Identify the Current Demanded Knowledge, Skills, and Abilities (KSA) in IT through Analysis of Job Advertisements in Sri Lanka: A Framework Using Natural Language Processing Techniques

Kosala Chamithri
Department of Industrial Management
University of Kelaniya
Sri Lanka
kosalachamithri99@gmail.com

P.P.G Dinesh Asanka
Department of Industrial Management
University of Kelaniya
Sri Lanka
dasanka@kln.ac.lk

2024 4th International Conference on Advanced Research in Computing (ICARC) | 979-8-3503-8486-4/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICARC61713.2024.10499754

***Abstract*— This research aims to develop a Natural Language Processing (NLP) framework to uncover the current demanded Knowledge, Skills, and Abilities (KSAs) in the Sri Lankan Information Technology (IT) sector. In the KSA, this paper focuses on professional qualifications and concepts, technical skills, and soft skills. Understanding the specific Knowledge, Skills, and Abilities demanded by industries is not only relevant to academics but also holds practical significance for job seekers, educational institutions, and employers. By employing Natural Language Processing techniques to analyze job advertisements, this research aims to bridge the skills gap, and support the relevant beneficiaries. The outcomes include the ability to use Generative AI for job advertisement annotation, an NLP framework to analyze job advertisements, identify the main areas in the IT sector according to ESCO (European Skills/Competences, Qualifications, and Occupations) classification-based customization and their specifically demanded KSAs for each domain. Importantly, the results also highlight that Knowledge and Skills vary across different domains, while Abilities remain common with slight changes.**

Keywords*— *artificial intelligence, generative artificial intelligence, information technology, knowledge-skills-abilities, natural language processing

I. Introduction

A. Knowledge-Skills-Abilities (KSA)

Knowledge, Skills, and Abilities (KSA) are the three pillars that define a person's qualifications and potential for success in a particular field. Together, they are a powerful combination that sets individuals apart and enables them to excel in their chosen professions [1]. KSA is a commonly used framework in job advertising and recruitment processes that are typically written by the employer or the organization responsible for. It helps them to effectively communicate the requirements and qualifications necessary for a particular job position, ensuring that potential candidates have a good understanding of the skills and knowledge they should possess to succeed in the role.

Knowledge – Knowledge is the collection of all the facts, data, and information people have stored in their memory. It is usually gathered via formal education, professional training, or research [1].

Skills – Skills refer to any capabilities or demonstrated proficiencies developed via training or hands-on experience [1].

Abilities – An ability is often a personal quality that is not trainable. Some abilities might be what some HR professionals call "soft skills" [1].

This research primarily focuses on exposing educational qualifications and certifications within the area of Knowledge, examining experienced proficiencies for Skills, and addressing soft skills for the category of Abilities.

B. Background of the Research

The field of Information Technology (IT) plays an important role in the global economy, driving innovation, productivity, and digital transformation across various industries. The main areas of IT relate to computer and hardware, software, analytics, network and infrastructure, internet and web technologies, multimedia technologies, information systems, IoT, cybersecurity, etc. They evolve frequently with new languages, tools, architectures, concepts, frameworks, etc. As reported by the Sri Lanka Association for Software and Services Company (SLASSCOM), the Sri Lankan ICT industry has experienced an upward trend with growing requirements for ICT services and solutions [2].

The COVID-19 pandemic has significantly increased Sri Lankans' interest in IT careers. The sudden shift towards remote work engagements highlighted the capability and flexibility of IT professions, leading many to view them as attractive career options. According to an article published on Daily News on April 2023, "There has been a 22% rise in the Sri Lankan ICT workforce as a whole, implying a favorable view of the job market according to the demographic analysis conducted, by the '2022 Compensation and Benefits Report for Sri Lanka's IT/BPM Industry' by SLASSCOM" [3]. Additionally, there is a sense of importance around the acquisition of IT-related skills because of the increasing demand for digital skills across industries, driven by the rapid digital transformation.

From time to time, the demand for various IT areas changes in every country. According to a study conducted in Bangladesh, the most frequent job titles in 2021 were identified as Software Developers, Computer Systems Engineers/Architects, Web Developers, and Project Management Specialists. It showed a statistically significant decline in the demand for both Software Developers and Web Developers between 2019 and 2020. However, it was interesting to note that there was a statistically significant increase in the demand for Web Developers in the next period from 2020 to 2021. Additionally, the study observed a

979-8-3503-8486-4/24/$31.00 ©2024 IEEE

significant upward trend in the demand for Computer Systems Engineers/Architects and Computer Network Support Specialists in recent years. On the other hand, the demand for Web and Digital Interface Designers, as well as Business Intelligence Analysts, showed a decreasing trend [4].

As mentioned before, due to the evolution of IT, the KSAs needed for specific job roles are being changed. Therefore, companies are also seeking candidates who are competent with upcoming technologies. 61% of business executives say new technologies such as automation and artificial intelligence (AI) that require new skills will be a primary driver of their organization adopting a skills-based approach [5]. Both upskilling and reskilling are crucial in the dynamic landscape of industries, where technology and job requirements continually evolve. Organizations often invest in these strategies to ensure that their workforce remains adaptable and capable of meeting current and future challenges. Individuals, too, can engage in upskilling and reskilling to enhance their career prospects and stay relevant in the ever-changing job market.

The growing demand for the IT sector in Sri Lanka has encouraged the establishment of numerous job opportunities and the emergence of new institutes offering IT degree programs. These institutes can be categorized into government universities, private degree-awarding institutes, government vocational and tertiary training institutes, as well as private diploma and certificate-awarding training institutes. Each of these categories provides a range of degree programs in diverse IT disciplines, catering to the increasing need for skilled professionals in the field [6]. Educational institutions, mainly universities and higher study institutions, play a crucial role in preparing individuals for the job market. Despite the rapid technological advancements, some universities still have outdated syllabuses that do not reflect the current industry standards.

The aforementioned factors highlight the growing prominence of the Information Technology (IT) sector in Sri Lanka, underscoring the need for a comprehensive study of its Knowledge, Skills, and Abilities (KSAs). Therefore, this research attempts to analyze the Sri Lankan IT sector by examining job advertisements in Sri Lanka. From the beneficiary's perspective, this research will show the students and job seekers what KSAs they should focus on to get good jobs in the tech industry in Sri Lanka. It will be easier for them to choose the right courses, certifications, and training programs. For companies, it will help them find the right people with the skills they need for their tech teams. Universities and educational institutions can use this research to understand what students need to learn to be successful in the IT industry and align their courses and assignments more accordingly.

II. Related Work

Initially, previous researchers have manually analyzed job advertisements to understand skill requirements, focusing on a limited number of advertisements. However, with the shift to online job portals, studies started using Natural Language Processing (NLP) techniques to automate skill identification. NLP methods like information extraction were applied to create personalized skill databases from textual knowledge bases. Additionally, Machine Learning techniques, including deep neural networks and word embeddings, were used to accurately capture and extract skills from textual sources [7].

A knowledge base is a compilation of records in a database, typically representing some form of information about the world. Previous studies on skill identification from job ads, focusing on the utilized skill bases, can be categorized into predefined skill bases and customized skill bases. Skill bases developed by experts include ESCO (European Skills/Competences, Qualifications, and Occupations), O*NET base (Occupational Information Network), ROME, and ISCO-8 (International Standard Classification of Occupations). Customized skill bases encompass manually built skill bases and generated skill bases derived from knowledge bases and word embeddings [7].

The referenced study [4] has used NLP techniques to map unique job titles with overlapping roles to only 26 standard O*NET job titles. They manually inspected ICT related skills along with building unigram, bigram, and trigram models to extract skills consisting of more than one word and sorted words by frequencies. They also conducted a one-tail t-test on the top 10 job titles in their dataset to determine whether there is a statistically significant decline or increase in job vacancies and applicant numbers. It allows to identify the trends in the rankings of various technologies. Machine learning techniques for developing the text classifier, including Support Vector Machines (SVMs), Random Forests (RFs), and Artificial Neural Networks (ANNs) have been used as a single-label classifier that exploited both the titles and descriptions of job postings to classify multilingual Web job vacancies [8]. A study utilized text and web mining techniques to create a dataset of 244,460 job advertisements and titles in the United States. They extracted advertisement requirements by defining specific keywords and to identify and extract job skill terms from ad texts, the initial set of terms was based on prior research [9]. A methodology involving Natural Language Processing, hierarchical clustering using the Weighted Pair Group Method with Arithmetic Mean (WPGMA), and association mining techniques for skills identification in the IT field within the Commonwealth of Independent States (CIS) region was implemented. They identified skills from the job advertisements by sets of 0 to 30 elements which consist of unstructured texts each up to 100 symbols. The Hierarchical clustering algorithm was applied to the identified "hard" skills, resulting in the explicit distribution of 544 technical competencies across 9 distinct clusters. It used skill-based mapping which helps to match information from job postings with descriptions obtained from official classifiers of occupations and skills [10].

The KSAs needed for Entry Level Business Analytics have divided the hard skills section into 3 parts namely Business, Analytical, and Technical, and soft skills, divided into Interpersonal and Organizational. However, it hasn't identified the KSAs separately. They have not organized soft skills as a separate category but considered several soft skills as business skills [11]. A later study refined the framework by introducing soft skills as an independent category within the framework. This improvement aimed to recognize the importance of soft skills in addition to technical and business skills for business analytics positions [12]. An approach that allows to find and visualize the interrelation between non-technical skills and combinations of technical competencies characterizing particular IT occupations using the data from the Commonwealth of Independent States (CIS) labor market has also been presented in the literature [10].

Within the skill identification literature, four distinct methods can be discerned. The initial approach involves a skill count comparison between the skill base and the content of job advertisements. The second method employs topic modeling to extract skills mentioned in job ads. The third method utilizes skill embedding, validating skills through the application of word embedding techniques. Lastly, the fourth method incorporates Machine Learning (ML) techniques, including text classifiers and deep neural networks, for the classification of job ad sentences or skill tagging [7]. Skill count, although time-consuming when relying on annotators, remains the most reliable method for skill identification, whether utilizing a skill base or involving expert judgment and manual tagging of skills in job ads. The presence of a skill term can be assessed using a Boolean value or the TF-IDF schema, weighing its importance based on frequency in the job ad and the entire corpus.

When considering the above, it becomes evident that the majority of research in the IT sector has primarily focused on identifying either hard skills, soft skills, or a combination of both. However, a notable gap exists in addressing the professional qualifications necessary for candidates. While hard skills are built upon a foundation of knowledge, this aspect has often been overlooked in existing research. Therefore, this study bridges this gap by distinctly identifying and analyzing Knowledge, Skills, and Abilities. As noted, previous research has predominantly relied on manual skill identification or keyword tagging within the job advertisements' text section. In contrast, this research utilizes a skill count approach, with several other NLP mechanisms to identify more granular data from the text analysis. Previous studies have classified the skills using machine learning algorithms with the identified skills in a job description and their title. An innovative aspect of this research is the application of a Generative AI method to classify KSA. In summary, this research addresses the existing gap by introducing a more advanced and automated approach to skill identification and classification, contributing to a more thorough analysis of the Knowledge, Skills, and Abilities.

III. METHODOLOGY

This section discusses the methodology presented in Fig.1, used in this research to fulfill its objectives. The methodology consists of a systematic process involving data collection, annotation, preprocessing, NLP processing and data analysis.

The initial step in the methodology involves gathering essential data for the research on IT job vacancies in Sri Lanka. Recognizing various online sources, including TopJobs.lk, LinkedIn, XpressJobs.lk, and CareerFirst.lk, the decision to use LinkedIn is based on its popularity and reliability. Despite the absence of the latest pre-existing dataset, a custom web scraper was developed using Node.js, utilizing Axios, Cheerio, and Objects-to-CSV libraries as dependencies. The scraping URL was aligned with parameters, specifying Sri Lanka as the location and public jobs as the track. The scraper collected information such as job title, company, location, industry, job level, job description and date posted from the job advertisements.

The scraper was executed periodically, producing separate Excel files during each execution. These files were later combined into a single Excel file which serves as the final dataset for the research. The focus of the study was narrowed down to key IT roles by filtering the industry column only to

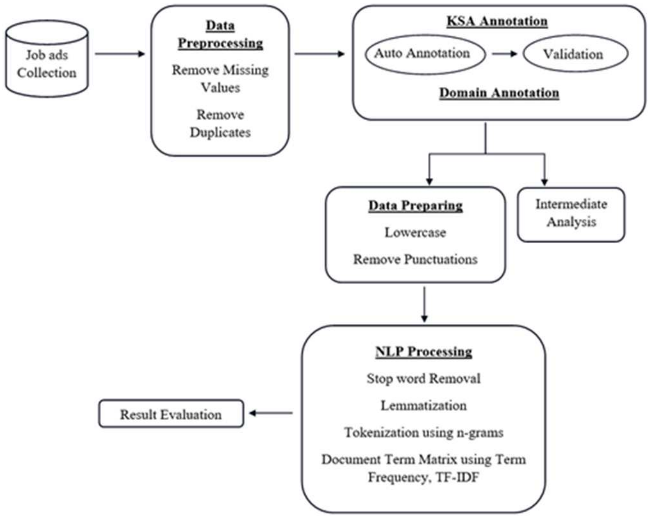

Fig. 1. Methodology

IT services, IT consulting, Software Development, Computer and Network security, Technology, Information and Internet options, in order to exclude non-IT positions.

As mentioned before, this research used the ESCO Level 3 Occupation classification for better classification of the job title into relevant industry areas. The job titles falling under the classifications "Software and applications developers and analysts not elsewhere classified" and "Database and network professionals not elsewhere classified" were mentioned with common domain names based on their job title. Therefore, domains named Software Quality Assurance and Project Management were added to this classification. After classifying accordingly, 10 main domains were identified as, Application Programmers, Computer Network Professionals, Cyber Security, Database Designers and Administrators, Project Management, Software Developers, Software Quality Assurance, System Administrators, System Analyst, and Web and Multimedia Developers.

The challenge with this classification was that distinct job roles were consolidated into a single group. For instance, both Data Engineers and Database Engineers were placed under Database Designers and Administrators, despite the clear differences in their job titles and responsibilities. When the study classified these job titles to a lower level ESCO classification, then the number of job postings across various domains was very limited. Consequently, to address these limitations, a customized approach, built upon the initial classification and referring to the job titles was carried out to identify domains without collapsing distinctions and agreeing to ESCO classification.

Finally, there were 15 domains: Business Analyst, Cyber Security, Data Analyst, Data Engineer, Data Scientist, Database Engineer, DevOps Engineer, Network Engineer, Project Management, Software Engineer, Software Quality Assurance, Solution Consultant, System Engineer, Technical Consultant and UI/UX Designer. Table I shows they are distributed according to the identified ESCO domains.

As per the main objective to identify the KSAs using the job descriptions, each sentence in the job requirements was needed to classify into either Knowledge, Skill, or Ability separately. But annotating each sentence in the dataset is time consuming.

TABLE I. ESCO BASED CUSTOM CLASSIFICATION

Domain	Count
Application Programmers	**7**
Software Engineer	7
Computer Network Professionals	**5**
Network Engineer	5
Cyber Security	**6**
Cyber Security	6
Database Designers and Administrators	**18**
Data Engineer	11
Database Engineer	7
Project Management	**36**
Project Management	36
Software Developers	**226**
DevOps Engineer	18
Software Engineer	208
Software Quality Assurance	**58**
Software Quality Assurance	58
System Administrators	**35**
System Engineer	35
System Analyst	**51**
Business Analyst	13
Data Analyst	14
Data Scientist	3
Solution Consultant	14
Technical Consultant	7
Web and Multimedia Developers	**7**
UI/UX Designer	7
Grand Total	449

Therefore, the initial annotation was done using a Generative AI script, importing OpenAI in a Google Colaboratory file as the auto annotation phase. The Generative AI script was instructed with the command, "Classify the sentences below into knowledge or skill or ability or other." Each job description was input into the script, and the generated results were categorized into Knowledge, Skills, Abilities or Other and those were appended manually to new columns as Knowledge, Skills, Abilities and Other in the final dataset. In here, Other refers to those sentences that do not belong to job requirements. Sometimes one sentence belonged to more than one label based on its content. This auto annotation improved the efficiency of the classification. After the completion of the auto annotation, the results were provided to an HR professional for validation.

It's important to note that job descriptions often encompass both job responsibilities and requirements. For precise skill identification, the focus should be solely on considering the job requirements. The HR validation process revealed that the Generative AI tended to categorize entire sentences into Knowledge, Skills, and Abilities without specifically isolating the job requirements from the broader job description. For an example, "Participate in the development of technical specifications, architecture, and estimations." is a sentence that belongs to a job description of a software engineer. It is a job responsibility but categorized as an Ability by the Generative AI script. During this validation, several modifications were done, including the removal of sentences related to job responsibilities from KSA categories and changing the category of the several sentences they belong.

Following the annotation process, the sentences under each group underwent NLP processing written using Python for further analysis. The sentences were lowercased, removed punctuation, removed stop words, lemmatized, and then tokenized into n-grams. As the first step, the sentences were lowercased to eliminate variations due to capitalization. When using NLP, removing punctuations and special characters is a common preprocessing step to clean and simplify text data. Punctuation is often unnecessary as it doesn't add value or meaning to the NLP model. In the context of handling an IT dataset, it is imperative to preserve specific programming languages such as C++, C#, and .NET. During the removal of punctuation marks, the symbols "++" and "#" were intentionally excluded to avoid altering the representation of programming languages, as both C++ and C# could be misconstrued as "C" without these distinctions. However, the period (.) in .NET was retained in the punctuation removal process, as it does not impact the semantic meaning. The next step involves stop word removal. Stop words are typically those frequently occurring words in a language, such as articles, prepositions, pronouns, and conjunctions. Eliminating stop words from text helped here to eliminate less important details, allowing us to concentrate on more significant information. In this process, sentences are tokenized, and "English" stop words are removed using the Natural Language Toolkit (NLTK) library. Lemmatization was used because it aimed to reduce words to their base or dictionary form, considering the context and meaning of the word. For example, the word 'developing' becomes 'develop' after the lemmatization. This process utilized the WordNetLemmatizer provided by the NLTK library.

Subsequently, the processed KSA sentences underwent tokenization into unigrams, bigrams, and trigrams. Upon analyzing token frequencies, it was observed that certain high-frequency tokens, such as 'experience,' 'understanding,' 'knowledge,' and 'bachelors,' were prominent. This prominence was attributed because of the sentence structures like 'experience in,' 'knowledge of,' 'understanding of,' etc. So, to eliminate this issue, TF-IDF (Term Frequency-Inverse Term Frequency) was used. Considering each job description, its identified KSA grouped sentences were treated as a document separately and then TF-IDF values which represent of the importance of a term in a specific document relative to the entire corpus, were calculated. From each group in a job description, the top 5 tokens with the highest TF-IDF values were selected. Afterwards, unique lists for Knowledge, Skills, and Abilities were generated, each representing the most significant terms based on TF-IDF. These tokens were analyzed with the job descriptions to identify them correctly.

For result validation, the identified KSAs were provided to professionals working in the respective domains.

IV. RESULTS AND EVALUATION

Under the given command for the Generative AI script, the exclusion of job responsibilities was not considered for the classification of knowledge, skills, abilities, or other, accounting for 0% of considering only the job requirements. Along with job responsibilities, the job requirement sentences were classified into one of these specified categories, and the "Other" classification consistently encompassed sentences related to company information, salary, benefits, etc., excluding job responsibilities. Taking both sets of annotations into account, the accuracy, recall, precision, and F1-score was calculated as shown in Table II. These metrices show how the Generative AI script made a positive impact on the overall effectiveness of the classification process.

Table II. GENERATIVE AI SCRIPT EVALUATION RESULTS

Metric	Percentage
Accuracy	82%
Recall	82%
Precision	85%
F1-Score	83%

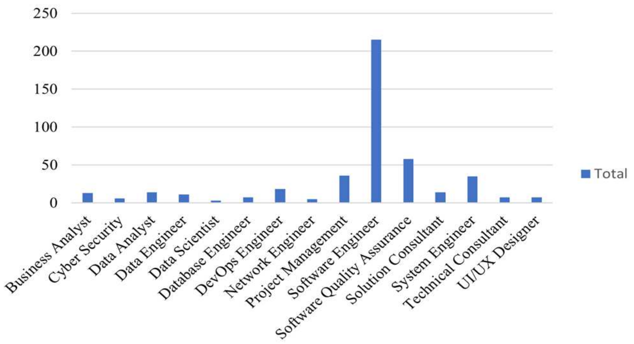

Fig. 2. Job Advertisement Count

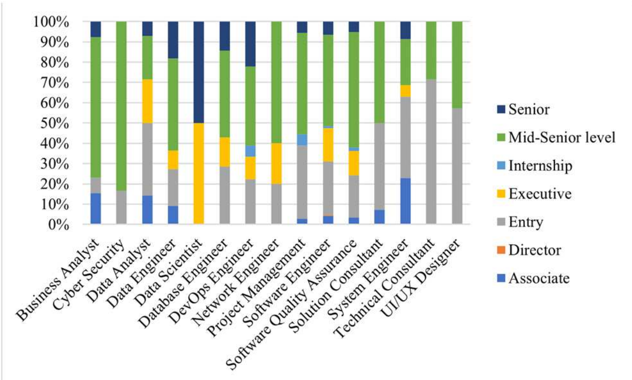

Fig. 3. Level Count in Domains

By analyzing the final dataset, the top 5 domain areas were identified as Software Engineering, Software Quality Assurance, Project Management, System Engineering, and DevOps Engineering as shown in Fig.2. Fig.3 shows that most job advertisement vacancies are for the mid-senior level and Entry level.

From the TF-IDF technique, the paper was able to catch the Knowledge, Skills, and Abilities separately for each domain. However, this paper exclusively covers the KSAs of the top 3 domains, while the complete results for all domains are published in figshare [13].

A. Software Engineering

In the knowledge section, to excel in software engineering, candidates are expected to possess at least a Bachelor's degree in Computer Science or Information Technology or Software Engineering or a degree equivalent to, with Master's qualifications considered advantageous. Certifications, particularly in Azure, AWS, Google Cloud Platform, App Development, Power Platform App Maker, ITIL, and Boomi, are recognized. A knowledge base is essential, covering design patterns, object-oriented programming, algorithmic concepts, best practices, and familiarity with automation, application deployment, version control systems, and cloud computing.

Considering the skills needed, proficiency in various programming languages and frameworks such as Java, Spring, Angular, React, Node.js, Next.js, JavaScript, TypeScript, Vue.js, .NET, Laravel, Python, CSS, HTML, PHP, and jQuery is expected. Database skills encompass SQL, PL/SQL, NoSQL, MongoDB, and PostgreSQL. Additionally, expertise in cloud computing on Azure, AWS, Google Cloud, microservices architecture, REST architecture, Docker, Kubernetes, version control tools like Bitbucket, GitHub, GitLab, project management tools such as Jira, and agile methodologies like Kanban are considered. The ability to conduct unit testing, implement Behavior-Driven Development (BDD), integrate CI/CD (Continuous Integration/Continuous Delivery), and demonstrate proficiency in DevOps practices further enhances the skill set for this dynamic role.

The most identified abilities needed by a software engineer include communication skills, creativity, problem-solving, analytical thinking, active participation, initiator, positive attitude, collaboration, working independently, proactive, adapting to new trends, continuous learning, leadership skills, novelty, multi-tasking, and time management.

B. Software Quality Assurance

To excel in Software Quality Assurance, a Bachelor's degree or equivalent in Software Engineering, Computer Science, Business Information, or Information Technology is required, with Master's qualifications considered advantageous. Identified certifications such as ISTQB or equivalent are also highly valued. The knowledge of QA principles, best practices, architectural concepts, basic cloud concepts, testing methodologies, automation, and CI/CD practices are considered.

Skills in Quality Assurance require automation experience with QA tools, particularly in Cypress, Cucumber, JMeter, Appium, Selenium, and Playwright. Proficiency in programming languages, particularly Java and JavaScript, and skills in SQL, PostgreSQL, and database management system debugging, are important. Experience in API Testing, Performance Testing, Security Testing, Accessibility Testing, Manual Testing, Mobile Testing, Regression Testing, TDD, and BDD is highly desirable. Documentation, delivery planning, test case design, execution, and report investigation are also important aspects. Familiarity with version control tools like Bitbucket, and GitHub, project management tools such as Jira, and Agile methodologies, and skills in cloud computing, particularly in Azure and AWS, also identified here.

The required abilities include excellent communication and presentation skills, attention to detail, analytical skills, proactivity, problem-solving, collaboration, a positive attitude, time management, the ability to work in a team, work with minimum supervision, and be a continuous learner.

C. Project Management

To excel in Project Management, a Bachelor's degree or equivalent in Computer Science, Business Management, or Information Technology is required, with Master's qualifications considered advantageous. Certifications include PMI ACP, CIMA, CIM, CSM, CSPO, PMP, PRINCE2, ITIL. The knowledge of project management methodologies, agile methodologies, cloud computing, and artifact definitions is considered.

Skills required include experience in project management, proficiency in agile methodologies such as Jira, Kanban, and Scrum, participation in stand-ups and retrospective meetings, proficiency in computer applications, especially Excel, PowerPoint, and SharePoint, demonstrated skills in ERP and SAP, with experience in project lifecycles. Also, proficiency in forecasting, estimation techniques, product management, accurate prioritization, roadmap planning, timely delivery, reporting, and the ability to work on multiple projects are identified.

Abilities require include communication skills, presentation skills, problem-solving, critical thinking, creativity, decision-making, coordination, working independently, ability to prioritize, strong planning, leadership skills, and time management.

The above results were then validated by professionals who work in those domains.

V. Conclusion and Future Work

This approach involves the utilization of IT job advertisements to find the demanded KSAs in different IT areas. The results demonstrate the effectiveness of employing Generative AI and NLP techniques for qualitative data analysis. Notably, these results successfully pinpoint the required Knowledge, focusing on educational qualifications and certifications which the previous studies have overlooked, as well as the hands-on experience, skills, and abilities needed for the identified roles. Moreover, it used the job descriptions as it is without tagging and mapping with KSAs. Importantly, these results highlight that knowledge and skills vary across different domains, while abilities remain common with slight changes.

When considering future work improvements, these KSAs are only considered as currently demanded based on the current job postings gathered at the time of research, which the data from June 2023 to November 2023. For certain domains with limited data availability, collecting more job advertisements can provide additional KSA data. Gathering data from multiple hiring platforms, as well as exploring relevant hiring groups on platforms like WhatsApp and Facebook., would provide a more holistic understanding of the diverse and dynamic demands for IT skills across various channels in the job market.

Feedback received from the result validation indicated that all KSAs are not equally important. The KSA requirements, mainly Skills, vary significantly based on the job position's level and the technological context of the employing company. Therefore, this work can be improved by a mechanism to identify which KSAs will demand in future and identifying the distinct KSAs required by various organizational levels and job position levels. This refinement would contribute to providing more precise data and tailored recommendations for prospective candidates.

Utilizing the TF-IDF words identified for Knowledge, Skills, and Abilities, a multi-labeled classification model can be developed to effectively categorize the KSAs mentioned in a job advertisement. Notably, the model's extensibility can be tailored to the specific level of the job position, enabling it to accurately identify and classify relevant KSAs for each level.

References

[1] "23 KSA (Knowledge, Skills & Abilities) Examples + How To Use KSAs." Accessed: March 10, 2023. [Online]. Available: https://www.aihr.com/blog/knowledge-skills-abilities-ksa-examples/

[2] "IT / BPM Industry of Sri Lanka Employability Skills Survey 2021." Accessed: July. 03, 2023. [Online]. Available: https://old.slasscom.lk/it-bpm-industry-employability-skills-survey--2021/

[3] "sri Lankan ICT workforce rise by 22% | Daily News." Accessed: Nov. 28, 2023. [Online]. Available: http://archives1.dailynews.lk/2023/04/11/business/301186/sri-lankan-ict-workforce-rise-22

[4] S. S. R. Jony, T. Kano, R. Hayashi, N. Matsuda, and M. S. Rahman, "An Exploratory Study of Online Job Portal Data of the ICT Sector in Bangladesh: Analysis, Recommendations and Preliminary Implications for ICT Curriculum Reform," *Educ Sci (Basel)*, vol. 12, no. 7, Jul. 2022, doi: 10.3390/educsci12070423.

[5] "Skills-based organizations | Deloitte Insights." Accessed: Jan. 09, 2024. [Online]. Available: https://www2.deloitte.com/us/en/insights/topics/talent/organizational-skill-based-hiring.html

[6] R. Werawatta and S. Amarasooriya, *Analysis of future demand for Sri Lankan ICT undergraduates in ICT industry: Mapping the ACM/IEEE computing degrees with emerging technologies*. 2021.

[7] I. Khaouja, I. Kassou, and M. Ghogho, "A Survey on Skill Identification from Online Job Ads," *IEEE Access*, vol. 9, pp. 118134–118153, 2021, doi: 10.1109/ACCESS.2021.3106120.

[8] R. Boselli, M. Cesarini, F. Mercorio, and M. Mezzanzanica, "Classifying online Job Advertisements through Machine Learning," *Future Generation Computer Systems*, vol. 86, pp. 319–328, Sep. 2018, doi: 10.1016/j.future.2018.03.035.

[9] Litecky, C.; Aken, A.; Ahmad, A.; Nelson, H.J. (2010). Mining for Computing Jobs. , 27(1), 78–85. doi:10.1109/ms.2009.150.

[10] A. Ternikov, "Soft and hard skills identification: Insights from IT job advertisements in the CIS region," *PeerJ Comput Sci*, vol. 8, 2022, doi: 10.7717/PEERJ-CS.946.

[11] C. G. Cegielski and L. A. Jones-Farmer, "EMPIRICAL RESEARCH Knowledge, Skills, and Abilities for Entry-Level Business Analytics Positions: A Multi-Method Study," 2016. doi: 10.1111/(ISSN)1540-4609.

[12] H. C. Chang, C. Y. Wang, and S. Hawamdeh, "Emerging trends in data analytics and knowledge management job market: extending KSA framework," *Journal of Knowledge Management*, vol. 23, no. 4, pp. 664–686, May 2019, doi: 10.1108/JKM-02-2018-0088.

[13] K. Gangodawila and P. D. Asanka, "RESULT SHEET - Identify the Current Demanded Knowledge, Skills, and Abilities (KSA) in IT through Analysis of Job Advertisements in Sri Lanka: A Framework Using Natural Language Processing Techniques.PDF". figshare, 09-Jan-2024, doi: 10.6084/m9.figshare.24966165.v2.