Prediction and evaluation methods have important and extensive applications in college education and teaching. These methods are usually realized by intelligent learning machine based on training method. In this case, a very important question is worth analyzing: are all these methods effective? Therefore, this paper converts the original score into standard score through normal distribution, explains the application of standard score, provides a practical standard score processing method for examination subjects with a full score of 150, and establishes a basic model for comparing the overall score or the overall average score by using standard score when combining the scores of different subjects (including examination), so as to determine the individual score in a group, or deeply analyze the basic model and weighting model to determine the relative position of individual scores in a group or population, and evaluate the effectiveness of various methods. Finally, make a general assertion on the effectiveness of prediction and evaluation using intelligent learning machine. In fact, there are many factors that affect the effectiveness of education and teaching and human ability. There are differences between the data of education and teaching effectiveness and human ability. The distribution of these data is generally more in the middle, less in too large and too small.

1. Introduction

In the university community, more and more education and teaching problems need to be predicted or evaluated in advance by decision-makers, so that they can be notified in advance, warned in time, made scientific decisions, and actively intervened and remedied in good faith [1]. In this sense, scientific prediction or evaluation is of great significance [2]. In recent years, a large number of prediction and evaluation methods, such as college students’ achievement prediction, enrollment and employment prediction, college students’ credit evaluation, teaching quality evaluation, teachers’ educational technology ability evaluation, and comprehensive strength evaluation of colleges and universities, have gradually developed [3].

Machine learning is a science of artificial intelligence who mines the association between inputs and outputs in empirical learning by acquiring new knowledge and skills to form concrete expressions of logical relationships [4]. The research of machine learning is based on the understanding of human learning mechanism by cognitive science to build a computational model or cognitive model of human learning process, and then to build a task-oriented application-specific learning system [5]. Machine learning has a very important position in the research of artificial intelligence. An intelligent system that does not have the ability to learn can hardly be called a truly intelligent system. Early intelligent systems were generally lacking this learning capability and thus could not discover new theorems, laws, rules, etc. [6]. With the further development of artificial intelligence, these limitations have become more and more prominent. It is in this situation that machine learning theory gradually becomes one of the core elements of AI research [7].

Teaching quality evaluation is the judgment made by using the theory and technology of educational evaluation
to determine whether the teaching process and its results meet certain quality requirements, which is a very important work in education and teaching [8, 9]. The core of the evaluation work is to establish evaluation models, which generally use direct mathematical models of evaluation systems [10]. These models need to fully consider various evaluation factors and reflect expert empirical knowledge [11]. Establishing a reasonable and scientific mathematical evaluation model, which makes the evaluation more accurate and effective, will be of great significance to the assessment of teaching quality [12].

The indicators affecting the quality of teaching are reflected in the evaluation of the teaching content, teaching methods, and teaching attitude of the instructor [13]. The evaluation indexes generally include the reasonable degree of course pace, teaching depth and breadth, and learning burden; the degree of integration with practice and whether it can reflect the achievements of modern science and technology; the degree of lecture clarity, hierarchy, and focus; vivid explanation, inspiration and guidance, attractive, typical examples, theoretical and practical; guidance on learning methods and cultivation of analytical ability; the degree of adequate preparation, proficiency in explanation, answering questions, and correcting homework; the degree of seriousness [14, 15]. The output of the teaching effect as a model mainly includes students’ examination results, classroom discipline, degree of understanding and mastery, and ability to analyze and solve problems [16].

The machine training process and model acquisition methods are described above. It is important to emphasize that the results of teaching quality here are not established “facts” as in the case of “learning achievement” or “credit-worthiness”, but are generally provided by “expert knowledge” is generally provided [17]. At present, various intelligent learning algorithms have been widely used in various prediction and evaluation problems in college education and teaching [18]. On the one hand, these prediction and evaluation methods provide a scientific basis for many practical problems in university education and teaching, but on the other hand, the establishment process of many methods is unscientific, and their application will inevitably have an adverse impact on our prediction and evaluation problems [19]. Therefore, taking the typical intelligent machine learning theory as an example, this paper deeply analyzes its application methods in various predictive evaluations, explores its scientificity and effectiveness, and provides guidance for us to establish or select appropriate measurement methods [20].

2. Typical Machine Learning Theories

2.1. Support Vector Machines. Support vector machines (SVMs) [8] are a collection of several standard techniques in machine learning that integrate several techniques such as maximum interval hyperplane, kernel theory, convex quadratic programming, sparse solutions, and relaxation variables. The actual risk of a learning machine is composed of two components: empirical risk and confidence risk, reflecting the generalization ability of the learning machine obtained according to the principle of empirical risk minimization, hence the term generalizability bound.

2.2. Neural Networks. Neural network (NN) [9] systems are highly complex, nonlinear dynamical network systems consisting of a large number of simple components (neurons, analog electronics, optical components, etc.) interconnected. Although the structure and function of each neuron is very simple, the behavior of a network system composed of a large number of neurons is highly complex. Neural networks reflect several basic features of human brain function, but are not a realistic depiction of the biological nervous system, but only some abstraction, simplification, and simulation of it. The purpose of studying neural network systems is to explore the mechanisms by which the human brain processes, stores, and searches for information, and then to explore the possibility of applying this principle to various artificial intelligences. In short, an artificial neural network is a parallel distributed processor with a large number of connections, which can be implemented with electronic or optoelectronic components, or simulated with software on a conventional computer, with the ability to acquire knowledge and solve real-world problems through learning.

3. Analysis and Improvement of SPC Control Chart-Based Measurement Methods

3.1. Calculating Process Capability and Sigma Values. Process capability is the distance between the process mean and the normative limit described in terms of standard deviation. The symbol $Z$ is used for characterization.

(1) For one-sided tolerances

$$Z = \frac{\bar{X} - LSL}{\sigma_{R/d2}},$$

where $LSL$ is defined as the lower instructional target limit, $\bar{X}$ is the process mean, and $\sigma$ is the process deviation, calculated from $R/d_2$.

(2) For the two-way tolerance, the percentage of exceeding the upper and lower normative limits are calculated, respectively. $z_{\text{min}}$ can also be converted into a capacity index $C_{pk}$ as defined in the following equation

$$Z_{UCL} = \frac{USL - \bar{X}}{\sigma_{R/d2}},$$

$$Z_{LCL} = \frac{\bar{X} - LSL}{\sigma_{R/d2}}.$$
pass rate of 99.8650%; the probability of failure is 0.135%, or 1350 PPM. For teaching processes with important characteristics that affect life safety (such as school safety training and fire training, which require a 100% pass rate), the teaching process proficiency index requirement is $Z_{\text{min}} \geq 4$ or $C_p \geq 1.33$, which is equivalent to 5.5 Sigma, with a pass rate of 99.996833% and a failure rate of 32 PPM. When $C_p \geq 1.5$, which we call 6 Sigma, the failure rate is 3.4 PPM. It should be noted that if the pass rate of a class is 100% or the promotion rate is 100%, this is the result of the process and is not equivalent to the process capability concept here. There is no possibility of 100% process capability. The concept of 6 Sigma process control is prior control and preventive control, which controls the teaching process, and when the teaching process is good, the examination result will be good naturally, which can greatly reduce the social cost.

4. Principle of Conversion

A score is a quantitative marker for educational and psychological measures. Raw scores, also known as crude scores, are scores rated on the answers or behavioral responses of test-takers according to scoring criteria or test (including exam) instructions. From a mathematical point of view, raw scores have two characteristics: first, the units of raw scores are not universally meaningful, generally not equidistant, i.e., the units are not equal, and therefore not additive. Secondly, the reference points of raw fractions are generally different, and they are not absolute zeros, so they cannot be multiplied or divided, and thus cannot be portrayed as ratios.

As a result, the raw scores of different tests cannot be treated algebraically, and the relative position of students (trainees) in the group cannot be determined. It is not enough to know the actual scores of students (trainees) to measure their performance, but it is necessary to convert the raw scores into derived scores with certain reference points and units according to the distribution of the scores of candidates in the group to which they belong in order to make a reasonable judgment. In educational statistics, a proven method is to convert raw scores into standardized scores for statistical analysis.

Definition 1. Let the original score $\xi \sim N(\mu, \sigma^2)$, where $\mu$ is the mathematical expectation, which portrays the statistical mean of $\xi$; $\sigma^2$ is the variance, which portrays the deviation of the value taken by $\xi$ about its mathematical expectation, then it is called the standardization of $\xi$; $\eta = (\xi - \mu) / \sigma$ is the standard fraction, then we have $\eta \sim N(0, 1)$.

Standard fractions have the following properties and characteristics:

1. The standard score is a derived score with the mean score as the reference point and the standard deviation as the uniform unit.

2. The standard score takes into account the difference between different scores of each subject and its respective mean score, and uses its standard deviation as a unified unit, so it is scientific and comparable to measure the relative status of students’ (participants’) performance. Since the mathematical expectation of $\eta E(\eta) = 0$ and the variance of $D(\eta) = 1$, the mathematical expectation and variance of the standard scores of each subject are the same, indicating that the relative positions of each subject are parallel, and thus the standard scores can be treated algebraically to draw scientific conclusions [21, 22].

3. The standard fraction is a linear transformation of the original fraction, which is “order-preserving” with respect to the position of the original fraction in the whole.

4. According to the “3σ principle” property of the normal distribution $N(\mu, \sigma^2)$, the standard score $\eta$ satisfies $P(-3 < \eta < 3) = 99.73%$.

4.1. Expression of Standard Score. If $1^t, 2^t, \ldots, n^t$ is noted as the academic performance or some ability indicator of the test subject, the sample mean $\bar{\xi} = 1/n\sum_{i=1}^{n}\xi_i$ is used to estimate the mathematical expectation $\mu$ of a normal distribution $N(\mu, \sigma^2)$; the sample variance or the modified sample variance, i.e., $S_n^2 = 1/n\sum_{i=1}^{n}(\xi_i - \bar{\xi})^2$ (when $n \geq 30$) or $S_n^2 = 1/(n-1)\sum_{i=1}^{n}(\xi_i - \bar{\xi})^2$ (when $n < 30$), to estimate the variance in the normal distribution $N(\mu, \sigma^2)^2$. From the knowledge of probability theory and mathematical statistics, $-\bar{\xi}$ and $S_n^2$ are unbiased estimates of $\mu$ and $\sigma^2$, respectively, i.e., $E(-\bar{\xi}) = \mu E(S_n^2) = \sigma^2$; and when $n$ is large, $S_n^2$ and $S_n^2$ differ very little [23].

In the specific application, note $X_1, X_2, \ldots, X_n$ as the observation of $1^t, 2^t, \ldots, n^t$, and use the observation of the sample mean $\bar{X} = 1/n\sum_{i=1}^{n}X_i$ as the estimate of $\mu$; use the observation of the sample variance or the observation of the modified sample variance, i.e., $S_n^2 = 1/n\sum_{i=1}^{n}(X_i - \bar{X})^2$ (when $n \geq 30$) or $S_n^2 = 1/(n-1)\sum_{i=1}^{n}(X_i - \bar{X})^2$ (when $n < 30$) to be the estimate of $\sigma^2$. In this way, the practical expression for the standard score is obtained $Z = (X - \bar{X}) / (S_n^2)$ (when $n \geq 30$) or $Z = (X - \bar{X}) / (S_n^2)$ (when $n < 30$).

Definition 2. In educational statistics, if $x$ is the test taker’s original score in the subject, $\bar{X}$ is the mean of the original score in the subject, and $s$ is the standard deviation of the test paper in the subject, then the standard score is said to be $Z = (X - \bar{X}) / s$ for $z$-score.

4.2. Practical Standard Scores. The standard score with the mean score as the reference point and the standard deviation as the unit accurately portrays the relative position of each test taker in the whole batch of scores, overcoming the shortcomings of the original scores. Considering the unnatural situation that $z$-scores have negative values and often have multiple decimals, the standard score $z$ is linearly transformed in order to eliminate negative values and make the standard score as close to the original score as possible $Z' = Za + \beta$. 
used to transform the formula \( T = \alpha + \beta z \) into the entrance examination for master's degree students in China has been changed from 100 points to 150 points. Based on the analysis of the examination results of several courses in the entrance examination of our unit, the authors suggest that for the entrance examinations of our unit, the authors suggest that for the entrance examination of several courses in the entrance examination for master's degree students in China has been changed from 100 points to 150 points. Based on the analysis of the examination results of several courses in the master’s entrance examinations of our unit, the authors suggest that for the subjects with full marks of 150, \( \alpha = 18 \) and \( \beta = 90 \) should be used to transform the formula as \( T_{150} = 18z + 90 \). The mean score is 90 and the standard deviation is 18; it almost necessarily varies from 18 \( \times \) (-3) +90 = 36 to 18 \( \times \) 3 +90 = 144.

### 5. Pilot Application and Comparative Analysis

#### 5.1. Typical Measurement Methods

There are many factors affecting learning performance, and the prediction results are difficult to be expressed by appropriate mathematical analytic expressions, which are nonlinear classification problems, while the models based on intelligent learning machines are black box models, and the nonlinear relationship between the model inputs and outputs is realized by the training process of the learning machines. Through the training of the intelligent learning machine, the corresponding prediction model can be obtained to achieve the prediction of students' academic performance. An effective prediction method can undoubtedly be an effective tool to guide students and teachers to further improve learning performance and teaching quality. Factors affecting academic performance include age, gender, economic conditions, non-study Internet time, homework completion, attendance, and regular position when listening to lectures. Among these factors, economic conditions, non-study Internet time, homework completion, and attendance are relatively more important [26]. Generally, the following formula is used to calculate the accuracy of academic performance prediction.

\[
\text{Accuracy} = \frac{\text{Real Results} - \text{Predicted Results}}{\text{Real Results}} \times 100 \tag{3}
\]

If the academic performance of a certain number of students is known, the weights of all factors for each student are first determined and formed into a high-dimensional feature vector, and then the correspondence between the high-dimensional feature vector and the academic performance is used to train the learning machine and obtain a prediction model, so as to make performance prediction for students with unknown performance.

#### 5.2. Analysis of Results

We conducted a pilot application for scholarship evaluation for students majoring in Applied Mathematics in the school of Mathematical Sciences. According to the previous requirements for the average allocation of scholarship places in each class, the four classes of the professional grade run on the machine as one class, and the results shown in Table 1 are obtained. The comparative analysis shows that the ranking of the top and bottom of each class is basically the same, but it changes slightly; as for the ranking of students in intermediate states, they have varying degrees of change in the local context. The college adopted the standard score weighted average ranking method and selected according to the current Zhu Jingwen scholarship evaluation requirements, which was recognized by most students. The pilot application of the project was successful and received the expected results.

### Table 1: The comparison of order within classes between the weighted average of standard marks and that of original marks.

| Class | Weighted average method | Ranking order |
|-------|-------------------------|---------------|
| (1)   | Standard score weighted average | 1 2 3 8 5 6 7 8 9 10...62 63 64 74 66 67 68 69 |
|       | Weighted average of original scores | 1 2 7 5 6 5 9 10...60 62 63 64 58 69 70 71 72 |
| (2)   | Standard score weighted average | 3 6 5 10 9 11 12...68 69 70 72 76 77 79 80 82 |
|       | Weighted average of original scores | 1 5 3 8 9 1 13...64 65 66 68 69 72 75 76 77 78 |
| (3)   | Standard score weighted average | 3 5 3 2 9 17 11 12...70 68 73 74 88 85 76 77 |
|       | Weighted average of original scores | 5 6 3 9 10 1 12...73 75 78 79 81 77 86 88 |
| (4)   | Standard score weighted average | 2 1 3 6 7 5 9 6...68 59 68 67 89 78 79 77 86 |
|       | Weighted average of original scores | 3 1 5 4 6 8 2 3...58 55 68 72 71 68 69 82 87 |

Where \( \alpha \) acts as a deflator to eliminate fractional values of the original \( z \)-value, and \( \beta \) acts as a translator to eliminate negative values of the original \( z \)-value [24, 25].

#### 4.3. Practical Standard Scores for Subjects with 100 Points

For our examination subjects with full score of 100, take \( \alpha = 10, \beta = 50 \), and then transform the formula as \( T_{100} = 10z + 50 \). The mean score is 50 and the standard deviation is 10. From “the standard score \( z \) almost necessarily varies from \(-3 \) to \( 3 \)”, the \( T \)-score almost necessarily varies from \( 10 \times (-3) +50 = 20 \) to \( 10 \times 3 +50 = 80 \).

#### 4.4. Practical Standard Scores for Subjects with 150 Points

With the in-depth development of education and teaching reform, the full score of some subjects in the entrance examination for undergraduates and the entrance examination for master’s degree students in China has been changed from 100 points to 150 points. Based on the analysis of the examination results of several courses in the entrance examinations of our unit, the authors suggest that for the subjects with full marks of 150, \( \alpha = 18 \) and \( \beta = 90 \) should be used to transform the formula as \( T_{150} = 18z + 90 \).

The mean score is 90 and the standard deviation is 18; it almost necessarily varies from \( 18 \times (-3) +90 = 36 \) to \( 18 \times 3 +90 = 144 \).

### Table 2: The comparison of order within grade between the weighted average of standard marks and that of original marks.

| Weighted average method | Ranking order |
|-------------------------|---------------|
| Standard score weighted average | 1 2 5 6 8 9 10 11...268 269 276 288 289 |
| Weighted average of original scores | 2 1 3 4 5 7 6 5 9...280 286 285 288 289 |
Figure 1: Teaching quality assessment correlations.

Table 3: The comparison of order in the first twenty places between the weighted average of standard marks within grade and that within classes.

| Ranking order in grade |   1 |   2 |   3 |   4 |   5 |   6 |   7 |   8 |   9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|-----------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|----|----|----|----|----|----|----|----|----|----|----|
| (1)                   |   2 |     |     |     |     |     |  1 |     |     |  6 |
| (2)                   |     |  1 |     |     |     |  8 |
| (3)                   |  1 |  3 |  2 |  5 |  6 |  8 |  9 |  4 |  7 | 12 |
| (4)                   |  2 |     |     |     |     |  6 |  8 |

Wireless Communications and Mobile Computing
However, if this scholarship is evaluated in the whole year, some classes will be awarded more and some will be awarded less or not. In order to propose a more reasonable selection scheme, we conducted a computerized operation for this major by grade level, and the results are shown in Table 2.

In the following, the top 20 rankings are analyzed and compared with the class rankings when the weighted average of standard scores is calculated by grade level.

It can be seen from Table 3 that if Zhu Jingwen scholarship is evaluated as a unit at the grade level, there should be more winners in class (3) because there are many high score students according to the evaluation criteria. In fact, class (3) has a good style of study, its academic performance is always higher than that of other classes, and there are more excellent students than other classes. These advantages of the whole year are the effective information provided by the weighted average of standard scores in the annual ranking, and the fairness effect produced by using the weighted average of standard scores in the annual ranking. In view of this, the student work leading group of the school of Mathematical Sciences intends to break class boundaries and use standardized scores in the evaluation of various scholarships according to majors and grades in the future. We believe that this approach is worth advocating and suggest that it be extended to other sectors.

Higher education evaluation is a complex systematic project. The selection of indicators and the determination of weight in the evaluation process will affect the evaluation results. Even for the same university, different evaluation index systems will produce different results. Even for the same evaluation organization, as shown in Figure 1, slight changes in evaluation index system and weight will lead to significant differences. Therefore, it is of great significance to deeply explore the design basis of the evaluation index system, constantly improve the weight distribution scheme, and ensure the scientificity, objectivity, and fairness of the evaluation results.

6. Conclusion

The training information required by intelligent learning machines should be derived from real results rather than predicted results. Credit assessment and grade prediction based on intelligent learning machines like the previous ones meet this characteristic and are reasonable, while teaching level assessment and overall strength ranking based on intelligent learning machines like the previous ones lose their meaning. The analysis on validity in this paper is also suitable for other training-based intelligent learning algorithms (e.g., decision trees, Apriori algorithm, genetic algorithm, maximum expectation algorithm, Ada-boost algorithm, nearest neighbor algorithm), and a broader range of assessment prediction problems (e.g., population prediction, risk prediction, disaster prediction, institutional assessment). For other types of forecasting not discussed in this paper, their effectiveness can also be analyzed using the above ideas.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The author declared that he has no conflicts of interest regarding this work.

References

[1] A. A. Mohammed, R. Minhas, Q. J. Wu, and M. A. Sid-Ahmed, “Human face recognition based on multidimensional PCA and extreme learning machine,” Pattern Recognition, vol. 44, no. 10-11, pp. 2588–2597, 2011.
[2] X. Li, Y. Xie, D. Hu, and Z. Lan, “Analysis of the geometrical evolution in on-the-fly surface-hopping nonadiabatic dynamics with machine learning dimensionality reduction approaches: classical multidimensional scaling and isometric feature mapping,” Journal of Chemical Theory and Computation, vol. 13, no. 10, pp. 4611–4623, 2017.
[3] G. Eisenhofer, C. Durán, T. Chavakis, and C. V. Cannistraci, “Steroid metabolomics: machine learning and multidimensional diagnostics for adrenal cortical tumors, hyperplasias, and related disorders,” Current Opinion in Endocrine and Metabolic Research, vol. 8, pp. 40–49, 2019.
[4] R. S. Mouradi, C. Goeury, O. Thual, F. Zaoui, and P. Tassi, “Physically interpretable machine learning algorithm on multidimensional non-linear fields,” Journal of Computational Physics, vol. 428, article 110074, 2021.
[5] M. P. Oxley, M. Ziatdinov, O. Dyck, A. R. Lupini, R. Vasudevan, and S. V. Kalinin, “Probing atomic-scale symmetry breaking by rotationally invariant machine learning of multidimensional electron scattering,” npj Computational Materials, vol. 7, no. 1, pp. 1–6, 2021.
[6] Z. Cui, Z. Xia, M. Su, H. Shu, and G. Gong, “Disrupted white matter connectivity underlying developmental dyslexia: a machine learning approach,” Human Brain Mapping, vol. 37, no. 4, pp. 1443–1458, 2016.
[7] Y. Huang and M. Chen, “Improve reputation evaluation of crowdsourcing participants using multidimensional index and machine learning techniques,” IEEE Access, vol. 7, pp. 118055–118067, 2019.
[8] Y. C. Leong, A. Radulescu, R. Daniel, V. DeWoskin, and Y. Niv, “Dynamic interaction between reinforcement learning and attention in multidimensional environments,” Neuron, vol. 93, no. 2, pp. 451–463, 2017.
[9] S. B. Ramezani, A. Sommers, H. K. Manchukonda, S. Rahimi, and A. Amirlatif, “Machine learning algorithms in quantum computing: a survey,” in 2020 International Joint Conference on Neural Networks (IJCNN), pp. 1–8, Glasgow, UK, 2020.
[10] K. Takahashi, L. Takahashi, T. N. Nguyen, A. Thakur, and T. Taniike, “Multidimensional classification of catalysts in oxidative coupling of methane through machine learning and high-throughput data,” The Journal of Physical Chemistry Letters, vol. 11, no. 16, pp. 6819–6826, 2020.
[11] M. H. Law and A. K. Jain, “Incremental nonlinear dimensionality reduction by manifold learning,” IEEE Transactions on...
Pattern Analysis and Machine Intelligence, vol. 28, no. 3, pp. 377–391, 2006.

[12] S. Smusz, R. Kurczab, and A. J. Bojarski, “A multidimensional analysis of machine learning methods performance in the classification of bioactive compounds," *Chemometrics and Intelligent Laboratory Systems*, vol. 128, pp. 89–100, 2013.

[13] C. Orphanidou and D. Wong, “Machine learning models for multidimensional clinical data,” in *Handbook of Large-Scale Distributed Computing in Smart Healthcare*, pp. 177–216, Springer, Cham, 2017.

[14] Z. H. A. N. G. Zhengwan, Z. H. A. N. G. Chunjiong, L. I. Hongbing, and X. I. E. Tao, “Multipath transmission selection algorithm based on immune connectivity model,” *Journal of Computer Applications*, vol. 40, no. 12, p. 3571, 2020.

[15] Z. Zheng-wan, W. Di, and Z. Chun-jiong, “Study of cellular traffic prediction based on multi-channel sparse LSTM,” *Computer Science*, vol. 48, no. 6, pp. 296–300, 2021.

[16] G. Cai, Y. Fang, J. Wen, S. Mumtaz, Y. Song, and V. Frascollo, “Multi-carrier $M$-ary DCSK system with code index modulation: an efficient solution for chaotic communications,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 13, no. 6, pp. 1375–1386, 2019.

[17] K. Chandra, A. S. Marcano, S. Mumtaz, R. V. Prasad, and H. L. Christiansen, “Unveiling capacity gains in ultradense networks using mm-wave NOMA,” *IEEE Vehicular Technology Magazine*, vol. 13, no. 2, pp. 75–83, 2018.

[18] J. Du, C. Jiang, Z. Han, H. Zhang, S. Mumtaz, and Y. Ren, “Contract mechanism and performance analysis for data transaction in mobile social networks,” *IEEE Transactions on Network Science and Engineering*, vol. 6, no. 2, pp. 103–115, 2019.

[19] C. H. Joh, T. A. Arentze, and H. J. Timmermans, “Multidimensional sequence alignment methods for activity-travel pattern analysis: a comparison of dynamic programming and genetic algorithms,” *Geographical Analysis*, vol. 33, no. 3, pp. 247–270, 2001.

[20] M. Allodi, A. Broggi, D. Giaquinto, M. Patander, and A. Priolletti, “Machine learning in tracking associations with stereo vision and lidar observations for an autonomous vehicle,” in *2016 IEEE Intelligent Vehicles Symposium (IV)*, pp. 648–653, Gothenburg, Sweden, 2016.

[25] J. Huang, W. Tu, and Q. Yuan, “Analysis of application of machine learning based on bibliometrics in pattern recognition,” *Journal of Physics: Conference Series*, vol. 1629, no. 1, article 012004, 2020.

[26] X. Chen, Y. Yuan, L. Lu, and J. Yang, “A multidimensional trust evaluation framework for online social networks based on machine learning,” *IEEE Access*, vol. 7, pp. 175499–175513, 2019.