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RESEARCH ARTICLE

Efficient Resume-Based Re-Education for Career Recommendation in Rapidly Evolving Job Markets

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ABSTRACT The impact of the COVID-19 pandemic and the introduction of artificial intelligence-based tools created significant job losses across various sectors in all countries around the world. A large portion of these job losses is permanent. Furthermore, the hidden unemployment numbers are higher than currently reported and the impact of Generative Pretrained Transformer (GPT) based tools will further increase the unemployed population in the coming years. Most businesses are likely to experience significant disruptions to their business-as-usual operations and will face business underperformance for long periods. To ensure business continuity and a smooth recovery process following severe disruptions, it is crucial to establish a recovery strategy. To provide enough workforce for the recovery strategy of various businesses, a large-scale rapid re-education of the workforce is required. Intelligent and virtual workplaces will replace traditional offices in various sectors in the upcoming years and many low-skilled jobs are in danger of being permanently lost. In this paper, an artificial intelligence-based framework for rapid work-skill re-education for evolving markets named Career-gAIde is presented. The proposed framework uses automatic analysis of the job resume of the workers for recommendations of a suitable new job with a higher salary and the best rapid re-education path toward that job. Custom build deep neural networks based on CNN-Random along with customized natural language processing tools are designed for large-scale automatic recommendation of a personalized education and career path to each job seeker. The proposed work is focused on software engineering job search and resume upgrades. There is also a book recommendation module for obtaining the knowledge of job seekers. Precision criteria were used to evaluate the job offer recommendations and the proposed framework achieves 67% in this measure. The Recall criteria were used to assess the required skills, with results of 84% and 79%, respectively. The experimental results show that the proposed framework can provide a solution for rapid work-skill re-adjustment for large-scale workforces.

INDEX TERMS Job recommender system, learning path recommender, deep neural networks, natural language processing.

I. INTRODUCTION

Economic situation, globalization, cultural diversity, and technological evolution are known as some affecting factors on the transformation of human resource management (HRM) [1]. The outbreak of the COVID-19 pandemic followed by these changes faced human resource managers with a variety of challenges. If these challenges are not managed well, this can harm productivity [2]. Companies affected by COVID-19 must keep their operation while employees also work from home. Human resource management plays a critical role in achieving operation and strategic success during and after the pandemic [3]. The pandemic deeply affects the labor market [4], [5]. The COVID-19 pandemic will have significant and long-term consequences for the reallocation of jobs, workers, and capital across firms and locations. The US jobs report for April 2020 shows that the country had lost more than 20.6 million jobs since mid-March, leading

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to an unemployment rate of 14.7%, which is not seen since the Great Depression in the 1930s [6]. The unemployment rate in Canada in April 2020 was 13%, which is 5.2% higher compared to March 2020 and more than 7.2 million people have applied for emergency unemployment assistance [7]. In Australia, more than 11% of jobs during the COVID-19 pandemic were lost [8]. This trend is just a sample of the great impact of the COVID-19 pandemic across all economies around the world. More companies are experiencing operational disruption and significant shifts in consumer demands and behavior are impacting sectors from consumer and retail, to manufacturing. Furthermore, the Generative Pretrained Transformer (GPT) based family of artificial intelligence tools will create significant job losses in many countries around the world in the coming years. Such rapid job losses can cause serious social and political disruptions in many countries around the world. A significant portion of job losses was in hidden jobs and the rapid reduction of family income led to mortgage stress in many families around the world.

One of the solutions to the above-mentioned problems is to look at the current crisis as an opportunity for reshaping the business landscape. It is believed that effective and efficient post-pandemic changes in leadership style, competence management, and organizational culture may provide some opportunities for an enhanced HRM [9], [10]. Many companies are permanently shutting down their offices and outlets and changing their business model to a virtual and work-from-home model. The concept of a digital workplace can reduce the company's operational costs significantly and is used as a solution for business continuity in a crisis scenario. However, this change of operation model along with GPT-based solutions will lead to a massive job loss in low to middle-skilled service positions. This large unemployed workforce is in various age groups and traditional university-based re-education is not an option for many members of these financially stressed groups.

Several studies have been conducted on frameworks that improve workers' job status. Most of these studies have focused on job-proposing systems in which the main function of the system has been to offer job opportunities that are close to the skills extracted from people's resumes and there was a limited ability to improve the job status. This is known as one of the important values proposed in the employee lifecycle, meaning the life cycle of an employee from initial employment to outplacement [11]. The advantages of human resource practices have changed moving along the life cycle. It caused a shift from descriptive or diagnostic human resource analytics toward a predictive or prescriptive perspective [12]. Using machine learning and analytics clarifies the path that employees are more likely to pass through their careers; predicts the reason for their exits and even decreases the rate of employee turnover and attrition [13]. For example, Paparrizos et al. [14] have developed a machine learning-based model that predicts a person's future career change based on the job seeker's work history, resume data, and organizational data. Most of the approaches presented have used content-based techniques, group recommendations, or a combination of these techniques to generate job offers. Zhang et al. [15] compared user-based and item-based recommendation algorithms for using resume information to generate job offers. Bakar et al. [16] have introduced a Bayesian network-based solution for proposing software skills required for each job, using a set of data collected by extracting job advertisement information and interview sessions. Patel et al. [17] have introduced a job offer framework called CaPaR. CaPaR uses text-based models and combines them with group refinement algorithms to create two types of recommendations for users: job recommendations and skills required for the recommended position. Guo et al. [18] developed a resume analysis system called ResuMatcher that intelligently extracts the job seeker's experience directly from his or her resume and matches this information with the relevant jobs. Using a new statistical similarity index, they find job advertisements that are closer to the experiences, qualifications, and technical skills of the job seekers. Their approach has improved the quality of search results by up to 34% compared to existing frameworks.

To address the shortcomings of the above-mentioned frameworks, in this study a new framework for personalized career re-adjustment called Career-gAIde is proposed. The proposed framework creates a model for estimating the salary based on the resume of the individuals and proposes job opportunities with more salary than the current salary of the resume owner. Furthermore, it identifies the skill deficiencies for the proposed job positions and suggests a learning path for those skills. The Career-gAIde uses deep neural networks for learning the models from the job seekers' resumes and job advertisements in different salary categories. the proposed framework can be considered as an assistant tool in the recruiting and retention stages of the employee life cycle. The importance of the proposed framework can be justified considering the real costs of employee recruitment, and its importance on employee retention. Gee et al. [19] examined the costs of recruitment fraud. Pan et al. [20] also discussed the application of AI in the recruitment process. Studies revealed the significant effects of recruitment and positioning strategies on employee retention [21] The importance of this framework can be highlighted considering the costs of losing good employees [22].

Comparing the proposed framework to similar frameworks shows significant advantages and contributions for the Career-gAIde:

1. Similar frameworks use a predetermined dictionary for information technology jobs and they cannot function in all other industries.
2. Similar frameworks only address the issue of matching resumes with jobs and does not identify the skill deficiencies that make it difficult to get that job.
3. Similar frameworks do not take into account the individual's current income status.
4. Similar frameworks only offering jobs and not improving the career path of the job seeker.

5. Similar frameworks do not introduce learning paths that are needed to get the recommended job.
6. The Career-gAIde can be used in various fields and occupations, it can identify skills deficiencies to achieve the proposed jobs, it can estimate the current income status of individuals, it can improve and optimize the career of a person in uncertain situations like post-pandemic job market by offering a learning path to achieve skill deficits and it guarantees the privacy of the job seekers as it does not require any personal information.

The rest of the paper is organized as follows: Section II presented a review of related works to the proposed framework. Section III describes the proposed Career-gAIde framework. In Section IV the dataset, experimental setup, and experimental results are detailed. Finally, Section V concludes the paper.

II. BACKGROUND AND RELATED WORK

Recent research shows that the demand for information technology-based systems for human resource management and recruitment processing is growing rapidly. Most companies focus on their e-employment platforms as their main recruitment channel. As a result of the popularity of these platforms, a huge amount of job descriptions and candidate resumes are available online. On the other hand, among the multitude of job advertisements, people should find their ideal job opportunity, which is usually a tedious and time-consuming task. This huge amount of information provides a good opportunity to improve the quality of service using artificial intelligence-based recommender systems to help employers to manage this information more effectively as well as to help job seekers to reach the right job position.

Recent advances in machine learning techniques have made it possible to automatically extract information from job seeker resumes as well as job advertisements. In this regard, Guo et al. [18] introduced a system for recommendations of job advertisements that are closer to the experiences, qualifications, and technical skills of the job seeker. In this system, the model of a resume is used to search for the most suitable job position. It calculates the similarity of the "job candidate model" and the "job model" created by the resume and job advertisements to determine the appropriateness of a job for the individual. This method changes the basic nature of job search from "keyword matching" to "model matching." Search results are also sorted based on the similarity score.

Patel et al. [17] introduced a framework for proposing a career path that creates two recommendations for users: job positions and skill recommendations. The proposed system consists of several modules. The users first create their professional profile through the user interface module after logging in to the system by uploading a resume. The next module processes user requests and the user profiles are stored in the database. A similar operation is performed for job advertisement data. The text data module analyzes users' profile data and job description details from the database and generates the data needed to enter the recommendation engine. In the text processing module, the user profile becomes a set of tokens, and each token is compared to a dictionary, which includes predefined skills. After identifying the skills of the job seeker, the user is asked to determine the level of competency in that skill with numbers from one to three. Then, the system analyzes job advertisements and extracts information such as job titles, company names, required skills, and so on. The recommendation module includes two different sub-engines. This module receives the user's current profile, preferences, and skills. The output of two recommenders, called job and skill recommenders, generates personalized recommendations.

Almalis et al. [23] have introduced a content-based recommendation algorithm that extends the Minkowski distance to solve the problem of matching individuals and job positions. The proposed algorithm, called FoDRA, measures the job seeker's fitness for a job position. This is performed through the candidate's job profile. Diaby et al. [24] introduced a classification-based job recommendation system that introduces related jobs to Facebook and LinkedIn users. They use a network of jobs and job information to create a vector model for a job recommendation. They offer two similarity functions based on fuzzy logic operators "AND" and "OR" that are suitable for the proposed model. The experimental results show that the proposed classification-based vector model performs better than the traditional TF-IDF-based models. Gupta et al. created a job recommender based on the candidate's profile and his or her behavior and preferences. First, the rules for predicting the general preferences of different user groups are extracted. Then, based on the content and preferences of the user, job offers are created for the target user. Wenxing et al. [25] implemented a mobile job recommendation system called iHR. The mutual preferences are calculated based on a similarity index to receive the best job offer. Mirza et al. [26] focused on identifying suitable job maps for a person looking for a career in information technology through personality analysis. They have also suggested relevant and potential skills that a person can use to achieve a significant advantage in the job position. They used "Dutch Personality Codes" to identify personality and determine job roles. They also used the 5-factor model to enhance the quality of the offers. Identifying skills related to a job is done by analyzing job lists available on web portals. Nguyen et al. [27] have introduced employee clustering to create job offers for users of different groups. They first cluster employees into different groups. An appropriate model is then selected for each cluster based on the empirical evaluation. The proposed models include "CB-Plus", "CF-jFilter" and "HyR-jFilter" which have been applied to the clusters.

In job recommender systems, both the personal and the professional requirements of the job seeker must be considered. Özcan et al. [28] have introduced a two-way job recommendation system called CCRS, which uses user profiles, interactive features, and preferences to provide appropriate recommendations. Their proposed system is evaluated by data received from job search websites. An important advantage of this approach is that it avoids the problem of a cold start in the case of job candidates. Razak et al. [29] have introduced a job recommender system that uses fuzzy logic to provide job offers to students based on a job test. In this system, the strengths of students' skills, abilities, and personality elements are measured, and appropriate jobs are offered through fuzzy logic-based matching.

Malherbe et al. [30] proposed a novel structure for job offer text processing. They have introduced a new model that helps reduce the dimensions of the input text by reducing redundancy and unnecessary information. Chala et al. [31] provided a general framework for the online recruitment system through the analysis of social networks. In this context, they have considered the role of social media data as an effective factor in improving the measurement of skills of job seekers. Their study focuses on extracting useful knowledge from the relationships that exist between users of social networks. Each person's skills, experiences, expertise, and attitudes are effective in assessing the job seeker's fitness for the job position.

To this end, they first extract the skills and characteristics of job seekers from social networking sites and forums to create a template for modeling individuals. The affirmations and votes that others have given to the skills of these people show their ability in the desired specialty. Measuring the skills of job seekers involves assigning weights to skills through "Subjective", "Semi-subjective" and "Objective" measurements. In Subjective measurement, the weight assigned to each skill is based on the individual's evaluation. In Semi-subjective measurement, weighting is done through factors such as the duration of having a particular skill, as well as endorsements from other people on the job seeker's social network. Finally, in the Objective measurement, weights are obtained through short tests that people attended to determine the level of each skill.

To solve the problem of finding suitable jobs for job seekers, Paparrizos et al. [14] have considered this problem as a supervised machine learning problem. They create an automated system that can offer jobs based on the work history of a person. A set of attributes extracted from the candidates' resumes. This approach considers all past work changes, along with information from organizations and individuals, to suggest a new job change. They teach a machine learning model by using a large amount of job change information extracted from profiles on the web. Singh et al. [32] have introduced a system that, based on decision support tools, helps employers to obtain a short list of candidates' resumes lists.

The system extracts information such as skills, education, and experience from candidates' profiles. This system uses information retrieval techniques to rank people for a particular job position. The system ranks candidates for each job profile based on the similarity between the job profile and the person's resume. This index is based on candidates' data and information extracted from their resumes.

The technology-based economy of the 21 century emphasizes the importance of acquiring digital skills and competencies for success in the competitive post-pandemic job market. Furthermore, the job seeker should constantly keep their skills up to date to maintain their position and be able to aim for higher positions. Therefore, planning the learning path to ensure that the skills acquired are tailored to the needs of the job market is very important. Furthermore, companies should plan their training activities appropriately to keep their workforce up to date and education providers should match the needs of the labor market and the skills of students. Traditionally, it is the responsibility of the education providers to compare the skills of the job seekers and the needs of companies.

However, automated recommender systems can play an important role in this field. Learning path design systems help self-learners to find the most appropriate LO (Learning Objects) and create efficient learning pathways to achieve them. IEEE defines anything that is used digitally or non-digitally for the learning, teaching, and learning process as a LO. Data mining of educational issues creates innovative methods for constructing systems that suggest educational goals. Durand et al. [33] have introduced a model for constructing a learning recommender system based on graph theory. If we consider a graph such as G = (V, E) for the personalized learning path, each vertex or node refers to a LO. The two vertices are connected if there is a dependency relationship between them. Therefore, each edge between the two vertices of (u, v) means that the learning objective v can be achieved through u.

A learning path is an implementation of an educational program that includes a set of activities that allow students to learn the skills and knowledge they need. Since there are different types of students with different learning styles and abilities, it is not easy to create the right approach for a particular person. Designing educational content for different students is time-consuming for teachers. No matter what the learning process is like, both the teacher and the student must be satisfied with the quality of learning and teaching. To achieve this, Yang et al. [34] have presented a result-based learning path model that allows teachers to explicitly develop and plan learning activities as learning pathways. This also allows teachers to design criteria for assessing knowledge in a particular field or general skills. Apart from defining educational approaches, they needed to provide educational materials appropriate to the courses, so that different types of students could learn the appropriate knowledge more optimally, according to their learning abilities and prior knowledge. To this end, they have proposed a method of generating learning pathways to automatically identify relationships between web resources. This method allows resources that can be obtained for free from the web to be converted into learning resources with the right structure.

It also defines the path of learning, the things that need to be learned, and how they learned, and the teacher only monitors the student's learning path.

Personalization of the learning path is an important research topic in e-learning systems because no fixed learning path is suitable for all learners. Many researchers have focused on developing an online learning system with personalized learning mechanisms to improve the quality of learning. However, most e-learning systems often only pay attention to the difficulty of the courses offered and the proposed educational programs to match the learner's abilities. Chen et al. [35] developed a personalized e-learning system based on a genetic algorithm that can generate appropriate learning paths through pre-experiments. Their approach involves several steps: First, the learner performs a pre-test based on randomly selected items in the learning unit to create a personalized learning path. The system then collects the wrong answers in the pre-test and the corresponding training program. Then, among all the wrong items, the training program related to the lowest degree of difficulty is selected as the first training course. This system creates the optimal learning path for a person through a genetic algorithm appropriate to the incorrect answers in the tests.

In e-learning systems, personalization can be achieved through the design and development of intelligent systems. Kurilovas et al. [36] proposed a new approach to suggesting appropriate learning paths for different learners. They consider choosing a learning path as a combination of the LO sequences according to the learner's tastes and preferences and learning style. Their method is based on ant colony optimization. The results of this research show that learning through this technique can improve the learning outcomes of students and reduce their learning time. They obtain their data through learning-style questionnaires, tests, and log files that include the user's interactions with the system over a while. These log files include information about user clicks on various parts of the system's user interface, as well as user reactions to system suggestions.

Based on the above review of the literature, it was concluded that previous systems provided for the learning path recommendation only help the learners to find the most appropriate LO and efficient learning pathways. These learning path recommender systems do not take the skills needed for the job market into consideration. Furthermore, the job-recommender systems have focused only on job recommendations and have not provided guidance and direction for achieving the proposed jobs. In the recommendation stage, the only issue is the adaptation of the skills of the candidates to the job, and they do not consider analyzing the current situation of the person and bringing him to a higher position.

In recent years the application of deep neural networks was able to model complex problems with high accuracy [37], [38]. In the proposed Career-gAIde, deep neural networks are used to close the gap between job-recommender systems and model-based learning systems by integrating them into a more comprehensive system.

III. THE CAREER-gAIde FRAMEWORK

The proposed Career-gAIde framework uses natural language processing and deep neural networks and content based recommendation techniques. These recommendation techniques are a significant part of employment branding that can enhance the attraction of employees to the job [39]. Following an intelligent and electronic recommendation increases the intention of applicants to apply for a job [40].

In this section, first, the general structure of the proposed framework is introduced and then the details of each part are presented. The career improvement section consists of five main modules as illustrated in Figure 1.

This section starts with job advertisement analysis and resumes analysis modules. The job advertisement analysis module finds web pages of job positions from a job search network and extracts them through a web crawler, and after performing the necessary processing, creates a model of job advertisements. In the resume analysis module, an initial model of the resume of the job seeker is created.

For the system to be able to provide career improvement for a person, it is necessary to first be aware of the person's current career position. The modeling module is responsible for estimating the salary equal to the abilities extracted from the initial resume model using a deep neural network that has been trained with the job advertisement data. This module eventually produces the model which contains the equivalent salary for the resume as output. In the next step, the job promotion proposal module uses the advertisement and resume models created in the previous steps. The resume is then referred to the nearest higher-paying job. In the next step, in the recommendation module, the system finds the skills deficiencies for the proposed job and introduces a learning path for these skills. In this section, each module and its components are explained in detail.

A. THE JOB ADVERTISEMENT ANALYSIS MODULE

For the proposed system to be able to recommend suitable job opportunities, it is necessary to process job advertisements and create appropriate models for the job opportunities. The advertisement analytics module first extracts job advertisement web pages from the job search engines via a web crawler and then creates a refined model of job advertisements by natural language processing. In this module, a series of basic information is obtained by parsing HTML pages, including job titles and job descriptions. After storing this information, it is necessary to perform a text search operation to use the data in the next steps. This operation is performed in the job search module.

In this module, there are two text search engines: one for text search on job ads and the other for text search on resumes. These two modules are very similar to each other. Figure 2 shows the operation performed in this module. In this module, the preprocessing is performed on the text of different parts of the job advertisement. Deleting punctuation and numbers, converting capital letters to small letters,

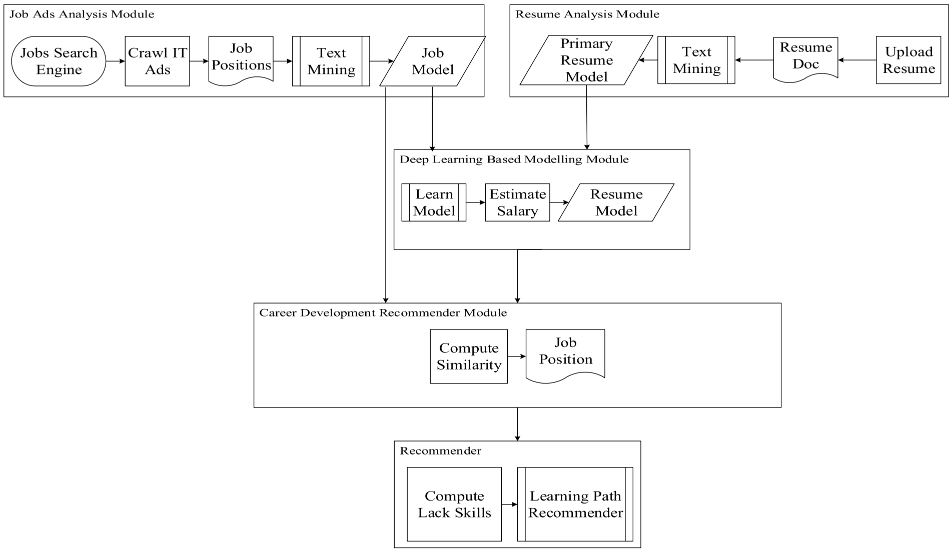

FIGURE 1. The career-gAIde framework.

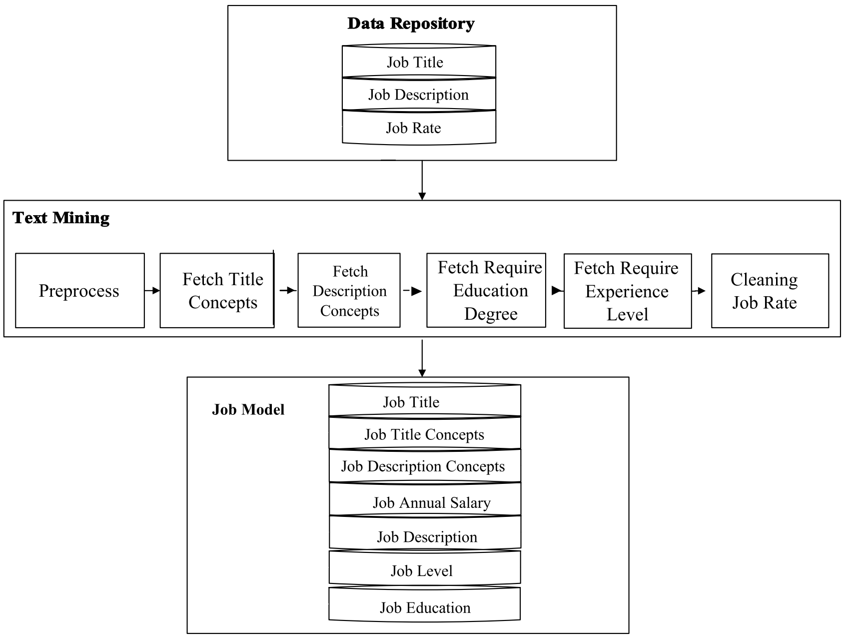

FIGURE 2. The job search module.

tokenization, stemming, shortening extensions, and deleting extra words (stop words) are some of the pre-processing functions. Then, it is necessary to extract the keywords and concepts, and skills that are mentioned in the title and the job description.

This operation is based on DBpedia [41] which is a database for extracting structured information based on Wikipedia data. In this module, structured information and concepts in both the title and the job description sections are extracted using the Spotlight web server for automatic tagging based on DBpedia [41].

Spotlight provides links to explore phrases (identifying phrases that need to be tagged) and disambiguation (linking entities). The standard ambiguity algorithm in the Spotlight system is based on cosine similarity and TF-IDF weight adjustment. The main algorithm for detecting phrases is the string-matching algorithm [41].

After receiving concepts extracted from job titles and job descriptions by the Spotlight system, the stop words are again removed from the list of extracted concepts. Figure 3 shows how these sub-modules work. An Example of Spotlight returned information for a job opportunity in the field of information technology is presented in Table 1.

Spotlight has also been used to extract the required qualifications in the text of the job advertisement. In this section, six categories of "diploma", "postgraduate", "bachelor's

TABLE 1. Example of spotlight returned concepts.

Title concepts	"Software Engineer", "DevOps", "Engineer", "Heathrow"
Description concepts	"Software Engineer", "DevOps", "Heathrow", "ASAP", "Software Engineer", "DevOps", "Software Engineer", "DevOps", "DevOps", "Key Skills", "DevOps", "Software Engineer", "CI", "CD", "Python", "Linux", "C++", "Ansible", "cloud"

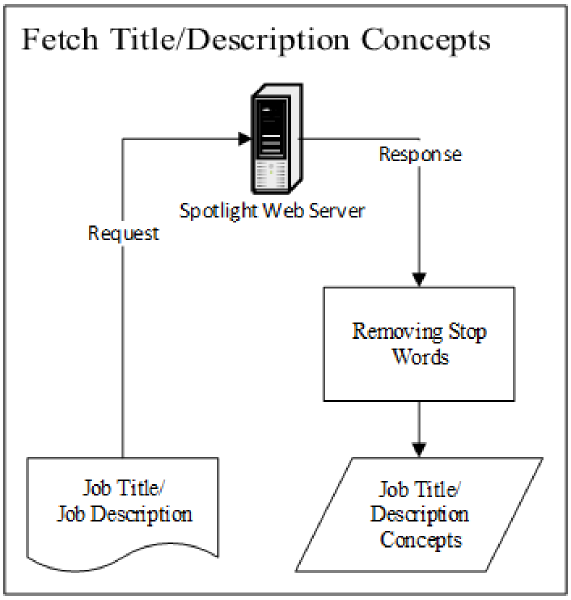

FIGURE 3. Extraction of the concepts from the titles and descriptions.

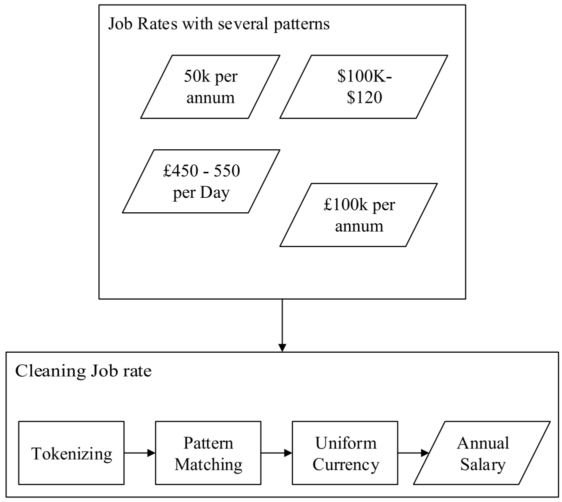

FIGURE 4. Sub-module for job salary processing.

degree", "master's degree", "doctorate" and "not mentioned in the text" have been considered. Each of these categories can be displayed in different ways. For example, a master's degree can be referred to as a Master of Science, MSc, or MS. Therefore, the answers that come back from the Spotlight system, are further processed to determine which of the main categories they belong to. Also, to determine the level of experience, seven levels of "Senior", "Junior", "Leader", "Entry-Level", "Mid-Level" "Manager" and "Not mentioned in the text" are considered. These levels are listed with different phrases and abbreviations in the text too. By creating patterns for each level and by matching these patterns with the phrases in the text, the level of experience required to accept people is determined.

Another issue is that the salaries mentioned in job advertisements have different structures. For example, some salaries are listed on an hourly basis, some monthly, and so on. The monetary units of the salaries mentioned in each ad are also different. Some are in USD, some in Pounds, and some in Euros. Therefore, all data needs to be converted into a single structure so that they can be used in later stages. It should be noted that ten different income levels with different ranges are used in the proposed framework. The job rate sub-module first converts salaries into patterns and then according to the various phrases and patterns created, it is categorized as one of the ten predetermined salary levels. Then, the information obtained at this stage, through the process of unification of the units, first becomes the annual salary and is then converted to USD currency. Figure 4 shows this sub-module in detail.

Finally, the model of the job advertisement is created. This model has seven sections: "Title", "Concepts of title", "Descriptions", "Concepts of details", "Required degree", "Required professional level" and "Annual salary".

B. THE RESUME ANALYSIS MODULE

As input to the Career-gAIde, the job seekers enter their resumes for processing. The first information extracted from the resume is the "Title" and "Summary of resume". This information is delivered to the text analysis module for the construction of an initial model of the resume. From a text processing perspective, the resume analysis module is similar to the job advertisement analysis module. However, as usually there is no mention of the current salary in the resume, it is necessary to calculate the current salary of the job seeker in this module. In the resume analysis module, after the pre-processing stage, the keywords in the title and summary of the resume are extracted, and the academic level and work experience level of the person is calculated using a similar process to the process described in the job advertisement analysis module. The output of this module is an initial model of the resume, which includes six sections: resume title, title concepts, resume summary, resume summary concepts, degree, and professional and experiment level. Figure 5 shows this module in more detail.

Details of the collection of biometric data using Softbank's humanoid robot Pepper as well as the processing and

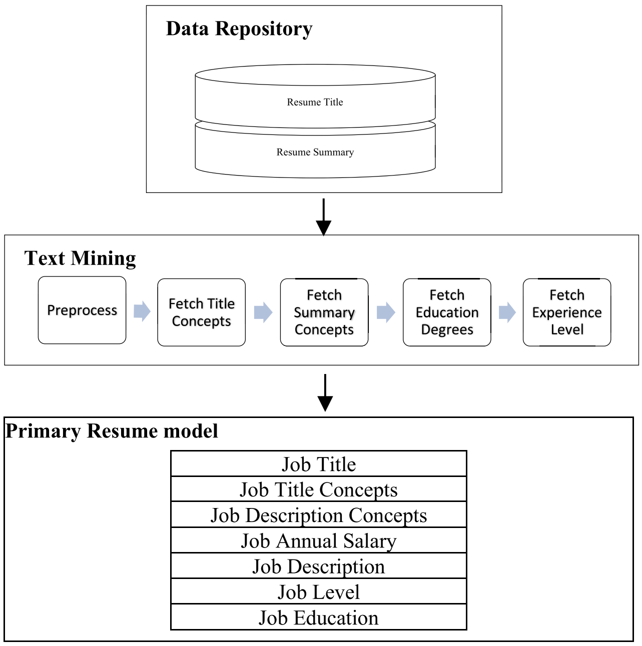

FIGURE 5. Resume analysis module.

extraction of visual, audio, and signature-related biometrics are presented in Sections IV-A and IV-B, respectively.

C. MODELING THE JOB SEEKERS' INCOME USING DEEP NEURAL NETWORKS

To recommend a job with a higher salary to the job seekers, the Career-gAIde must estimate the job seekers' current salary. The Career-gAIde estimates the current income of job seekers based on their skills and experience. In the salary estimation module, a custom-made deep neural network is trained using job and resume datasets. Ten income levels are considered for the classification of the job seekers' resumes. Figure 6 shows the salary estimation module in more detail.

The inputs of this module are the text of the title and description (summary) of "job positions" in the resume and job advertisement datasets. First, the text needs to be converted to appropriate numerical structures. Because the data we are looking for is also in the form of text, in the first process it is necessary to make a dictionary of all the words in the titles and descriptions of the job models. If the total number of distinct words in a dictionary is equal to v, the dictionary will be:

$$\text{Vocab} = [< W_0 : I_0 >, \ldots, < W_{v-1} : I_{v-1} >] \qquad (1)$$

in which, $< W_i : I_i >$ is a mapping of the words in the dictionary to their corresponding index. Then, the input text of the job model samples, as well as the resume, are converted to fixed-length vectors for training the neural network. Table 2 shows examples of these vectors.

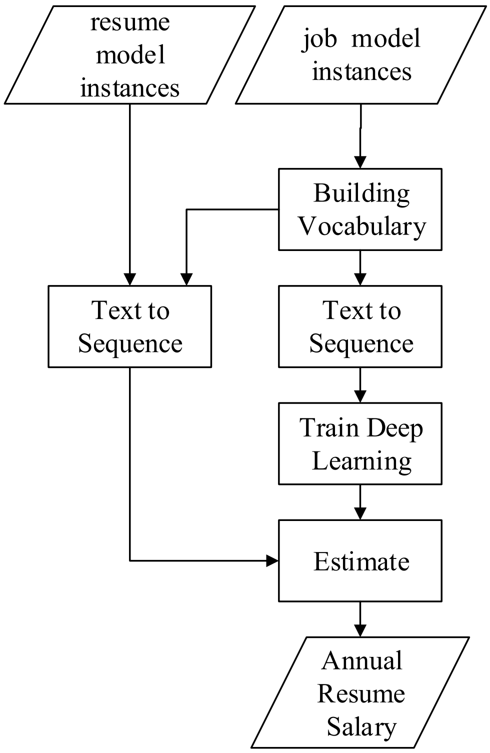

FIGURE 6. The salary estimation module.

TABLE 2. Example of the vector obtained from text to sequence operation.

Sample input text	"Software Engineer, C# .Net Programmer"
Equivalent sequence	{4, 12, 157, 12,32}

D. SALARY ESTIMATION NEURAL NETWORK ARCHITECTURE

A custom-built deep neural network is proposed for modeling the salary levels. Figure 7 shows the architecture of the proposed deep neural network. The input of the network is resumes and job advertisements. The length of the largest document (the document with the most words) is considered the length of all documents, and shorter documents are zero-padded. The first layer of the network is the embedding layer. This layer converts the document text sequence to the document matrix. In the convolution layer, 32 filters are assigned for feature extraction from the word embedding matrix. A global max pooling layer is used for the pooling of the network. To reduce overfitting, the dropout with a rate of 0.2 is applied to the network. The Relu activation function is used throughout the network. A Softmax layer finalizes the network.

The main deep-learning architecture used in the manuscript is presented in Figure 7. This architecture is a simple convolution-based architecture that despite its simplicity can extract the required features from the input data and then provide a salary category based on these features. The simple architecture provides satisfactory

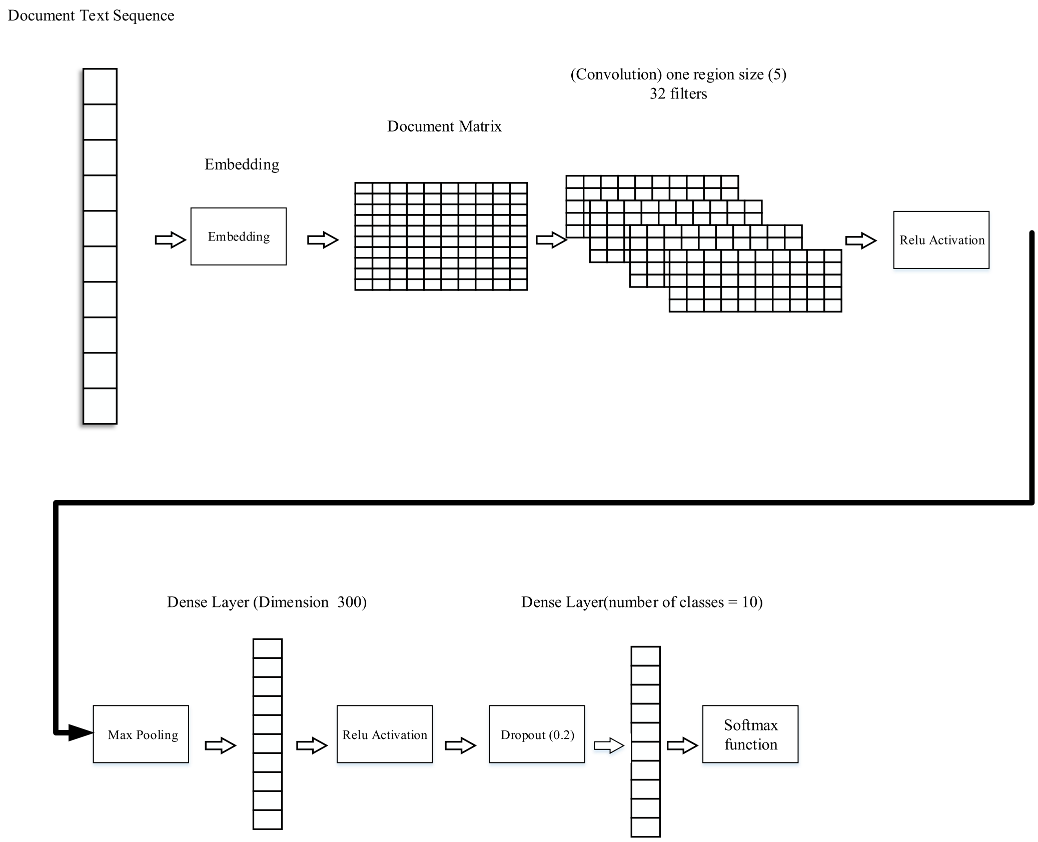

FIGURE 7. The architecture of the salary modeling deep neural network.

performance for the framework and using more complicated architectures only increases the complexity of the presented solution. Table 9 is only the comparison of various parameters on the performance of the proposed architecture for the selection of the best parameters. The reason for choosing the convolution-based architecture for salary estimation is that this architecture is very effective in handling tabular data. While convolution-based neural networks were initially developed for image processing tasks, they can also be used for handling tabular data, such as the kind of data used in a salary classification task. The convolutional models are capable of automatically extracting features from the data, which can be useful in a salary classification task where there may be many different features that are relevant for classification. This can reduce the need for manual feature engineering and make the classification process more efficient.

E. THE JOB PROMOTION MODULE

The results of the previous modules are the creation of similar job advertisements and job seekers' resume models. To recommend a job with a higher salary to the job seekers the Career-gAIde should be able to find the most similar job advertisement to their resume with the shortest learning path.

To determine the similarity between the job advertisements and resume models, the similarity of five common fields of both models is used: Title concepts, Description concepts, Experience level, Education, and Salary. If we consider a job model as mj and a resume model as mr, the similarity between these two models is calculated as:

$$sim\left(m_j^i, m_r^i\right) = \sum_{i=1}^{n} \lambda_i(m_j^i, m_r^i) \times \omega_i \tag{2}$$

in which, λ_i is a function of the similarity between the i fields of both the job model and the resume models, and ω_i is the weight that is determined experimentally.

The similarity function is different for each field of the models:

1) THE SIMILARITY FUNCTION FOR THE "TITLE CONCEPTS" FIELD

To determine the similarity between the concepts in the resume and the job sample headings, a reference T-length vector is created from all the unique concepts contained in the titles of all the job samples. Then two T-length vectors are assigned to each of the jobs and resume samples with zero initial values. Then, for each job and resume vector, for each concept that is available in the reference vector and also in the concepts of job or resumes titles, a value of one is created in the job vector or resume vector. Therefore, a binary vector

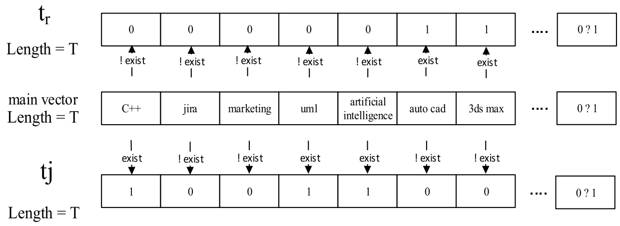

FIGURE 8. **The process of building the concept vectors.**

is created for each of the job and resume samples. Figure 8 shows this operation.

To determine the similarity between these two vectors, the φ coefficient is used. This coefficient is a criterion for the determination of the correlation between binary variables and is similar to Pearson's correlation coefficient:

$$\lambda_t\left(t_j, t_r\right) = \frac{(ad) - (bc)}{\sqrt{(a+b)(a+c)(b+d)(c+d)}} \tag{3}$$

in which λ_t indicates the similarity between the two vectors of concepts of job (t_j) and resume (t_r), a is the number of times that both values for a field are equal to 1; b is equal to the number of times that the vector of t_j is equal to 0, and the vector t_r is equal to 1; c is equal to the number of times the vector t_j is equal to 1 and the t_r vector is equal to 0, and finally, d is the number of times that both vectors are 1.

2) THE SIMILARITY FUNCTION FOR THE "DESCRIPTION CONCEPTS" FIELD

This similarity function is the same as the previous one, except that instead of the concepts in the titles, the concepts in the descriptions are considered:

$$\lambda_d(d_j, d_r) = \frac{(ad) - (bc)}{\sqrt{(a+b)(a+c)(b+d)(c+d)}} \tag{4}$$

3) THE SIMILARITY FUNCTION FOR THE "EXPERIENCE LEVEL" FIELD

The level of experience required for the job and the level of the current experience of the job seeker were extracted from the text of the job description and resume and placed in one of the seven predefined categories. The similarity level between these values is calculated as follows:

$$\lambda_l\left(l_j, l_r\right) = \begin{cases} 0, & if\ l_r > l_j \\ 1, & if\ l_j - l_r \ll 2 \\ 0.5, & if\ l_j - l_r > 2 \end{cases} \tag{5}$$

in which, l_r is the level of experience of the job seeker and l_j is the level of experience required for the job opportunity. In this function, if a person's level of experience is larger than the level of experience required for the job, the value is zero, if the difference between the level of the resume and the level of experience required for the job is less than two, the value of one, and if the difference of the level of the job is larger than two, the value of 0.5 is assigned as the output.

4) THE SIMILARITY FUNCTION FOR THE "EDUCATION DEGREE" FIELD

The similarity between the education degree in the job advertisement and the applicant's resume is defined as follows: For all jobs that have a lower level of education than the educational level of the job seeker, zero, the jobs with a required level of education of at least two levels above the job seekers level value of one, and finally occupations with a level of education more than two levels above the job seeker the value 0.5 are assigned.

$$\lambda_e(e_j, e_r) = \begin{cases} 0, & if\ e_r > e_j \\ 1, & if\ e_j - e_r < 2 \\ 0.5, & if\ e_j - e_r > 2 \end{cases} \tag{6}$$

5) THE SIMILARITY FUNCTION FOR THE "SALARY" FIELDS

To recommend jobs with more annual income to a jobseeker, the similarity function of salaries is defined as follows:

$$\lambda_e(s_j, s_r) = \begin{cases} 0, & if\ s_r = s_j \\ \dfrac{1}{k}, & if\ s_j - s_r = k > 0 \\ k, & if\ s_j - s_r = k < 0 \end{cases} \tag{7}$$

in which, k is the difference between the salary level of the job and the resume.

If the salary level of the job is higher than the salary level of the resume, for each level of difference (larger k) the amount of output will be smaller. If the job salary level is lower than the resume salary level, the difference which is a negative value is obtained and is the output of the function.

F. THE RECOMMENDATION MODULE

After the selection of the most suitable jobs for job seekers, there may be some skills that the job seeker should master to be eligible for applying for that job. Therefore, the skills deficiencies of the job seeker are calculated by comparing the vectors of requirements of the job description and the resume of the job seeker. Figure 9 shows an example of a job offer in which the estimated income level for the resume, the income level of the job, the skills needed that the job seeker already has, and the skills deficiencies required for the job opportunity are displayed to the user.

As the focus of this research is on rapid self-education and not the time-consuming and expensive courses that are offered by educational institutions, the learning path for the job seeker is provided through books. To acquire the skills, the best available books are selected automatically from an online retailer and recommended to the job seeker. This action is performed using the learning path recommendation module. The two major online book repositories namely Google Books and Amazon are selected for creating the model for a book recommendation. When the career path recommender selects a skill for education, it is sent to Google's library service, and the most relevant book to that skill is identified.

However, as the main criteria for selecting a useful book for learning a skill is the previous experiences of the readers

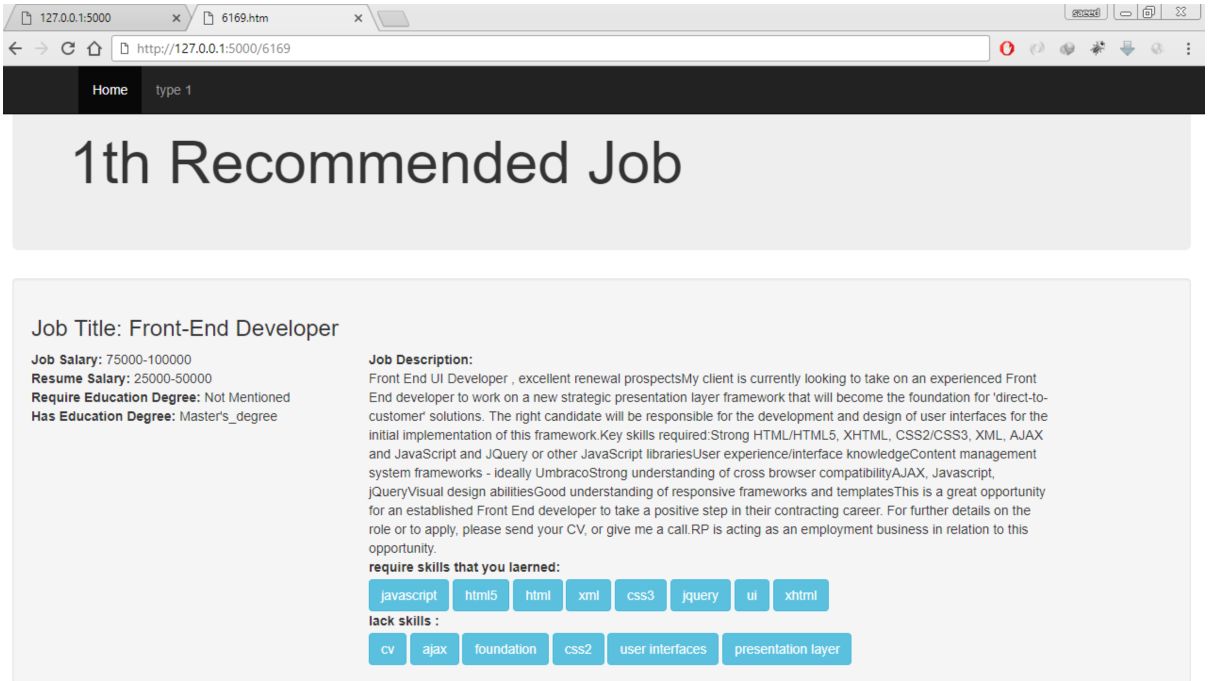

FIGURE 9. The output of the skill recommendation module.

of the book, in the next stage the Amazon user ratings are used for finding the best book related to the required skill. To find the best-reviewed book, first, the Amazon books are clustered based on the TF-IDF of the Description field of the books using the K-means algorithm. The book cluster with TF-IDF vector most similar to the TF-IDF of the Description of the book selected by Google Book is used for finding the most suitable book as determined by the users. The user feedback is collected from the Amazon user rating field. Finally, to determine the best book the following score is calculated:

However, as the main criteria for selecting a useful book for learning a skill is the previous experiences of the readers of the book, in the next stage the Amazon user ratings are used for finding the best book related to the required skill. To find the best-reviewed book, first, the Amazon books are clustered based on the TF-IDF of the Description field of the books using the K-means algorithm. The book cluster with TF-IDF vector most similar to the TF-IDF of the Description of the book selected by Google Book is used for finding the most suitable book as determined by the users.

The user feedback is collected from the Amazon user rating field. Finally, to determine the best book the following score is calculated:

$$Score_i = \frac{\sum_1^c point_i \times helpful_i}{C_i} \tag{8}$$

in which $point_i$ represents the score given by the reviewers to book i, C indicates the total number of reviews written about book i, and $helpful_i$ indicates the usefulness of a review for the book i, which is equal to m/n, where m is the number of people who believe in the usefulness of the review and n is the total number of people who have participated in deciding whether the review is useful or not. After the calculation of the Score, the books are arranged according to the highest to the lowest score. The top three books will be displayed as a list of suggested books to achieve the desired skill. The output of this module is presented in Figure 10.

IV. EXPERIMENTAL SETUP AND SIMULATION RESULTS

A. EXPERIMENTAL SETUP

In this section, first, the datasets used in the proposed framework are detailed. Then the evaluation criteria are presented. Finally, the experimental setup and simulation results are discussed and compared with similar research for a job recommendation. All operations performed in this module are presented in Figure 11 in detail.

- **Data collection**

To implement and evaluate the proposed framework, three different datasets are collected: 1. Job advertisement dataset, 2. Job seeker's resume dataset and 3. Education resources dataset.

1. Job advertisement dataset: To collect this dataset, the web pages related to the job opportunities of an online job search network (https://www.jobserve.com) have been extracted through a web crawler. The specifications of this dataset are given in Table 3.

From this information, after parsing the labels, a set of basic features as described in Table 4 is obtained.

2. Job seeker's resume dataset: A set of people's actual resumes has been used to evaluate various parts of the

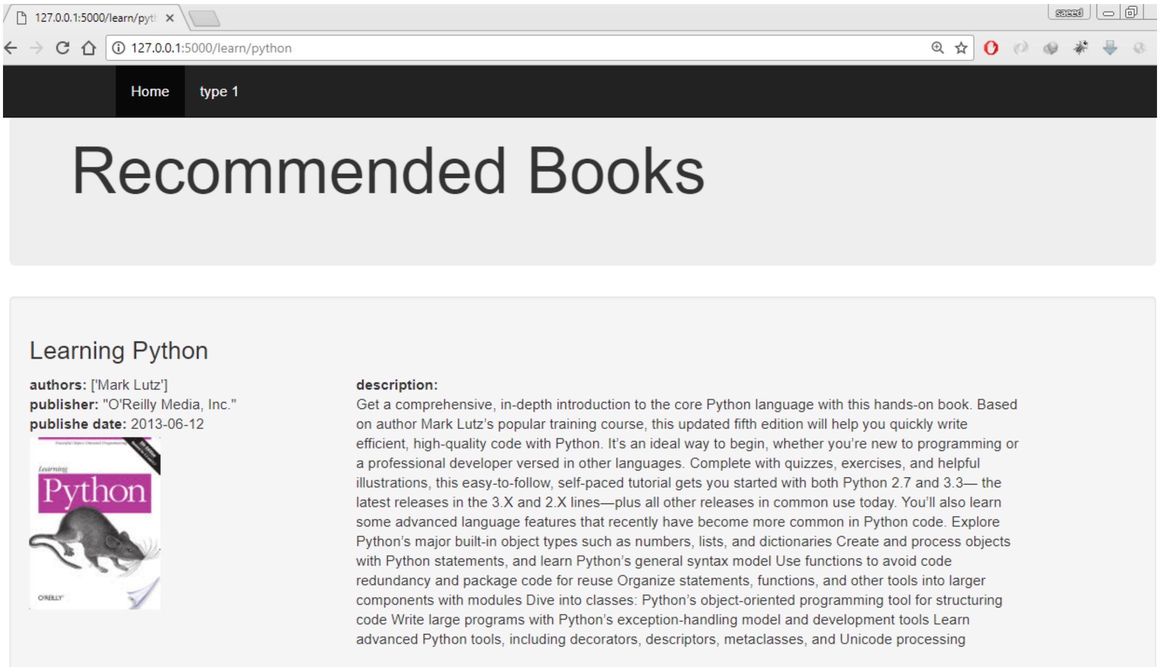

FIGURE 10. The output of the book recommendation module.

TABLE 3. Job opportunity dataset specifications.

Language	Structure	Number
English	JSON	8870

TABLE 4. Preliminary features obtained from the job opportunities dataset.

Name	Description
Job Title	Job title
Job description	Describes the job position and may include the required skills, the required degrees, the necessary work experience, etc.
Job rate	The salary for the job.
	The salaries may be listed on an hourly, daily, monthly, or annual basis

TABLE 5. Characteristics of resume dataset.

Name	Description
Title	Resume title
Summary	Summary of work experience and skills and education

proposed framework. The information contained in the resumes is presented in Table 5.

3. Educational resources dataset: For educational resources, the online services from Google Books and the Amazon book dataset are used. Google Books outputs a series of features for each book as presented in Table 6.

To model the Amazon bookstore, the offline Amazon book dataset is used. The characteristics of the Amazon dataset are presented in Table 7.

TABLE 6. Google books features.

Name	Description
title	Book title
description	General description of the content of the book
authors	Authors
publisher	Publisher
imUrl	Url related to book cover photo

TABLE 7. Amazon dataset fields.

Name	Description
asin	Book ID
title	Book title
description	General description of the content of the book
price	Book price in USD
imUrl	Url related to book cover photo

Data preprocessing steps such as text cleaning, tokenization, stemming, part-of-speech tagging, named entity recognition, and feature selection are necessary steps in any machine learning system. Job advertisement text may contain irrelevant elements such as HTML tags, URLs, punctuation, and stop words that must be cleaned. To make the natural language processing system capable of analyzing the text at a more granular level the text must be tokenized.

Features from user review data on the Amazon dataset are listed in Table 8.

To let words with the same roots, have cumulative influence in analysis, stemming is necessary. The role of the word in any sentence affects the meaning, part-of-speech

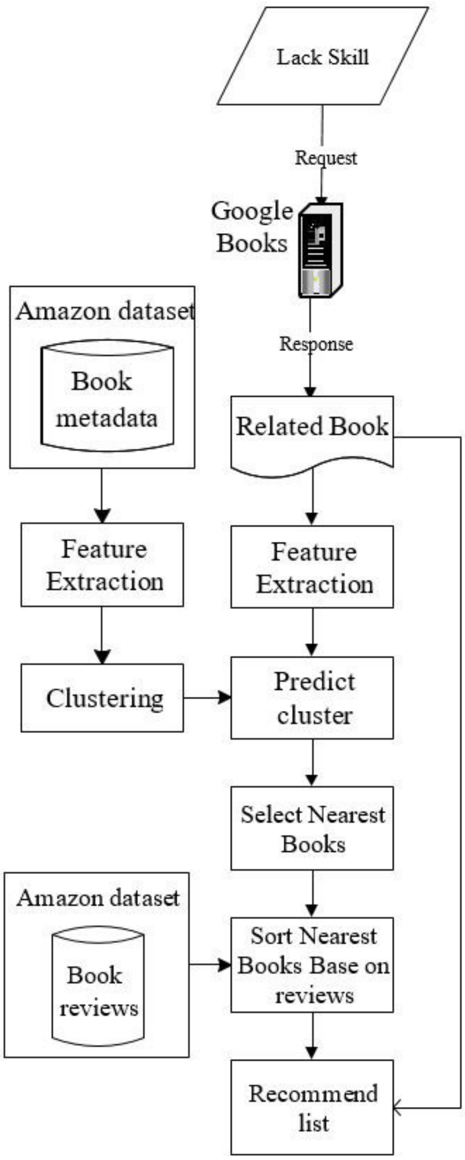

FIGURE 11. Learning path recommendation module.

TABLE 8. Features of user review data in Amazon dataset.

Name	Description
reviewerID	The ID of the person who created the review for the book.
asin	Book ID
summary	Summary of the review of the book
overall	The overall score is given by the reviewer of the book
helpful	This value is determined by other users and indicates the usefulness of the review

tagging is used to determine if the word is a noun, a verb, or an adjective. Named entity recognition can be useful for identifying important features in the text such as company names, job titles, and locations, that may be relevant for job recommendations. Feature selection is important to identify the most important keywords and phrases in the text for job recommendations.

B. SIMULATION RESULTS AND DISCUSSION

Python programming language has been used to implement the Career-gAIde. In this project the NLTK library is used for natural language processing, Keras and Tensorflow are used for the implementation of deep neural networks, and the Flask library is used for designing the user interface. The evaluation of each subsystem is performed separately and finally, the overall framework is compared against similar job recommendation systems. The evaluation is performed both using data analytics methods and by human participants.

As mentioned in the previous section, a custom-built deep neural network was used to estimate the income level from a resume. To achieve the best results, three neural network models are evaluated: the random model, the static model, and the dynamic model. In the random model, the deep neural network requires word embedding in its first layer. A matrix is used to write a word to its corresponding vector, and then the word is identified with this vector. This model does not have a pre-trained matrix for embedding operations. Rather, a matrix that is randomly assigned to the weights is considered first. Then, during the training of the network, this weight matrix changes the weights according to the outputs to obtain the most appropriate values.

In the static model, for embedding existing words, vectors with values pre-created by "Glove" are used. The glove is an algorithm for displaying words in vector mode. In fact, with Glove, words can become vectors with the dimensions we want, given the number of repetitions in the text and the closeness to other words. This model uses an embedding under the Glove algorithm with dimensions of 100, which is calculated based on four hundred thousand words in the English Wikipedia dump. However, due to the static nature of the model, these vectors do not change during network training and they remain static. Similar to the static model, the dynamic model uses Glove-based vectors for embedding. The difference is that in this model, the weights start with the trained value of the Glove.

As mentioned in Table 3, 8870 job advertisements were extracted and the models were created from them. To evaluate the accuracy of these three models, the k-fold Cross-Validation technique has been used. Table 9 shows the accuracy results of the three models presented. As can be seen in this table, the most accurate is the CNN-Random model, with the bag of the words technique, along with stemming the words in the text which has an accuracy of 70.7%. The CNN-Rand model has not increased accuracy even with the addition of different region sizes. Figure 12 shows the confusion matrix for the best model based on the ten job levels. As can be seen, the highest detection of the correct class is related to job level three.

In CNN-Random models, randomly generated filters are used to train the network instead of pre-defined or learned filters. The CNN-Random model is often used as a reference

TABLE 9. The accuracy of the three salary classification models using different settings.

CNN Model	Embedding Matrix	Embedding Algorithm	Epochs	Embedding Dimension	Dense Layer Dimension	Number of filters for each region	Convolution Type	Feature Extraction	Accuracy
CNN-Random	Randomly initialized and trained	_	20	100	300	32	One region Size [18]	bow with stemming	70.70
								bow	69.67
							Multi-region Size [16-18]	bow with stemming	66.40
								bow	65.78
CNN-non-static	Trainable Glove	Glove	20	100	300	32	One region Size [18]	bow with stemming	68.51
								bow	67.91
CNN-static	Pre-trained Glove	Glove	20	100	300	32	One region Size [18]	bow with stemming	55.08
								bow	53.07

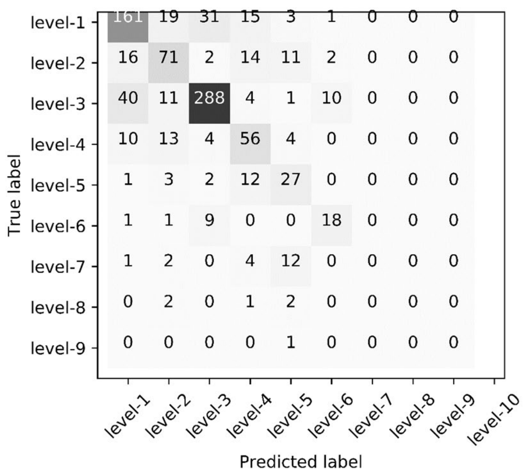

FIGURE 12. The confusion matrix of the best model.

model for evaluating the performance of other CNN models that use pre-defined or learned filters.

To evaluate other parts of the framework, such as "suggesting a job with a higher income level", "identifying the skills needed" and "identifying skills deficiencies", the results of the evaluation of a group of thirty users were used. The criteria for evaluating the proposed framework are precision, recall, and F1 as follows:

$$precision = \frac{TP}{TP + FP} \tag{9}$$

$$recall = \frac{TP}{TP + FN} \tag{10}$$

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall} \tag{11}$$

- **Job offers evaluation**

The output of the framework is the top ten jobs that are most suitable to optimize the job seeker's career. The goal of the framework is to offer the most similar jobs to the person's resume, which also has a higher level of income. To evaluate the results of this part of the framework, thirty participants were asked to evaluate the results. The precision criterion is used for this purpose and the TP and FP parameters are considered as follows: TP: Recommended jobs that have properly considered career advancement. FP: Recommended jobs that do not bring any career advancement and income increase. The results are listed in Table 10.

TABLE 10. Job offer evaluation.

Evaluation method	Similarity measure	
	φ coefficient	Jaccard similarity coefficient
Precision	0.67	0.65

TABLE 11. Comparison of career-gaide with CapaR.

System	Precision
CapaR	0.73
Proposed system	0.67

As discussed in Section II, the CapaR system [18] also recommends job offers based on resumes. The results of comparing the job recommendation section of Career-gAIde with the job recommendation based on the content of the CapaR system are presented in Table 11.

As can be seen, the CapaR system accurately suggests jobs with 73% precision. However, The CapaR does not pay attention to various characteristics such as level of experience, current individual salary, etc. Also, the scope of jobs in the CapaR system is only jobs in the field of information technology.

- **Evaluation of job skill requirement module**

To evaluate the correctness of the identification of the skills required for each job, precision, recall, and F1 score has been used. The participants are asked to determine the skills needed for the jobs from the advertisement and the evaluation criteria are calculated based on their assessment of the framework results. For example, if four of the skills identified by the framework were correct, three other skills were required by the job but the framework did not recognize them, and two

TABLE 12. Evaluation of the job skill requirement module.

Evaluation method	Similarity measure	
	φ coefficient	Jaccard similarity coefficient
Precision	0.82	0.79
Recall	0.84	0.81
F_1 score	0.83	0.80

TABLE 13. Evaluation of skill deficiency diagnosis.

Evaluation method	Similarity measure	
	φ coefficient	Jaccard similarity coefficient
Precision	0.77	0.74
Recall	0.79	0.76
F_1 score	0.78	0.75

TABLE 14. Comparison of the skill deficiency suggestion accuracy of the proposed framework with capar.

System	Recall
CapaR	0.65
Proposed framework	0.79

skills were misdiagnosed by the framework, then the recall value is equal to 0.57 and the precision value is equal to 0.66. Table 12 shows the results obtained after evaluation by thirty users. As can be seen, the accuracy, recall, and F1 scores for the framework using the φ resemblance criteria are 0.82, 0.84, and 0.83, respectively.

- **Evaluation of the diagnosis of skill deficiencies**

The framework also identifies the job seekers' skill deficiencies based on the skills extracted from the person's resume. According to Table 13, the values of precision, recall, and F1 score in the case where the φ similarity criterion is used are 0.77, 0.79, and 0.78, respectively. Table 14 shows the comparison of the skill recommendation accuracy of the proposed framework and the CapaR system.

- **Comparison with similar frameworks**

The CaPaR [17] system is a career pathfinder and the ResuMatcher [18] system is a job and resume matching system. Table 15 shows the characteristics of these two systems along with the Career-gAIde. The ResuMatcher [18] system is a resume and job matching system and uses information retrieval techniques. The CapaR [17] system is also a career pathfinder that offers resume-like jobs and identifies the skills needed for these jobs. The Career-gAIde, designed to model career optimization, identifies and suggests job skills and skills deficiencies. The proposed framework can also be used for increasing the salary of job seekers. Another key feature of the proposed framework is that it suggests a learning path. Precision criteria were used to evaluate the job offer recommendations of the proposed framework achieving 67%. Recall criteria were used to assess the required skills and skill deficiencies, with values of 84% and 79%, respectively.

There are various features in the Career-gAIde leading to its superiority over similar frameworks. One of these characteristics is estimating the current income status of individuals, which is done using the text analysis of people's resumes using a deep neural network. This operation allows the framework to identify the current level of salary and to offer suitable jobs with higher income levels. The previous frameworks only offered jobs based on resumes and did not provide a solution for career advancement. Another key feature that distinguishes this framework is that the previous frameworks, at best, identified only the skills needed and the skills deficiencies, and did not provide a solution to achieve these skills. However, the framework presented in this research, in addition to recognizing the required skills and skills deficiencies, creates a path for the achievement of the desired skills. In the future in addition to the books, online training courses can be added to the framework. Furthermore, the accuracy of the framework can be increased by using a more comprehensive dataset.

Deep learning-based job recommender systems are preferred to traditional recommender systems because they can handle large and complex data, they can learn complex patterns and relationships in the data, they can learn from user behavior and preferences, they can automatically extract relevant features from the data, they can easily be adapted to different types of data, and they can continuously learn from new data.

However, there are several disadvantages of deep learning-based job recommender systems. Training these systems needs large amounts of data and without sufficient data for example in industries or regions where there may be limited data available, the model may not be able to learn complex patterns and relationships in the data, which can lead to less accurate recommendations. Deep learning-based job recommender systems cannot give proper recommendations to new users or users with limited data. If a deep learning-based job recommender has a too complex model it is prone to overfitting like any other deep learning model.

There is a big chance for Large Language Models (LLMs) based on the GPT (Generative Pre-trained Transformer) architecture to significantly improve the accuracy and relevance of job recommendation systems. There are several examples of GPT-based job recommenders that have been developed in recent years. Here are a few examples:

1. Mya Systems: Mya Systems company has developed a GPT-based chatbot that can help job seekers find relevant job opportunities based on their skills and experience.
2. Textio: Textio is a software platform that uses GPT-based models to analyze job postings and provide real-time feedback on the language and tone of the posting. The system can help employers optimize their

TABLE 15. Comparison of the proposed framework with similar frameworks.

Framework	Features	**Performance**
ResuMatcher	☐Multi domain ☐Salary estimator ☐Job required skills recommender ☐Lack of skills recommender ☐Learning path recommender ☐Job optimization ☒Ontology-based	37.44% improvement over existing information retrieval methods (using two measures: Precision@k and NDCG)
CapaR	☐Multi domain ☐Salary estimator ☒Job required skills recommender ☒Lack of skills recommender ☐Learning path recommender ☐Job optimization ☐Ontology-based	-Evaluation of Job Recommender: 0.7387 using Precision -Evaluation of skills recommendations algorithm (user-based CF): 0.65 using Recall
Career-gAIde	☒Multi domain ☒Salary estimator ☒Job required skills recommender ☒Lack of skills recommender ☒Learning path recommender ☒Job optimization ☐Ontology-based	-Evaluation of Job Recommender: 0.6724 using Precision - Evaluation of required skills recommendations algorithm 0.8463 using Recall - Evaluation of lack of skills recommendations algorithm 0.7921 using Recall

job postings to attract the most qualified candidates and reduce bias in the hiring process [42]

3. CareerBuilder: CareerBuilder is a job search platform that uses GPT-based models to provide personalized recommendations to job seekers based on their skills, experience, and job preferences. The system uses data from job postings and user profiles to identify relevant job opportunities and provide personalized recommendations to each user [43]
4. JobTeaser: JobTeaser is a European job search platform that uses GPT-based models to provide personalized recommendations to students and recent graduates based on their skills, experience, and career goals. The system uses data from job postings and user profiles to identify relevant job opportunities and provide personalized recommendations to each user [44].

GPT-based job recommenders have some limitations that should be considered such as:

1. Data bias: if the training data include job postings that are biased towards a certain demographic or industry, the recommender may prioritize those jobs, even if they are not the best match for the user.
2. GPT-based job recommender models can be difficult to interpret and explain, which can lead to a lack of transparency in the recommendations generated.
3. GPT-based job recommender models may not have enough knowledge about specific industries or jobs and such a model trained on general job postings may not be as effective at recommending jobs in a niche industry.
4. GPT-based job recommender models are computationally expensive to train and run.
5. GPT-based job recommender models may not recommend suitable job opportunities since it over relies on past behavior to generate recommendations.

The rapid emergence of artificial intelligence-powered technologies that are driving a new era of automation requires a large-scale workforce in the information technology sector. In the short term, AI will continue to create unprecedented reliance on digital skills and we can expect the digitization of the economy to continue to advance at an accelerated speed. As companies respond to a new technologies by increasing efficiency, this need for digital transformation will increase even further. In the long term, the economic recovery will take place amid the longer-term and already unfolding wave of automation based on new technologies.

Well-designed and well-implemented deep-learning-based job recommender systems are highly usable. Managerially, the proposed system can be beneficiary both for organizations and job applicants. Empirical studies found a significant relationship between employee selection and recruitment procedure with organizational performance [45]. This importance is mostly adjusted by the role of employee performance in creating and improving an organization's competitive advantages [46]. From a different viewpoint, a well-designed recommendation system as a part of the recruitment process can be considered as a component of employee value proposition (EVP). EVP means what a company offers to attract and retain its current and future employees [47]. EVPs can increase the employees' intention to stay [48]. Generally, there is a mutual relationship between EVP and the recruitment process. While EVP is an attractive factor in enhancing the chance of recruiting competent employees, an appropriate and designed recruitment process seems to be a component of a company's EVP. According to Panneerselvam and Balaraman, digital-enabled recruiting and onboarding are a suitable starting point for providing the digital experience for employees as a meaningful component of EVP. This enhanced recruiting process can reduce the socialization phase and new hires' engagement in the company's culture [49]. Therefore, managers can benefit from the proposed system as a part of their path toward AI-enabled human resource management [50], [51].

V. CONCLUSION

In this paper, a framework for rapid work skill re-adjustment for evolving markets named Career-gAIde is presented. The proposed framework uses automatic analysis of the job resume of the workers for a recommendation of a suitable new job with a higher salary and the best rapid re-education path toward that job. Custom build deep neural networks along with customized natural language processing tools are designed for large-scale automatic recommendation and analysis of evolving education and career paths. The experimental results show that the proposed framework can provide a solution for rapid work-skill readjustment for large-scale workforces. Precision criteria evaluate the job offer recommendations of the proposed framework achieving 67%. The Recall criteria were used to assess the required skills and skill deficiencies, with values of 84% and 79%, respectively.

The COVID-19 era of digital and virtual business operations along with the introduction of GPT-based tools, also created a shortage of skilled workers for information technology-based jobs in various companies. The rapid transformation of millions of office workers to the virtual workplace created digital infrastructure risks due to the lack of readiness for the higher demands and workload of employees working remotely. Setting up sufficient information technology support for remote employees is an issue for many companies which will become more severe as more and more businesses are moving online. The porposed framework can help in rapid re-education of the workforce required for these large scale changes.

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