AUGMENTED REALITY ENABLED KNOWLEDGE MESH

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In response to the evolving demands of knowledge management in complex environments, current systems face challenges in delivering real-time, context-aware knowledge. This work extends the principles of Data Mesh into the knowledge domain, introducing the concept of a Knowledge Mesh that fosters decentralization, knowledge democratization, and self-service infrastructure. The contribution centers on integrating Augmented Reality (AR) with Knowledge Product Contracts, utilizing Augmented Reality Markup Language as metadata to facilitate dynamic knowledge discovery and interaction. Leveraging GraphDB for ontology-driven management, the proposed framework supports AR-enhanced 3D knowledge visualizations while enriching ontologies with AR capabilities. These advancements significantly improve knowledge interoperability across industrial processes, enabling real-time knowledge integration and visualization.

Keywords: ARML (Augmented Reality Markup Language), XR (Extended Reality), Knowledge Product Lifecycle Management (KPLM), SPARQL (Protocol and RDF Query Language), Heritage Building Information Modelling (HBIM), SIFT (Scale-Invariant Feature Transform).

1. Introduction

In the digital transformation era, effective knowledge management is essential for organizing and utilizing information. The Knowledge Mesh framework, inspired by the Data Mesh, promotes domain-oriented ownership, decentralization, and interoperability of knowledge across organizations, enabling data democratization and self-service. Integrating Augmented Reality (AR) enhances this framework by making knowledge management immersive and interactive. AR allows users to visualize and interact with complex data in real-time, turning knowledge into actionable insights and creating a more intuitive experience.

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Interlinked spatial knowledge graphs are emerging as key tools for managing knowledge in decentralized systems. McEachen and Lewis [1] emphasize the importance of ensuring interoperability and managing dependencies for seamless knowledge sharing in distributed environments. Knowledge Meshes build on this by enabling flexible connections across domains while promoting self-governance and discoverability.

Dragoi et al. [2] emphasize the importance of Knowledge Management governance in virtual enterprise networks, highlighting how the PREMINV e-platform introduced by POLITEHNICA Bucharest supports real-time knowledge exchange and collaboration, ensuring effective governance across autonomous enterprises.

Surface mesh-based models, as demonstrated by Yang et al. in HBIM [3], show how 3D models can represent semantic information linked to physical objects, aligning with AR-enhanced Knowledge Meshes. Yan [4] also introduced knowledge meshes to support complex relationships, but integrating AR for enhanced discoverability remains underexplored.

With advancements in XR, as highlighted by R. Doerner et al. [5], AR is increasingly integrated into industrial systems for real-time visualization, paving the way for AR-driven Knowledge Meshes that enable interactive, 3D knowledge visualization.

An assessment of the relevance of AR and its impact on learning is adressed to mechanical engineering training by Scaravetti and François [6], a model-based approach to support AR-assisted product configuration based on the concept of Dynamic Software Product Lines is proposed by Gottschalk et al. [7], and a digital, mobile, flexible, and scalable solution, designed for pedagogic applications, allows to interactively design and engage with AR content [8].

A mathematical knowledge model of the product representation was developed by introducing a conceptual framework, implicit constraints and reference elements, as well as an outline model and case study [9].

The performance of major developments can be evaluated based on the definition and calculation of specific Key Performance Indicators [10, 11].

We explore the innovative integration of Augmented Reality (AR) within the Knowledge Mesh framework, extending Data Mesh principles to knowledge management. We also elaborate on how AR-enabled interfaces can revolutionize the creation, discoverability, and utilization of knowledge products in decentralized, self-service infrastructures.

2. Knowledge Mesh Architecture and Lifecycle Management

The Knowledge Product Lifecycle Management (KPLM) framework ensures that knowledge assets are governed, maintained, and utilized effectively within an organization. At its core, a Knowledge Product is a structured unit of a business domain specific knowledge that encapsulates technical, business, and regulatory metadata. The lifecycle includes creation, governance, maintenance, and utilization, with clear policies guiding its management.

A Knowledge Product is a well-defined unit including: core content - the actual knowledge, such as procedures or insights; metadata - information like source, ownership, and creation date; compliance data - regulatory and legal requirements; technical specifications - how the knowledge interacts with systems and processes. Each Knowledge Product is accompanied by a Knowledge Product Contract, detailing its structure, dependencies, and access controls.

The YAML schema, as presented in Fig. 1, reflects the key components of a Knowledge Product Contract, such as core content, metadata, compliance, and technical specifications.

```yaml
KnowledgeProductContract:
  knowledgeProductId: string           # Unique identifier for the knowledge product
  name: string                         # Name of the knowledge product
  description: string                  # Brief description of the knowledge product
  version: string                      # Version of the knowledge product
  createdDate: date                    # Date of creation
  modifiedDate: date                   # Date of the last modification
  owner:                               # Information about the owner of the knowledge product
    name: string                       # Owner's name
    role: string                       # Role of the owner in the organization
    contactInfo:
      email: string                    # Email of the owner
      phone: string                    # Phone number of the owner
  steward:                             # Information about the steward responsible for managing the product
    name: string                       # Steward's name
    role: string                       # Steward's role in the organization
    contactInfo:
      email: string                    # Email of the steward
      phone: string                    # Phone number of the steward
  metadata:                            # Metadata related to the knowledge product
    tags:                              # List of tags for categorization
      - string
    categories:                        # Categories that the knowledge product falls under
      - string
    lineage:                           # Lineage information tracing origin and evolution of the knowledge
      source: string                   # Source of the knowledge (e.g., system, document)
      versionHistory:                  # List of versions and modifications
        - version: string
          modifiedDate: date
          modifiedBy: string
          description: string
  ...
```

Fig. 1. Knowledge Product Contract example

In the Knowledge Mesh paradigm, Knowledge Products serve as central units of value. Effective lifecycle management ensures these products remain accurate and accessible, supporting data democratization and informed decision-making across the enterprise.

The Knowledge Product Contract, KPC, can be modelled as a directed labelled graph.

Let be a directed labelled graph, G_K, representing KPC with incoming and outgoing dependencies,

$$G_K = (V, E, D_{in}, D_{out}) \tag{1}$$

$$V = \{ v_i \mid i = 1, 2, \dots \}, v_1 = v_{KPC}, v_2 = v_{Metadata},$$
$$v_3 = v_{ComplianceData}, v_4 = v_{ARML}, v_5 = v_{Owner}, v_5 = v_{Steward}, \dots \quad (2)$$
$$E = \{ e_{ij} \mid e_{ij} = (v_i, v_j);\ i, j = 1, 2, \dots \}, (v_1, v_2) = (v_{KPC}, v_{Metadata}),$$
$$(v_1, v_3) = (v_{KPC}, v_{ComplianceData}), (v_1, v_4) = (v_{KPC}, v_{ARML}), \dots \quad (3)$$

$$D_{in} = \{ d_{ini} \mid i = 1, 2, \dots \} \quad (4)$$

$$D_{out} = \{ d_{outi} \mid i = 1, 2, \dots \} \quad (5)$$

where:
- V is the set of vertices (nodes) representing the components of the KPC, i.e., each vertex v_i, $v_i \in V$, represents an entity, within the KPC, such as the Knowledge Product, Metadata, Compliance Data, ARML, Owner, etc.;
- E - the set of edges (relationships) between the KPC components, i.e., each edge $e_{ij}, e_{ij} \in E$, represents a directed relationship between two vertices v_i and v_j, which denotes that there is a relationship from vertex v_i to vertex v_j;
- D_{in} - the set of incoming dependency edges from other knowledge products, i.e., each dependency $d_{in\,i}$ is a directed edge from another knowledge product KP_i to the current knowledge product;
- D_{out} - the set of outgoing dependency edges to other knowledge products, i.e., each dependency $d_{out\,i}$ is a directed edge from the current knowledge product to another knowledge product KP_i.

The following elements are also noted.

Vertex label function, as $L_V: V \to Labels$, that assigns labels to the vertices, representing the type of entity, e.g.,

$$L_V(v_{KPC}) = \text{"}Knowledge\ Product\ Contract\text{"}, L_V(v_{Metadata}) = Metadata.$$

Edge label function, as $L_E: E \to Relationship\ Types$, that assigns labels to the edges, describing relationships between two vertices, e.g.,

$$L_E((v_{KPC}, v_{Metadata})) = \text{"}contains\ metadata\text{"} \quad (6)$$

$$L_E((v_{Owner}, v_{Streward})) = \text{"}is\ managed\ by\text{"} \quad (7)$$

In graph-theoretic terms, each KPC now exists within a larger knowledge mesh where the nodes, KPCs, are connected through dependency edges. This allows us to represent and track complex relationships between knowledge products. If a knowledge product KP_A depends on another knowledge product KP_B (e.g., for data input, business rules, or metadata), we introduce a directed edge: $d_{in} = (KP_B \to KP_A)$. This means that KP_A relies on KP_B to function, so changes to KP_B may impact KP_A. If a knowledge product KP_A serves as an input or resource for another knowledge product KP_C, we introduce a directed edge:

$d_{out} = (KP_A \rightarrow KP_C)$. This indicates that KP_A provides necessary information or functionality to KP_C.

The adjacency matrix A_{mesh} captures the entire dependency structure within the knowledge mesh, showing both internal relationships within a KPC and external dependencies between KPCs:

$$A_{mesh}[i,j] = \begin{cases} 1, & if\ there\ is\ a\ dependency\ from\ KP_i\ to\ KP_j \\ 0, & otherwise \end{cases} \tag{8}$$

Knowledge Modelling using OWL/ RDF

Knowledge Modelling is a fundamental aspect of modern knowledge management systems (KMS), enabling the organization of knowledge in a structured, machine-readable format. The Web Ontology Language (OWL) and the Resource Description Framework (RDF) are key technologies used for defining and managing these knowledge structures.

In OWL, an ontology is a formal specification of the entities (classes) and their relationships (properties) within a specific domain. Entities are represented as classes, while relationships between these entities are defined using object properties and datatype properties. This allows organizations to model knowledge in a standardized, shareable format as presented in Fig. 2.

```
@prefix ex: <http://example.com/ontology#> .

# Defining Classes
ex:Product rdf:type owl:Class .
ex:Customer rdf:type owl:Class .
ex:Order rdf:type owl:Class .

# Defining Relationships (Properties)
ex:placedBy rdf:type owl:ObjectProperty ;
    rdfs:domain ex:Order ;
    rdfs:range ex:Customer .

ex:containsProduct rdf:type owl:ObjectProperty ;
    rdfs:domain ex:Order ;
    rdfs:range ex:Product .
```

Fig. 2. Example of basic ontology creation in OWL/RDF

In this example, we define three classes: `Product`, `Customer`, and `Order`. The relationship between them is modelled through object properties like `placedBy` (linking an order to a customer) and `containsProduct` (linking an order to a product). These relationships allow the knowledge graph to represent real-world interactions within the domain.

Managing Relationships Across Knowledge Graphs Using RDF

RDF provides a powerful framework for managing relationships across knowledge graphs, allowing for the representation of complex interactions between knowledge entities. Each fact in RDF is represented as a triple: subject, predicate, and object. Relationships between entities can be modelled using object properties in OWL/ RDF, as presented in Fig. 3.

```
@prefix ex:
<http://example.com/ontology#> .

ex:Customer123 rdf:type ex:Customer .
ex:Order456 rdf:type ex:Order .
ex:Order456 ex:placedBy ex:Customer123 .
    rdfs:range sales:CatalogUpdate .
```

Fig. 3. Managing relationships across knowledge graphs

In this case, RDF triple (`Order456`, `placedBy`, `Customer123`) represents the fact that an order was placed by a customer. This simple structure allows for the representation of complex, interconnected knowledge across domains.

It is to be emphasized that Knowledge Modelling using OWL/RDF provides a robust framework for representing, managing, and integrating knowledge across business domains in a Knowledge Mesh.

3. AR Integration with Knowledge Mesh via Ontologies

Integrating Augmented Reality (AR) into a Knowledge Mesh environment presents a cutting-edge opportunity to enhance knowledge discovery and visualization through OWL/RDF ontologies. Ontologies, which define structured relationships between entities, can be extended to include 3D models and AR-enhanced knowledge representations, enabling users to interact with complex knowledge assets in real-time and within spatial contexts.

In the context of AR-enabled Knowledge Mesh, ontologies act as a semantic backbone that helps structure the knowledge being presented in AR. Each entity, whether it's a product, process, or document, is defined within the ontology, allowing AR systems to retrieve and visualize relevant information. For example, in an industrial setting, a Product might be linked to its technical specifications, maintenance history, and safety protocols. Through an AR interface, a user could scan a physical product, triggering a SPARQL query that retrieves and displays relevant knowledge from the ontology, such as assembly instructions or troubleshooting guides.

The following query (Fig. 4) retrieves instructions and maintenance logs related to a specific product (`Product123`) and can be visualized via AR.

```
PREFIX ex: <http://example.com/ontology#>

SELECT ?product ?instruction ?maintenanceLog
WHERE {
    ?product rdf:type ex:Product .
    ?product ex:hasInstruction ?instruction .
    ?product ex:hasMaintenanceLog ?maintenanceLog .
    FILTER (?product =
<http://example.com/ontology#Product123>)
}
```

Fig. 4. SPARQL Query Example for AR Knowledge Retrieval

Representation of 3D Models as Nodes in Ontologies

One of the key challenges in AR-enhanced Knowledge Mesh systems is integrating 3D models with traditional knowledge representations. In OWL/RDF ontologies, 3D models can be treated as first-class citizens within the knowledge graph, represented as nodes that link to other entities (such as knowledge products or processes). In RDF/OWL, a 3D model can be represented as a resource with attributes such as file type, URI, and description. The ontology defines the relationships between the 3D model and the associated knowledge entities, such as a product, machine, or building. In the following example (Fig. 5), the product (`Product123`) is linked to a 3D model (`Model456`) that is described using metadata such as file format and URL.

```
@prefix ex: <http://example.com/ontology#> .

# Define a Product class
ex:Product rdf:type owl:Class .

# Define a 3DModel class
ex:3DModel rdf:type owl:Class .

# Link a product to its 3D model
ex:Product123 rdf:type ex:Product ;
    ex:has3DModel ex:Model456 .

# Define the 3D model with metadata
ex:Model456 rdf:type ex:3DModel ;
    ex:fileFormat "glb" ;
    ex:fileURL
"http://example.com/models/product123.glb" ;
    ex:description "3D model of Product123" .
```

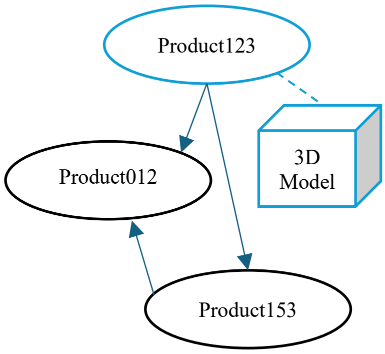

Fig. 5. Example of 3D Model Representation in RDF

Ontology-Based 3D Model Discovery

In a Knowledge Mesh, users can discover 3D models by querying the ontology. For example, a user might request all products that have associated 3D models for AR visualization. The following query (Fig. 6) retrieves all products with associated 3D models and provides the URL for the AR system to load the model.

```
PREFIX ex:
<http://example.com/ontology#>

SELECT ?product ?modelURL
WHERE {
    ?product ex:has3DModel ?model .
    ?model ex:fileURL ?modelURL .
}
```

Fig. 6. SPARQL Query for 3D Model

4. ARML as Metadata in Knowledge Mesh

This ARML snippet defines the spatial placement of a 3D model of a machine and links it to a maintenance guide, triggered by proximity. By embedding ARML within Knowledge Product Contracts (KPCs), AR applications can directly interpret these instructions, facilitating both knowledge discovery and visualization in real time.

KPCs govern how knowledge is structured, accessed, and utilized across domains. For instance, an ARML-enabled KPC for a machine might define where its 3D model is positioned in AR, how users interact with its various components, and what supplementary knowledge (like maintenance records or operational data) should be displayed, as presented in Fig. 7.

```
KnowledgeProductContract:
  knowledgeProductId: "12345"
  name: "Machine Maintenance Guide"
  version: "1.0"
  ARML:
    Location:
      Latitude: 37.7749
      Longitude: -122.4194
    3DModel:
      ModelURL: "../models/machine123.glb"
      Placement:
        Orientation: "0,0,0"
        Scale: 1.0
    Metadata:
      KnowledgeProduct: "MaintenanceGuide"
      Trigger: "Proximity"
```

Fig. 7. ARML enabled Knowledge Product Contract

5. Case Study on AR-Driven Knowledge Discovery

Scenario. A large manufacturing facility operates advanced robotic systems to automate critical production processes. Robotics engineers need real-time access to robot configurations, operation manuals, and diagnostic data to efficiently monitor, troubleshoot, and optimize the robotics infrastructure. The facility implements an AR-enabled solution using ARML with embedded SPARQL queries to streamline knowledge retrieval and enhance real-time decision-making.

Direct Knowledge Discovery. A robotics engineer is tasked with diagnosing a malfunction in RobotX123, a critical component of the facility's automated production line. Using an AR device equipped with ARML-embedded SPARQL functionality, she/ he scans the robotic unit.

The system detects RobotX123 and automatically triggers a SPARQL query, retrieving relevant robot configuration details, maintenance history, and diagnostic information from the facility’s Knowledge Mesh. Through an AR overlay, the engineer is presented with the real-time sensor data, error logs, and optimal configuration settings directly on the robotic unit, allowing her to quickly assess and address the problem without leaving the AR environment or manually searching for technical documents.

Example Query in Action. Upon detecting RobotX123, a SPARQL query runs, fetching the robot's detailed configuration data, operational history, and diagnostic reports from the Knowledge Mesh. The engineer instantly accesses these knowledge products, speeding up the troubleshooting process and ensuring precision in reconfiguring the robot.

Innovative Approach. The core innovation of this solution lies in its integration of the Knowledge Mesh framework with ARML. ARML here functions not only as a visualization tool, but as an essential component of the Knowledge Product Contract. These contracts are stored in the enterprise knowledge catalogue, similar to tools like Atlan or Collibra, defining the structure and retrieval mechanisms for knowledge products.

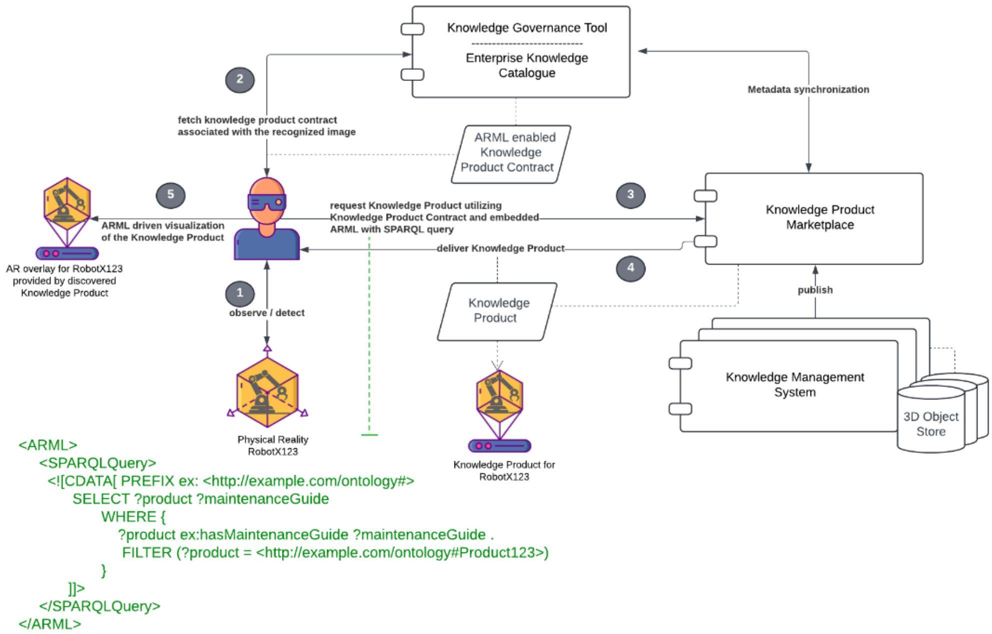

Fig. 8. AR-Enabled Dynamic Knowledge Retrieval via Knowledge Mesh

When the AR device detects RobotX123, it retrieves the relevant Knowledge Product Contract from the knowledge catalogue, which contains key information such as the configuration files, diagnostic tools, and performance metrics. The contract enables ARML and SPARQL-driven access to these resources, ensuring seamless interaction with the Knowledge Mesh, as illustrated in Fig. 8. This ensures that the AR interface is dynamically linked to the most relevant and up-to-date knowledge products, empowering robotics engineers to perform diagnostics and reconfigurations in a decentralized, self-service manner.

A real-world application of AR-driven knowledge retrieval is as presented in Fig. 9.

Fig. 9. Real-World Implementation and AR-Enabled Visualization of a One-Step Firestop Cast-In Solution

The left section of the figure introduces a photograph of a one-step firestop cast-in solution for pipe floor penetrations, while the right section shows a 3D-rendered model of the same device extracted from the knowledge base. When linked to the AR-enabled solution, the AR device dynamically retrieves the relevant knowledge product for the firestop solution. The device leverages ARML and SPARQL queries to present up-to-date information, empowering to efficiently assess and interact with structural elements in real-time.

6. KPIs for Evaluating the Efficiency of AR-Enabled Knowledge Mesh

To compare the efficiency of the AR-Enabled Knowledge Mesh approach with traditional Knowledge Management (KM) systems, the analysis will focus on calculating Key Performance Indicators (KPIs) across both environments. This allows for a direct, measurable comparison. The AR-enabled Knowledge Mesh enhances knowledge retrieval, visualization, and operational efficiency, which are critical metrics in this analysis.

So, the Knowledge Discovery Efficiency, E, is introduced, as a specific KPI, to characterize the process of finding relevant knowledge in the AR environment, E_1, and through traditional KM system, E_0, respectively.

The mathematical expressions of the effective above KPIs, namely, E', $E_1{}'$, etc. are defined as follows:

$$E' = 100\,\frac{N}{N_t},\ \text{i.e.}\quad E_1{}' = 100\,(\frac{N}{N_t})_1,\, E_0{}' = 100\,(\frac{N}{N_t})_0,\ \text{in}\,\% \tag{9}$$

or/and

$$E'' = 100\,\frac{T}{T_t},\ \text{i.e.}\quad E_1{}'' = 100\,(\frac{T}{T_t})_1,\, E_0{}'' = 100\,(\frac{T}{T_t})_0,\ \text{in}\,\% \tag{10}$$

where N is the number of successful knowledge retrievals, N_t – the total number of all attempts, T - the time consumed by successful knowledge retrievals, T_t – the total time consumed by all attempts.

Furthermore, to comparatively analyse the process of finding relevant knowledge in the AR environment with respect to traditional KM system, a specific KPI as Relative Efficiency, E_{1-0}, is defined, so that, the corresponding effective KPIs, namely, E'_{1-0}, and, respectively, E''_{1-0} are defined as follows:

$$E'_{1-0} = \frac{E_1{}' - E_0{}'}{E_0{}'}, \text{ in \% or/and } E''_{1-0} = \frac{E_1{}'' - E_0{}''}{E_0{}''}, \text{ in \%} \quad (11)$$

where the E'_1, E'_0, E''_1 and E''_0 are the KPIs defined by eqs. (9) and (10).

The results, presented in Fig. 10, for which E'_1= 88% and E'_0= 70%, E'_{1-0} = 25.7% , respectively, were obtained under controlled laboratory conditions, utilizing GraphDB as the underlying Knowledge Base platform, Atlan as the enterprise knowledge catalogue, and PTC Vuforia as the Augmented Reality (AR) framework. This setup facilitated the seamless integration of ARML- embedded SPARQL queries with knowledge products stored in the Atlan catalogue. By leveraging GraphDB for advanced querying and Vuforia for real-time AR visualization, the AR-enabled Knowledge Mesh demonstrated superior knowledge discovery efficiency compared to traditional systems. Laboratory tests confirmed the robustness of this approach in enhancing real-time, context-aware knowledge retrieval, significantly reducing operational inefficiencies. These tests were conducted in conjunction with a real-life implementation of an AR-enabled Google Cloud Platform driven R&D environment for OKO Suisse, Zurich [12] further validating the practical applicability and scalability of the system.

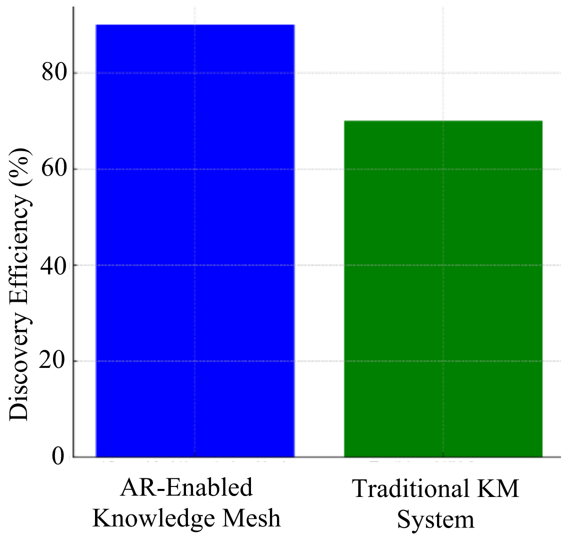

Fig. 10. Knowledge Discovery Efficiency for AR-Enabled vs. Traditional KM systems

The results demonstrate how the integration of AR, Knowledge Mesh, and real-time knowledge retrieval tools can enhance operational efficiency.

7. Conclusions

Integration of ARML into Knowledge Mesh, by embedding ARML in Knowledge Product Contracts, facilitates real-time interaction with knowledge assets, improving both explicit and implicit knowledge retrieval processes.

As impact on industrial processes, the research demonstrates that AR-enabled knowledge systems have the potential to greatly improve operational efficiency and decision-making across various industrial applications. By enabling real-time diagnostics, troubleshooting, and knowledge access through AR, the system can significantly reduce downtime and improve productivity.

The presented framework opens possibilities for further exploration, particularly in optimizing SPARQL queries, improving the performance of ARML-based visualizations, and expanding the application of this technology to fields like education and healthcare.

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