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Ontology-Driven Knowledge Graphs for Personnel Management Within the UK Ministry of Defence: A Conceptual Overview

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Abstract

Ontology-driven knowledge graphs visualise complex relationships between entities such as people and concepts. This conceptual paper explores the potential for using ontology-driven knowledge graphs to enhance personnel management within the Ministry of Defence (MOD). It reviews existing literature on ontologies, structured frameworks to store domain knowledge based on relationships between data, and knowledge graphs and outlines the concept of an ontology-driven knowledge graph for a skill management system. The paper argues that this approach can provide a unified, standardised method for managing personnel skills, improving decision-making, and enhancing operational efficiency. A further benefit identified is the potential for the system to be expanded to exchange information with other systems, such as the NATO Defence Planning Process (NDPP), allowing external data to improve the quality of inferences made by the system.

Keywords: ontology, knowledge graph, personnel management, defence, RDF, OWL, GraphDB

Introduction

To effectively manage personnel in today's competitive job market, organisations must have a clear understanding of the skills of their personnel. Organisations with comprehensive personnel skills data are better prepared to detect and assess skills, allowing them to plan and assign personnel with the right skills to the right job at the right time. This is especially important in the complex defence environment, where effective personnel management is critical for optimal delivery against defence's rapidly changing objectives. Previous Ministry of Defence (MOD) initiatives for managing and tracking personnel skills to support personnel management across the Whole Force, while significant, have faced challenges in achieving full integration and coherence across the MOD. Some efforts, including Army Talent Framework, DLMC, Project Selbourne, and Project Castle, have been fragmented. This partly due to the fact that front line commands, Top Level Budgets (TLBs), and arms-length bodies (ALBs) manage their own workforces separately, resulting in data silos, hinders the ability of front-line commands to exchange critical skills, such as service movers, across different units when needed.

The Pan Defence Skills Framework (PDSF) is an ongoing initiative aimed at improving coherence and integration across the MOD by creating a standardised skill framework using taxonomy-based system to categorise skills. However, there is potential for further development for holistic people management by using ontologies capable of capturing complex relationships between skills, experience, personal characteristics, projects and goals going beyond traditional skills frameworks. This approach enables the MOD to manage not just skills but the full range of attributes that influence whole people management, allowing the MOD to quickly and effectively identify the right personnel for tasks across the Whole Force, considering factors such as cultural fit, experience, and traits to projects or roles. Furthermore, it creates possibilities for supporting non-linear career paths, personalised training opportunit, and improved personnel management and performance evaluation.

A comprehensive review of existing literature reveals a substantial foundation of knowledge on ontologies and knowledge graphs and their potential in various domains, yet their application within HRM remains underexplored within MOD. An ontology is a tool used for the formal representation of knowledge. It involves the visualisation of entities or concepts and their presumed relationships within a specific domain. It represents a formal conceptualisation, along with structure of information and standardised vocabulary, to enable communication and sharing a common understanding. Essentially, an ontology acts as a foundational model or a framework that defines the possible concepts (groupings of entities) and relationships that exist within a particular domain. On the other hand, knowledge graph is the practical application or realisation of the ontology. It is a structured representation of knowledge that interconnects entities through relationships, forming a network of related information. In the context of HRM, a knowledge graph could map out the relationships between various HR-related entities such as employees, skills, roles, departments, and projects, among others. This networked data model enables more sophisticated querying and analysis, making it possible to uncover insights that would be difficult to obtain from traditional databases. Figure 1 below shows a simple example of a knowledge graph. It shows the relationship between an actor and their roles. In this case, the knowledge graph has been colour coded by an ontology which classifies locations, people, films and organisations.

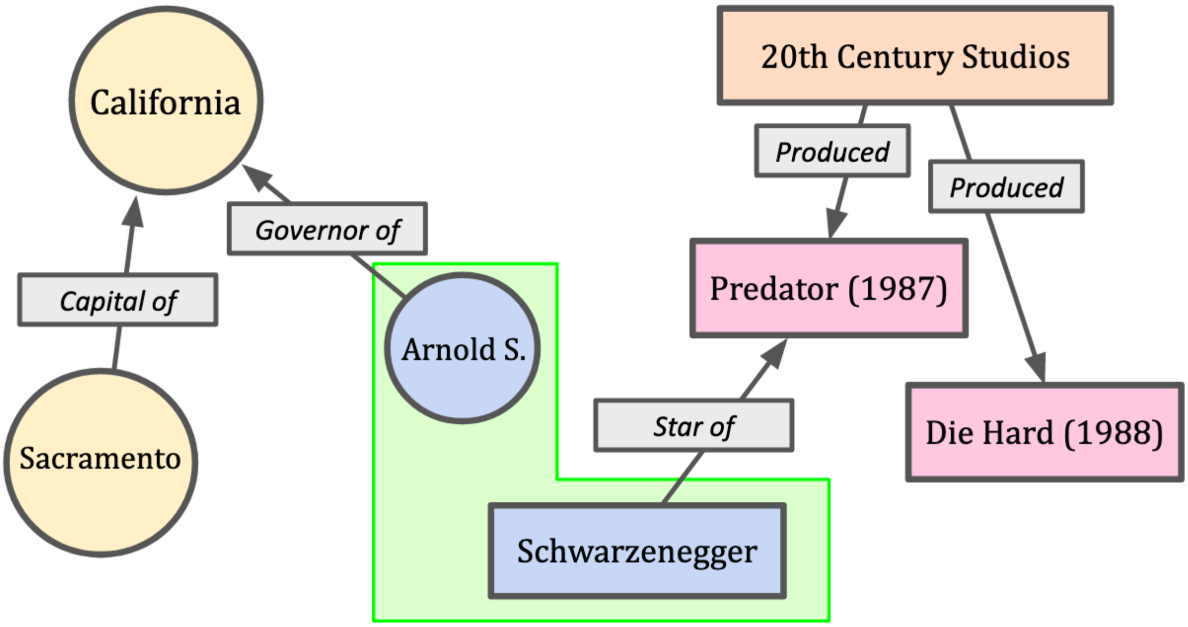


Figure 1: A simple example of a knowledge graph

By leveraging both ontologies and knowledge graphs, HRM systems can move towards a more integrated and intelligent approach, facilitating better decision-making, enhancing talent management, and improving overall organisational efficiency. It would facilitate better interoperability, data sharing, and holistic skill assessment, helping to achieve a modern, future-focused strategic workforce planning capability. Despite their potential, the adoption of these technologies in HRM has been slow, indicating a need for further research and practical application to fully realise their benefits. Therefore, this paper presents the concept of an ontology-driven knowledge graph HRM system, designed to enhance decision-making and personnel management within the MOD. An ontology driven system could be used to build on the steps already taken by PDSF and allow integration of other data sources to enrich the captured skills data. An ontology can also be used to integrate other skill frameworks to allow comparison of MOD skills with civilian skills, such as those held in the SFIA skill framework. This system is based on understanding the skills, qualifications, and experiences of personnel, collectively referred to as Knowledge Skills Experience and Other Attributes (KSEOs). This paper also discusses the potential benefits and implications of an ontology-driven knowledge graph HRM system in the MOD context. Progress with knowledge graph technology has been relatively slow until recently where the application within advanced AI such LLMs has resulted in a large push to develop machine readable databases which can be used for retrieval.

Literature Review

This literature review builds upon the foundational concepts introduced in the introduction, exploring the development and design decisions for a knowledge graph-driven HRM system using OWL/RDF. The backdrop of this research lies in the imperative need for a sophisticated understanding of HR skills management and validation to enhance personnel management and decision-making processes.

Ontology: Definition and Development

The term ontology, though rooted in philosophy where it concerns the nature of being, has evolved in computer science and information technology to represent a more practical concept. In this field, Gruber's (1993) definition of ontology as "a formal, explicit specification of a conceptualisation" has been widely adopted, emphasizing that an ontology structures and formalises domain-specific knowledge in a machine-readable form. The various studies examined offer distinct perspectives on how ontologies are used to manage and represent complex information systems, yet common themes emerge around flexibility, adaptability, and the evolving nature of information management.

An overarching theme across the literature is the tension between traditional, more rigid ontological models and newer, more flexible and adaptive approaches. For instance, Wand and Weber's (1990) foundational work focused on structured, formal models that were essential for static and dynamic analysis in information systems. However, these models, while methodical, lack the expressiveness required for modern, rapidly evolving information systems, as later works argue. In contrast, Motara and Van der Schyff (2019) propose a more dynamic, functional ontology that allows for more complex relationships between entities, which better aligns with the needs of contemporary information systems, particularly those with dynamic environments like Human Resource Management (HRM) systems.

Another central theme is the application of ontologies in specific domains, demonstrating the adaptability and customisability of ontological models. Rani et al. (2016) emphasise the benefits of ontology in Learning Management Systems (LMS), highlighting its capacity to provide personalised learning experiences by aligning learner profiles with appropriate resources. This approach starkly contrasts with traditional LMS models, which typically offer limited adaptability. Savić et al. (2019) extend this discussion by examining ontology networks, where they highlight the growing complexity in ontology structures, particularly within Semantic Web technologies. Their research suggests that richer, interconnected ontology networks can provide deeper insights into information systems, enhancing both system interoperability and information management.

Methodological approaches to ontology development also feature prominently in the literature, pointing to the different ways ontologies can be built depending on the domain's requirements. De Nicola, Missikoff, and Navigli's (2009) UPON methodology, for example, applies principles from software engineering, making ontology development more structured and efficient, particularly in eBusiness. Their approach contrasts with methodologies like those discussed by Ding and Foo (2002), who focus on ontology mapping and evolution. The challenge here lies in the adaptability of ontologies to capture changing meanings and relationships over time, with current semi-automatic solutions still heavily reliant on human expertise.

The literature also covers diverse strategies for making ontology development more manageable, especially in domains with limited structural resources. For example, Zhou, Booker, and Zhang (2002) propose the Rapid Ontology Development (ROD) methodology, which focuses on efficiency and collaboration to build ontologies in underdeveloped domains. Meanwhile, Garrido and Requena (2012) introduce an algorithm to create "brief ontologies" by extracting key concepts from larger structures without losing semantic complexity, offering a user-centric approach that addresses the challenge of large-scale ontology development.

In summary, the literature on ontology development and application in information systems reveals a broad range of approaches, each suited to different challenges. Traditional models offer structured, methodical frameworks but may lack the flexibility required by modern systems. Newer approaches, such as functional ontologies, ontology networks, and adaptive methodologies like UPON or ROD, emphasise flexibility, efficiency, and the capacity to evolve alongside the systems they support. Together, these studies underscore that successful ontology development requires not only methodological rigor but also adaptability to the specific needs and complexities of the domain in question. By integrating multiple approaches, organizations can improve the efficiency and effectiveness of their information systems, ultimately fostering more adaptive and responsive operations.

Standardised Technologies for Ontology Development: Web Ontology Language (OWL), Knowledge Graphs, and Other Technologies

Web Ontology Language (OWL) is a semantic web language designed to represent complex information about things, groups of things, and relations between things. As a World Wide Web Consortium (W3C) standard, OWL provides a formal specification for representing ontologies, enabling machines to process and reason about the information on the web (Antoniou & van Harmelen, 2004). It provides mechanisms for ensuring the consistency of ontologies, even as they evolve.

Haase and Stojanović (2005) discuss the importance of maintaining consistency of ontologies using OWL, presenting a model for the semantics of change that ensures structural, logical, and user-defined consistency during the evolution of ontologies. OWL capabilities in handling rich semantics make it an ideal choice for building skill frameworks that need to be both comprehensive and interoperable.

Rodríguez-García and Hoehndorf (2018) developed a method to transform OWL ontologies into graph structures using automated reasoning. Their approach leverages deductive inference to identify implied relations between classes, enhancing the ontology's semantic content and improving data analysis capabilities.

Skill management systems are designed to identify, manage, and develop skills within organisations. Traditional systems often rely on specific frameworks, making them inflexible and difficult to adapt to new requirements or integrate with other systems. Ontologies, particularly those defined using OWL, offer a solution by providing a formal structure for representing skills that can be easily extended and modified.

Framework agnosticism refers to the ability of a system to operate independently of specific skill frameworks. This flexibility is essential for organisations that need to integrate various skill taxonomies and adjust to evolving industry standards. OWL's formal semantics and support for reasoning allow for the creation of a unified skill ontology that can map to multiple frameworks (Noy & McGuinness, 2001). This mapping capability ensures that the skill management system can interpret and relate skills from different sources effectively.

Knowledge graphs provide a structured and interconnected representation of data. When combined with OWL, these knowledge graphs leverage OWL's rich semantic capabilities to perform advanced reasoning tasks, ensuring data consistency and that logical relationships are maintained across the system. A knowledge graph can also allow for the seamless integration of external data sources, enhancing the system's ability to generate insights and support decision-making. Recent studies highlight the importance of using OWL in knowledge graph systems due to the support for automated reasoning and ability to handle evolving ontologies. More complicated structures such as Bayesian networks (networks using statistics to draw inference) can also be stored within a knowledge graph to enable probabilistic reasoning (Freedman et al., 2023).

Other technologies such as Large Languages Models (LLMs) can take advantage of graph structures. One notable example of this is Graph Retrieval Augmented Generation (GraphRAG) which can be used to explain data within the graph as well as any inferences made by the OWL ontology. In certain cases, this can improve the output of a LLM by up to 71% (Karthik Soman, Peter W Rose et al. 2023). In the case of Soman, the improvement of 71% was measured on biomedical yes/no questions or multiple-choice questions. This has an analogue with suitability to role in the context of human resource management.

Proposed Conceptual Framework – Ontology-Driven Knowledge Graph Skill Management System

The paper outlines the conceptual framework for the proposed ontology and knowledge graph driven skill management system is used to manage and utilise skills effectively within defence. This conceptual framework, which serves as the foundation of the skill management system, was developed following a comprehensive literature review, including previous scoping studies and discussion with stakeholders. By leveraging an ontology and knowledge graphs, the proposed system can create a rich, interconnected representation of skills, employees, job roles, and training programmes.

A system utilising GraphDB as the backend with a Python web server, provides a scalable and flexible architecture. GraphDB was chosen for its performance as an RDF triple store and additional features, such as the ability to integrate other software. Python was chosen as a web server due to its usefulness for prototyping and ability to also process data before it is sent to the database or when it is retrieved. The design of this system integrates components and infrastructure elements to achieve an efficient skill management framework. These components include:

- Ontology
- Web server backend
- Database
- API (Application Programming Interface) endpoints
- User interface
- Analytics and reporting

Ontology Design: The ontology forms the backbone of the knowledge graph, defining the [classes], [relationships], and [attributes] that structure the data. The choice of [classes] such as Skill, Employee, JobRole, TrainingProgram, and Department allows for a comprehensive representation of the organisational structure and its requirements.

[Relationships] such as HAS_SKILL and REQUIRES_SKILL capture the essential connections between employees and their capabilities, and job roles and their requirements, respectively. This structured representation facilitates efficient querying and data manipulation, enabling advanced analytics and decision-making processes.

[Attributes] provide detailed descriptions of each entity (individual piece of data), ensuring that the system captures all necessary information for effective skill management, such as skill level or skill framework.

Additionally, OWL will form the backbone for the ruleset used by the reasoning framework (AI part of the database which automatically classifies data). The ontology, through the nature of being machine readable, will allow explanation generation which will be discussed further later. The ontology proposed in Figure 2 is capable of holding both structured data and unstructured data. For example, the appraisal score is structured data which can be used for logical reasoning while the text of an appraisal is unstructured text but may give useful context for a LLM to generate explanations. Dotted lines in the ontology show inferred links, for example, the link between Person_ID and KSEO is inferred using data from events, competencies/qualifications or previous roles. Several of these inferred relationships exist within this ontology. This one allows the capture of **how** the skill was acquired, for example in a training event or an exercise.

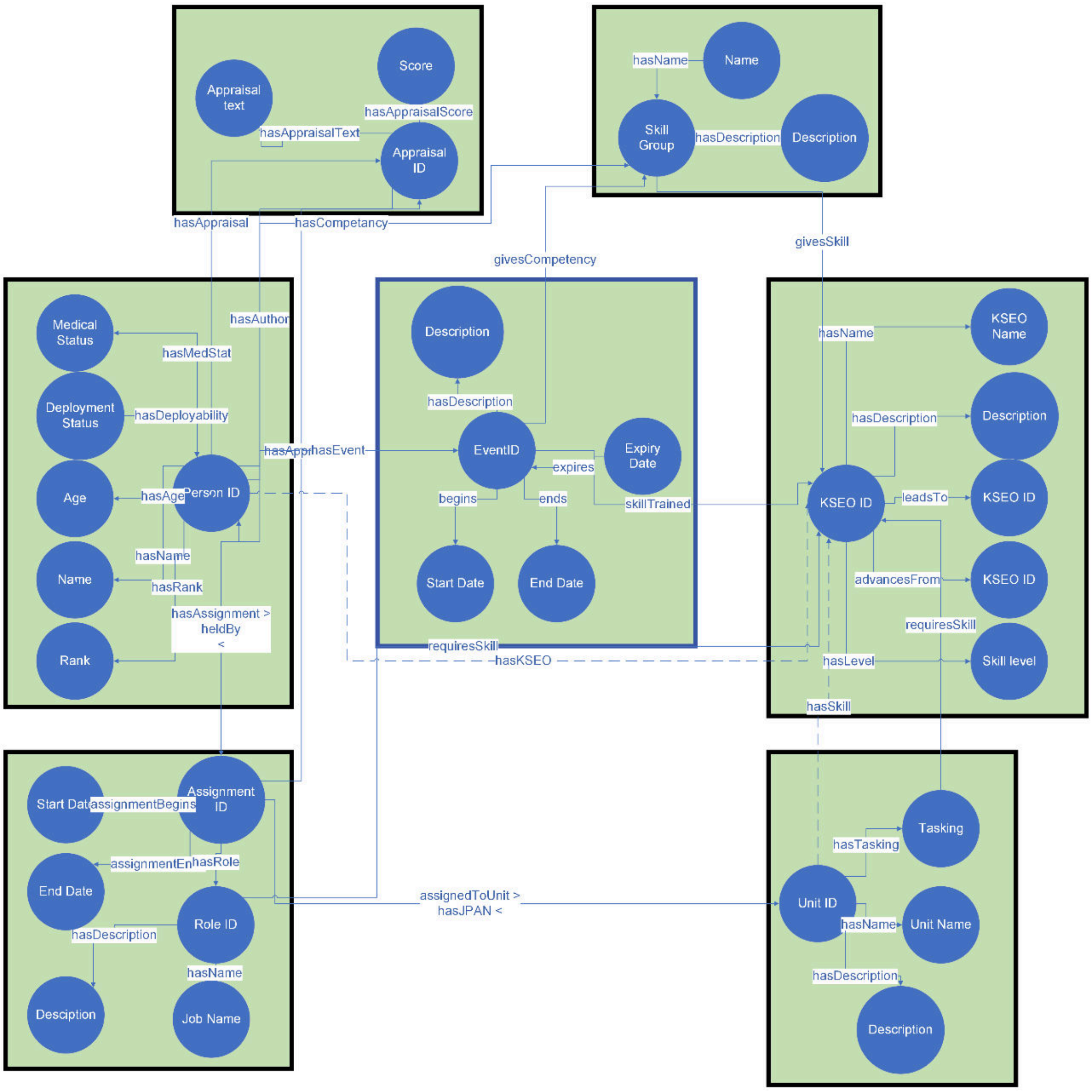


Figure 2 Proposed Ontology to link personnel to skills, units and roles.

Backend and Database: GraphDB is chosen as the database to manage the ontology and data because of its robust support for semantic data modelling and querying. GraphDB stores RDF triples (rows of three pieces of data) which allows for linked data relationships, which are essential for accurately representing complex organisational structures and relationships. A python web server is connected to improve the functionality of GraphDB in the form of API endpoints. This webserver can also host the user interface/front end of the application. This combination ensures that the backend is scalable, reliable, and capable of handling complex queries and large datasets.

API Endpoints: The web server will expose various endpoints to interact with the system, enabling users and other systems to add and retrieve data efficiently. API endpoints such as /add_employee, /add_skill, and /assign_skill_to_employee allow for management of the knowledge graph, facilitating easy updates and maintenance. Retrieval endpoints like /get_employee_skills and /get_job_role_requirements provide critical data access points for analytics and decision-making. By exposing these endpoints, other organisations can interact with the system without the need to understand the underlying technology, enhancing overall productivity and efficiency. Using system models to define and document API endpoints could improve consistency and traceability while also streamlining API interactions.

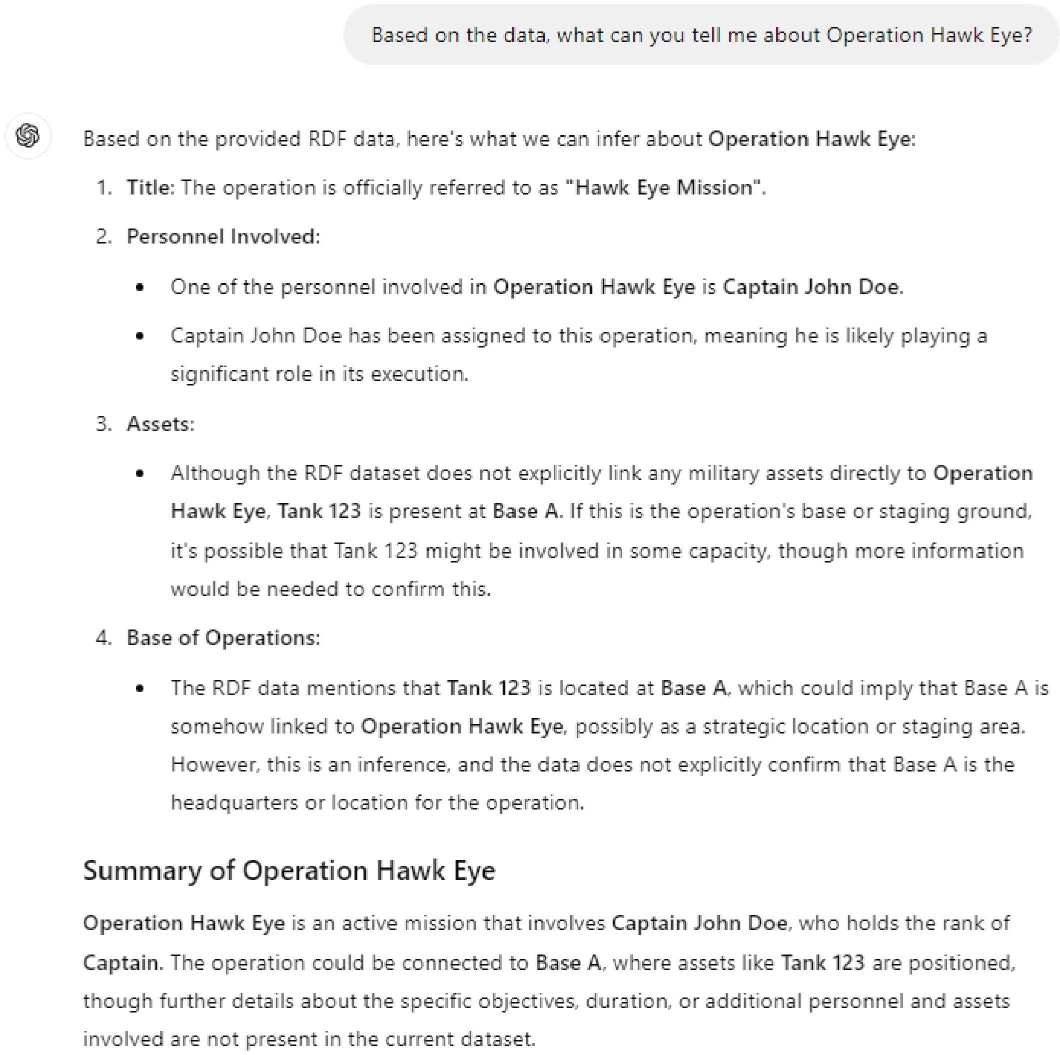
User Interface: The user interface will provide a platform for interacting with the system, making it accessible to various stakeholders within the organisation. A comprehensive dashboard (an example of an interface) would offer an overview of key data and metrics, such as employee skills and training programs, enabling quick insights. A skill matrix can be used to visualise the distribution of skills across employees and job roles, identifying gaps and opportunities for development. This user-centric design enhances usability and encourages regular interaction with the system. A key benefit of having API endpoints is to allow users to customise the interface they see to fit the needs of their organisation.

Analytics and Reporting: The system will provide analytical tools to derive insights from the data, driving strategic decision-making. Skill gap analysis identifies areas where the organisation lacks necessary skills, guiding targeted training and hiring efforts. Training effectiveness metrics measure the impact of training programs, helping to optimise learning and development investments. Career pathing visualises potential career trajectories for employees based on their skills, fostering employee growth and retention. This would be based on historic data from other employees in similar roles, or based on skill growth over time.

Reasoning and Explanation Generation for Knowledge Graph-Based Systems

Knowledge graph-based systems are still relatively new for organisations and the presence of inference, an AI generated entity or relationship, can make users feel uncomfortable and requires careful validation and verification to ensure trust and data integrity is maintained. In the human resources domain, any system must be idempotent[1] and transparent in order to give managers the confidence they need to make decisions. OWL provides definitive reasoning and should always conclude with the same answer, however this explanation would be difficult for a typical user to understand. ChatGPT can be configured to interpret RDF data based on a particular dataset, as provided in the example below.

[1] The ability to execute the same operation multiple times without changing the result.



Based on the data, what can you tell me about Operation Hawk Eye?

Based on the provided RDF data, here's what we can infer about **Operation Hawk Eye**:

1. **Title**: The operation is officially referred to as **"Hawk Eye Mission"**.
2. **Personnel Involved**:
   - One of the personnel involved in **Operation Hawk Eye** is **Captain John Doe**.
   - Captain John Doe has been assigned to this operation, meaning he is likely playing a significant role in its execution.
3. **Assets**:
   - Although the RDF dataset does not explicitly link any military assets directly to **Operation Hawk Eye**, **Tank 123** is present at **Base A**. If this is the operation's base or staging ground, it's possible that Tank 123 might be involved in some capacity, though more information would be needed to confirm this.
4. **Base of Operations**:
   - The RDF data mentions that **Tank 123** is located at **Base A**, which could imply that Base A is somehow linked to **Operation Hawk Eye**, possibly as a strategic location or staging area. However, this is an inference, and the data does not explicitly confirm that Base A is the headquarters or location for the operation.

Summary of Operation Hawk Eye

Operation Hawk Eye is an active mission that involves **Captain John Doe**, who holds the rank of **Captain.** The operation could be connected to **Base A**, where assets like **Tank 123** are positioned, though further details about the specific objectives, duration, or additional personnel and assets involved are not present in the current dataset.

Figure 3: An image to show ChatGPT interpreting RDF data

Use Cases

The proposed ontology-based system can be implemented to support various use cases in the defence context including those discussed below.

Skill Management and Tracking: This system would enable detailed tracking of personnel skills and competencies at several granularities. Existing skills frameworks such as the "Defence Cyber Competency Framework" may only represent one or two levels of granularity. The OWL aspect of the ontology would be able to map between granularities in a similar way to how locations are mapped in ontologies (e.g. London is in England, which is in the UK which is in Europe etc.). This hierarchical mapping allows for reasoning to happen at all levels of detail. Furthermore, analytics and reporting tools would be able to make use of the linked data to identify skill gaps.

Recruitment and Training: The ontology and the data within it would allow the role matching of personnel based on skills and move defence away from a focus on trade and rank which may not deliver the agility defence now needs in its workforce. By integrating additional capabilities, such as a Natural Language Processing (NLP) to analyse a CV and populate identified skills data to the graph, the system could improve the way recruits are assigned to units and trades and identify suitable jobs depending on their backgrounds. Furthermore, training pathways could be shortened through the personalisation of training programmes to cover only the additional skills required for an individual by a role, rather than training everyone in all aspects.

Career Management: Employees would be empowered to manage their own careers through use of a "graph-explorer", a graph that shows the skills they have now and roles which would complement their skill set. If they have skill gaps relating to the desired role, they would be directed to suitable training resources. Other data could be factored into the graph, such as appraisals and feedback, which could be used to validate the KSEOs acquired in a role. Additionally, KSEOs outside of a normal role could be captured, such as secondary duties. A combination of data, mapped to a skill ontology, could support more intelligent, objective and efficient decision making in determining suitability for a role and the training required to improve success in that role.

Capability Management: Since the ontology could also link personnel to a department or unit, it can classify a unit based on the skills held by its members. This could be extremely useful for succession planning as Defence could identify the changes in capability if a member leaves the unit for a new role. This could allow other personnel to be trained in a timely manner to reduce any disruption caused. This could also be used to identify complementary units which could work together to perform a specified task. This would reduce the number of resources required to maintain advanced capabilities. This is particularly useful to Defence as it is required to operate in a wide range of operating environments. For example, having an easy system for the secondment of niche capabilities to special operations. This could include advanced networking, offensive cyber or engineers to modify drones.

Benefits and Implications

The proposed system presented in this paper would bring benefits and implications to MOD, as discussed below.

- **Standardisation and Integration:** The proposed system provides a standardised approach to managing skills data, integrating disparate data sources into a cohesive framework. This would remove friction when different areas of the MOD are required to understand each other's capabilities, such as in a joint operating environment, enhancing interoperability and data consistency across the MOD. For example, it would allow the combination of skill frameworks, such as those created by Project Castle with the Pan Defence Skill Framework (PDSF).
- **Enhanced Decision-Making:** By providing a comprehensive view of personnel skills and competencies, the system supports better decision-making in recruitment, training, and career management. AI-driven recommendations could further enhance decision accuracy and speed. For example, the system

would allow filtering of individuals based on how experienced they are in a specific skill or identifying critical skills which may have been affected by skill fade. This would help particularly with the planning of pre-deployment training, for example open-source intelligence, which requires a refresher course prior to deployment to use the equipment required. Additionally, this knowledge of skills could aid with strategic workforce planning which focuses on the gap between current and future needs.

- **Operational Efficiency**: The integration of ontologies and knowledge graphs streamlines personnel management processes, reducing redundancy in data collection and management and improving efficiency. The system's ability to adapt to changes in requirements ensures its long-term relevance. This would allow new skills and roles to be integrated and personnel to be managed according to the organisation’s priorities.
- **Improved Personnel Management:** The system facilitates better tracking and management of personnel skills, ensuring that the right personnel are assigned to the right roles. This enhances overall operational effectiveness and readiness. The ontology would also support a move from rank-based roles to skill based roles in specific trades, enabling benefits and reward to be aligned with the organisation’s skills objectives and succession plans. The ontology proposed in Figure 2 also includes the relationship between skills and other personnel characteristics as well as performance and events they have volunteered for. This would allow career managers to better understand the goals of personnel and units/roles which will be a good fit for them.
- **Multinational Interoperability:** There is potential for the system to be expanded to exchange information with other systems, such as the NATO Defence Planning Process (NDPP) allowing external data to improve the quality of inferences made by the system. This could provide insight to NATO planners of the skills and capabilities of the UK military force but also inform the UK on skills it needs to develop in order to maintain joint capabilities with other nations. The system can also be extended to include economic and labour force data on the UK to inform recruitment campaigns and options for growing capability and niche skills.
- **Non-Linear Training/Career Pathways:** Many advanced and emerging roles require a niche set of skills and training, good examples of this are drone operators and cyber specialists. The use of an ontology driven system would allow the combination of training course data with an individual’s data. This would allow the generation of a personalised training plan. The benefit of this when applied with a KSEO based framework such as PDSF would be the granularity of the training plan, it may for example mean that an individual (based on prior learning) would only be required to complete the second week of a training course to gain a competency. Building a training pathway with linked data in this way would allow a career manager to minimise resources when required, to either find an individual who can be training in the quickest way possible based on available courses. Some natural niche career paths may emerge as an individual organically gains relevant skills throughout their career either intentionally or through secondary duties or voluntary events.

Conclusion and Future Research Directions

This paper has explored the innovative application of ontology-driven knowledge graphs for personnel management within the Ministry of Defence (MOD). By reviewing relevant literature and conceptualising an ontology-driven knowledge graph HR system, this paper has highlighted the substantial benefits such a system can offer. Key advantages include the standardisation and integration of skills data across the whole force, improved decision-making processes, and enhanced efficiency. The use of advanced technologies ensures a robust and scalable framework for managing personnel skills, which is capable of leveraging future advancement in AI.

The proposed system addresses the silos in which defence data is currently collected by offering a unified approach to managing KSEO. It leverages semantic web technologies and AI-driven inference to provide deeper insights and facilitate better personnel management decisions. Additionally, the system's ability to integrate with other databases and systems further enhances its utility and effectiveness.

Future research directions should focus on development of a proof of concept, validation and verification of such a system, expanding its scope, and validating its interoperability with existing systems. Model Based Systems Engineering (MBSE) could be implemented throughout the development process to document challenges and limitations, this would allow changes to be made quickly if external pinch points change, such as organisational AI policy. Integrating more detailed skill classifications and optimising AI elements for retrieval and explanation generation will be crucial for maximising the system's potential. As the MOD continues to evolve in a complex defence environment, adopting an ontology-driven knowledge graph system can significantly enhance its personnel management capabilities, ensuring readiness and operational effectiveness There will be many challenges to overcome with the development of such a system, mainly focussed on the integration with current MOD systems, the ethics around the use of AI to deal with such data. The next step would be to create a system, beginning with the creation and validation of the ontology as the is the key foundation for the rest of the system.

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