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AI-Driven Knowledge Graph Systems for Enterprise Service Management Automation

Shashikala Valiki

Independent Researcher, India

ABSTRACT: Enterprise service management (ESM) utilizes technology to integrate services across the enterprise, improving service workflows, performance, customer experience, and time-to-market for new and changed services. Traditional ESM tools rely on rules and workflow automation to help IT operations teams. Organizations now seek more automation, using so-called AIOps for tasks such as event correlation and alert prioritization, applying artificial intelligence (AI) techniques to manage infrastructure and services, and detect incidents and problems.

A suitable approach to further automation throughout the enterprise is AI-driven knowledge graph (KG) systems that automate the construction and continual enhancement of a KG from heterogeneous data sources. Such KGs can include rich semantic representations for services and the service-management functions (incident, problem, change, configuration, service-level, and knowledge-management) and processes supporting these services. Automating the construction of the KG is key, since maintaining a KG manually quickly becomes untenable. ESM KGs can therefore be enhanced by AI techniques that find, learn, and reason over meaningful embeddings or higher-order relations, enabling, for example, incident resolution and problem-management support.

KEYWORDS: Enterprise service management, service management automation, artificial intelligence, knowledge graphs, ontologies, taxonomies, linked data semantic interoperability architecture AI techniques enhancement applications.

I. INTRODUCTION

In the rapidly changing landscape of businesses and IT service management, creating an interconnected set of data and system information is fundamental to efficient operation. Deployed in AI systems and cognitive assistants, knowledge graphs drive the sharing of enriched data and semantic search. These domain-specific knowledge graphs automate Enterprise Service Management (ESM) tasks such as incident resolution, problem diagnosis, and change evaluation.

Supporting tasks such as incident resolution, problem diagnosis, change evaluation, or knowledge-sharing in an organization, ESM offers an extended framework for managing resources across IT and non-IT functions. Knowledge graphs in this context allow the systematization of data distributed over multiple sources, making it accessible for AI processing and recommendation engines. Organizations can better manage the interconnected aspects of ESM by developing and applying a foundational set of methods in knowledge graph research as applied to ESM.

1.1. Background and Significance

Enterprise Service Management (ESM) refers to application of service management principles beyond information technology to other service domains, with enterprise service management automation (ESMA) facilitating the design and implementation of ESM automation solutions. Industrial-scale ESMA applications face challenges related to knowledge acquisition, knowledge representation, knowledge persistence, knowledge propagation, and knowledge utilization. An Enterprise Knowledge Graph (EKG) driven by AI is a technology suite that addresses these challenges by leveraging large datasets to support the semi-automated collation and formalization of knowledge in an EKG. AI techniques combine within the EKG to create a self-improving knowledge repository that enables scalable automation of enterprise services. Knowledge Graph (KG) technology is a practical implementation of an EKG that enables data aggregation from multiple sources together with reasoning and inference capabilities.

Knowledge graphs have long been recognised as key components in the representation and management of knowledge associated with Service Management processes and activities. Knowledge graphs leverage ontologies, taxonomies and linked data concepts, and can be augmented with a diverse set of AI capabilities to facilitate decision making and knowledge acquisition. Such AI capabilities include embeddings and similarity comparisons, graph neural networks for

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node classification, and knowledge graph completion. Within the enterprise service management domain, the functionality of KGs has been applied to problem and incident management and other areas of service operation, with particular emphasis on decision support.

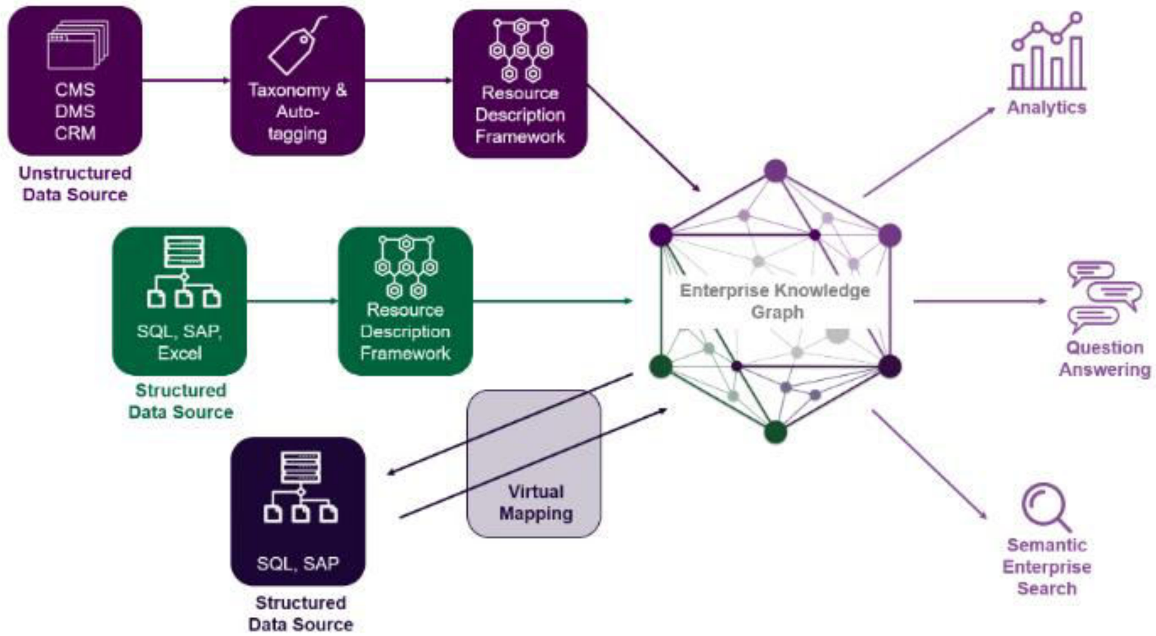

Fig 1: Enterprise Knowledge Graph Design

1.2. Research design

Investment in Knowledge Graphs (KGs) to support complete operating automation of enterprises is currently underestimated, despite the optimistic projections for their economic impact. KGs, which can also be considered innovative, enterprise service management (ESM) information systems, have their foundations based on ontological structures that characterize an organization's assets, processes, and relations in a knowledge area. These structures become KGs together with links to other relevant KGs on the web of data and are enriched through reasoners and semantic-similarity AI techniques to allow any enterprise process to be automatically driven, triggering and managing at least the IT parts of processes such as incident/problem/change/configuration management. KGs make it possible, for managing ESM automation processes, to apply and enhance instruction-based AI techniques (special case of KGs), including Generalized and Domain-Specific Zero-Shot Learning, and Tool-Use with Affordance Association, type techniques.

The current stage of knowledge within the areas of KGs and ESM is sufficient to create a preliminary architecture for all KGs supporting enterprises' operating automation. Such an architecture would highlight these KGs' structure and provide a preliminary list of processes that these KGs must be able to execute or support, together with an outline of innovation areas for instruction-based techniques applied to the KGs. These are then enriched by the identification of main AI-driven processes that enhance any KG and by the specification of principal types of applications in ESM automation.

Equation 1: RDF triple (the atomic fact)

A knowledge graph stores facts as triples:

$$(s, p, o)$$

Step-by-step meaning

1. Pick a **subject** entity s(e.g., an Incident, Service, CI).
2. Pick a **predicate** p(relationship) (e.g., *affectsService*, *runsOn*, *ownedBy*).
3. Pick an **object** entity/value o.
4. The triple becomes an edge in the graph: $s \xrightarrow{p} o$.

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II. FOUNDATIONS OF KNOWLEDGE GRAPHS IN ENTERPRISE SERVICE MANAGEMENT

A proper foundation is necessary for the construction of knowledge graphs, including ontologies or taxonomies that define the possible classes and relationships in the graph and linked data principles that support semantic interoperability among independently constructed knowledge graphs. Ontologies and taxonomic classification provide the basis for the knowledge graph, as well as a structure and vocabulary to enable semantic interoperability with other data in the enterprise ecosystem. Class relationships declared in the taxonomic schema can also facilitate the automated creation of the knowledge graph. Linked Data principles govern the combination of independently produced datasets, including external ontologies, using uniform Resource Description Framework (RDF) identifiers. Knowledge graphs can, in turn, support the development of other datasets using linked data principles, facilitating outsourcing or crowd-sourcing.

Information technology (IT) services span an enterprise and often involve multiple IT service management (ITSM) products, requiring shared repositories of knowledge, configuration data, and model data. Knowledge graphs can therefore provide a central data store for enterprise ITSM to support incident and problem management, change and deployment management, logical service configuration, and service-level management. When stored in a knowledge graph, these relations can enable enhanced management automation, because the most straightforward solution is often a matter of finding the correct shortest path between nodes and choosing the lowest-cost relation for each traversal. Knowledge graphs also enable the analysis of service configurations for combinations of factors such as stability, availability, and cost. When the knowledge graph contains appropriate simulation and prediction data, the enterprise can also predict how changes in service configuration will impact the desired outcome.

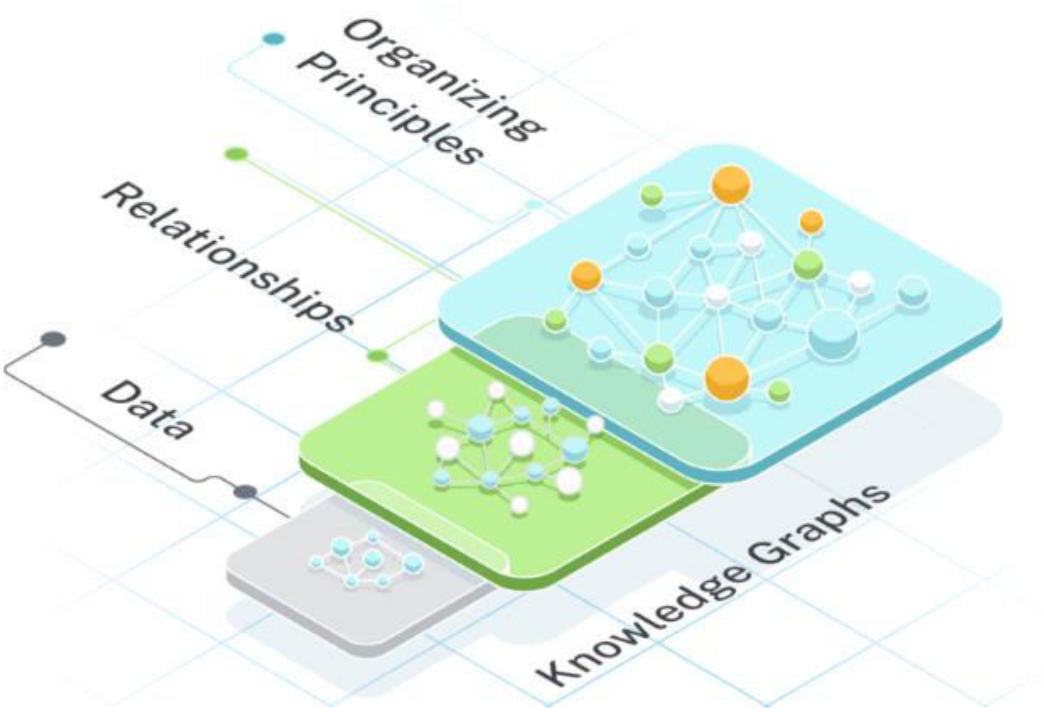

Fig 2: Knowledge Graphs in Enterprise Service Management

2.1. Ontologies and Taxonomies

As artificial intelligence takes a greater role in enterprise service management automation, the use of knowledge graph systems is growing. Knowledge graphs serve to offer domain-specific knowledge by connecting entities (service tickets, applications, IT infrastructure, teams, etc.) in a rich semantic representation and are now increasingly employed for enterprise service management automation. Although these graphs have been widely developed, a shortage of domain knowledge still needs to be addressed in order for AI to deliver meaningful results. Ontologies can express rich domain knowledge and are able to enrich these existing knowledge graphs. By using ontologies, automatic reasoning and inference capabilities can be applied within the knowledge graph. In addition to that, the combination of ontologies and

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machine learning techniques also enables the automatic discovery of domain knowledge from various data sources and unstructured information.

Ontologies are meant to describe a specific domain in a formal and machine-readable way. They define a vocabulary for the domain and enable sharing and reuse of domain knowledge. An ontology can represent knowledge in a formal, machine-readable format for use within a system. An ontology may describe taxonomic relationships in a domain and represent a formal specification of a set of concepts and relationships in a given domain. In contrast to an ontology, a taxonomy is a hierarchical structure that defines categories and their relationships through specialization and generalization. A taxonomy organizes concepts in a hierarchical manner.

Equation 2: Adjacency matrix *A*

For a directed graph with $n$nodes:

$$A \in \{0,1\}^{n \times n}, A_{ij} = \begin{cases} 1 & \text{if edge } i \rightarrow j \text{ exists} \\ 0 & \text{otherwise} \end{cases}$$

Step-by-step build

1. List nodes $v_1, \dots, v_n$.
2. Create an $n \times n$table.
3. For each directed edge $v_i \rightarrow v_j$, set $A_{ij} = 1$.

For $n$nodes and $m$edges:

$$B \in \{0,1\}^{n \times m}, B_{ve} = 1 \text{ if vertex } v \text{ touches edge } e$$

Step-by-step build

1. Columns are edges $e_1, \dots, e_m$.
2. Rows are nodes $v_1, \dots, v_n$.
3. If edge $e_k$connects to node v_i, mark $B_{i,k} = 1$.

2.2. Linked Data and Semantic Interoperability

Linked Data principles defined by Tim Berners-Lee promote the exposure, connection, and re-use of structured data across institutions and domains to foster the global, Web-scale data graph. Data sets become more valuable when associated with a dedicated, resolvable Uniform Resource Identifier (URI) serving as a machine-readable link to the publisher's metadata, a dereferenceable location for human-readable documentation, and a discovery point for related resources. The first three principles focus on publication, while the fourth guides discovery and use:

1. Use unique identifiers (URIs) to name things.
2. Make those URIs dereferenceable so that others can discover and use the things you name.
3. Use and publish standard data formats (e.g., RDF, SPARQL) that allow easy integration into existing components designed for the Web.
4. Generate links to related things when you publish your data, so that others can incorporate those links into theirs and everyone benefits.

Semantic interoperability enables data from various sources to be combined and used together seamlessly. The focus is on data integration, so it does not directly address data quality or fitness for use, but recognition of domain relationships or exchange data embodying standardized semantics are crucial for such quality issues. For example, to integrate a purchased car's maintenance service records into the original owner's vehicle maintenance work history, the integration process must recognize that "Car" in the service organization's domain may not mean the same as "Car" in the other organization's domain. If the relevant data means essentially the same thing (e.g., it involves a Ford car within the Ford car domain), such semantic integration can help provide greater accuracy.

III. ARCHITECTURES FOR AI-DRIVEN KNOWLEDGE GRAPHS

A number of different components are considered to be requisite for building an AI-driven knowledge graph. The information storage and representation, reasoning mechanism, and methods for enhancing the knowledge graph with AI techniques that use machine learning (ML) or deep learning (DL) algorithms, such as natural language processing (NLP) or computer vision (CV), all actively contribute to deep learning. Together, these components comprise an enabling architecture for AI-powered knowledge graphs.

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Appropriate data store, storage model, or database technology should be selected, with classic graph databases typically being the preferred choice. Predicates should be defined for representing relationships among ontology instances in knowledge representation languages such as Resource Description Framework (RDF)-like languages. Besides enabling data to be structured in a graph that supports traversal with join-like constructs, a back-end storage technology with good scalability, high availability, and fault tolerance as well as a front-end serving engine with native graph query capabilities can be applied. State-of-the-art graph databases support fast, built-in inference capability. If these features are not provided, a suitable inference engine may be integrated into the knowledge-graph system.

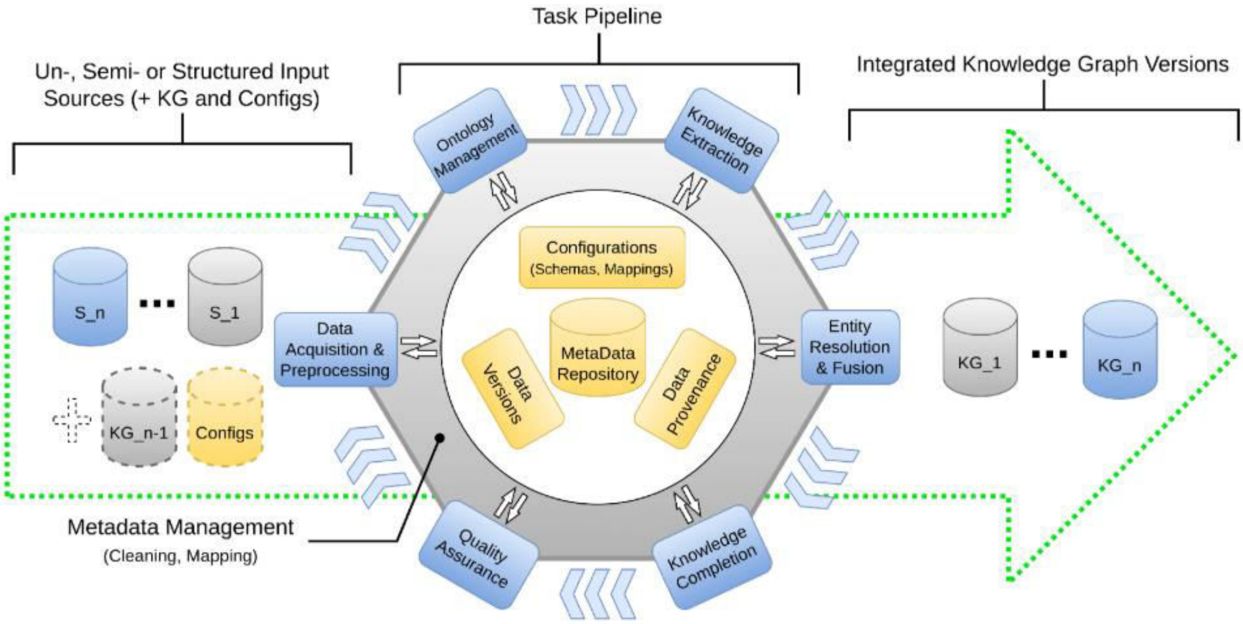

Fig 3: Architectures for AI-Driven Knowledge Graphs

3.1. Graph Databases and Storage Models

Numerous databases support hybrid graphs, with various features aimed at one or several of the three main axes—structuring semistructured, dynamic, or referential data. A growing trend in popular NoSQL databases is the support of graph data models in direct response to the explicit hierarchical and referential relationships represented in polymorphic JSON documents. The native graph databases' more specialized implementation supports, in a more efficient manner, the high-level graph model queries seen in typical Enterprise Service Management (ESM) applications.

The standard storage layout of native graph databases, particularly the edge-oriented databases focused on directed graphs, consists of a highly compressed adjacency list that incorporates different link lists for incoming and outgoing edges. Availability graphs usually have thousands of nodes and millions of links, generating a very sparse structure corresponding for the most part to the reachability of the subgraph; in consequence, its adjacency list representation enables high compression rates. Nevertheless, for Service Request Management, the management of FCM (Service Request – Problem) and PM (Service Request – Change) patterns requests a formulation as a topological matrix, making necessary the uncompressed representation for performance reasons. The construction of the incidence matrix of FCM patterns in failed operations is achieved by a bipartite graph model that expands the set of conditions.

Equation 3: Shortest-path automation equations (dependency chain to resolution)

Let a path P from node s to node t be a sequence of edges:

$$P = (e_1, e_2, \dots, e_m)$$

Each edge has weight $w(e_k)$ (e.g., time, risk, cost, confidence penalty).

Total path cost:

$$C(P) = \sum_{k=1}^{m} w(e_k)$$

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$$P^{*} = \arg \min_{P \in \mathcal{P}(s,t)} C(P)$$

Step-by-step

1. Enumerate candidate paths P from s to t (in practice, use Dijkstra/A*).
2. For each path, sum edge weights $C(P)$.
3. Choose the path with minimum sum P^{*}.

3.2. Reasoning and Inference Mechanisms

Graph reasoning attempts the deduction of new facts using the relations and properties available in the graphs, moving from metadata to inferences that improve the quality of the Knowledge Graph. Graph inference combines the requested graph reasoning with additional techniques to compute numeric values or learn new representations. To enable additional reasoning operations, Knowledge Graphs can be enriched with knowledge that is typically expressed in form of rules or queries, usually using the languages associated with W3C standards in the Semantic Web. SPARQL is the language for querying graph structures, OWL2 is the framework to reason about class membership and temporal relations, and SWRL can be used to formalize a broad set of logical rules. Inclusion of knowledge contained in these languages enables a deeper exploration of the Knowledge Graphs.

Graph embeddings combine latent semantic space representations with the topology of the Knowledge Graphs to represent the data in a space that is suitable for the application of deep learning techniques. The resulting Knowledge Graph Embedding (KGE) enables neural networks or similar techniques to generalize beyond the training data. By combining the relational information in the data with the identification of similar entities, KGE techniques seek to assign similar representations to pairs of entities that are semantically similar or that are situated in similar contexts. The description of the system can benefit from the fact that KGE represent embeddings of the interacting entities. In the case applied to the Enterprise Service Management, the system dynamically captures the patterns signalled in service operations (for example, security incident, downtime period, service degradation). A further extension considered the need to aggregate services and other entities having different roles depending on the application context. Graph Neural Networks (GNN) are a specific instance of KGE that learn features of the underlying graph topology and enhance the vertex representations accordingly.

IV. AI TECHNIQUES FOR KNOWLEDGE GRAPH ENHANCEMENT

A Knowledge Graph (KG) contains lots of resources. Not every resource is equally suitable for every purpose. Instead, it is common to have a small query-specific subset of resources that deliver the best results. Finding these resources can be a computationally expensive task. Hence, using any resources that are similar to the resources contained in the query is a valid approach. The challenge lies in discovering these suitable resources that can deliver quality results. A relevant quality metric for KGs is, therefore, their resource similarity. Finding similar resources is not simple. The complexity arises from the high volume of edges and the heterogeneous semantic types of the resources contained in a KG. KGs lend themselves naturally to the use of Embeddings.

Embeddings that approximate the distances between resources and can be used to find similar resources are a promising area of research. Another area of research is leveraging GNNs to relate KGs with those of other modalities such as text or images. In enterprise service management, the semantic relationships that can be produced by KGs, such as resource similarity, can also produce connections with the Deterministic Finite Automaton (DFA) that represents the textual descriptions of the services and the Knowledge-Based (KB) that acts as the repository of images illustrating the services.

Equation 4: Embeddings + similarity (for ticket matching, dedup, recommendation)

Given embedding vectors $u, v \in \mathbb{R}^{d}$,

$$\cos(\theta) = \frac{u \cdot v}{\parallel u \parallel \ \parallel v \parallel}$$

Step-by-step derivation

1. Dot product:

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$$u \cdot v = \sum_{i=1}^{d} u_i \, v_i$$

2. Vector norms:

$$\| u \| = \sqrt{\sum_{i=1}^{d} u_i^2}, \| v \| = \sqrt{\sum_{i=1}^{d} v_i^2}$$

3. Normalize dot product by magnitudes to get angle-based similarity.

Interpretation

- 1: very similar direction (high semantic similarity)
- 0: unrelated
- -1: opposite direction

Given query embedding $q$and incident embeddings $\{x_j\}$,

$$\text{score}(j) = \frac{q \cdot x_j}{\| q \| \| x_j \|}, \text{TopK} = \arg \text{topK}_{j} \text{score}(j)$$

Step-by-step

1. Embed new incident text/logs to q.
2. Compute cosine similarity to each stored incident x_j.
3. Sort and return top-K for likely duplicates / known fixes.

4.1. Embeddings and Similarity

In Knowledge Graphs (KGs), node and edge feature vectors can be learnt through embedding techniques from the hypergraph structure. Distributed Representation of Knowledge Graphs (DisR-KG) relates the hypergraph structure with the point distribution property in an innovative way. The node distribution and hyperedge distribution of DisR-KG embed the hyperedge structure in the node space. Distributed graph neural networks calculate the features in local spaces instead of global embeddings. The reliability of distributed representations selects similar distributed Hyper-graph Neural Network leaves to obtain K nearest node generations with a common hyperedge distribution. The Geodesic Distance of the learned node distribution describe pair-wise semantic similarity. The Distance Variable Distribution Model represents latent nodes with distribution and utilize the proposed Approximate Distribution Maximization to infer the generate model. Then, the Hyper-graph View Network integrates the hierarchical information and sieve Valid Heterogeneous-typed Hyper-edge View in a Hyper-graph View-like Style.

Semantic similarity metrics have been proposed to measure similarity between Knowledge Graph resources based on their structure. An augmented similarity score enhances the quality of similarity measures between instances. Implementations of these measures for the WordNet and DBPedia KGs demonstrate their applicability. For Very Large KGs (VLKGs), semantic similarity measures consider the semantic dissimilarities of KB elements to enable effective similarity comparison and ranking with respect to a particular query entity. In view of the semantic hierarchies, properties, and relationships of elements in KGs, similarity measures take into account both the structure and the contents of VLKGs. Meta-based super parameters control the extent of content or structure considerations, making the proposed measures adaptable to diverse similarity tasks.

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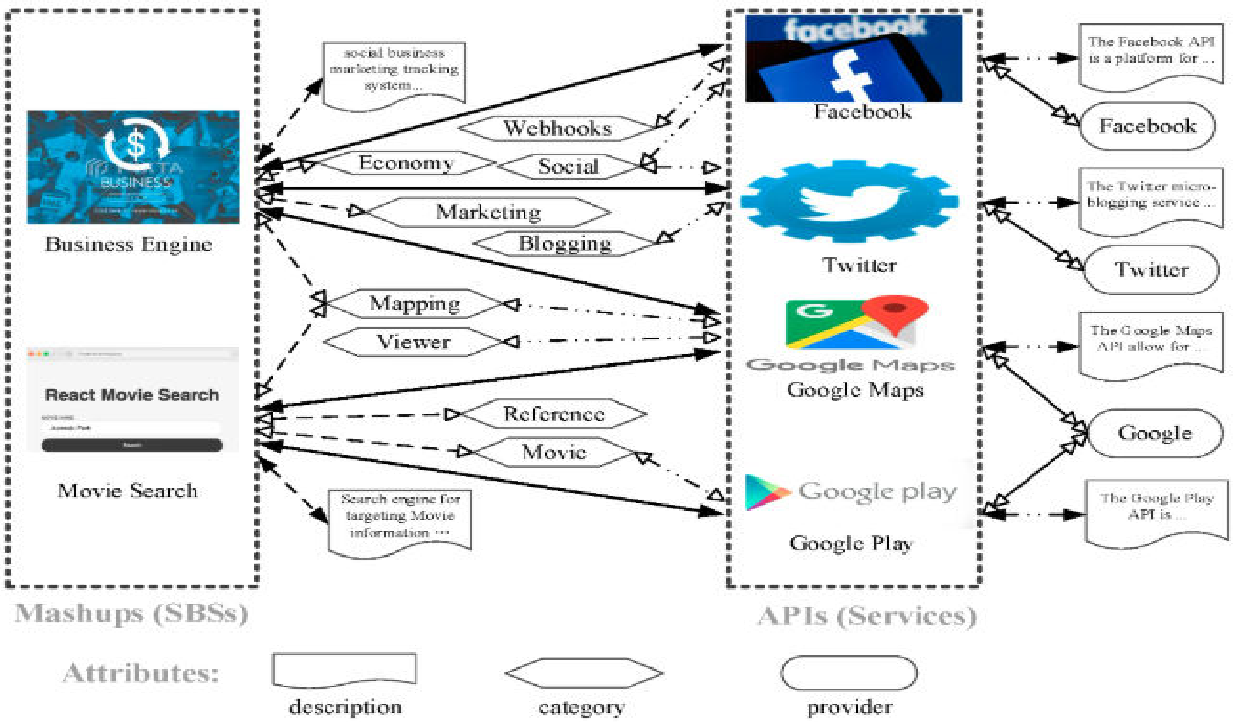

Fig 4: A Knowledge Graph Embedding Based Service

4.2. Graph Neural Networks in Service Contexts

Pitfall 1: Too much help at the wrong time When care for children with a chronic illness predominates, and a trusted person is close at hand to lend a helping hand, this feels good. However, a temporary informal helping offer is often perceived as a threat: "I can also walk on my own!" This can endanger self-acceptance. Pitfall 2: Help at the wrong time Helping others find something can also be offensive – for example, when the helper is in a hurry. In another cultural context, the unsolicited invitation to eat something can be regarded as contemptuous: "What a pity that you have no one to feed you!" Here, the urgency of help does not match the urgency of the need: "My God, don't just sit there, be helpful!" Pitfall 3: Help as entertainment, not as help Help becomes dangerous when the provider has self-centered motives that divert him. Self-centered motives for help are related to altruism and lead to self-sacrificing. The aim of this self-business must be to check for himself that the sick can actually lead their lives as before. And he wants proof now!

Not to be loved more, not to be loved at all All these relationships meticulously avoided the fallacy of the so-called love of the sick: "My God, what lonely people want is only a little loving." The sick generally do not want love; they are fundamentally not differentiable sensations but rather need to see exactly how things are. The request therefore revolves around a gift that is light and cool to the giver and therefore fun. The offer is thus to evoke a necessary magic in the others that removes the surface of indifference.

V. APPLICATIONS IN ENTERPRISE SERVICE MANAGEMENT AUTOMATION

Knowledge graphs in enterprise service management (ESM) contexts provide a clear representation of relationships between the enterprise's services and its resources. Their underlying data models need not be in the form of graphs, but they must contain the shape and semantics of graphs: e.g., an Acyclic-Graph modelfor structured data; or an attributed model that integrates content with a standard Graph format through similar properties existing in both models. Beyond explicit information, knowledge graphs also support relevance determination, i.e., knowledge that is used and related to possible solutions or predictions for a user query.

Industry-wide acceptance of Artificial Intelligence (AI) opens avenues for new AI-driven systems. In these systems, specific AI techniques automatically create or enhance knowledge graphs; the enhanced knowledge graph then serves as a central component in the service management automation process. Enabling the underlying knowledge graph

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techniques fosters rapid evolution of these systems. These advances can be classified into two categories: how AI is used for knowledge-graph enhancement and process applications that leverage enhanced knowledge graphs, which are discussed in the following sections.

Equation 5: Graph Neural Networks (GNNs) for reasoning over service contexts
Let $h_v^{(l)}$ be node v's embedding at layer l. Neighbor set $N(v)$.

$$m_v^{(l)} = \mathrm{AGG}\big(\{h_u^{(l)}: u \in N(v)\}\big)$$
$$h_v^{(l+1)} = \sigma\big(W_l \cdot [h_v^{(l)} \parallel m_v^{(l)}]\big)$$

Step-by-step

1. Collect neighbor embeddings $\left\{h_u^{(l)}\right\}$.
2. Aggregate them (mean/sum/max attention) into $m_v^{(l)}$.
3. Concatenate current state with neighbor summary.
4. Apply linear transform W_l then nonlinearity σ.

5.1. Incident and Problem Management

Automation of incident and problem management within the ESML and its environment is primarily through a hybrid taxonomy-ontology that serves at least three purposes: classification of reported incidents and problems in both the natural language of the requestor and the formal language of the resolver; automated classification of log entries based on the taxonomy and content similarity; and prevention of incidents by engaging experts across technology domains to investigate known problem areas and develop plans to implement changes that mitigate the risk. Knowledge graph–based extensions add automation at other levels, for example, by detecting incidents and invoking the incident management process with synthesized natural-language summaries to end users or sending management notifications when resources are in alarm state.

Natural-language text mining of historical incident, problem, and change records facilitates the development of the training set for the image-processing model and enhances application of risk control images. The ESML environment is populated with time-series data alarms that form the basis of the automated incident detection mechanism. Other knowledge graph attributes support the vocations of associated resources, enabling automated invocation of service anticipation for suppliers responsible for the failed resources. This supply/service anticipation mechanism can be extended into the domain of change management through knowledge graph linkage to configuration management data, allowing automated approval when a change request affects only supplier resources on the external edge of the incident graph.

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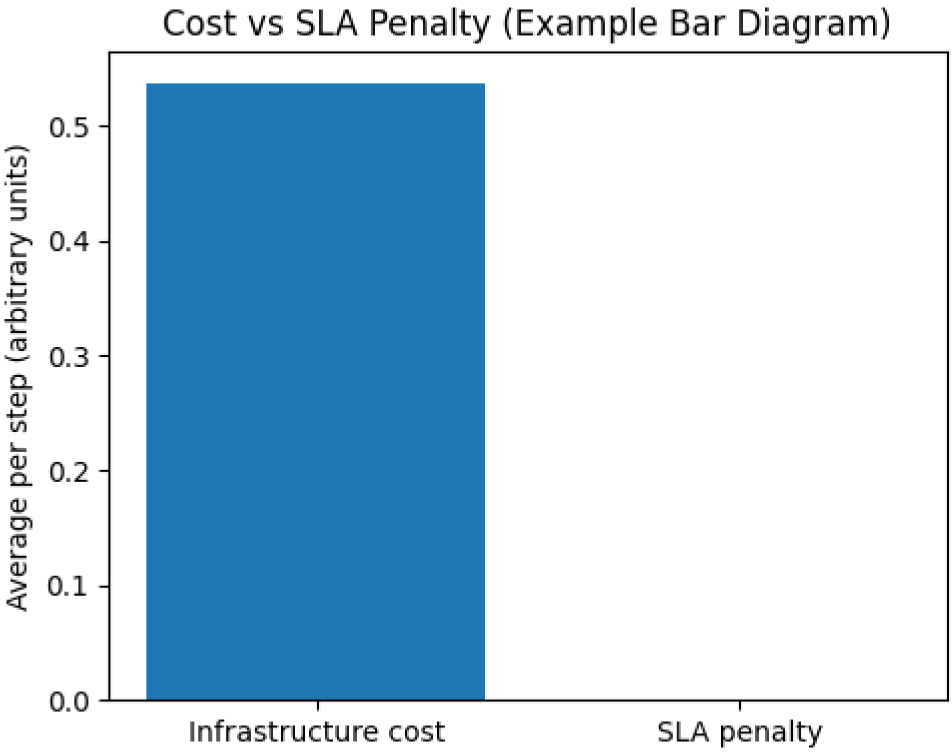

5.2. Change and Configuration Management
The change management process should minimize the risk of adversely impacting service quality, availability, and performance. To help achieve this, a thorough analysis of the potential consequences of each planned change, together with detailed procedures for rollout and backout, should be undertaken. The actual changes, their effects and any related incidents should all be recorded; the information is valuable for future planning. Change management has close links with incident, problem and configuration management.

The goal of configuration management is to obtain the data needed to assist in change and release management as well as in delivering high-quality services. Configuration management provides information to support other processes (incidents, problems, changes, applications, etc.) and thus should concentrate on the information requirements of those processes and on enhancing service quality. Configuration management should ensure that the data is accessible, reliable, complete, and up to date and is viewed as a "highly valuable asset" within the organization. Configuration, asset, and financial information is potentially valuable for many different groups, covering change-related activity, operational performance, audit, management reporting, and ongoing development. Configuration management databases (CMDBs) are used to collate configuration information, though there can be confusion over the nature and content of such databases. Change management ensures that all potential security risks associated with a change are assessed correctly to prevent problems arising and that any ad hoc changes are logged at the very least.

VI. CONCLUSION

The creation of a digital framework based on an AI-driven knowledge graph greatly increases an enterprise's service management capabilities by inferring, correlating, and predicting relevant information at any time, making service management work faster, easier, and higher in quality.

In addition to correlation, prediction, recommendation, adaptation, and enhancement, other ongoing AI-related technology developments also support or exhibit practical applications with respect to service management. Addressing these developments will assist enterprises in progressively moving toward full-service management automation. AI-related applications can accelerate the automation process of incident management by obtaining automatic solutions for recurrent incidents and detecting and classifying anomalous time series data. Dialogue systems, chatbots, and avatar

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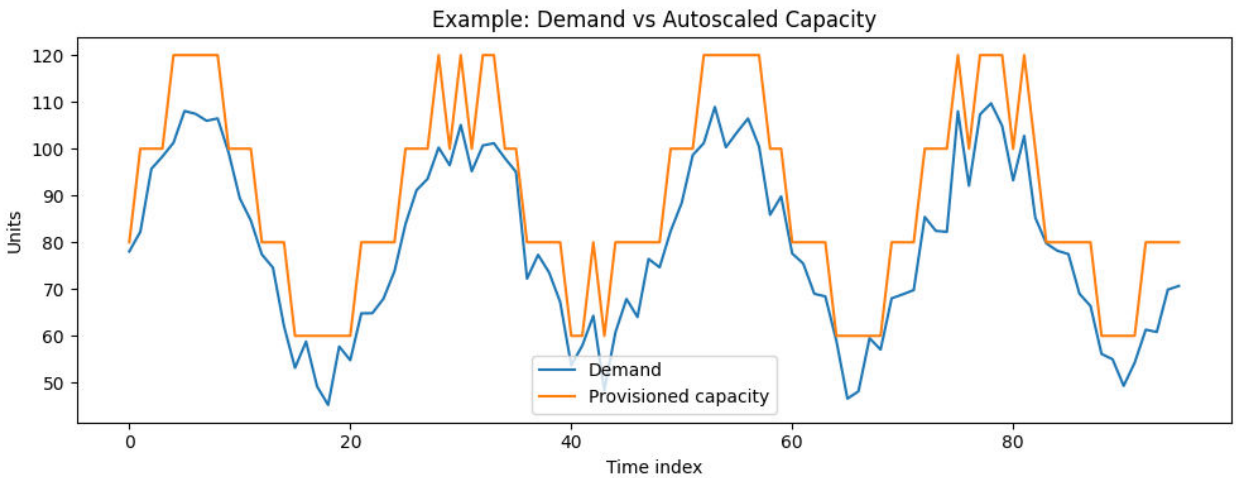
systems can help users to quickly solve inquiries. AI-based recommendation services are capable of suggesting the best service for each user based on data associated with the user's profile and preferences.



6.1. Future Trends

The affordability of large language models (LLMs) opens a new era. The ongoing push to create complex knowledge agents accessible to any developer with little AI-specialised knowledge promises to democratise even advanced AI capabilities through cloud APIs that will get cheaper and faster with use. A new level of middleware will allow the creation of comprehensive AI services leveraged by cloud architecture without managing the infrastructure. Such systems can collect and integrate data about enterprise services and support interactions with customers, service agents, and boards of directors. Large multimodal models merging visual and textual contents represent another commendable step towards a general intelligence that will likely impact service automation.

Given the ongoing developments in knowledge augmentation using LLMs or graph neural networks built on multimodal embeddings, no major changes in knowledge graphs seem imminent. Guidelines can be established to create AI-driven systems that generate large quantities of knowledge graphs with the minimum effort and a lot of data and metadata from enterprise knowledge stores. Such systems would use LLMs and other AI methods to populate incident management databases with maintenance queries and incident logs, use generative AI for problem management by identifying and suggesting fixes for complex queries from the Service Information Library, or propose changes to improve service resilience and incident prevention.

Concept (from paper themes)	**Core equation**	**ESM/KG use in context**
Softmax + cross-entropy	p(y|x)=softmax(Wx), L= -∑ y log p	Typical classifier loss for incident categorization
TransE scoring	f(h,r,t)=||e_h + e_r − e_t||	A simple KGE method for link prediction / KG completion
GNN message passing	h_v^{(l+1)} = σ(W_l · AGG({h_u^{(l)}: u∈N(v)}))	Learn node representations from neighbors (dependency reasoning)

Table : Equation map (conceptual)

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