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Analyzing and development professional competencies using graph models

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Abstract

This research explores the application of graph models and visualization tools for analyzing professional competencies with Kazakhstan labor market, provided by the National Chamber of Entrepreneurs “Atameken”(NCE). Using professional standards parsed from the National Chamber of Entrepreneurs “Atameken” documents, a comprehensive graph model was developed to represent the relationships between job positions, skills, knowledge, and qualification levels to better understand career pathways. Visualization and analysis of the graph models, constructed according to the professional standards provided by the National Chamber of Entrepreneurs, revealed several key insights into the structure of professional competencies. The model was implement using the graph database for querying and traversing the information . One major finding was the dependence of skills and knowledge on the Skills Qualification Framework levels, where foundational competencies were observed to span multiple qualification levels, while advanced, specialized competencies were concentrated at higher levels. This distribution emphasizes the layered nature of professional growth, with foundational skills acting as prerequisites for advanced roles. Furthermore, the graph analysis highlighted overlaps in skills and knowledge across related professions. Overall, the graph model successfully captures the layers and overlapped nature of professional growth as required and defined by the NCE standards. In Addition, the results demonstrate the utility of graph-based models for analyzing and visualising professional standards, offering a robust framework.

Keywords: Data analysis, Data structure, Graph databases, Graph models, Neo4j, Professional competencies, Qualification levels.

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1. Introduction

The primary objective of this research is to analyze the acquisition of professional skills through the development and release of graphical models. The research aims to build a system that can adequately capture the interrelationships between a variety of skills, qualifications, and job functions with an emphasis on professional standards. To achieve this visual model along with python based visualizing tools were developed out of the data gathered by National Chamber of Entrepreneurs (NCE) of the Republic of Kazakhstan "Atameken" (a pioneer organization in regard to the development of professional standards), and analyses were made to gain meaningful insights that can be helpful to educators, employers, and policymakers to design effective curricula and career development programs. This research provides new framework for work function linkages to skills and their structuring towards better educational and occupational results. Professional standards are important reports that define the skills, abilities and knowledge necessary in certain professions, such standards provide the basis used to identify abilities needed in different occupations and inform the creation of education programs. In foreign countries, the like organizations NCE "Atameken" contribute significantly towards creating and upholding professional standards to be able to fit into the requirements of industry, so that education programs are in a position to prepare the individuals competent enough to be ready for the demands of the job market. The European Qualifications Framework does the same thing in harmonizing professionals' qualifications in Europe [1]. National Chamber of Entrepreneurs (NCE) "Atameken" responsible for the development of professional standards in Kazakhstan [2]. It offers a framework that outlines the required skills, knowledge, and competencies for several job roles across sectors. These norms constitute the framework for career and educational pathways, providing a structured approach to align the workforce's skill set with market needs [3, 4]. NCE "Atameken" created the professional standards that educational institutions, employers, and government bodies use to make sure that curricula and training programs remain relevant and effective [5]. This study aims to find out how these professional standards can be turned into a graph model, making the complicated connections between several skills accessible and helpful. Graph model maps out the professional standards and visualization allows for in-depth analysis, identifying patterns, dependencies, and paths that and could enhance the alignment of education and career progression.

2. Research Objectives

2.1. Research Aim

The purpose of this study is to develop, analyze and visualize graph model for professional competencies assessment using the data of the National Chamber of Entrepreneurs "Atamaken". Using graphs as a main source, this study seeks underlying patterns, hierarchical relationships, and interdependencies between job positions, skills, and qualification levels [3]. This graph database, which analyzes the level of adherence of educational programs to standards, enables control over semantic relations between educational components, competencies, and learning outcome enabling more informed decision-making regarding the adoption or enhancement of an educational program.

2.2. Objectives of the Research

The objective of this research is to analyze professional standards developed by NCE "Atameken" to identify relevant information on skills, knowledge, and qualifications through graphical models. A graphical model is created to display the relationship between skills, knowledge, qualifications, and job roles defined in the professional standards. Furthermore, graphical modeling is supplemented with information collected from these professional standards, hence a reflection of the interrelations with high accuracy. Finally, analysis of the graph was completed by visualization methods to reveal trends, such as the most demanded skills and knowledge, overlapping professions, and dependencies related to qualification levels, which adds clarity as well as accuracy to this research.

2.3. Core Focus of Research

The core focus of this research is to visualise professional competencies, which circumscribe skills, knowledge, and qualification skills. The key focus was to construct a graph-based model that captures interconnections between skills, knowledge, and job roles based on standards suggested by NCE "Atameken."[4] Additionally, it identifies patterns and dependencies in competency structures using graphical analysis decoding in-demand skills and overlapping competencies across professions, which concentrates on drawing important conclusions that can help policymakers, employers, and educators for creating frameworks for career development and successful curricula. The higher education system in the Republic of Kazakhstan plays a key role in national development, and it's management requires constant improvement [6]. The entire educational process is regulated by a significant number of normative legal acts, particularly the laws of the Republic of Kazakhstan.

Designing educational programs implies the availability of large amounts of initial factual knowledge, the source of which are professional competencies formed on the basis of analysis of the content of academic disciplines in their connection with the requirements of educational and professional standards, taking into account the requirements of the labor market to professional disciplines and the orientation of the educational program [7]. The development of educational programs based on professional standards implies the creation of a working group, including both representatives of professional education and employer's representatives, in order to ensure the harmonization of all development results [8]. The requirements of employers are understood as their expectations regarding the competencies of employees of a particular profession and a particular job level. The structural elements of the educational program design are shown in Figure 1, in the form of process diagrams.

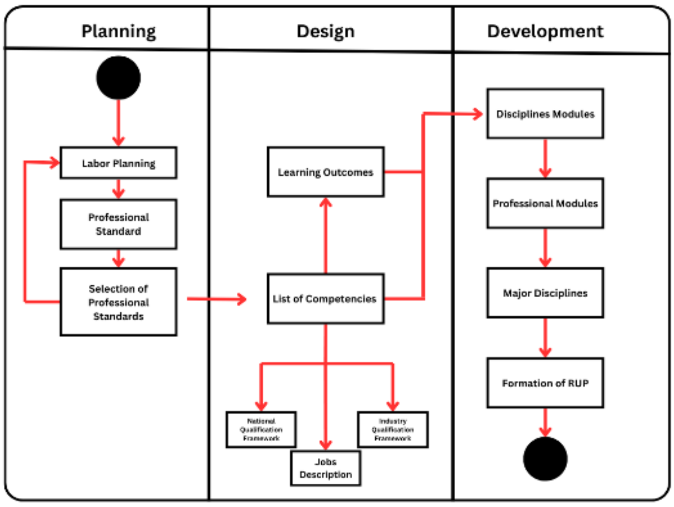

Figure 1.
Diagram of educational program formation processes

3. Methodology

Atameken provides a foundation for competency-based education and workforce development, helping to align educational outcomes with the demands of employers and enhancing the employability of graduates in the Kazakhstani job market .One of Atameken's significant initiatives is the development of professional standards aimed at bridging the gap between the educational system and the evolving demands of the labor market. These standards served as a framework for defining the specific skills, knowledge, and competencies required for various professions. By outlining these requirements, the standards support educational institutions in tailoring their curricula to meet industry needs, ensuring that graduates are equipped with relevant, job-ready skills [6, 7]. The professional standards are structured to capture the core functions, responsibilities, and competency levels needed for different roles across sectors. They encompass both technical and soft skills, reflecting a holistic approach to professional readiness.

3.1.1. Data Collection

The data collection process involved the following crucial steps:

3.1.1.1. Identifying Relevant Standards

Utilizing the NCE "Atameken" website, professional standards relevant to the Information and Communication Technologies (ICT) category were identified and retrieved.

3.1.1.2. Extracting Competency Information

Each standard was carefully reviewed to extract information pertaining to the required competencies for each profession within the NQF framework. This included details like knowledge, skills, and abilities associated with each professional role. The process of downloading professional standards from the NCE "Atameken" portal is carried out in several stages. The diagram of the entire process is shown in Figure 2.

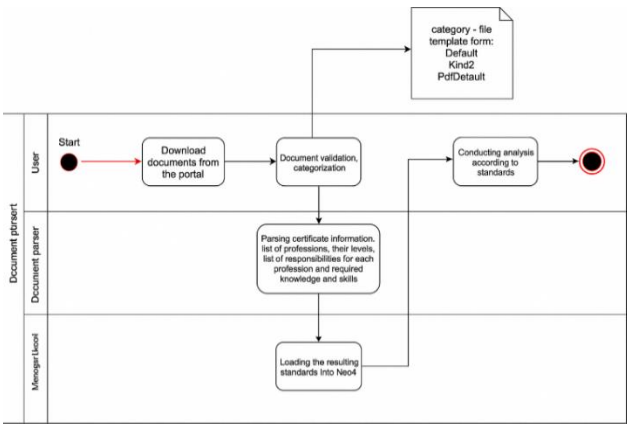

Figure 2.
The process of parsing and loading professional standards involves downloading, parsing, and loading the received data into the graph databases and tools.

Once the correct document was identified from the Atameken website, custom Python-based parser was used to parse the required information from the document. Through this process, essential information such as qualification levels, labour functions, etc. were parsed. After parsing, the extracted data was transformed into a structured CSV form where each node (e.g., skill, knowledge, labor function) and relationship (e.g., HAS_FUNCTION, REQUIRES_SKILL) were clearly mapped [9].

3.1.2. Data Preparation

After parsing the data ,the next crucial step was to prepare the data for a graphical database. This step involved organizing the parsed content into three structured CSV files, one of the file contains all the nodes(nodes.csv), another is responsible for defining the relationship between them(edges.csv) and one csv file was created for feeding the required data to visualisation tools.

Each node entry has unique identifiers, a textual label (label), and a category (type) that classifies it as an ORK level, labor function, skill, or knowledge. Relationships were structured with source and target node IDs and a descriptive relationship type (HAS_FUNCTION, REQUIRES_SKILL, REQUIRES_KNOWLEDGE).

	id	label	type
0	level_4	Level 4	ORKLevel
1	level_4_4842	Gathering requirements	LaborFunction
2	skill_36886	Collection of information for formalization of...	Skill
3	skill_63066	Interviewing stakeholders	Skill
4	skill_1013	Conducting express surveys	Skill

Figure 3.
Structure of the node.csv file, where id acts as a unique identifier, type provides clear explanation on what kind of data it is and label uniquely provides textual labels for better understanding.

This step helped in easy loading of the data in graphical database and building graphical models. These csv are not only used to build graphical models, but also provides the structure to unstructured data downloaded from the official website

3.2. Graph Construction

For graphical analysis of the data, the prepared data was imported into a graph database environment using Neo4j. Each parsed entity was modelled into the graph node, and relationships were used for directed edges [10].

The CSV files created during the preparation phase were then loaded using Neo4j's LOAD CSV function. Relationship types such as HAS_FUNCTION, REQUIRES_SKILL, and REQUIRES_KNOWLEDGE were used to encode the dependencies between nodes.

3.2.1. Graph Representation

The parsed competency data is modelled as a directed, labelled, and attributed graph. Mathematically, the graph is represented as

$$G=(V,E,\tau,,A) \quad (1)$$

where

- V is the set of vertices
- $E \subseteq V \times V \times \lambda$ is a set of directed and labelled edges
- $: V \rightarrow T$ is the node-type function assigning each node a type from $T = \{ORKLevel, LaborFunction, Skill, Knowledge\}$.
- $\lambda : E \rightarrow R$ is the relationship-type function mapping each edge to a type in R = {HAS_FUNCTION, REQUIRES_SKILL, REQUIRES_KNOWLEDGE}.
- $A: V \cup E \rightarrow P$ is the attribute function assigning each node or relationship a set of key–value properties (e.g., id, label, OrkLevel, etc.)

In practice, this graph model was implemented using Neo4j using Cypher Query Language for pattern-based analysis.

3.2.2. Graph Development

Once the node and relationships were defined in the CSV file, these files were imported into the Neo4j database using the LOAD CSV function as mentioned in section 3.1.2. Neo4J Cypher query language was used to process these CSV files and create the graph model in accordance with the schema defined. To ensure accuracy and flexibility during graph construction, Neo4j's LOAD CSV function and the APOC (Awesome Procedures on Cypher) library, which allows dynamic creation of relationships based on values stored in CSV columns.

3.2.2.1. Node Creation

Each node in the graph represents a unique entity such as an ORK level, labor function, skill, or knowledge component. Nodes were created using a unique identifier (id), Additional properties like label and type helped in providing semantic meaning. The MERGE command in Cypher ensures that nodes are created only if they do not already exist, while SET assigns attributes, preserving the structure and integrity of the graph. Algorithm 1 provides pseudo code for generating a graph node.

Algorithm 1 Pseudo code for creating a Graph Node

Input:`id`, `label`, `type`
Output: Created or matched node n
Check if a node with identifier `id` exists
If node does not exist
Create node n with attributes: `id` ← id `label` ← label `type` ← type
Return node reference n

3.2.2.2. Relationship Creation

Once all nodes are created and uniquely identified, relationships are established between them to model the structure of the competency framework. Each edge connects a source node to a target node and is labeled with a specific relationship type, such as:

- HAS_FUNCTION — connects an ORKLevel node to a LaborFunction
- REQUIRES_SKILL — connects a LaborFunction to a Skill
- REQUIRES_KNOWLEDGE — connects a LaborFunction to Knowledge

These relationships are read from the edges.csv file and created in Neo4j using the MATCH and CALL apoc.create.relationship() functions. Algorithm 2 represents the pseudo code for generating graph relationships.

Algorithm 2 Pseudo code for Creating Graph Relationships

Input:`source_id`, `target_id`, `relationship_type`
Output: Created or matched relationship r between nodes
Step 1: Match node a with `id = source_id`
Step 2: Match node b with `id = target_id`
Step 3: Check if a relationship of type `relationship_type` exists from a to b

If relationship does not exist
Step 4: Create relationship r from node a to node b Set r.type ← `relationship_type`
Step 5: Return reference to relationship r

3.2.2.3. Graph Validation and Schema Verification

After creating nodes and relationships, Graph structure is validated to ensure data consistency and completeness. This involved checking the total number of nodes Figure 4 and relationships, verifying relationship types, and ensuring correct connectivity between ORK levels, labor functions, skills, and knowledge. Cypher queries were used to count entities by type and confirm semantic relationships, ensuring the graph was ready for traversal and analysis. Algorithm 3 provides pseudo code for validation of the graph where Step 1 counts the total number of nodes, Step 2 retrieves all the relationships, and Step 3 and Step 4 provide verification.

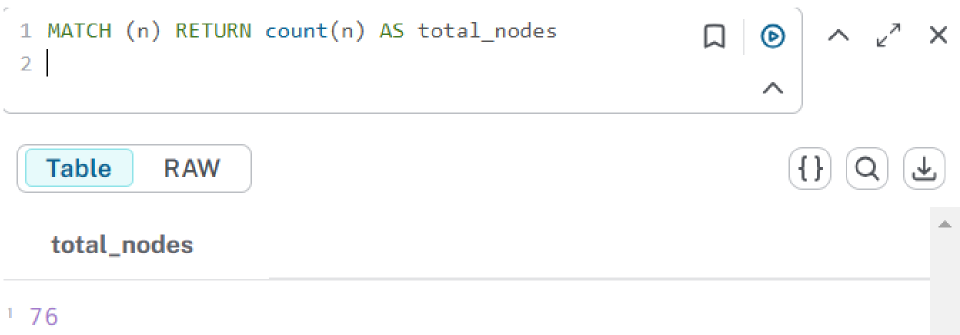

Figure 4.
Cypher query to check how many total number of nodes are present.

Algorithm 3 Pseudo code for Graph Validation

Input: Constructed Graph $G = (V, E)$
Output: Validation
Step 1: Count total nodes and group by type Execute Cypher: `MATCH (n) RETURN n.type, count(*)`
Step 2: Retrieve all relationship types Execute Cypher: `CALL db.relationshipTypes()`
Step 3: Verify critical path structure exists Execute Cypher: `MATCH (l:ORKLevel)-[:HAS`$_FUNCTION]- > (f : LaborFunction) - [: REQUIRES_SKILL]- > (s : Skill)RETURNl, f, sLIMIT10;$
`Step 4: Check connectivity and data completeness any step returns empty or missing types FAIL PASS`

3.2.2.4. Node Labelling and Visualisation

After the successful creation and validation of nodes and relationships, semantic labels were assigned to each node corresponding to its type. Nodes were categorized into four types: ORKLevel, LaborFunction, Skill, and Knowledge. This step enhanced the semantic expressiveness of the graph and enabled structured querying using label-based patterns in Cypher.

To verify the constructed graph, a Cypher based query was performed to retrieve the nodes and relationships. Node colors and labels were customized to distinguish different types and enhance interpretability.

Figure 5.
Graph model of Business Analysis in ICT professional standard, where red colour shows Labor Functions, violet colour shows knowledge, and green colour shows skills.

Directed edges capture the hierarchical and semantic relationships defined in the parsed standard. Specifically, ORKLevel nodes are connected to their respective LaborFunction nodes through HAS_FUNCTION relationships. LaborFunction nodes, in turn, are connected to both Skill and Knowledge nodes via REQUIRES_SKILL and REQUIRES_KNOWLEDGE relationships, respectively [11, 12].

The graph confirms the layered structure of professional standards, with each level connected to multiple job-specific functions, and each function further linked to a set of required competencies. The graph allows easy identification of shared skills and knowledge among functions or levels, which becomes essential for later analysis and overlap detection.

3.3. Visualisation

The csv file created during the data preparation stage was used to perform various visualisations through python-based tools. Correlation matrix was used to find the relationship between different SQF levels, parallel coordinate plot helped visualizing the distribution of competencies across various levels, radar chart was used to provide insights into the distinct competencies at different SQF levels. Venn Diagram, stacked bar chart and Jaccard Similarity(Equation 2) index helped indicating the overlap between various levels.

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{2}$$

- Where A and B are levels which are compared to find overlapping between the levels
- $A \cap B$ is the count of competencies common to both SQF levels
- $A \cup B$ is the count of all distinct competencies appearing in either SQF level.

Python libraries such as matplotlib and it's modules helped in better visualisations of the competencies data and helped provide better results.

4. Graph Analysis and Interpretation

After developing the professional standards graph model, applying various graph analysis algorithms to extract valuable insights. The primary objective of this analysis is to provide the structure and relationships within the data, which will provide a deeper understanding of competencies, skills, and professional standards. To address, the analyses are as follows:

4.1. Dependence of Skills and Knowledge on the SQF Level

One of the analyses is how skills and knowledge requirements vary across different levels of the Skills Qualification Framework (SQF) within a single profession. This involves identifying whether certain competencies are duplicated across levels or if each level demands a unique and progressive set of skills and knowledge [13]. By analysing this dependency, clarity and progression of professional development within a speciality can be assessed. If skills are overly duplicated, it may indicate a lack of clear distinction between levels, which could result in confusion for both educators and industry stakeholders. Conversely, identifying unique competencies for each level could help in designing more targeted training and development programs for professionals at different stages of their careers.

Algorithm 4 Extracting SQF Level Dependence of Skills and Labor Functions

Input: Graph database containing `LaborFunction`, `Skill`, and `ORKLevel` nodes with appropriate relationships.

Output: List of labor functions, their required skills, and the associated SQF levels.

Step 1: Identify all `LaborFunction` nodes connected to `Skill` via the `REQUIRES_SKILL` relationship.

Step 2: Retrieve the `ORKLevel` associated with each `LaborFunction` via the `HAS_LEVEL` relationship.

Step 3: For each `LaborFunction` and its associated `Skill`, collect the corresponding `ORKLevel`.

Step 4: Group the results by `LaborFunction` and `Skill`, aggregating distinct levels.

Step 5: Return the structured list showing each labor function, the required skill, and their corresponding qualification levels.

It is very clear that many skills and knowledge are duplicated for different levels. Referring to Table 1, here is an illustration supporting the above statement, where the skill "Using tools and methods for access control to a database" applies to the position of "Database Administrator" and the functional responsibility "Maintaining DB IS" applies to two levels of the ORK at once [14].

Table 1.
SQF level dependence of skills and knowledge.

Function Levels	Skill Levels	Knowledge Name
Europass [4] and Kaibassova and Ashimbekova [15]	Europass [4]	Managing access levels for database user groups.
Europass [4] and Kaibassova and Ashimbekova [15]	Europass [4]	Compliance with the information security policy in the organization Zinovieva, et al. [16].
Europass [4] and Kaibassova and Ashimbekova [15]	Kaibassova and Ashimbekova [15] and Europass [4]	Using tools and methods to control access to the database.
Europass [4] and Kaibassova and Ashimbekova [15]	Kaibassova and Ashimbekova [15]	Analysis of possible threats to database security.
Europass [4] and Kaibassova and Ashimbekova [15]	Europass [4]	Creation, modification, deletion of database user accounts.
Europass [4] and Kaibassova and Ashimbekova [15]	Kaibassova and Ashimbekova [15]	Development of regulatory and technical documentation to ensure information security of the database.

4.2. Identifying the Most Essential Skills and Knowledge

Identifying the skills and knowledge that are most frequently required across multiple professions is crucial for aligning educational programs with labor market demands. By examining the graph model, Nodes (representing specific skills and knowledge) are connected to the greatest number of job roles or position functions [17]. These high-degree nodes indicate competencies that are universally valued and widely applicable. Understanding these in-demand competencies enables educational institutions to prioritize their inclusion in curricula, ensuring that graduates are equipped with skills that will enhance their employability and versatility in the workforce. Query to implement this is shown in Algorithm 5.

Algorithm 5 Identification of the Most Frequently Required Skills

Input: Graph database containing `LaborFunction` and `Skill` nodes connected via `REQUIRES_SKILL` relationships. Output: Ranked list of the most frequently required skills across all labor functions.

Step 1: Traverse all `LaborFunction` nodes connected to `Skill` nodes using the `REQUIRES_SKILL` relationship.

Step 2: Count the total number of distinct `LaborFunction` nodes each `Skill` is associated with.

Step 3: Rank the `Skill` nodes by their frequency of occurrence in descending order.

Step 4: Extract the top n most frequently required skills.

Step 5: Return the list containing skill names along with their respective demand counts.

Table 2.
Most Demanded Skills.

Skill	Demand
Formation of reporting documentation based on the results of the work performed	15
Compliance with the information security policy in the organization	7
Study of the requirements and functionality of the supported software	3

Table 3.
Most Demanded Knowledge.

Knowledge	Demand
Methods and principles of information security.	8
Principles of information security.	7
Standards for the development and execution of technical documentation.	6
Composition of the hardware and software complex.	4

As shown in Table 2 and 3, the most in-demand skills and knowledge areas are strongly concentrated in the field of Information Security. Skills such as "Adherence to Information Security policies within the organization" and knowledge items like "Methods and principles of Information Security" and "Principles of Information Security" highlight a significant organizational focus on security practices and compliance. This trend suggests that proficiency in implementing and maintaining information security protocols is critical across various roles.

Additionally, the high demand for documentation skills, such as "Generating report documentation based on completed work," underscores the importance of clear reporting and standardized documentation. Knowledge of "Standards for developing and formatting technical documentation" is also valued, supporting transparency and consistency in technical communication, particularly in the context of security and information systems management

4.3. Comparison of Skills and Knowledge Within One Position Card Across Levels

Another analysis is the extent to which a specialist with a lower SQF level can perform the duties assigned to a higher-level professional within the same position card. By analyzing the overlap in skills and knowledge between levels, evaluation of the feasibility of task delegation or role substitution within an organization can be done. For instance, if a significant proportion of the skills required for higher-level responsibilities are already present in lower-level competencies, it suggests that lower-level professionals could potentially perform advanced tasks with minimal additional training. Conversely, significant gaps between levels may highlight the need for more structured progression and training pathways to prepare professionals for higher responsibilities. The algorithm to implement this is shown in algorithm 6 and algorithm 7.

Algorithm 6 Identification of Knowledge Duplicated by Levels

Input : Graph database containing `LaborFunction`, `Knowledge`, and `ORKLevel` nodes, with `REQUIRES_KNOWLEDGE` and `HAS_LEVEL` relationships.

Output : List of knowledge elements that are reused across multiple qualification levels within the same profession.

Step 1: Identify all `LaborFunction` nodes associated with the target profession.

Step 2: Retrieve `LaborFunction` nodes linked to a lower-level qualification (e.g., Level 5) via `HAS_LEVEL`.

Step 3: Collect all `Knowledge` nodes connected to these functions via `REQUIRES_KNOWLEDGE`.

Step 4: Repeat Steps 2–3 for higher-level qualifications (e.g., Level 6).

Step 5: Identify knowledge items that appear in both levels by comparing the two sets.

Step 6: Return the duplicated knowledge elements along with their overlap count.

Algorithm 6 identifies skills that are common across two specific OrkLevel qualifications (levels 5 and 6) within the Database Administrator position. Here's a step-by-step breakdown of what the query shown in Algorithm 6 does:

1. Find the Target PositionCard: MATCH (card:PositionCard Name: "«Администратор баз данных»") matches the PositionCard node with the name «Администратор баз данных»".

2. Match Skills at OrkLevel 5:MATCH (card)-[:HAS_FUNCTION OrkLevel: 5]->(funcLow:PositionFunction)[:REQUIRES_SKILL OrkLevel: 5]->(skill:Skill) finds PositionFunction nodes related to PositionCard through a HAS_FUNCTION relationship at

1. OrkLevel 5. It then matches Skill nodes connected to these PositionFunction nodes through a REQUIRES_SKILL relationship, also at OrkLevel 5.

2. Match Skills at OrkLevel 6: MATCH (card)-[:HAS_FUNCTION OrkLevel: 6]->(funcHigh:PositionFunction)-[:REQUIRES_SKILL OrkLevel: 6]->(skill) performs a similar operation for OrkLevel 6, that is finding PositionFunction nodes linked to the same PositionCard and matching Skill nodes connected at this higher level

3. Return Overlapping Skills: RETURN skill.Name AS CommonSkill, COUNT(skill) AS OverlapCount returns the names of skills (CommonSkill) that appear in both OrkLevel 5 and OrkLevel 6 for this PositionCard, along with the count of these common skills (OverlapCount).

Algorithm 7 Knowledge Duplicated by Levels

Input : Graph database containing `LaborFunction`, `Knowledge`, and `ORKLevel` nodes, with `REQUIRES_KNOWLEDGE` and `HAS_LEVEL` relationships.

Output : List of knowledge elements that are reused across multiple qualification levels within the same profession.

Step 1: Identify all `LaborFunction` nodes associated with the target profession.

Step 2: Retrieve `LaborFunction` nodes linked to a lower-level qualification (e.g., Level 5) via `HAS_LEVEL`.

Step 3: Collect all `Knowledge` nodes connected to these functions via `REQUIRES_KNOWLEDGE`.

Step 4: Repeat Steps 2–3 for higher-level qualifications (e.g., Level 6).

Step 5: Identify knowledge items that appear in both levels by comparing the two sets.

Step 6: Return the duplicated knowledge elements along with their overlap count.

Algorithm 7 analyzes the Knowledge nodes associated with the PositionCard named «Администратор баз данных»" ("Database Administrator") [18, 19] by counting how often each knowledge item is required through REQUIRES_KNOWLEDGE relationships. Here's a step-by-step breakdown of what the query shown in Algorithm 7 does:

1. Find the Target PositionCard: MATCH (card:PositionCard Name: "«Администратор баз данных»")-[:HAS_FUNCTION]->(func:PositionFunction) Matches the PositionCard node named "«Администра- тор баз данных»" and retrieves all its associated PositionFunction nodes via the HAS_FUNCTION relationship.
2. Find Related Knowledge: MATCH (func)-[rel:REQUIRES_KNOWLEDGE]->(knowledge:Knowledge) Finds all Knowledge nodes connected to these PositionFunction nodes via the REQUIRES_KNOWLEDGE relationship.
3. Count Knowledge Relationships: COUNT(DISTINCT rel) AS KnowledgeRelation-Count counts the distinct REQUIRES_KNOWLEDGE relationships for each Knowledge node. This shows how many times each knowledge item is explicitly required across the position's functions.
4. Order Results: ORDER BY KnowledgeRelationCount DESC sorts the results in descending order of KnowledgeRelationCount, showing the most frequently required knowledge items first.
5. Return Results: RETURN knowledge.Name AS Knowledge, COUNT(DISTINCT rel) AS KnowledgeRelationCount returns:

a) Knowledge: The name of the knowledge item.
b) KnowledgeRelationCount: The number of distinct times this knowledge is required for the position

Using these queries, an in-depth analysis is conducted to determine the extent to which lower-level professions meet the requirements for higher-level positions. This analysis offers a clear understanding of the overlap in skills and knowledge, revealing the areas where lower-level professionals already possess essential capabilities and where further training is necessary to bridge competency gaps.

4.4. Identifying Overlapping Professions

One of the key insights from the graph model is identifying professions that share a notable overlap in their sets of skills, knowledge, and position functions. By analyzing this overlap, the connections between professions that are not straight away apparent can be uncovered. For instance, two distinct job roles in different industries might share a common foundation of technical or soft skills, indicating potential career pathways for professionals seeking to transition between fields. This analysis is valuable in understanding the versatility of specific skills and knowledge, which can inform decisions on reskilling or upskilling programs. Recognizing overlapping professions is useful in dynamic labor markets, where the ability to adapt and transfer skills between roles is becoming important. To collect information of overlapping, professions can be implemented this by these steps:

1. Collects all functions, skills, and knowledge for each PositionCard into separate lists (functions, skills, and knowledge).
2. Sets up pairs of PositionCard nodes (card1 and card2) and collects functions, skills, and knowledge for both nodes.
3. Calculates the overlap by using list comprehensions to count matching items between card1 and card2 collections without nested aggregates.
4. Returns the overlap counts and total overlap score, ordered by most related pairs.

Algorithm 8 Identification of Overlapping Competencies Between Professions

Input : Graph database containing `LaborFunction`, `Skill`, `Knowledge`, and `PositionCard` nodes, with appropriate relationships.

Output : Top overlapping profession pairs based on shared functions, skills, and knowledge elements.

Step 1: For each `PositionCard`, collect all associated `LaborFunction` nodes.

Step 2: From each `LaborFunction`, retrieve linked `Skill` and `Knowledge` nodes.

Step 3: For every pair of `PositionCard` nodes, compare their functions, skills, and knowledge sets.

Step 4: Compute the intersection counts for: • `FunctionOverlapCount`
• `SkillOverlapCount`
• `KnowledgeOverlapCount` **Step 5:** Calculate the total overlap score as a weighted or summed combination of the three metrics.

Step 6: Return the top k pairs of positions with the highest total overlap scores.

Algorithm 8 displays the steps involved in building the query for identification of overlapping competencies between the different professions

The analysis reveals a significant overlap between the professions "System and Network Administration Specialist (Network Administrator)" and "System and Network Administration Specialist (System Administrator)." These two roles share 2 common functions, 40 overlapping skills, and 31 overlapping knowledge areas, indicating a high degree of similarity in their required competencies.

The professionals in these specialities can largely replace each other in practice due to these overlaps. The shared functions, skills, and knowledge suggest that a "Network Administrator" has the foundational and practical expertise to handle many responsibilities of a "System Administrator" and vice versa, with minimum additional training. This flexibility could facilitate resource allocation within teams, allowing organizations to make adaptable staffing decisions in response to workload demands or personnel availability. Additionally, training programs for these professions could be enhanced by emphasizing on some aspects of each specialization, instead of duplicating efforts in skills already common. This technique could save on training costs and time while ensuring faster cross-functional aid throughout system and network administration roles.

5. Result and Discussion

During analysis of the competencies graph, the following outcomes were collected as results. These outcomes are briefly analysed through graphical representations and well documented in this research.

1. Dependence of Skills and Knowledge on the SQF Level: Analysis revealed that certain skills and knowledge are unique to specific SQF levels, while others are shared across levels, indicating a structured progression of competencies within professions. Some skills and knowledge are also shared between different positions and standards. Table 1 justifies the result and shows the significant findings of how skills and knowledge are dependent on SQF Levels.

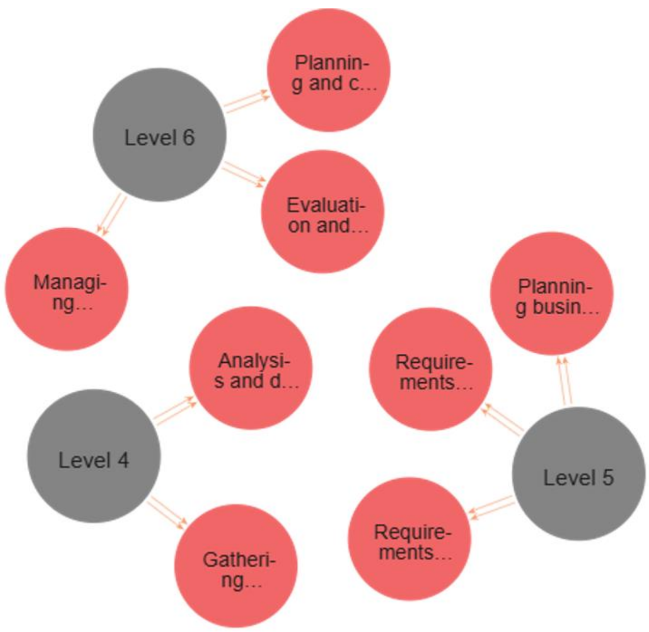

Figure 6.
Subset of graph showing dependence of the skills and knowledge on SQF Levels.

2. Finding the Most In-Demand Skills and Knowledge: Frequently recurring skills and knowledge across multiple professions were identified as communication, problem-solving, and industry-specific technical expertise. Tables 2 and 3 map the most depending on skills and knowledge in the Atkamen Framework.

Figure 7.
Word cloud of ICT data collected from the Atkamen website

Another interesting finding is shown in Figure 7. It clearly shows that how some compentencies have higher demands as compared to others. Larger the word is present in the word cloud more is it's demands. This provide a visual idea of which skills are more demand, and which are less. Smaller is the size of the word in this cloud lesser is it's demand.

3. Comparison of Skills and Knowledge Within One Position Card Across Levels: Higher levels generally require a broader scope of skills and knowledge, but significant overlap exists, suggesting that the lower-level professionals can partially perform higher-level duties with additional training.

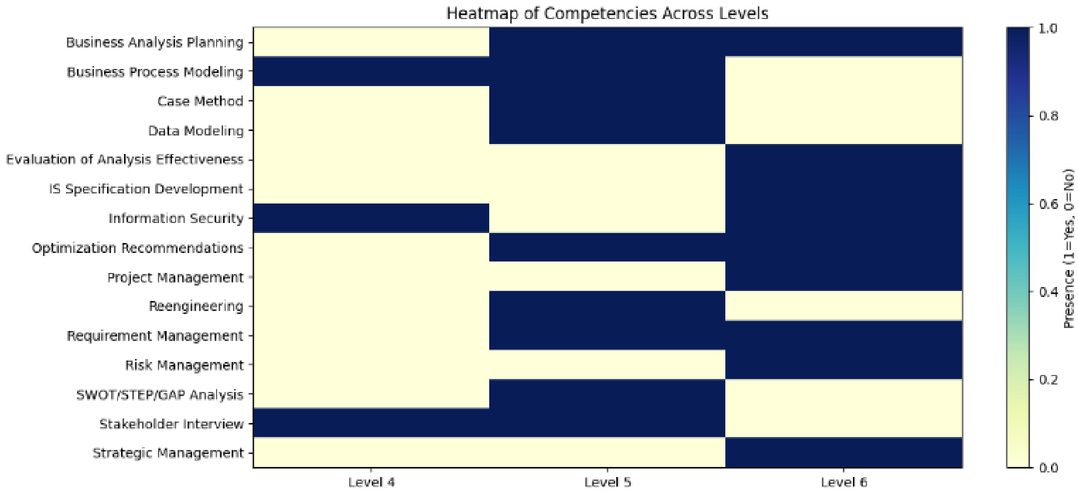

Figure 8.
Heatmap of Competencies across levels.

As shown in Figure 8, level 4 displays limited set of competencies which indicates that at level 4 there are relatively more specialized and foundational roles are present but as we move further level 5 and level 6 displays broader array of competencies signifying the scope of responsibility increases as it advances. However competencies like stakeholder interview, business process modelling and information are overlapped in all the three levels confirming the fact that there is significant overlap in between.

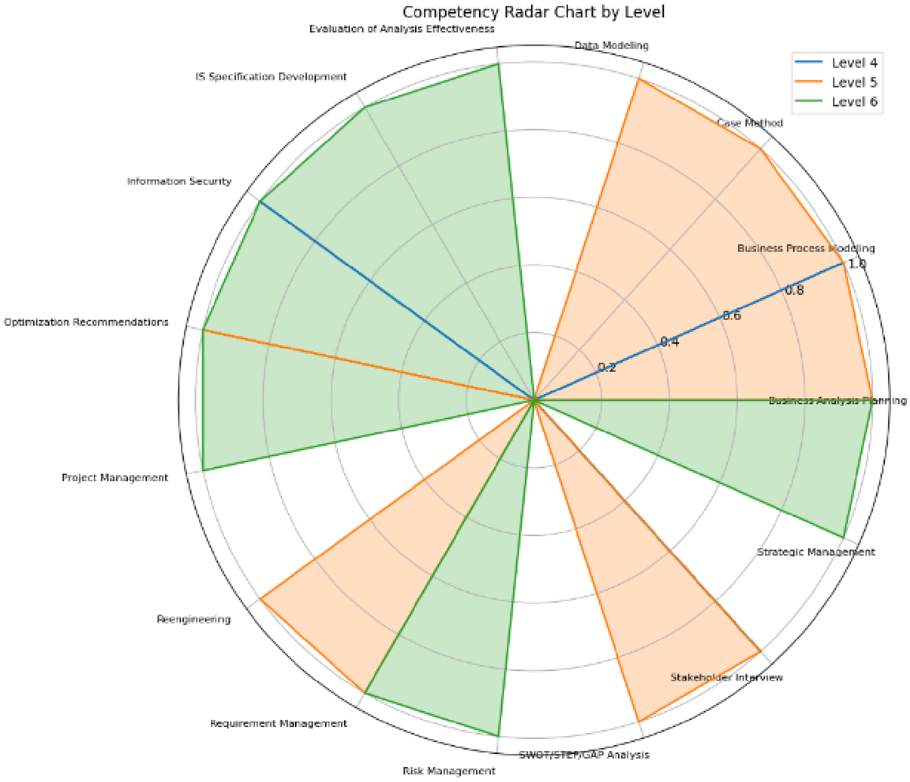

Figure 9.
Radar chart by levels.

Figure 9 presents evidence to the statement that higher levels require broader scope of skills and knowledge. It is very clear through the figure that level 6 and level 5 significantly occupies broader area of skills resulting into the fact that increasing SQF level requires in depth knowledge in various fields. The significant overlap is also clearly seen through this radar chart where some of the competencies share same SQF levels

4. Identifying Overlapping Professions and Compentencies: Overlapping professions were identified based on shared skills, knowledge, and position functions, highlighting areas for cross-sector training and career mobility.

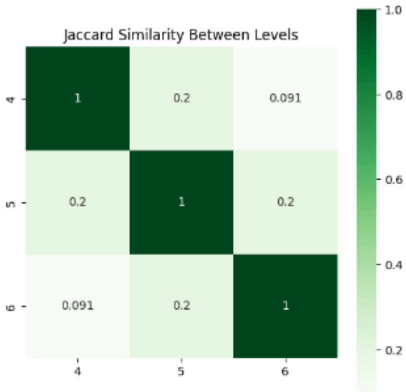

Figure 10.
Jaccard Similarity between the levels.

Figure 10 is illustration of jaccard similarity between various levels. The positive numbers in the heat map clearly shows that levels have similar values or in our case have similar competencies. Professions with higher values shows higher similarity and lower values indicate that there is less overlap of skills between the levels. Another interesting fact is that level 4 and level 6 don’t share to much similarity(0.091) or overlap but level 4 and level 5 have higher similarity similarly level 5 and level 6 have higher similarity this shows the transition of skills and competencies while growing in the professional career.

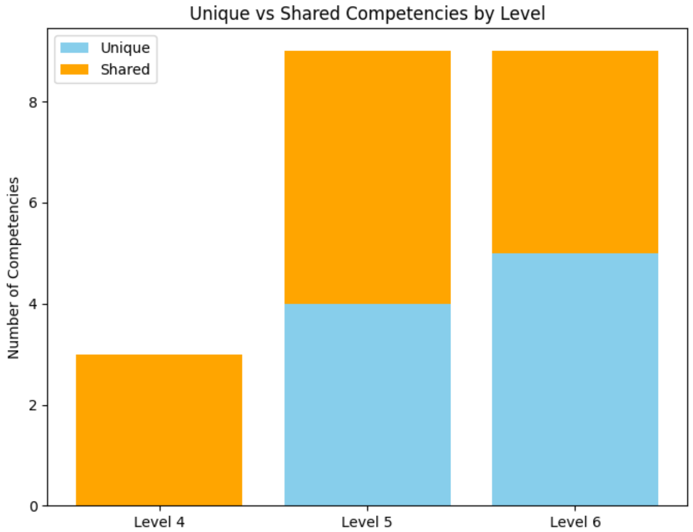

Figure 11.
Stacked bar chart for comparison of unique v/s share competencies.

Figure 11 is clear visualisation of how some of the competencies are overlapped across various levels. This provide explanation to the fact that level 4 is shared across all the levels as it is more of foundation and then is carried on level 5 and level 6. It clearly shows the overlapping of professions across SQF levels.

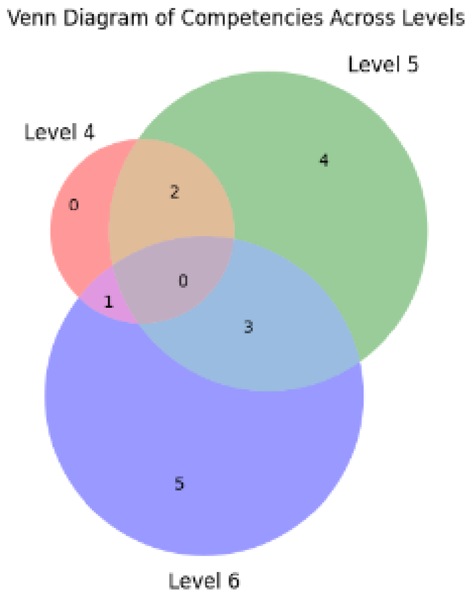

Figure 12.
Venn Diagram of Competencies across levels.

Venn Diagram gives clear idea of intersection and uniqueness of skills at each level, larger intersections indicate more overlapping competencies, such as in Network Administration roles whereas professions with fewer intersecting competencies have smaller overlap areas

During the analysis of the competencies graph, various major insights emerged. The analysis revealed that some skills and knowledge are unique to specific SQF levels, while others are shared across levels, indicating a structured progression of competencies within professions. For example, some skills and knowledge, like communication, problem-solving, and industry-specific technical expertise, were identified to be shared between different positions and standards.

Higher-level professionals in general require a broader scope of skills and knowledge, but significant overlap exists, suggesting lower-level professionals can partially perform higher-level duties with additional training. The overlapping professions were identified based on shared skills, knowledge, and position functions, highlighting areas for cross-sector training and career mobility Figure 12.

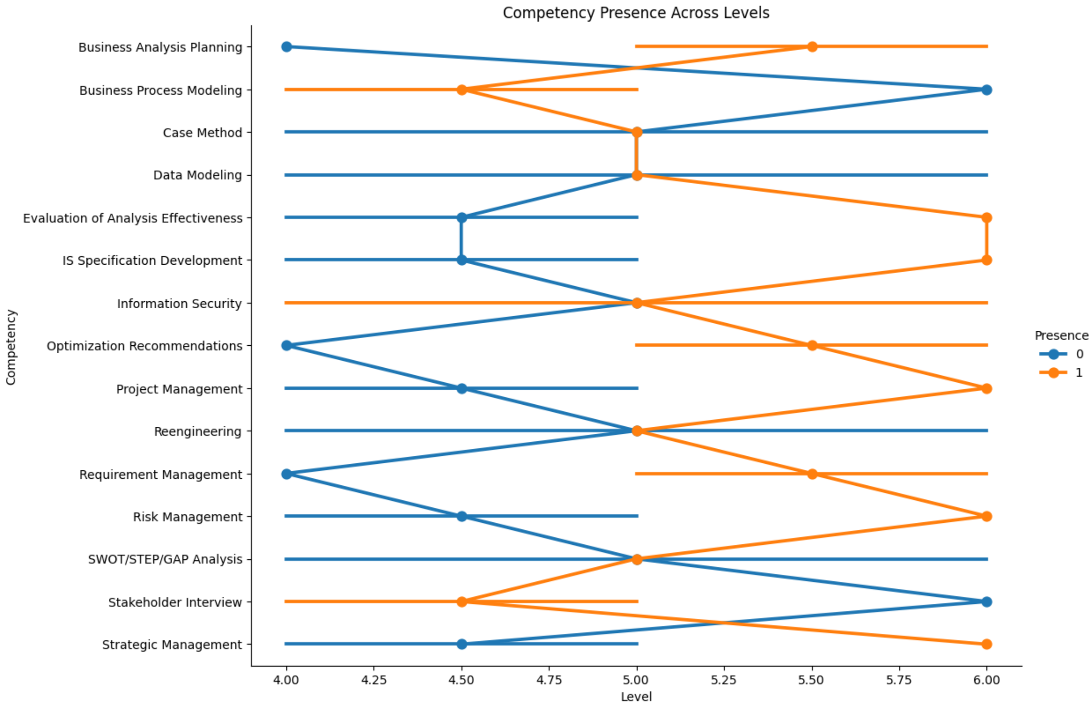

Figure 13.
Parallel Coordinate Plot.

Figure 13 shows the structured career progression competencies like "Information Security," business analysis planning," and stakeholder interview increase in presence at higher levels, reflecting a progression of required competencies. Competencies such as evaluation of analysis effectiveness and project management appear and intensify at higher SQF levels, showing how lower-level professionals could perform higher-level tasks given additional training. This helps providing the fact that with additional training a lower SQF level professional can be utilized for higher level of skills. This figure clearly shows intersection and potential career mobility paths.

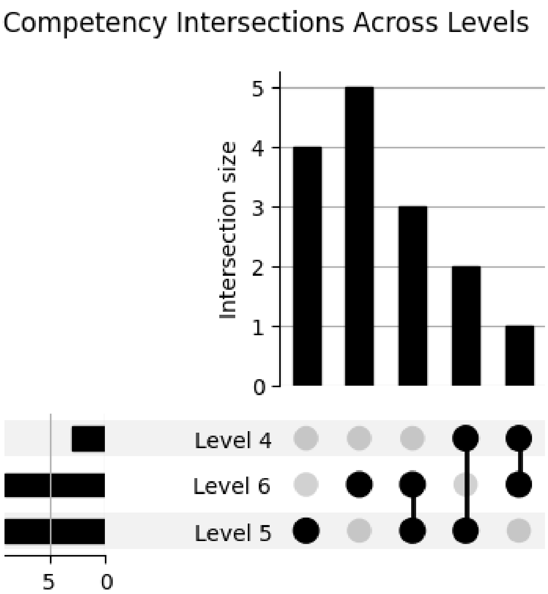

Figure 14.
Upset plot showing competency intersection across levels.

Figure 14 plots the significant intersections and uniqueness of competencies across various levels. As seen in figure the largest overlap exists between level 5 and level 6 giving the idea that how both the level share similar skills. This upset plot also helps in visualising competency progression and potential career pathways across profession levels

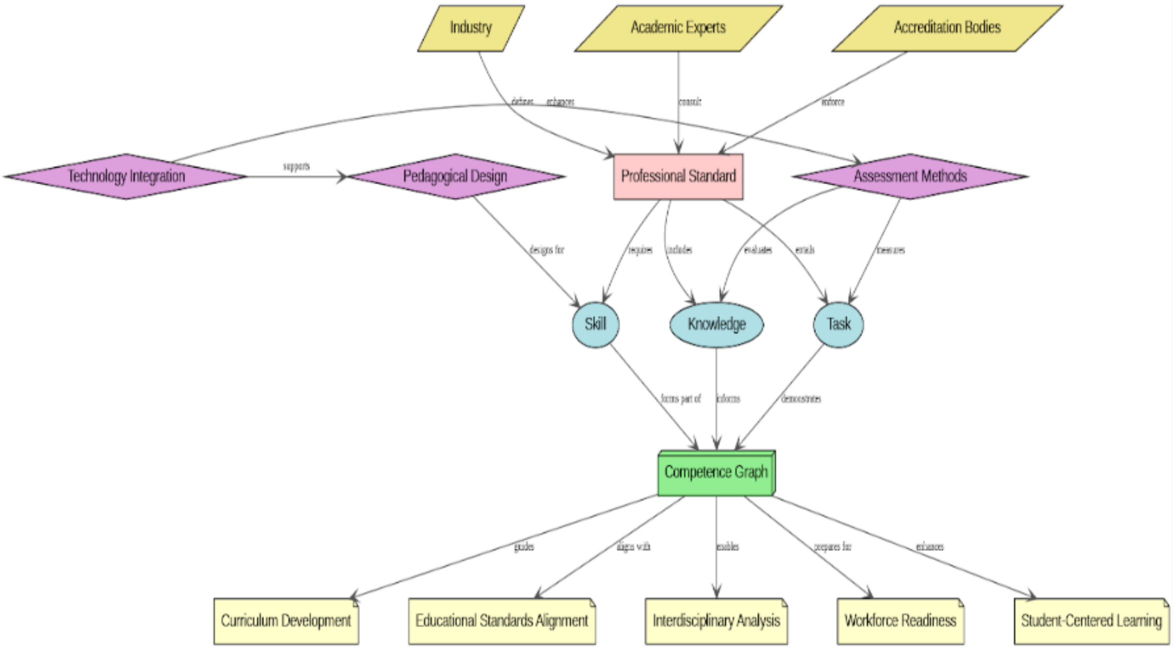

Figure 15.
Competence Graph from Professional Standards.

Figure 15 shows a high-level structure of how professional standards are used to build the competency graph. The topmost layer of the diagram shows the top-level sources or influences which include industry, academic experts and accreditation bodies. These top-level sources provide their input to build Professional Standards. These Standards are aided by technology Integration, Pedagogical Design and Assessment Methods which contribute to building these standards. Moving to the building blocks for Competency Graphs, Skills, Knowledge and work functions contribute in mapping the competency graphs. The Competency graph enables analysis which further helps in Curriculum Development, Educational Frameworks, Workforce Readiness and Interdisciplinary Analysis. Overall Figure 14 provides a complete method of building and utilising competency Graphs for professional standards.

6. Conclusion

The research questions were adequately addressed, leading to important findings. An extensive analysis of professional standards offered by NCE "Atameken" was carried out to obtain relevant data, involving a detailed examination of professional standards in various sectors. Key data relating to skills, knowledge, and qualifications was obtained for use in building the graph model. A graph model was also successfully created using nodes to represent important entities like skills, knowledge, and job roles, while edges were used to show their relationships. This model allowed precise graphical representation of the complex interrelationships inherent in professional standards, ensuring that all competencies and professional requirements relationships were accounted for. Data obtained was incorporated into the graph model, ensuring relationships between competencies and professional requirements were accurately captured. This incorporation allowed for considerable analysis and provided insight into professional standards structuring. Graph analysis revealed interesting trends, where the most demanded skills included communication and problem-solving, while technical knowledge showed variability depending on the industry. Research also included the determination of overlapping professions, demonstrating commonality of competencies across sectors, as well as a clear progression of skills and knowledge aligned with SQF levels.

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