured, data sources and external learning through ongoing engagement with customers, partners, and the public. Enterprise search and knowledge bases partly address knowledge needs; however, the knowledge repository represents a small sliver of the knowledge required to fulfill even the simplest of tasks. Customer-support queries are often resolved through product documentation, user-contributed manuals, comments on product features, service tickets, and responses to service tickets. Yet, these systems do not reveal their own key weaknesses: quality, completeness, and relevance of the returned results.

2.1.1. Overview and Scope of the Study

Enterprise knowledge platforms must support a wide range of organizational knowledge needs. Such platforms are content and data intensive, using data and information to generate knowledge-based perspectives on the organization and its environment and to build ready-to-use knowledge for the enterprise. To help with the design of such platforms, a set of architectural patterns is proposed. In the context of this study, a pattern describes a recurrent solution to a problem within a given context. A fundamental characteristic of such a pattern is that it may be implemented in various ways depending on the circumstances, while achieving the desired outcomes. Three criteria are proposed for assessing whether a particular pattern serves its purpose. First, the pattern must be suitable for the capability being addressed. Second, if the pattern describes a grouping of elements, these elements must interact according to a defined contract. Third, if the pattern concerns a layered architecture, the purpose of the layers must be clear.

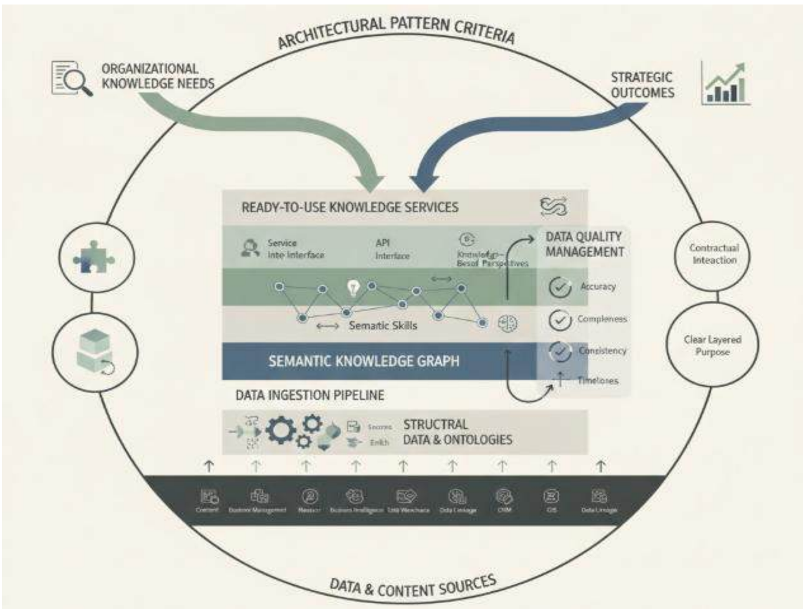

Fig 2.1: Architectural Patterns for Enterprise Knowledge Platforms: A Layered Framework for Semantic Integration and Data Quality Governance

A layered architecture established during previous work shapes the design patterns of business knowledge platforms. Enterprise systems such as content management, business intelligence, data warehouse, data mart, master data management, relationship management, business process management, and geographic information systems provide content and/or structure to some of the layers. The other layers rely mainly on data ingestion pipelines that process, sanitize, and enrich the data before exposing them through data services or a knowledge graph. Such pipelines are composed of individual elements that ingest data, extract metadata, and examine data quality. The pipelines position the data into the layers according to well-known domain ontologies, apply semantic skills to make services smarter, use data quality rules to cleanse the data, and organize the data quality dimensions directly exposed on the layers' interfaces. Data quality is therefore not a menacing ghost; it is a set of dimensions that must be soundly monitored without muscling it away. Data lineage and preprocessing play a critical role in this context.

2.2. Core Concepts and Vision

An enterprise knowledge platform aims to support knowledge-intensive activities by enabling an organization to capitalize on the knowledge it generates, acquires, processes, transmits, consumes, or otherwise uses in executing transactions and delivering products and services. The accomplishment of such activities requires the existence of specific capabilities—extended to a fuckin' knowledge domain—that affect and are affected in a coherent manner by the realization of those specific activities as a joint initiative.

To address the knowledge-intensity of an organization's activities, knowledge–related capabilities, guiding principles, and strategic vision must be defined and aligned with existing or emerging knowledge needs. When properly articulated and aligned, a semantic foundation functionally extends the role of organizational knowledge as an enabler. Such an articulation also allows the iterative inclusion of new or enhanced knowledge-related capabilities that are isomorphic to such a foundation, whether formally defined, implemented, and operationalized or not. The semantic foundation can be summarized in three propositions: Knowledge-intensive activities generate, acquire, process, transmit, consume, or otherwise use knowledge. The relevance of that knowledge is expanded when the related capabilities are explicitly defined at the organizational level, articulated as a joint initiative, and isomorphically aligned with the activities generating it. A semantic foundation is a semantic model of the ontology of business, providing a precise and unambiguous description of the domain concepts employed by an organization. In addition, the formal reflections on the notion of knowledge-intensity reveal a strategic-vision approach that systemically integrates all the elements and considerations implied in the concept of knowledge intensity.

2.2.1. Fundamental Principles and Strategic Vision

These principles underpin a vision of unified enterprise knowledge platforms systems designed explicitly for creating, curating, managing, sharing, and consuming knowledge. Capable of effectively leveraging the organization's collective experience and expertise, they enable solutions to complex and recurrent problems by facilitating early and unencumbered access to the knowledge required for informed participation. They provide mechanisms and processes for presenting credibility- and context-enhancing background information, fact-checking, and synthesizing independently produced findings. They also furnish the structure and sanctioned roles necessary for creating, storing, and alerting about relevant new knowledge as easily and truthfully as possible.

Enterprise knowledge platforms are integrated and reflective by design. Their layered integration patterns guarantee cohesion across the core functions and empower other systems to exploit the shared knowledge. Reflection is facilitated by dedicated data management patterns that generate and maintain a real-time inventory of all available data assets, ensuring visibility and trustworthy qualification. Data producers and users alike are warned about quality issues through lifecycle-based monitoring, enabling proactive remediation and true-to-identity usage.

2.3. Layered Architecture for Knowledge Platforms

A layered architectural blueprint depicts the high-level technical fabric of knowledge platforms. It encompasses essential components and their collaboration mechanisms without prescriptive dictates over design particulars. Each layer possesses a distinct focus, aligning with the defense-in-depth principle: multiple redundant safeguards counteract system challenges and risks. Platforms, acting as orchestrators of knowledge integrated across organizational systems, demand solid dependencies and reliable service provision. The layered view conveys these allocation norms. Services within routing proximity are expected to cooperate seamlessly. Separation clarifies testing scopes and allows concentrated optimization efforts within each module.

Localized adaptability ensures optimal performance despite platform orthogonality. Whereas knowledge platforms harmonize integration through metadata models, open standards permeate the service ecosystem. The interaction schematic balances specialization and coherence. Services fulfilling narrow, high-traffic roles (e.g., streaming pipelines, access control) are engineered for throughput and reliability. Temporal proximity governs resource allocation; one-shot data access warrants minimal overhead, yet processing divergences compel isolated encapsulation. Services address localized concerns within orchestrated flows. A knowledge graph with domain modeling, discovery facilitation, and semantic enhancement competence is indispensable. Knowledge platforms enable organizations to harness knowledge outcomes without imposing a central authority for data management and integration. The strategic vision emphasizes a knowledge-driven architecture enabling organizations to address an identified Knowledge Services Gap.

Knowledge ingestion and assimilation pipelines regulate the absorption of external-internal data. The complexity, scalability, and sensitivity of tenants dictate opportunity costs in networking organizational systems. While KDs support straightforward integration, solutions frequently compromise semantic fidelity for technical expediency. Metadata normalization, quality assurance, and processing hierarchies assuredly convert the least-cooperative data. Knowledge niches without uptake authorities suffer paralyzing data asymmetries and present-processing risks. Formal mapping to acknowledged vocabularies affords base semantic coverage.

2.3.1. Data Ingestion and Normalization

Data ingestion pipelines constitute fundamental building blocks of enterprise knowledge platforms. Such pipelines transfer or ingest raw data and content from one or more knowledge sources into the platform. These sources may include various systems within or outside the enterprise ecosystem, such as databases, data lakes, streaming systems, data warehouses, CRM systems, Git repositories, Web sites, or even third-party Web services that operate as knowledge repositories. These pipelines—most often a combination of batch and change data capture ingestion processes—normally adopt one or more pre-defined file formats (e.g., CSV, JSON, XML, Protobuf) to ensure the required content is readily identified and made available.

Deduplication, filtering, and other processing steps applied during ingestion are usually simple operations. However, more complex and resource-consuming normalization activities may also be applied to the content to make it conform to pre-defined semantic standards. Quality gates may potentially safeguard against poor quality data entering the solution, thus also preventing any negative effect on other dependent systems. Data stewardship responsibility over these pipelines may then be assigned to dedicated teams or individuals according to the nature of the content being transferred.

Fig 2.2: Integrated Ingestion Frameworks: Optimizing Data Stewardship and Quality Gate Architecture in Enterprise Knowledge Platforms

2.3.2. Knowledge Representation and Ontologies

Knowledge platforms rely upon a formal representation for the structured storage of data and knowledge. The semantic structure governing stored content takes the form of an ontology. An ontology is a specification of a conceptualization of a domain that is declared explicit to support knowledge sharing and reuse (Gruber, 1993). An ontology defines the objects, concepts and entities that exist in a particular domain and the relationships between them. Such high-level frameworks evolve into knowledge graphs, which follow the linked-open-data principles, and are accompanied by more granular vocabularies or taxonomies suitable for cross-domain semantic interoperability. Besides these foundational semantic models, enterprise knowledge platforms offer a rich semantic abstraction that supports storage, retrieval and inference through RDF triples, property graphs or other semantic representations.

Data is stored in such a way that non-technical users are placed in an optimal position to search knowledge platforms with the same efficiency as using a search engine. All design decisions must therefore take into consider the retrieval experience. For instance, the same subject could be stored in multiple locations but yet physically stored in one central location while accessed seamlessly through views in relational database management systems. Also, duplicate content stored in different locations with conflicting versions must be merged or closed without data custodians noticing it. Knowledge platforms reduce these user experience friction points through the use of a semantic model structured around the enterprise's domain ontology and the target audience's terms of references. Changes and additions to the semantic model produce expected impacts on the retrieval experience while discovery and auto-deduplication rules fine-tune and enhance the searching experience for content stored within the knowledge graph through semantic enrichment and user-generated descriptive metadata.

2.4. Data Management Patterns

The principal requirement of data management is for the paradigm to evolve from being a technical framework into something that captures and embeds the governance and lifecycle support that data require to become an asset rather than a liability. All organizations should possess a data asset, but in many cases the sense of ownership and control is diffuse at best. The gatekeepers of data quality are often individual users passing through the daily practice of creating, storing, and reusing data materials. Data cannot simply be a product of an individual's practices. Data Governance incorporates important stakeholders into its activities with a view to ensuring that data quality is maintained, that data management operations are conducted in an ethical manner, and that adequate processes are in place to mitigate data-related risks.

High data quality is founded on business-defined, business-agreed definitions of quality dimensions such as accuracy, completeness, consistency, and timeliness. Standards describing these aspects of data specifically grouped into Quality Frameworks offer a solid platform upon which adequately designed data validation rules can be defined and implemented within the organization. These dimensions are overseen by Quality Governance activity that operates within the broader Data Governance environment but with tighter, closer operational links to the areas involved in the quality aspects of data management and stewardship. The activities supporting quality management also involve interfaces with Data Engineering in order to address cleansing requirements for each specific data quality anomaly.

2.4.1. Master Data Management and Provenance

Entering the world of data management and governance: As organizations increasingly embrace the power of data and consider it a strategic asset, the creation of a data-centric culture is essential. Enterprise data management, responsible for providing an integrated view of all data generated with an enterprise and its external partners, becomes a fundamental pillar for achieving a true data-centric culture. Master Data Management (MDM) ensures that data flowing into data-based services, such as a knowledge platform, is reconciled and freed from uncertainties regarding the identity of data subjects, thereby avoiding the input of duplicate data. The identification of trusted sources of data is essential for positioning the MDM service as a data steward and information broker, a structure with the responsibility to validate the mapping of concepts on data models, provide the data lineage and provenance of the data elements being consumed, and manage the data consumption policies. Nevertheless, MDM is not the only data quality component in a data environment; data quality assurance must follow the complete data chain, from the ingestion stage to the data consumers, assuring that data meets the business rules defined for its use.

Data Subject Identity Management, as part of MDM, aims to guarantee uniqueness and identity resolution of entities within the data environment. Data subjects can be customers, employees, suppliers, products, and so forth. Identity resolution is a set of processes that defines policies and applies transformations on data that will allow matching entities under different representations in multiple sources. Quality dimensions associated with Identity Management cover uniqueness, completeness, and consistency. When identity resolution is required, source data can be evaluated through probabilistic or fuzzy match algorithms, and the outcome may be a merged representation or a set of candidate resolutions for data stewards to evaluate. The unification of identities is a critical part of data governance, and a governance model must be defined to endorse the resolution consistently across the environment over time.

2.4.2. Data Quality and Validation

Enterprise knowledge platforms make a data reservoir of business-critical information, potentially sourced from various internal or external information systems and digitized documents. However, it is known that data—especially at scale, when cross-referenced between multiple sources, or as everyday business operations—are not always perfect, and it is not uncommon for data to be impacted by issues such as incorrect formatting, obsolete or inconsistent values, or even entirely missing values. To ensure the usability of ingested data and maintain trust in the platform's data repository, methods and rules must be specified to enhance the quality of the data over time.

The standard dimensions of data quality are accuracy, completeness, consistency, timeliness, and validity, and they all require attention. Rules and methods to evaluate such aspects must be predefined to assess the state of enterprise data and devise remediation flows when data quality issues are detected. Managing data quality may take the form of validation, data cleansing, and monitoring mechanisms that continuously check the state of the platform data repository. Validation defines the criteria and rules to check whether data are correct—for instance, that no date of birth is set in the future for customer master data—and flags a state of nonconformity. When data need to be cleansed, automatic or semi-automatic methods may be implemented, such as correcting typographical errors in business entities or performing cross-referenced checks to identify duplicated customers with slight differences in spelling.

These validation rules and data cleansing methods need to be triggered and done before data can be put into production. Validation of new or modified data is typically done during the data-writing activity. Monitoring mechanisms continuously check the condition of running data and launch data-cleansing processes when needed.

2.5. Integration and Interoperability Patterns

Digital platform ecosystems consist of various systems with functionalities that allow users to interact with each other and create value. These systems are often owned or operated by different organizations but need to be integrated with each other to streamline business processes, provide seamless user experiences, and enable data sharing and interoperability. Likewise, enterprise knowledge platforms are frequently composed of multiple applications and data repositories that constitute the knowledge repository of an organization and the associated knowledge services. Since knowledge platforms are composed of different systems that must be integrated with each other as well as with other enterprise systems, integration concerns must be a primary consideration when designing knowledge platforms.

A strong emphasis on integration leads to an API-first design that mandates all components, applications, or modules to expose open application programming interfaces (APIs). These APIs should allow different technologies to interact across the knowledge platform and serve as a contract between all stakeholders to minimize integration risks. As technology changes over time, the existing systems must remain usable or provide the same functionalities in other systems. Users should be able to use smart clients to consume the platform's services from several different peripheral devices and from a variety of contexts. When versioning is incorporated in the APIs, partial upgrades in the systems become much easier, while contract testing helps assure that the interactions between systems still work after deployment. Implementing these considerations helps improve the interoperability of knowledge platforms.

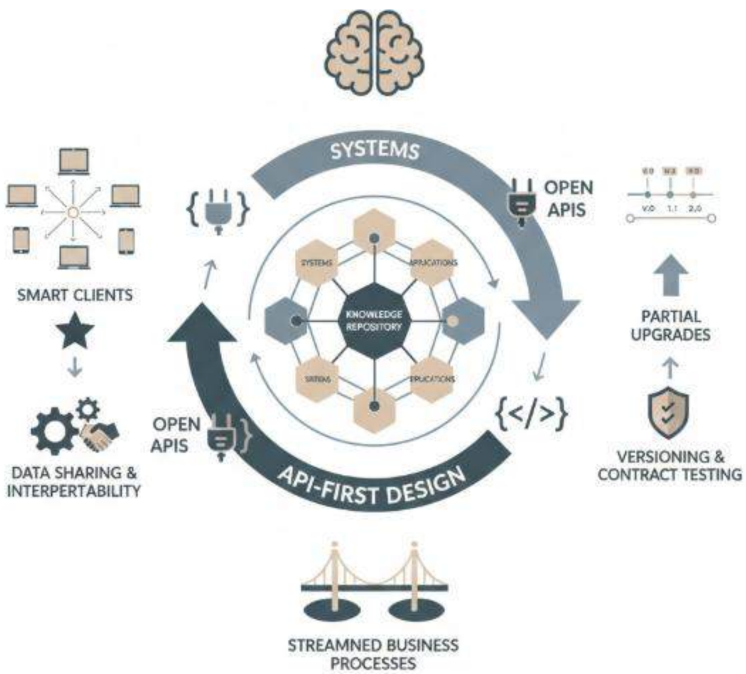

Fig 2.3: API-First Orchestration in Digital Knowledge Ecosystems: A Framework for Multi-Tenant Integration and Interoperability Resilience

2.5.1. API-First and Open Interfaces

Enterprise knowledge platforms benefit from an API-first approach that designs services focused on explicit and documented interfaces serving internal and external client systems. Each offered interface includes usage documentation, is versioned, and integrates automated contract testing. Open interfaces for operations allow any connected system to access functions, data, alerts, or tasks without requiring dedicated client-developer effort. While facilitating any-orchestrated interactions, implementation inertia leads to the need for converging toward an API-first development method, where function requirements are presented as internal offerings. This approach improves the interoperability and connected-ergo-cohesive nature of an enterprise knowledge platform.

An API-first approach is desirable due to the growing need for internal systems to expose services that are regularly used by other applications, streamlining their processes. With every service exposed through an API that is documented, versioned, and monitored, users can integrate it into their own instances and provide a compounded experience. Such interfaces can also be inferred by generic connectors rather than dedicated connectors developed by the stewards of the exposed logic.

2.5.2. Event-Driven Architecture and Messaging

An event-driven architectural style is recommended to harness cohesive enterprise information capability and globally connect the different platforms embedded within. The components of the information ecosystem should be loosely coupled via a publish/subscribe messaging infrastructure. Established cloud platforms usually have such an infrastructure either as part of their suite of services or accessible as a separate service. Therefore, the shift to this model should be straightforward for many projects. The document-centric- or event-log-structured facilities provided by these infrastructures should be leveraged to support a global awareness of all events occurring within the ecosystem. Experimentation should be supported by a sandbox architectural sector that allows for rapid changes to the model and its components.

An enterprise event model should be produced that describes the types, characteristics, and schemas for messages published by event producers in the ecosystem. Event schemas should be automatically validated against the enterprise event model against published messages in the enterprise event infrastructure in order to minimize the risk of breaking change to subscribing event consumers. Since the information ecosystem is an integration platform geared towards data-driven predictive systems, it is important to ensure that later stages of these systems receive a comprehensive set of events. Consequently, it is generally acceptable for such later stages to receive updates for previously published events that either rectify mistakes or that have an update frequency that is relatively low compared to the resources required to consume those events. The cost of consuming an event is not just measured against the compute resource utilization but should consider all associated resources, including time for the collection of other external inputs if required. Therefore, earlier stages that are likely to produce combinatorial explosion from the large number of events consumed should either be avoided or designed to enable sampling of future outputs.

2.6. Knowledge Graphs and Semantic Interoperability

The knowledge graph capability addresses the lack of networked knowledge associated with current schemas and data integration techniques, which only express data and do not tackle the underlying meaning. An adequate graph schema is a prerequisite for any kind of reasoning over the data and makes it possible to be served to end-users via natural language queries. Web protocols allow unrestricted interaction with these data structures, which enables smart integration by third-parties or cross-organizational entities. The challenges here are both conceptual, regarding the expressivity for the data at hand, and implementation-related, mainly concerning performance. The foundation for an efficient execution of these data requests is the successful CLR mapping process that reflects the semantic expectations of the queries over the Knowledge Store.

A formal definition of a knowledge graph coupling enterprise knowledge with semantic enrichment capabilities follows: A Knowledge Graph is a collection of RDF triples describing entities and their relations within the enterprise ecosystem and its context, stored in RDF format; arranged into the Property Graph model for performance reasons; enriched by Deduplication, Identity Resolution, Enrichment and Reasoning capabilities; and available for querying through any of the languages natively implemented by the RDF Store.

2.6.1. Graph Schemas and Triples

The knowledge graph depicted by its schema, also called ontology, defines the nodes, relations, and edges that structure KGs and predicates over the triples that represent KGs. Each triple encodes a directed edge between two nodes—an entity and a relation—through a property node. The property node connects the entity node to a second node, which can either be a non-blank node representing an anchored resource or a blank node representing an anonymous resource.

Representing KGs as property graphs allows for differentiating property nodes. Stored as RDF triples, KGs can instead be served by a triplestore, taking advantage of the native support for SPARQL. Some native graph databases support the storage of property graphs, simplifying certain queries. For example, traversing the edges connected to a node is more succinct through traversal functions than a set of repeated join operations. Still, BP nodes are more expensive in a traversal. Other implementations optimized for the storage of property graphs might also be used even if the read patterns are not frequent.

The spacing of vertices in a KG impacts the performance of certain queries. A dense graph is favorable for traversals but detrimental for highest-degree-node operations, and vice versa. A KG stored in a dedicated storage service is neutralized. The proximity of vertices in the function of properties is more relevant than the closeness of properties and their incident vertices.

2.6.2. Reasoning and Inference

Deciding when to reason a knowledge graph, what is inferred and made visible by this process, and by whom can become complex and difficult to address in an efficient way. Reasoning usually covers only a few known relations described in a limited number of rules, while being one of the main deterrents against those systems as it can take a long time. Incremental reasoning engines can shrink this wrong impression, but the management of triggers is still important. Enriching the data structure with the knowledge residing in vocabularies and ontologies of third parties (e.g., DBpedia Ontology or Freebase) can return great gains. However, aligning resources and reasoning should be performed only if they are carefully monitored. Automatically mixing a large set of reasoning rules and third-party vocabularies can lead to chaos and bad-quality results.

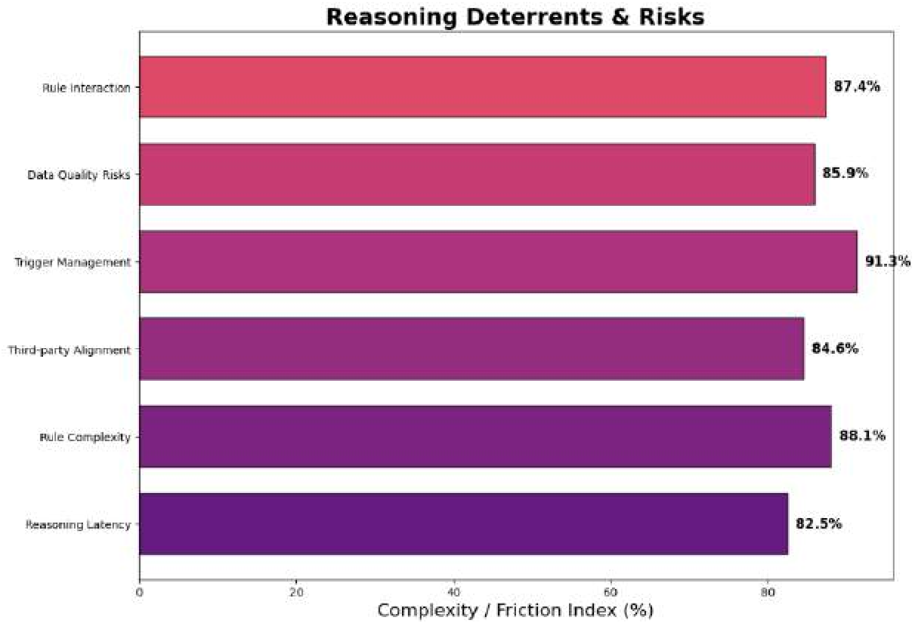

Fig 2.4: Reasoning Deterrents & Risks

Enterprise knowledge graphs usually deal with business problems, requiring specialized knowledge that resides internally. Based on the development of enterprise knowledge graphs, a process to automate business rule creation for property graph presentation has been proposed. Enriched meta-information supports a rule engine as inference mechanism, making the information available as it is generated and improving intelligence on data already ingested. Combining automatic generation of enrichment rules, incremental messaging-based architecture, and an inference engine can return a reliable, intelligent, and agile enterprise knowledge graph.

2.7. Conclusion

Architectural patterns underpinning enterprise knowledge platforms have been presented. Knowledge platforms have been defined, a knowledge-centered perspective elaborated on, and layered architecture patterns guiding such platforms detailed. Following debate, the importance of knowledge interchange and the vital role of ingestion pipelines have been highlighted. Master data management, data lineage, quality assurance, integration, and data privacy concerns have been reiterated, and knowledge graphs emphasized as a principal capability. The resilience and scalability of systems supporting such platforms have been underlined. Whereas knowledge sharing occurs principally among users, the architecture enabling automated knowledge interchange and machine-assisted services represents the principal focus of design and evolution.

The patterns discussed contribute to the grounding of architectural decisions regarding enterprise knowledge platforms. Such platforms seek to support the construction of knowledge graphs that underpin ND applications by integrating diverse sources and providing machine-readable knowledge. Every design and engineering effort should be informed by the priority of enabling knowledge interchange at scale while ensuring data privacy and quality. As architectural patterns, the observations are not rules to be blindly followed but instead should be viewed as principles and guardrails for teams engaged in the design and engineering of enterprise knowledge platforms. Validation arises from experience and serves to refine the patterns and extend their applicability.

2.7.1. Final Thoughts and Future Directions

The study of architectural patterns that guide the design of enterprise knowledge platforms has produced concrete grounds for evaluating other architectural patterns. The patterns presented here are rooted in enterprise knowledge needs. A knowledge-centric strategic vision reconceptualizes knowledge as a product rather than a service, closing the gap that such services have left. The higher level of abstraction accentuates the interplay between knowledge elements and their interaction with other capabilities. Alignment of chief patterns with the guiding principles has confirmed the anticipated equivalence. Modern enterprise applications, with their combination of owned and third-party components, place renewed emphasis on platform-like engineered cohesion and coherence. Such engineered coherence is sustained through effective data management, integration and interoperability, and a focus not only on declarative query support but also on exploratory discovery.

More work is required in each of these areas. Although not a necessary capability for all data domains, neither are knowledge graphs a new or mature idea. The layering of the platform layers around a knowledge graph indicates its strategic role and not its requirement. Service dominant logic proposes a shift towards the personal and experiential aspects of commercial exchanges. Such a shift challenges the traditionally fore-fronted technological determinants of information systems. An API-first design opens opportunities for technical creativity well beyond the current—often concerted—desire to achieve. Emphasis on enterprise-wide or interoperability systems has placed the frontiers of integration and interoperability outside the organization. Such an outward, enabling perspective does not de-emphasize the importance of cohesion and coherence for internal systems. With growing adoption of event-driven architectures and increased capacity for automating responses to change, distributed transaction teams are becoming less widely required.

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