J. Electrical Systems 20-3 (2024): 1259-1271

[1,*] Li Li

Research on the Characteristics of Industrial Talent Demand Depending on Big Data Technology

***Abstract:* -** For a long time, there is a mismatch between supply and demand for industrial talents, and it is difficult to achieve a dynamic balance between talent supply and job demand. This paper aims to mine and analyze the characteristics of industrial talent demand through big data technology, so as to provide skills training reference for talent supply and provide talents with high matching degree for job demand. In this paper, TF-IDF is used as a feature selection method to extract highly representative feature words to help distinguish different talent information data to a greater extent. In addition, combined with the construction method of statistical analysis, quantitative indexing analysis of talent information data is carried out, which enhances the expansion of label system and makes talent portraits more precise and accurate. Through the experimental research, it is proved that the research system of industrial talent demand characteristics proposed in this paper can effectively analyze and match the characteristics of industrial talents. Therefore, in the social employment and higher education, we can combine the methods proposed in this paper to assist decision-making, and promote the dynamic balance between the demand and supply of industrial talents.

Keywords: Big Data; Industrial Talents; Demand; Characteristics; Matching

I INTRODUCTION

At present, generally speaking, the work of talent demand forecasting is still very weak, and it has a macro guiding role, and the standardized, institutionalized and socialized talent demand forecasting has not been generally started. Moreover, most of the talent demand forecasts are concentrated at the enterprise level, and most of them use traditional talent forecasting methods. It only pays attention to the time series itself, and does not consider the influence of external factors, so when the external environment changes greatly, it will be difficult to meet the needs of talent demand prediction.

There is relatively little research on industries and industry levels, lacking breadth and universality, and the reference role for government decision-making is not significant. Research on talent demand prediction started in the early 1980s, mostly following the idea that economic development determines talent demand, using relevant data on economic growth as the prediction basis and talent demand as the prediction quantity to design prediction models. This approach only focuses on the impact of economic factors on talent demand, which is more applicable in the industrial economy era. The development level and main direction of science and technology guide the type of industrial structure and core competitiveness of countries and regions. Transformation will inevitably have an impact on the quantity and structural changes of talent demand. Therefore, in the process of predicting talent demand, the influence of scientific and technological factors cannot be ignored. There are many factors that affect talent demand, and the data system involved in its prediction has certain characteristics, This also poses certain difficulties in predicting and modeling talent demand

The traditional recruitment method often involves manually posting recruitment notices and disseminating them through paper media. The current places for enterprises and job seekers to exchange information are mostly concentrated on the Internet platform. The recruitment information collected from the internet has a large amount of data and strong differences. Compared with small sample data obtained manually, analysis based on a large number of samples is more capable of mining more information and its results are more reliable [1]. Secondly, compared to general structured features, unstructured data (referred to as textual data in this article) provides another perspective for analyzing job requirements[2]. The focus of online recruitment information is on the description of job requirements by the enterprise, and these textual data reflect the true needs of the enterprise to the greatest extent. By using statistical analysis and text mining methods to deeply mine corresponding types of data, job seekers can understand the overall needs and detailed job requirements of the position, cultivate corresponding skills as early as possible, and prepare for job hunting[3].

The purpose of this paper is to improve the analysis of industrial talent demand characteristics through big data method, and promote the dynamic balance between industrial talent demand and supply. This paper innovatively combines TF-IDF feature selection method with statistical analysis method, and carries out

[1] Organization Personnel Department, Zhengzhou Police University, Zhengzhou, Henan 450000, China
*Corresponding author: Li Li

quantitative indexing analysis on talent information data, which enhances the expansion of label system and makes talent portrait more precise and accurate. In social employment and higher education, the method proposed in this paper can be combined to assist decision-making, and promote the dynamic balance of industrial talent demand and supply.

II RELATED WORK

In the analysis of demand characteristics for recruitment information, the main research methods have undergone changes from simple descriptive statistics to exploratory data analysis, and to data mining methods (including text mining methods). In terms of structured feature analysis, reference [4] provides a detailed classification of recruitment advertisements, mainly including five types: end user support personnel, business analysts, trainers, web and interface designers, and technical writers. The article calculates the proportion of each type of position and lists the main job responsibilities, specific technical and other knowledge and skill requirements of each position in the form of text description; In addition, the article provides a detailed frequency statistical analysis of the demand for work experience. Based on the particularity of positions in the intelligence industry, reference [5] considered two types of recruitment information when selecting data sources: comprehensive enterprise recruitment websites and specialized intelligence industry recruitment websites. The research results showed that there are differences in job information published on different types of recruitment websites, with comprehensive recruitment websites reflecting the overall situation of positions, while specialized recruitment focuses on detailed descriptions of talent needs. Reference [6] set the search keywords as information related positions and obtained multiple job requirements from recruitment websites. In terms of work experience requirements, foreign language requirements, basic quality requirements, skill requirements, etc., corresponding fields were extracted from recruitment texts and statistically analyzed. Reference [7] analyzes the demand for scientific research data service personnel from two perspectives: job title and job requirements. The analysis conclusion indicates that data analysis skills and statistical analysis software operation skills are essential. In addition, some recruitment units require applicants to have programming and database management skills. Reference [8] analyzed the demand for various professional talents in the information age. In addition to searching for job information on recruitment websites, it also took into account the recruitment needs of enterprises, institutions, and national civil servants. The article describes the demand for different majors, educational backgrounds, and job functions in different positions through frequency statistics, especially comparing the differences in job requirements between academic master's and professional master's degrees. Reference [9] randomly selected recruitment information for multiple information management professions, and displayed the overall knowledge and skill requirements of the positions through statistical analysis. The variance analysis method was used to compare the differences in professional skill requirements between first, second, and third tier cities.

In terms of unstructured feature analysis, researchers have found that text mining techniques perform well in processing unstructured data such as talent demand information. Reference [10] conducted basic keyword frequency and frequency statistics for different job positions, and created a skill classification directory. The author combined existing dictionaries and new recruitment texts during the analysis[11]. Reference [12] used keyword search to identify the job positions that the research focused on, with a focus on studying the educational requirements of each position. Reference [13] extracted topics from recruitment information demand texts by constructing an LDA topic model, and counted the frequency of high-frequency words under each topic to reflect demand characteristics. Reference [14 used the K-means clustering algorithm to cluster the processed word vectors, and analyzed the demand for big data related positions based on the frequency of clustered keywords. Reference [15] applied text mining techniques to the analysis of demand information in the talent market and established a Chinese professional skills dictionary. Reference [16] studied the relationship between the characteristics of big data talent demand and academic research. After extracting keywords and drawing a co-occurrence network diagram, it can be clearly found that the hotspots of big data academic research lie in distributed, cloud computing, databases, and other aspects; The hotspots of job requirements are focused on algorithms, data mining, and the use of various tools such as C, R, SQL, and Hadoop. Reference [17] constructed a recruitment dictionary with multiple attribute features and later scalability, breaking through the limitations of limited sample size and small scale in previous dictionary construction. Reference [18] used text mining techniques to extract keywords from recruitment information, clarifying the employment knowledge demand relationship in recruitment information, namely "profession position knowledge point"; And display the results in conjunction with visual charts. The bottom layer being the knowledge points (i.e. professional skills). With the help of visual effects, the demand relationship between the three levels can be clearly displayed.

In summary, it can be found that statistical analysis usually describes the content and frequency/frequency statistics of enterprise recruitment information, and the conclusions are relatively simple and intuitive. In the later stage, some scholars used data mining methods for analysis, including introducing text mining techniques into job demand feature analysis, which is more accurate and in-depth compared to simple descriptive statistical conclusions. Many studies that use text mining methods have focused on building professional skill dictionaries, which has become one of the foundations for obtaining better analysis results

III PORTRAITS OF TALENTS

A. System Architecture

Based on the demand of the dynamic management system of industrial talents for the construction of talent portraits, this paper puts forward a specific process of building talent portraits, and designs a set of talent portrait model construction scheme that can accurately and comprehensively discover the characteristics of talent professional fields. After that, this paper divides the talent portrait construction system into modules, and the main functional modules are system management module, data collection module, talent map module and talent portrait module. The system functional requirements diagram is shown in Figure 1.

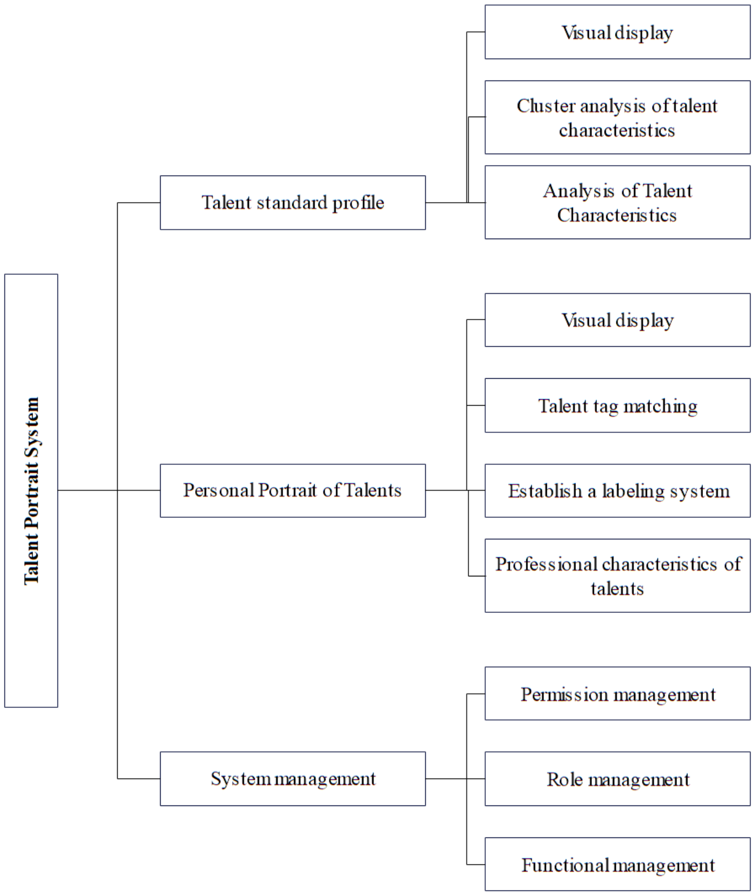


Figure 1: Functional requirements diagram of talent portrait system

First of all, the basic data information of talents, the academic achievements information of talents crawled by the open knowledge platform and the job demand information of recruitment websites are preprocessed, including word segmentation, removal of stop words and part-of-speech selection. Then, according to the theme model of LDA, the theme is divided, and a label system of talent portrait is established. Then, weighted matching and label matching are carried out, and finally talent portrait is formed. At the same time, through cluster analysis, the standard portrait of post talents can be constructed, and finally the results of the constructed portrait of talents can be visually displayed, as shown in Figure 2[19].

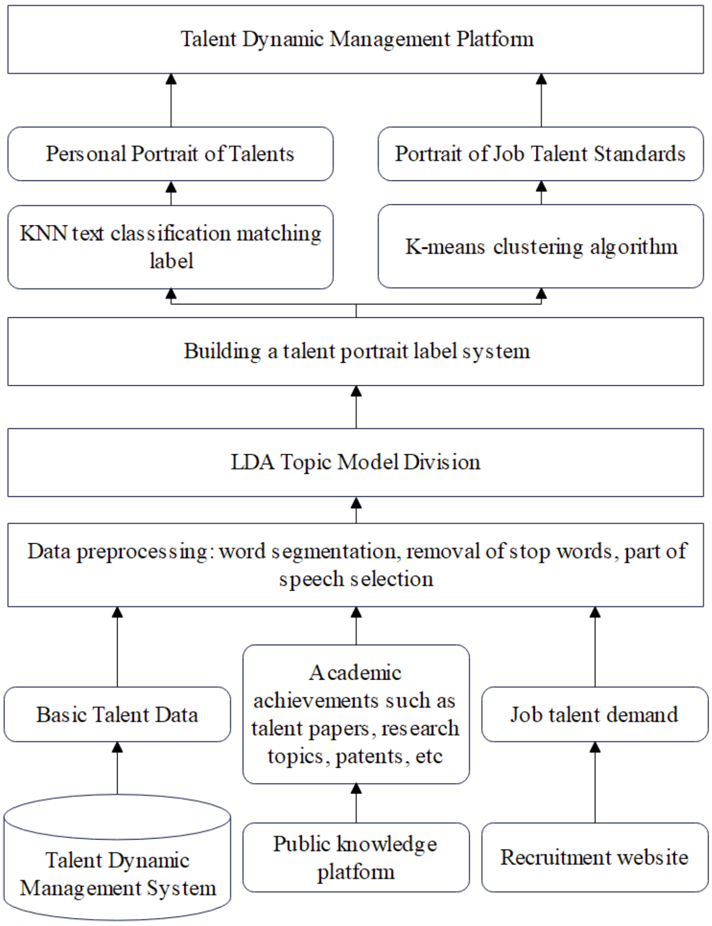


Figure 2: Overall flow design diagram of talent portrait system

B. *Data Preprocessing*

In this paper, based on the characteristics of talent portrait data, the text information of talent portrait system is expressed as $V\left(f_{1,}w_1; f_2,w_2;...; f_n,w_n\right)$ by vector space model, where f_i is used to represent each feature word after word segmentation in talent information data, and each feature word is a dimension of the talent information data. w_i represents the weight of each characteristic word, and its value can represent the importance of the characteristic word in talent information data. For example, the information data of each talent is composed of many parts, including the basic information of talent and the information of professional field. According to the research direction of this paper, the reference value of the feature words extracted from the information data of professional field of talent will be much higher than that of the basic information data of talent. At this time, it is necessary to give different weights to the basic information data of talent and the information data of professional field of talent, so as to make the weight parameter value of the data of professional field of talent higher than that of the basic information of talent[20].

Combined with the characteristics of talent information data in talent portrait system, this paper selects TF-IDF feature selection method. This method can not only give different weights to different feature items within the frequency and distribution range based on feature items, but also extract highly representative feature words to help distinguish different talent information data to a greater extent. TF-IDF feature selection method is to calculate the frequency of feature words in data and the inverse document frequency of feature words in all data, and the weight value of corresponding feature words can be obtained by multiplying these two data[21]:

$$w_{ki} = tf_{ki} \times idf_i \tag{1}$$

w_{ki} is the weight value of feature words t_i in data v_i, t represents the frequency of feature words in different data texts, and tf_{ki} represents the inverse document frequency of feature words in all data texts. The inverse document frequency is calculated as follows:

$$idf_i = log\left(\frac{N}{n_i}\right) \tag{2}$$

Among them, N represents the text number of all data, and n_i represents the text amount of data in which feature words appear. Because of the need to avoid the interference that may be caused by the operation when the value of idf_i is 0 and each data text contains the same feature item, it is necessary to add a constant to the calculation, so the formula is as follows:

$$idf_i = log\left(\frac{N}{n_i} + a\right) \tag{3}$$

Usually, the constant $a \in (0,1)$ is limited. However, because the length of data text will also affect the weight value of feature items, the weight value of feature items is limited within [0, 1] by processing TF-IDF formula, and the modified formula is:

$$w_{ki} = \frac{tf_{ki} \times log\left(\frac{N}{n_i} + a\right)}{\sqrt{\sum_{i=1}^{n} tf_{ki} \times log\left(\frac{N}{n_i} + a\right)}} \tag{4}$$

In view of the talent information data text, it is necessary to improve the importance of feature words in the professional field data text of talents, that is, the weight value given to them should be increased accordingly. At the same time, the weight value of feature words should be limited, and the feature words whose weight value is less than the threshold value μ can be filtered and removed, so as to achieve the purpose of feature space dimension reduction, which can not only retain more effective feature words for topic extraction, but also reduce the complexity of operation. This paper sets the threshold value as $\mu=0.0005$ after analyzing the results of TF-IDF operation, which can ensure that some interfering words are removed, and at the same time, more effective feature words extracted from the topic can be retained to the maximum extent for subsequent feature word matching.

C. Feature Label

Traditional user portrait construction methods mostly build the label system of the platform according to the actual business requirements of the platform used by users, so there is a problem that the feature description of multiple dimensions of users is poorly expanded. In order to solve this problem, this paper combines the construction method of statistical analysis to carry out quantitative indexing analysis on talent information data, which helps to establish a more comprehensive, scientific and accurate talent portrait label system, so that the label system does not have to be limited to actual business, and enhances the expansion of the label system, and makes talent portrait more precise and accurate. The construction design of the label system of talent portrait in this paper is shown in Figure 3.

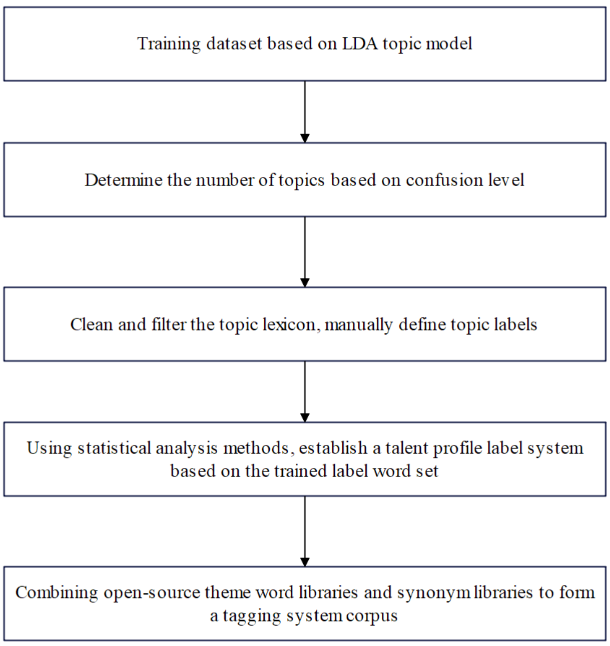


Figure 3: Construction process of talent portrait label system

In order to facilitate modeling, this paper uses Gibbs sampling method to learn the hidden variables in LDA topic model, and trains the professional domain topic model.

In the flow, firstly, a topic $z^{(0)}$ needs to be randomly assigned to each word in the talent information data text.The topic of the next word is continuously iteratively calculated until the topic distribution Φ of each talent information data text and the distribution Θ of words in each topic are obtained. Then, the distribution of words in each topic is obtained by outputting parameters of topic distribution Φ of the talent information data text and word distribution Θ in each topic. In order to calculate a better "topic-word" distribution to the maximum extent, the maximum number of cycles of Gibbs sampling is set to 500. The probability diagram of the LDA topic model is shown in Figure 4.

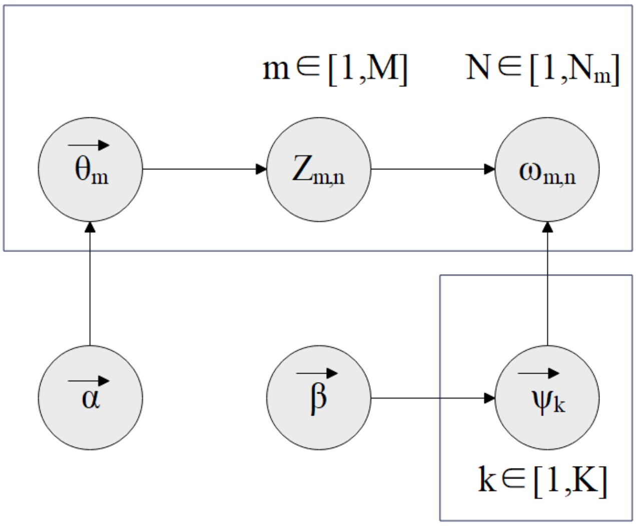


Figure 4: Probability diagram of LDA topic model

In the above Figure 4, K represents the total number of topics, M represents the total number of talent information data documents, N_m represents the total number of words in the m-th talent information data document, $\vec{\beta}$ represents the Dirichlet prior parameter of the multi-term distribution of words in each topic, and $\vec{\alpha}$ represents the Dirichlet prior parameter of the multi-term distribution in the topic of each talent information data document. $z_{m,n}$ denotes the subject of the n-th word in the m-th talent information data document and $\omega_{m,n}$ denotes the n-th word in the m-th talent information data document. $\vec{\theta}_m$ denotes the probability distribution of topics under the m-th talent information data document, and $\vec{\varphi}_k$ denotes the probability distribution of words under the k-th topic. After the text set of talent information data is determined, the known variables of $\omega_{m,n}$ can be seen, the parameters of $\vec{\alpha}$ and $\vec{\beta}$ can be assigned by operation experience, and the hidden parameters of $z_{m,n}$, $\vec{\varphi}_k$ and $\vec{\theta}_m$ can be learned by Gibbs sampling. After learning the LDA parameters by Gibbs sampling, the LDA joint probability distribution is calculated by using the corresponding parameters as follows:

$$p\left(\vec{\omega}_m,\vec{z}_m,\vec{\theta}_m,\Phi \mid \vec{\alpha},\vec{\beta}\right)=\prod_{n=1}^{N_m} p\left(\omega_{m,n} \mid \vec{\varphi}_{z_{m,n}}\right) p\left(z_{m,n} \mid \vec{\theta}_m\right) p\left(\vec{\theta}_m \mid \vec{\alpha}\right) p\left(\Phi \mid \vec{\beta}\right) \tag{5}$$

Then, we need to calculate the probability distribution of each word under different topics:

$$p\left(\omega_{m,n}=t \mid \vec{\theta}_m,\Phi\right)=\sum_{k=1}^{K} p\left(\omega_{m,n}=t \mid \vec{\varphi}_k\right) p\left(z_{m,n}=k \mid \vec{\theta}_m\right) \tag{6}$$

After the above data set training process, this paper trains K topics for the talent information data text and the probability distribution of characteristic words with the meaning of the topic under each different topic, as shown in Figure 5.

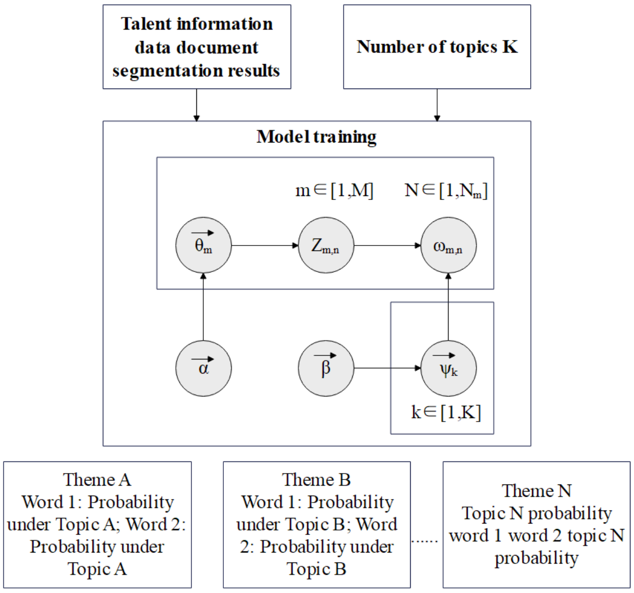


Figure 5: Training data of LDA topic model

The theme characteristics of excavated talent information are not comprehensive and fine enough. However, when the number of determined topics is too large, the topic division will have repeated results, resulting in low discrimination among topics. In the design of this paper, considering this problem, LDA perplexity is used to help determine a reasonable number of topics.

Perplexity is a kind of information theory used to measure the quality. Perplexity is defined by the following formula:

$$IPerplexity = e^{\frac{\sum log(p(w))}{N}} \tag{7}$$

P (w) is the probability . This probability is obtained by multiplying the distribution value of the word under all topics with the topic distribution of the text where the word is located. The calculation formula of this probability is as follows:

$$p(w) = \sum zp(z \mid d) * p(w \mid z) \tag{8}$$

The smaller the value of $IPerplexity$, the better the training effect of the probability model.

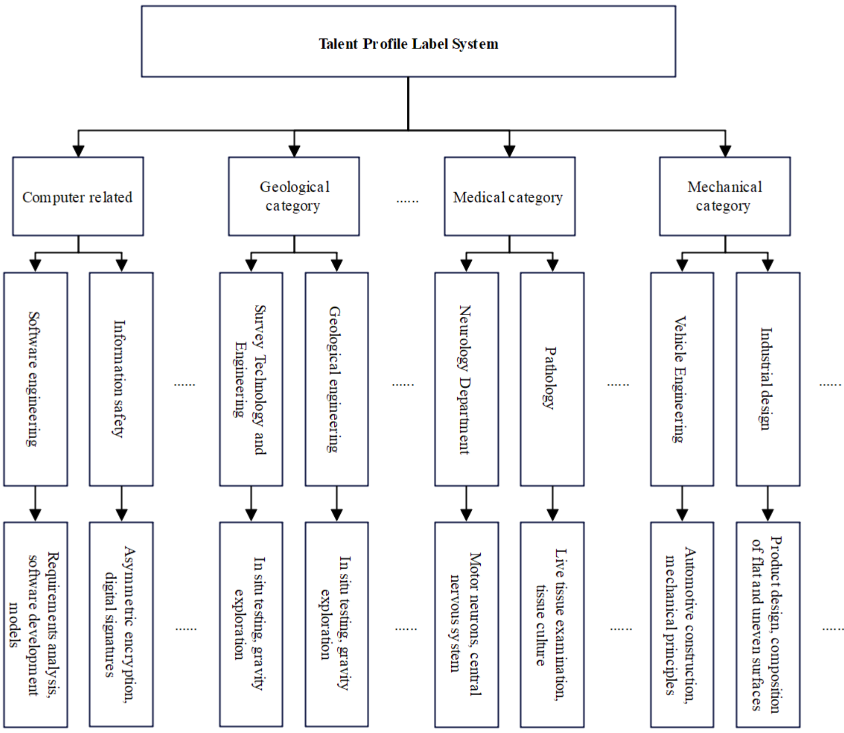


Figure 6: Example corpus of talent portrait labeling system

In this paper, we design a number of corpora for each different category of tags, and try to ensure that words can be matched under the corresponding category tags, including the topic corpus and synonymous corpus trained by LDA topic model. By setting different parameter values for matching words in each different corpus, each corpus can generate a text vector to help feature matching. An example corpus is shown in Figure 6.

When using KNN text classification algorithm to match labels of talent information data, firstly, both talent information data text and corpus text need to be transformed into text vectors, and then traversal calculation of cosine similarity between talent information data text vector and corpus samples corresponding to each label is carried out:

$$similarity\left(v_{talent}, v_{corpus}\right) = \frac{\sum_{k=1}^{M} V_{ik} \cdot V_{jk}}{\sqrt{\sum_{k=1}^{M} V_{jk}^{2}} \cdot \sqrt{\sum_{k=1}^{M} V_{ik}^{2}}} \tag{9}$$

The similarity results calculated by traversal are sorted from big to small, and the K texts with the highest similarity are extracted. Then, according to the similarity between the talent information data text and its K nearest neighbor corpus samples, the weights of the talent information data text under each similar category topic are calculated:

$$\mu(C) = \sum_{v_{corpus}} \in C^{similarity\left(v_{talent}, v_{corpus}\right)} \tag{10}$$

IV SYSTEM SIMULATION

A. *Experimental Research*

Talent portrait system is based on the dynamic management platform of talents, and the system architecture mainly has three layers: data processing layer, functional business layer and application display layer. The goal of the system is to use text mining technology to help enterprises and institutions to mine and manage talents.

The overall architecture of the talent portrait system is shown in Figure 7.

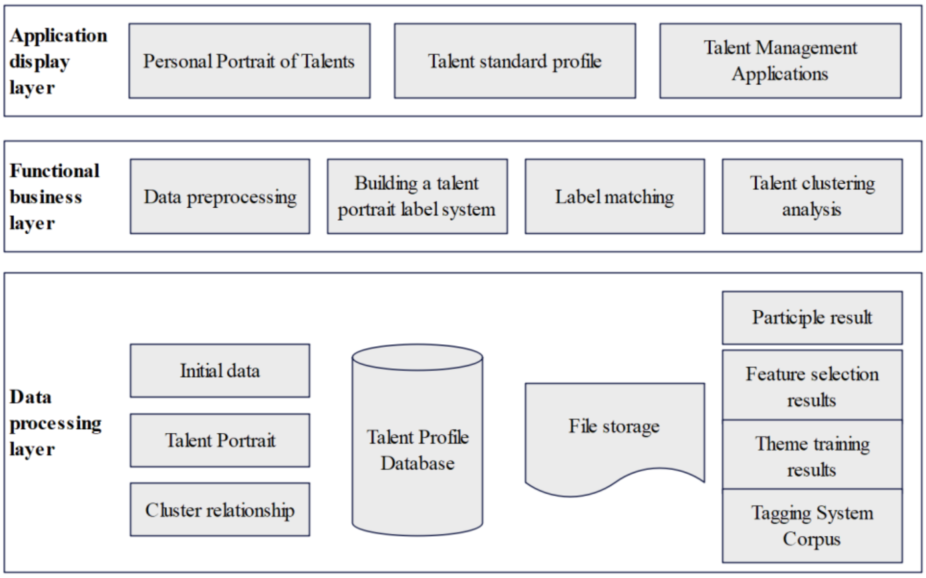


Figure 7: Overall architecture diagram of talent portrait system

The data processing layer includes the collection of original talent information data and the storage of data in the process of building talent portrait. The original talent information data come from the talent dynamic management platform, the information such as talent thesis project performance crawled on the open knowledge website and the talent professional demand information on the recruitment website. The functional business layer is the business implementation layer of the talent portrait system, which includes the preprocessing of initial talent information data, the construction of talent portrait label system, the label matching and clustering analysis of talents. The back-end development of this level uses domestic JFinal framework, adopts MVC pattern, and supports the development of three-tier architecture of persistence layer, business layer and persistence control layer of the system. It is light, concise and fast to develop, and also has a unique Db + Record data reading mode. The application presentation layer uses jQuery and Echarts plug-ins to visually display the results of talent portraits, and at the same time, it exchanges data with the back-end through Ajax technology to realize the asynchronous update of the front-end page data.

The test environment is similar to the formal environment, and its test environment is shown in Table 1.

Table 1: Test Environment of Talent Portrait System

Software name	**Configure**
Operating system	CentOS 8
Web application server	Apache Tomcat
JDK	JDK
Develop and test software	PyCharm
Development and test language	Java, Python, HTML

In order to avoid too many topics and over-fitting, and to better analyze each category, the perplexity is small, and the model effect is better. When the number of topics is 20, the perplexity is lower (Figure 8).

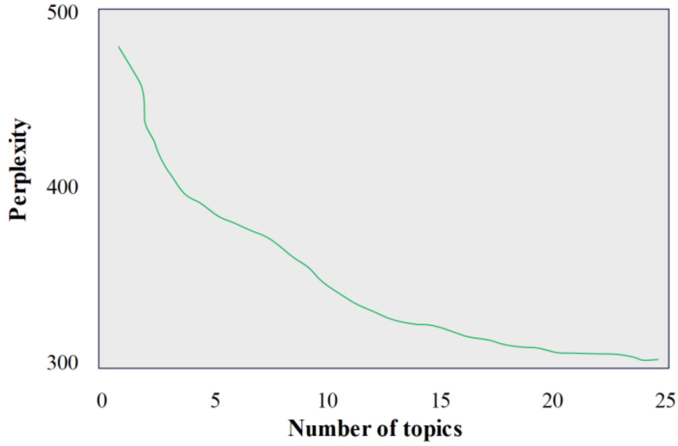
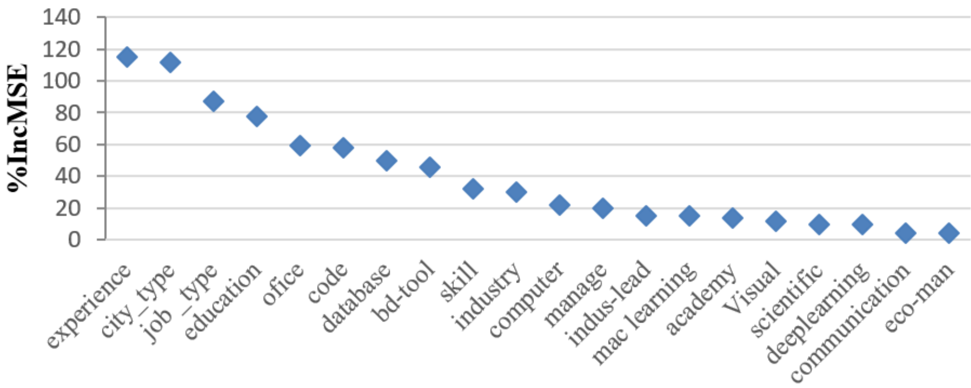
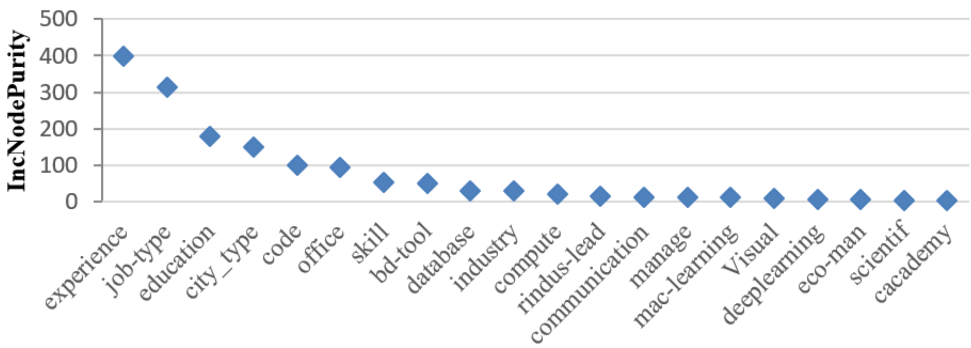


Figure 8: Subject headings-perplexity curve

The regression coefficient of multivariate linear regression model can reflect the quantitative relationship, but the regression coefficient is related to the value of independent variables, which can not show the relative importance of each prediction variable. The KNN model is established, the goodness of fit of the model is 0.711, and the mean square error is 0.091. Then, the results of KNN model are output, and the ranking diagram of variable importance is drawn, as shown in Figure 9.



(a) % IncMSE



(b) IncNodePurity

Figure 9: Ranking of variable importance

The market demand of all kinds of posts can be obtained by statistics of the total amount of each theme based on the talent demand of urban logistics industry. It can be seen that marketing, terminal distribution and strategic management account for a large proportion and have huge market demand. After that, procurement, products, freight and transportation account for a relatively large proportion, while administration and comprehensive categories account for a relatively small proportion. The comparison of market demand for different types of jobs is shown in Figure 10.

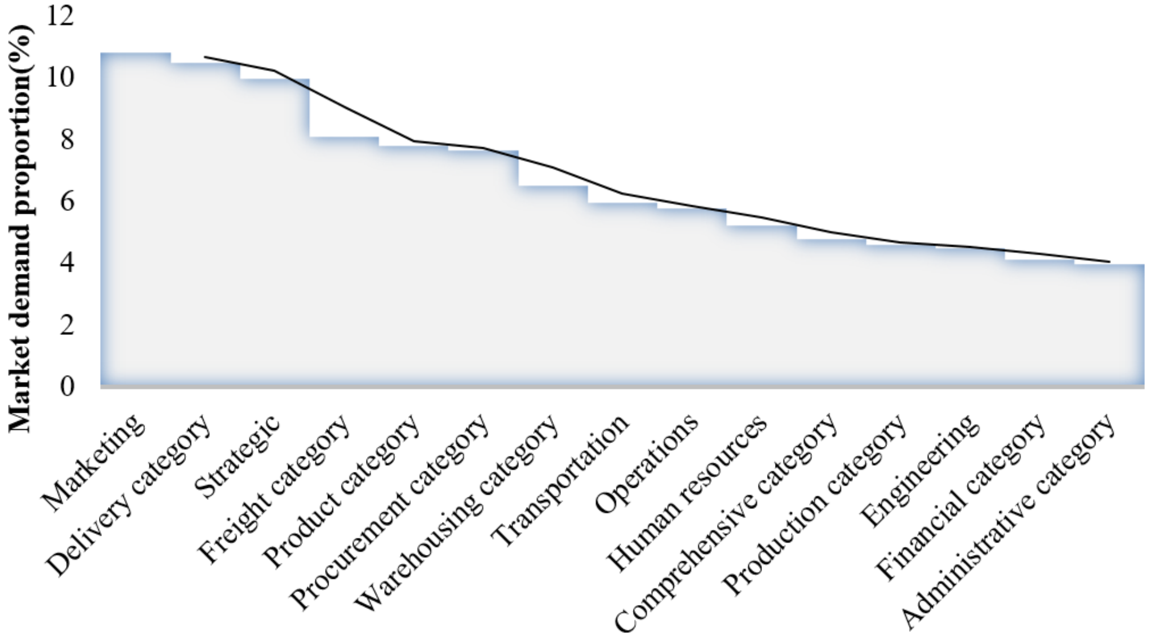


Figure 10: Comparison of market demand of different types of jobs

In order to further study the model effect of this paper, the model proposed in this paper is compared with the model proposed in reference [7], and its effect in the analysis of industrial talent demand characteristics is counted. Taking March 2023-February 2024 as the research cycle, the talent demand characteristics of the tertiary industry are analyzed, and the accuracy of talent demand characteristics analysis of the tertiary industry is obtained by comparing the actual data. The comparison results are shown in Table 2 and Figure 11.

Table 2: Comparative data of the accuracy of talent demand characteristics analysis in the tertiary industry

	The method of this article	The method of reference [7]
Mar-23	88.38	78.61
April 2023	85.26	74.47
May-23	82.85	75.93
Jun-23	83.46	75.46
Jul-23	83.96	78.91
Aug-23	81.30	78.91
Sep-23	83.35	77.63
Oct-23	85.36	77.35
Nov-23	83.46	79.63
Dec-23	83.17	73.39
Jan-24	87.27	77.53
Feb-24	84.83	76.99

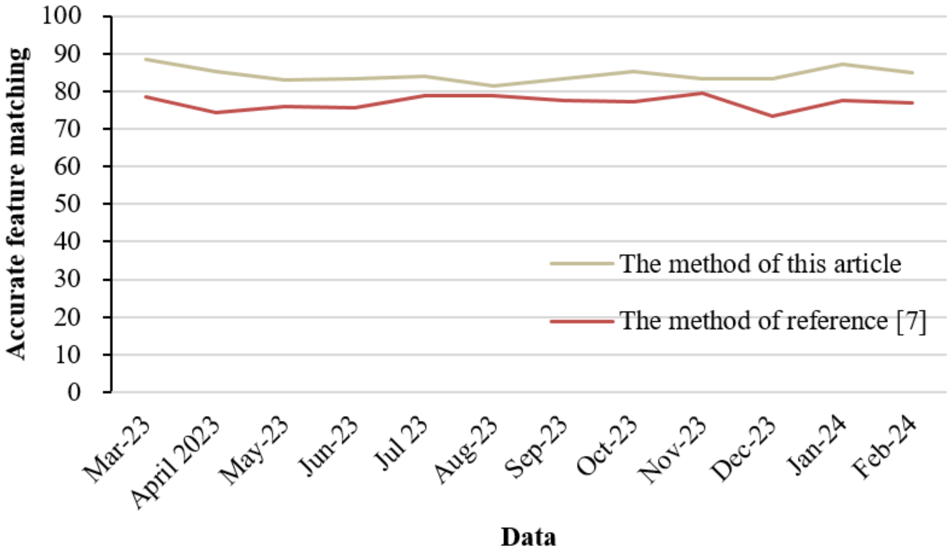


Figure 11: Comparative trend chart of accuracy rate of talent demand characteristic analysis in tertiary industry

B. Analysis and Discussion

Figure 10 calculates the importance of output variables from two angles. Among them, the left figure measures the importance of output variables from the angle of decreasing mean square error, and the right figure measures from the angle of decreasing sum of squares of residual errors. Combining the left and right charts, it can be seen that the minimum work experience requirement variable ranks first, indicating that work experience has the greatest influence on salary. The second echelon is post category, educational background and city category variables. The third echelon is all kinds of practical skills. The fourth echelon includes job seekers' own abilities (such as management ability, industry cognition and communication ability), professional knowledge (mainly machine learning and deep learning algorithms) and professional background.

Portraits of industrial talents can help enterprises recruit and select talents with high matching degree. To select talents according to the portraits of industrial talents, it is necessary to match posts with people's abilities and have both ability and political integrity. The superficial knowledge and skills of talent portraits are easy to improve and develop, while the deep characteristics of talent portraits, such as hidden motivation, behavior and personality traits, are difficult to evaluate and improve, but they are also very important. Only when employees highly recognize themselves and are willing to work for themselves can they get good career development opportunities. Therefore, enterprises need to promote the growth of talents through effective human resource management strategies. In this way, the matching between people and posts is not only the matching between knowledge and skills, but also the matching between quality and the bottom. By adopting this method, the basic values, strategic orientation and common goals of the enterprise can be transformed into the daily behaviors of employees, thus obtaining excellent organizational performance. Moreover, portraits of industrial talents can help companies find training needs more accurately. The purpose of training is to bring some abilities needed by the company for high performance, but the actual training content is usually not aimed at the most important abilities, so the expected training results are usually not achieved. As a brand-new human development tool, talent portrait module can not only identify the differences between different types of personnel, but also predict the behavior characteristics of different types of personnel. In addition, the training system is based on the training of talent portraits. Through the description of job content in job analysis, it can understand the ability characteristics of high-performance personnel, so as to assist enterprise managers to correctly judge the training needs, and make the whole training system do truly valuable work for enterprise managers, and make the training work really help enterprises and employees to achieve a win-win situation between enterprises and employees. From Figure 11, we can see that the industrial talent demand characteristics research system proposed in this paper can effectively analyze and match the industrial talent characteristics.

Through the comparison between Table 2 and Figure 11, we can see that the improved talent portrait system proposed in this paper has a certain effect in the analysis of industrial talent demand characteristics, and has higher accuracy compared with the existing research. Because the current talent training methods do not meet the needs of enterprises for talents, and the needs of similar posts in different enterprises are quite different, it is extremely urgent to solve the problem of matching people and posts. However, we can't simply analyze a certain post to realize personalized management. We need to make a group portrait of the whole field, so that using portrait technology will not waste resources, but also get more accurate results. By constructing scientific and reasonable post portraits, analyzing post portraits, constructing post matching system, and using data mining, we can get appropriate matching index weights, improve the accuracy of evaluation between enterprises and candidates, and avoid the influence of a certain index too large or too small on the total score. Meanwhile, user portraits can better consider that the selection of indicators conforms to the specific situation of the research industry, which is beneficial to the training of talents by training units, helps employees to make a short-term or long-term career plan, helps candidates to match their posts reasonably through the analysis of person-post matching, and avoids the phenomenon of "overutilization of high-caliber talents in low-skill roles" and "overburdening less-qualified individuals with high-level responsibilities" by users.

V CONCLUSION

Based on the talent dynamic management platform, considering the importance of talent construction to social development, in order to help enterprises and institutions to carry out talent mining, talent management and talent training, combined with the actual specific needs of various units and departments, the research work of talent portrait construction is carried out. Then, using the text mining technology based on theme model, the massive talent information is comprehensively considered from the aspects of specialty, knowledge and skills, and the characteristic labels of talents are mined and analyzed, thus effectively helping the platform to realize the core potential ability of talents at a deeper level and realize the construction of talent portraits. This paper obtains the following points through research:

(1) This system can effectively analyze the characteristics of industrial talents and the skills that industrial talents need to master, which is convenient for the level distribution of talents' skills in follow-up personnel training;

(2) The research system of industrial talent demand characteristics proposed in this paper can effectively analyze and match the characteristics of industrial talents;

(3) The improved talent portrait system proposed in this paper has certain effect in the analysis of industrial talent demand characteristics, and has higher accuracy than the existing research.

Through the above research, it is verified that the method model proposed in this paper has certain reliability. However, the model of this paper mainly focuses on the analysis of various information data of talents in professional fields, while the dimensional analysis of talents' personality characteristics and social habits needs to be improved, which is also the follow-up research direction.

REFERENCES

[1] Ma, H., & Ding, A. Construction and implementation of a college talent cultivation system under deep learning and data mining algorithms. The Journal of Supercomputing, 2022, 78(4), 5681-5696.

[2] Li, G., Yuan, C., Kamarthi, S., Moghaddam, M., Jin, X. Data science skills and domain knowledge requirements in the manufacturing industry: A gap analysis. Journal of Manufacturing Systems, 2021, 60(2), 692-706.

[3] Johnson, M., Jain, R., Brennan-Tonetta, P., Swartz, E., Silver, D., Paolini, J., & Hill, C. Impact of big data and artificial intelligence on industry: developing a workforce roadmap for a data driven economy. Global Journal of Flexible Systems Management, 2021, 22(3), 197-217.

[4] Chunmian, G. E., Haoyue, S. H. I., Jiang, J., Xiaoying, X. U. Investigating the demand for blockchain talents in the recruitment market: evidence from topic modeling analysis on job postings. Information & Management, 2022, 59(7), 103513-103525.

[5] Prüfer, J., Prüfer, P. Data science for entrepreneurship research: Studying demand dynamics for entrepreneurial skills in the Netherlands. Small Business Economics, 2020, 55, 651-672.

[6] Stanton, W. W., & Stanton, A. D. A. Helping business students acquire the skills needed for a career in analytics: A comprehensive industry assessment of entry - level requirements. Decision Sciences Journal of Innovative Education, 2020, 18(1), 138-165.

[7] Mezhoudi, N., Alghamdi, R., Aljunaid, R., Krichna, G., Düştegör, D. Employability prediction: a survey of current approaches, research challenges and applications. Journal of Ambient Intelligence and Humanized Computing, 2023, 14(3), 1489-1505.

[8] Persaud, A. Key competencies for big data analytics professions: A multimethod study. Information Technology People, 2021, 34(1), 178-203.

[9] Leigh, N. G., Kraft, B., Lee, H. Robots, skill demand and manufacturing in US regional labour markets. Cambridge Journal of Regions, Economy and Society, 2020, 13(1), 77-97.

[10] Gilch, P. M., Sieweke, J. Recruiting digital talent: The strategic role of recruitment in organisations' digital transformation. German Journal of Human Resource Management, 2021, 35(1), 53-82.

[11] Nti, I. K., Quarcoo, J. A., Aning, J., Fosu, G. K. A mini-review of machine learning in big data analytics: Applications, challenges, and prospects. Big Data Mining and Analytics, 2022, 5(2), 81-97.

[12] Yadav, R., Parwez, Z., Parimala, R. S., Priya, U., Rathore, S. K., Deepak, S. S. K. Analysis and prediction of future research trends in the state of industry 5.0. RES MILITARIS, 2023, 13(3), 2330-2339.

[13] Chen, Z. Artificial intelligence-virtual trainer: Innovative didactics aimed at personalized training needs. Journal of the Knowledge Economy, 2023, 14(2), 2007-2025.

[14] Bécue, A., Praça, I., Gama, J. Artificial intelligence, cyber-threats and Industry 4.0: Challenges and opportunities. Artificial Intelligence Review, 2021, 54(5), 3849-3886.

[15] Liu, S., Wang, J. Ice and snow talent training based on construction and analysis of artificial intelligence education informatization teaching model. Journal of Intelligent & Fuzzy Systems, 2021, 40(2), 3421-3431.

[16] Salih, S. Q., Sharafati, A., Khosravi, K., Faris, H., Kisi, O., Tao, H., Yaseen, Z. M. River suspended sediment load prediction based on river discharge information: application of newly developed data mining models. Hydrological Sciences Journal, 2020, 65(4), 624-637.

[17] Fu, X. M., Bao, Q., Xie, H., Fu, X. Diffusion of industrial robotics and inclusive growth: Labour market evidence from cross country data. Journal of Business Research, 2021, 122(2), 670-684.

[18] Ahmadi, S. A Comprehensive Study on Integration of Big Data and AI in Financial Industry and its Effect on Present and Future Opportunities. International Journal of Current Science Research and Review, 2024, 7(01), 66-74.

[19] Wei, G., Jin, Y. Human resource management model based on three-layer BP neural network and machine learning. Journal of Intelligent & Fuzzy Systems, 2021, 40(2), 2289-2300.

[20] Almeida, F., Santos, J. D., Monteiro, J. A. The challenges and opportunities in the digitalization of companies in a post-COVID-19 World. IEEE Engineering Management Review, 2020, 48(3), 97-103.

[21] Dinh, L. T. N., Karmakar, G., Kamruzzaman, J. A survey on context awareness in big data analytics for business applications. Knowledge and Information Systems, 2020, 62(9), 3387-3415.