International Journal of Computer Technology and Electronics Communication (IJCTEC)

| ISSN: 2320-0081 | www.ijctece.com | A Peer-Reviewed, Refereed and Bimonthly Journal|

|| Volume 5, Issue 4, July– August 2022 ||

DOI: 10.15680/IJCTECE.2022.0504007

Knowledge-Centric Architecture for Contextual Information Retrieval and Governed Digital Service Operations

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ABSTRACT: Digital interaction underpinning diverse services is intrinsically digital by nature. Hence, users and service providers may be perceived as part of a digital interaction. The digital experience of a user across disparate digital service interactions should ideally be governed and centrally controlled in order to maintain seamless contextual consistency. Governance-based modelling of contextual control of public digital service operations proposes an architecture for contextual contextuality-mediated contextual consistency and governed operations. The architecture is supported by evidence from ongoing digital transformation initiatives and view on fulfilment of the knowledge-centricity principle during contextual information retrieval processes, supported by an appropriate approach for sensing and representation of context.

Digital reliance on diverse services in day-to-day life is on the rise. Users can be seen as experiencing digital transformations across different domains managing public and private digital service interactions. Digital interactions are media for service facilitation that can be termed governed digital service interactions. Sense and respond economic control is a requirement for governed digital service operations. Users' perceived trustworthiness of individual digital service operations depends on their satisfaction with respective interactions, whereas contextual consistency across all digital service operations is moderated by governance. Therefore, the gradual evolution of any digital service ecosystem is a necessary condition for governed digital service operations.

KEYWORDS: Knowledge-Centric Architecture, Contextual Information Retrieval, Knowledge Graphs, Semantic Search, Digital Service Operations, Data Governance, Intelligent Knowledge Management, Context-Aware Computing, Service Orchestration, Governed Information Systems.

I. INTRODUCTION

Digital service operations are governed and executed by an evolving set of contextual information from multiple sources. Failures in achieving the desired states and outcomes of such operations may occur when the required contextual information is not sense-checked and retrieved. The outlines of contextual information retrieval mechanisms, an enabling aspect integral to governance in digital service operations, are therefore formulated. Context-sensing capabilities can assess the availability and readiness of pertinent contextual information, while a knowledge-centric approach enables the construction of search and access requests, including for contextual information stored in a federated manner. The systemic implementation of contextual information retrieval mechanisms also ensures the resilience of digital service operations by triggering their execution based on unnecessary conditions. Resulting knowledge-centric architecture features unique elements positioned within a comprehensive context-sensing framework.

In typical environments for digital service operations, a multitude of contextual information is indigenous. Yet digital service operations are often constrained because requisite contextual information has not been sense-checked and retrieved. Such contextual information is inherently costly and impractical to store in all relevant local sources. Without suitable context-sensing capabilities or mechanisms for accessing remote information stores, the retrieval of requisite contextual information relies on the service operation's awareness of its availability and readiness within the same local context, akin to executing the same query on different underlying databases. Such limitations culminated in severe failures during the COVID-19 pandemic, when operations of unparalleled scale were conducted under unprecedented conditions for which all requisite contextual information could not be specified in advance. Contextual-information-retrieval mechanisms mitigate these constraints, enabling the planned digital service operation to execute autonomously without regard to the status or quality of redundant information.

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Sufficiency of Knowledge within a Context is a perspective on Context-Sensitive Information Retrieval that proposes that the information deemed relevant to a particular task may have been located not because of a query but because it was available to the user when registering stimuli and exploring information. The need for CSIR applications arises most notably when users handle complex information-processing tasks with associated activities having high-level information needs, supported by other actors, and accessible in resources currently under active use. Context-sensitive information-retrieval applications are much more complex than other Information Retrieval applications due to the overhead in knowledge gathering and knowledge processing. The concept may be seen as an extension of natural-language processing and knowledge-based systems, with considerable achievements made in both fields, suggesting that an adequate resource for the CSIR concept can be generated with appropriate support for knowledge acquisition, representation, and reasoning.

Table I — Comparison of IR Paradigms (qualitative, for insertion as related-work table)

Dimension	Traditional IR	CSIR	Knowledge-Centric IR (proposed)
Context awareness	None	Task/activity-level	Full (sensed + reasoned)
Knowledge reasoning	None	Limited	Ontology/knowledge-graph based
Governance alignment	Not addressed	Not addressed	Embedded via constraint (3)
Query complexity handling	Keyword matching	Moderate	High (federated, semantic)
Scalability (as commonly reported)	High	Moderate	Domain-dependent

A. Governance in Digital Service Operations

Operations in digital service delivery context can significantly benefit from governance mechanisms to align demand fulfilment with enterprise policies, thereby minimising risks in service provision. Like just-in-time delivery projects, effective resolution requires response time for postponed governance checks to be acceptable to internal stakeholders. A governance framework realises these principles by implementing authorisation and trade-off checks using enterprise knowledge to mitigate operational risks in fulfilling incoming requests.

Digital services constituted by explicit or implicit asynchronous transactions are typically provided with service level guarantees. Destination organisations or individuals are seldom the original service request originators. Instead, internal stakeholders raise such requests which may bypass normal service fulfilment routing because of perceived urgency, non-conventional request characteristics, or special customer status. Destination service delivery organisations thereby assume the onus of making self-serving decisions that may have substantial ramifications for the organisations, the request originators, and the original service provider. The consequences of such unregulated decisions in fulfilling incoming requests can be misaligned service behaviour and provisioning risk, for example reputational or financial. Therefore, a digital delivery operation governance mechanism is warranted to ensure alignment with enterprise governance policies for effective and responsible resolution of these requests.

Table II — Notation Summary

Symbol	Meaning
S(t)S(t)	Context-sensing function output at time tt
KCIKCI	Knowledge-Centricity Index
G(op)G(op)	Aggregate governance risk for operation opop
θ_{risk}θrisk	Enterprise risk threshold

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Symbol	Meaning
R(c)R(q,d,c)	Contextual relevance score for query qq, document dd, context cc
E_{CIR}ECIR	Contextual information retrieval effectiveness

II. CONCEPTUAL FOUNDATIONS

An evidence-based, objective, formal study examining two distinct theoretical dimensions. The first dimension addresses the exploration of Knowledge Centricity in Information Retrieval. Knowledge is conceived as a function of human cognition and experience, then explored as a source of knowledge in Information Retrieval, delineating the relationship between Information Retrieval and Knowledge Centricity while establishing a rationale for knowledge-centered Digital Service ontologies. The second dimension constructs a knowledge-centric Web Information Model for all digital services on the WWW. The basis of knowledge-centricity is the axiomatic design principles of Information Theory used to synthesize the WWW Information Model, expanded by other axioms for Knowledge-Centricity and supported by Digital Service Governance considerations. The exploration authenticates that the proposed Model and its extension fulfill the requirements for contextual Information Retrieval of Digital Service Operations. Hence, this Knowledge-Centric Approach for Contextual Information Retrieval is established.

Information Retrieval (IR) enables locating and returning information from a repository to users' query. Retrieval systems utilize algorithms to match query words with words in the information stored. IR result cannot be assumed to be contextual because they may include information that are not relevant to the user's context or need. By orders of magnitude, Google dominates IR, and hence context-based applied IR seems irrelevant. However, the real-world application of Google demonstrates societal need for accurate context-sense systems and for a context-sensitive web information model. Such limitations of context-sense have attracted focus on the exploration of Knowledge Centricity in Information Retrieval.

Table III — Architecture Layers

Layer	Primary Function	Key Artifacts
Governance	Policy/risk authorization	Constraint (3), enterprise policies
Knowledge-centric reasoning	Ontological inference	Knowledge graphs, ontologies
Context sensing & representation	Capture dynamic context	param.sens, context vectors C_tCt
Contextual information retrieval	Query formation, federated access	Relevance score (4)
Digital service operation	Execution	Sensor data, service metadata

A. Knowledge-Centricity in Information Retrieval

Context-Sensitive Information Retrieval (CSIR) applications concentrate on finding relevant information automatically for a given task or activity in addition to for a specific user. Context-sensitive Information Retrieval (CSIR) applications are much more complex than other Information Retrieval (IR) applications due to the overhead in knowledge gathering and knowledge processing. The concept of CSIR may be considered as an extension of natural language processing (NLP) and knowledge-based systems. Considerable achievements can be noticed in the fields of NLP and knowledge-based applications. Therefore, the concept of CSIR can be successfully addressed in future CSIR applications with adequate support in knowledge acquisition, representation, and reasoning. Problem-specific or task-oriented information needs, rather than personalized, have led to the popularization of context-sensitive information access systems. These systems may be termed CSIR systems because the goal is to find task-specific information precisely.

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III. ARCHITECTURAL PRINCIPLES

An architecture or systems conception embodies a structured solution to meet the requirements of a real-world characteristic or class of problems. Governing digital service operations requires an Information Technology (IT) architecture focusing on contextual information retrieval and governing digital service operations. The architecture is centred on information models that define the information needed to manage digital service operations, capturing both the data requirements for managing the life-cycle execution of a specific service (typically called the Service Operating Model) and the data required to manage projects associated with that service. To be effective, the architecture must derive contextual information required during the execution of a specific service operation and govern that operation.

A Knowledge-Centric Information Retrieval and Operation Governance Architecture supports contextual information retrieval and provides the information needed to govern the operation. The governing requirements of a specific service operation are encapsulated within a formal inequality that provides the operational governance constraint under which the service is being executed. Information representing the state of the world is provisioned from sensor information and digital service operation metadata within the service operation context. Knowledge-Centricity enables contextual information retrieval by reason over recorded digital service operation artifacts, identifying states of the world for which analogous digital service operation artifacts exist and exposing them as additional sources of information within the specified context.

Mathematical Formulas:

(1) Context-Sensing Function (formalizes Section 4.A)

$$S(t) = f(C_t, E_t, \Delta t)$$

S(t)=f(Ct, Et, Δt)

where C_tCt is the context-parameter vector at time tt, E_tEt the environment-state vector, and ΔtΔt the sensing interval.

(2) Knowledge-Centricity Index

$$KCI = \frac{\sum_{i=1}^{N} w_i K_i}{\sum_{i=1}^{N} w_i},\ 0 \leq KCI \leq 1$$

KCI=∑i=1Nwi∑i=1NwiKi,0≤KCI≤1

where K_iKi is the degree of knowledge-grounding of information source ii, and $w_i$wi its relevance weight.

(3) Operational Governance Constraint (formalizes the "formal inequality" referenced in Section 3)

$$G(op) = \sum_{j=1}^{m} \lambda_j\, r_j(op) \ \leq\ \theta_{risk}$$

G(op)=j=1∑mλjrj(op) ≤ θrisk

where $r_j(op)$rj(op) is the risk contributed by policy dimension jj for operation opop, λ_jλj its weight, and θ_{risk}θrisk the enterprise risk threshold.

(4) Contextual Relevance Score

$$R(c) = \alpha \cdot sim(d) + \beta \cdot match(c, ctx(d)),\ \alpha + \beta = 1$$

R(q,d,c)=α·sim(q,d)+β·match(c,ctx(d)),α+β=1

(5) Contextual Retrieval Effectiveness

$$E_{CIR} = \frac{|\ Retrieved \cap Relevant \cap ContextValid\ |}{|\ Retrieved\ |}$$

ECIR=|Retrieved||Retrieved∩Relevant∩ContextValid|

A. Information Models and Ontologies

The e-Services and e-Governance Domains contain inherently complex Structures and Processes that require a deep understanding for their proper construction and support, especially since they have become indispensable Infrastructure for the functioning of Societies and Economies. Such e-Service Systems inter-operate at all Levels in any Economy and

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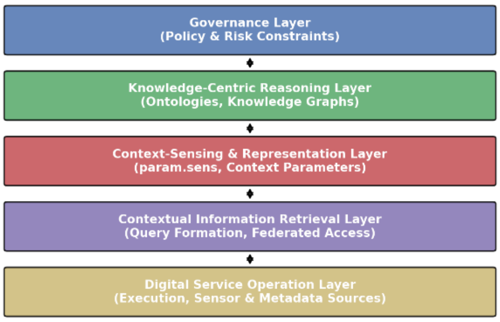
Society; i.e., Local, State or Regional, National, International or Trans-national. Their proper Working is dependent on the Quality of the Information they deal with, and thus requires Governance at all Levels.
The Knowledge-Centric Digital Architecture and its Infrastructure suggest a way to fulfil the Governance and Quality-of-Information Requirements at all Levels in the Digital Support of Societal Structures and Processes. In the Digital Services and E-Governance Domains, the Knowledge-Centricity Aspect introduces specific Quality Considerations for the Quality of Information, as well as its Modelling and Representation for Contextual Retrieval in a Sensed Context. The Information Models and Ontologies required for Contextual Retrieval based on Actual Attributes of Context and represented using Relevant Information Models or Ontologies can be captured in Ontological Structures distinct from those directly serving e-Governance and Digital Service Operations but still Required by them.

Fig. 1. Conceptual Layer Stack of the Knowledge-Centric Architecture (illustrative)



IV. CONTEXTUAL INFORMATION RETRIEVAL MECHANISMS

Space and resource constraints in printed publications often lead to the omission of substantial details, including the presentation of operational mechanisms and actual implementations. Omissions can be easily remedied in electronic publications. This section follows section 3, which presented the conceptual foundations of contextual information retrieval. The foundation is now mined via code generating routines governed by natural language descriptions at varying levels of detail.

Information retrieval remains a knowledge-centric problem. Current solutions to information retrieval initiate their information-capture phase by repurposing core Internet infrastructure and harvesting documents in its entirety. These documents are index-represented and coarsely associated with highly refined ontologies. A set of processed document collections is freely made accessible and, through the same infrastructure, served to information seekers. Information seekers are usually humans and often converse with computer-based agents. Their explicitly stated information queries are transformed into search queries that take the form of consecutively inspecting the core subset-collection of index-represented documents, and their coarser search queries take the form of giving direction to dedicated agents that search over their entirety without directly looking into them.

Current solutions are therefore best suited for traditional keyword-based commercial search, where computation speed and aggregate result set size are the two most valued attributes by both advertising sponsors and Internet users searching for consumer offers. In the Information Age, information retrieval must address a social need, and the search domain must be shaped in support of the entire digital society. This realization has led to an emerging new direction for information retrieval; it is the development of contextual search engines. In this new style of engines, a third party actively gathers and represents the semantically valuable content of the Internet that the third party feels society needs. Such a contextual search service is what all educational institutions should offer.

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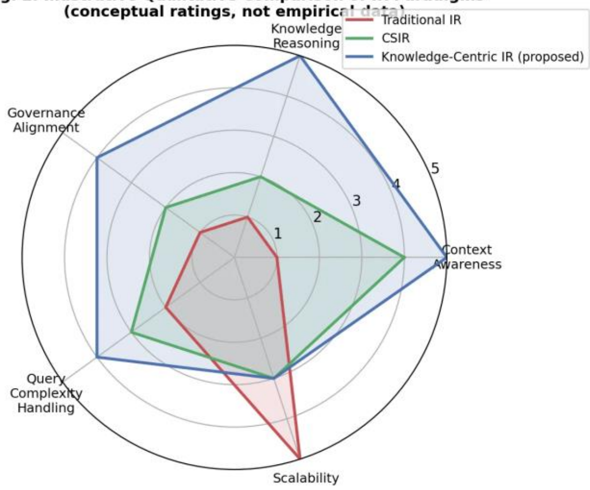


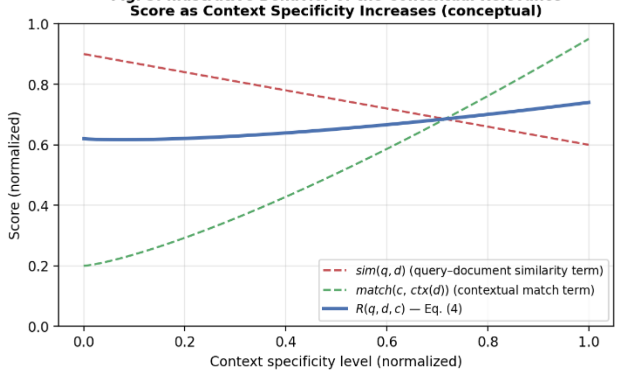
Fig. 2. Illustrative Qualitative Comparison of IR Paradigms (conceptual ratings, not empirical data)

A. Context Sensing and Representation

Context-awareness is fundamental for digital service operations and plays a crucial role in the contextual information retrieval process. Context information is often expressed as a collection of context-sensitive parameters chosen for a particular purpose. Nevertheless, context-sensitive parameters are insufficient to capture dynamic state changes accurately and expressively. Therefore, concepts of sensitivity or selection may be extended and formalized to capture dynamic-changing contexts from context-sensing sources.

A context-sensing function S can be defined over a dynamic context parameter space S as temporal, situational, and temporal–situational environment changes in a domain of interest affected continuously or discretely by other variables in the environment. The definition supports the contextual information retrieval process and expands knowledge space, thereby enhancing total contextual information retrieval and Digital Service lattice operation processes. For practical implementation, a context-sensitivity ontology (param.sens) can be specified to define context sensitivity for models, knowledge, and resources. Context-sensitivity parameters can be combined with context-sensing parameters into a context representation parameter set that supports the function scope of information retrieval.

Fig. 3. Illustrative Behavior of the Contextual Relevance Score as Context Specificity Increases (conceptual)



V. CONCLUSION

The presented Evidence-Centric Information System (ECIS) foundation promotes the effective retrieval of contextually- and situationally-relevant information to support the operation and governance of digital services. An ECIS integrates syntactic and semantic capabilities to sense and retrieve the information that users seek, that users are likely to need, or that is required for the proper operation of a system or the response to an event. Contextual information retrieval is facilitated by proper information models, data, and ontologies that support the operation of contextual information retrieval mechanisms.

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Contextual information retrieval mechanisms rely on a range of data and context models and ontologies to prepare a set of contextually- and situationally-relevant information at the time and upon delivery of an event. The knowledge-centric architecture, based on an evidence-centric information system, promotes the effective retrieval of information for supported digital service operations and their associated governance across the service-oriented enterprise.

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