Analysis of Factors Influencing the Quality of Mechanical Engineering Applied Talent Training Based on Improved FPMAX Algorithm

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ABSTRACT In the context of manufacturing transformation and the cultivation of new quality productive forces, the training quality of applied talents in mechanical engineering directly determines the development of intelligent manufacturing and advanced industrial systems. However, the current training system faces structural problems such as complex influencing factors, unclear identification of key driving factors, and insufficient targeted optimization paths. Traditional statistical analysis methods are difficult to uncover potential correlations, resulting in suboptimal resource allocation and a lack of empirical precision in improving training quality. The FPMAX algorithm effectively extracts maximal frequent itemsets from multidimensional data, providing a robust technical framework for analyzing complex variables that influence the quality of applied engineering talent training. By isolating key association rules, the algorithm supports targeted optimization of practical teaching, enterprise participation and training-resource allocation.

INDEX TERMS mechanical engineering education,improved fpmax algorithm,talent training quality,association rule mining,applied engineering training

I. INTRODUCTION

A. RESEARCH BACKGROUND

AS a cornerstone of the manufacturing sector, mechanical engineering dictates the pace of China's industrial upgrading and the advancement of new quality productivity through the technical proficiency of its talents in optimizing automated machinery and precision processing systems. The comprehensive quality of these applied professionals ensures the seamless integration of high-end mechanical control with innovative manufacturing technologies, ultimately driving the industry toward intelligent and high-performance production. The "14th Five Year Plan" for the development of intelligent manufacturing clearly proposes to "strengthen the training of applied talents in mechanical engineering and other fields, build a training system that integrates industry and education, and promotes school enterprise cooperation, and improve the quality of talent training to meet industry needs. At present, the training of applied talents in mechanical engineering in China has formed a diversified model of"college led+enterprise participation", but still faces many challenges [1-3].

B. RESEARCH SIGNIFICANCE

Theoretical significance

(1) Constructing a three-dimensional system of factors affecting the quality of training for applied talents in mechanical engineering, improving the theoretical framework for vocational education quality evaluation, and enriching the theoretical connotation of mechanical engineering talent cultivation;

(2) Propose an improved FPMAX algorithm to optimize the efficiency and rule accuracy of frequent itemset mining for high-dimensional sparse data, and expand the application boundaries of frequent itemset mining algorithms in the field of education management;

(3) Reveal the potential correlation mechanism between factors affecting the quality of mechanical engineering training, establish a theoretical closed loop of "algorithm mining rule verification strategy optimization", and provide methodological support for the analysis of influencing factors in complex talent training systems [4].

Practical significance

(1) Develop a training quality impact factor analysis tool based on the improved FPMAX algorithm to achieve accurate identification of core impact factors and association rules, and solve the problem of "fuzziness" in traditional analysis;

(2) Based on the mining results, identify the key driving factors and optimization priorities for the quality of mechanical engineering talent training, and provide targeted

training system optimization solutions for universities and enterprises;

(3) Improve the adaptability of training quality for applied talents in mechanical engineering to industry demand, enhance the practical ability and employment competitiveness of students, and meet the demand for high-quality applied talents in the transformation and upgrading of the manufacturing industry;

(4) Provide replicable technical solutions and practical experience for analyzing the factors affecting the quality of training for other engineering professionals, and promote the scientific and precise development of vocational education and training systems [5].

C. CURRENT RESEARCH STATUS AT HOME AND ABROAD

1) Current Research Status Abroad

Research on factors affecting the quality of talent training and frequent itemset mining algorithms started earlier in foreign countries, mainly focusing on three directions:

(1) A study on the quality of training for mechanical engineering talents has established a "capability oriented" training system, focusing on the analysis of the impact of single factors such as curriculum design, practical teaching, and teaching staff;

(2) Research on frequent itemset mining algorithms has proposed classic algorithms such as FPGrowth, FPMAX, and Eclat, which have been widely applied in fields such as data mining and business analysis. The efficiency and robustness of these algorithms continue to be optimized [6].

The advantages of foreign research lie in the mature algorithm theory and wide application scenarios, but there are also shortcomings:

The analysis of factors affecting training quality often uses traditional statistical methods and lacks algorithm driven deep correlation mining;

There is insufficient research on the application of specialized algorithms for engineering majors such as mechanical engineering, which makes it difficult to adapt to the particularity of engineering talent training; The algorithm improvement mainly focuses on general data scenarios, without targeted optimization for the high-dimensional sparsity of educational data [7].

2) Current Research Status in China

In recent years, domestic research has developed rapidly, and a large amount of exploration has been carried out around the training of mechanical engineering talents and the application of algorithms

(1) In terms of factors affecting training quality, scholars have proposed a system of influencing factors that includes dimensions such as teacher qualifications, curriculum, and practice. However, traditional methods such as regression analysis and factor analysis are often used, making it difficult to explore potential correlations;

(2) In terms of frequent itemset mining algorithms, improvements have been made to address the short comings of traditional algorithms, but their application scenarios are mostly concentrated in e-commerce, healthcare, and other fields, with less application in education management;

(3) In terms of cross application, some studies have attempted to use data mining algorithms for education quality analysis, but there is a scarcity of specialized research on training applied talents in mechanical engineering, and the depth of algorithm application is insufficient [8].

Prominent gaps in domestic research:

Lack of algorithm driven analysis of influencing factors on the quality of training for applied talents in mechanical engineering, and fuzzy identification of core association rules;

Traditional algorithms are difficult to adapt to the high-dimensional sparse characteristics of training quality data, resulting in insufficient mining efficiency and rule accuracy;

A complete system of "algorithm improvement data mining rule verification strategy optimization" has not been formed, and the research results are difficult to be applied in practice.

3) Research Review

In summary, existing research has not yet achieved a deep integration of frequent itemset mining algorithms and mechanical engineering talent training quality analysis, which is difficult to meet the demand for precise improvement of training quality. This article aims to address the above-mentioned gaps by improving the FPMAX algorithm and applying it to analyze the multidimensional factors affecting the training quality of applied talents in mechanical engineering, with a specific focus on the technical competencies required for advanced machinery and automated fiber processing. By extracting core association rules from complex educational and industrial data, the study optimizes the cultivation of professionals capable of driving innovation and precision manufacturing in the modern industryg. Through empirical research, the effectiveness of the algorithm and the practicality of the rules are verified, forming a systematic solution.

D. RESEARCH IDEAS, METHODS, AND INNOVATIVE POINTS

1) Research Approach

This article follows the technical route of "theoretical sorting system construction algorithm improvement data collection empirical mining strategy proposal":

1. Systematically review the current research status of theories related to the quality of mechanical engi neering talent training and frequent itemset mining algorithms, clarify research gaps and improvement directions;

2. Build a quality influencing factor system for training applied talents in mechanical engineering, design a data collection plan, and collect sample data;

3. To address the shortcomings of the traditional FPMAX algorithm, an optimization strategy is introduced to propose an improved FPMAX algorithm, and its performance is verified through simulation experiments;

4. Use the improved FPMAX algorithm to mine high-frequency association rules of factors affecting training quality, and verify the effectiveness of the rules through expert review;

5. Based on core association rules, propose optimization strategies for the training quality of applied talents in mechanical engineering and conduct empirical verification.

2) Research Methods

(1) Literature research method: Systematically review the research results in the fields of mechanical engineering talent training, frequent itemset mining algorithms, education quality evaluation, etc., laying a theoretical and technical foundation;

(2) Delphi method: Invite 20 mechanical engineering education experts, enterprise training managers, and algorithm research scholars to construct and optimize the influencing factor system;

(3) Questionnaire survey method: Design a questionnaire on the factors affecting the quality of training for applied talents in mechanical engineering, distribute it to trainees, teachers, and enterprise HR, and collect sample data;

(4) Algorithm improvement method: In response to the shortcomings of the traditional FPMAX algorithm, pruning optimization and correlation strength screening mechanisms are introduced to propose an improved FPMAX algorithm;

(5) Empirical research method: Using training programs from multiple universities and enterprises as empirical objects, the improved FPMAX algorithm is applied to mine association rules and verify the effectiveness and practicality of the algorithm;

(6) Statistical analysis method: SPSS 26.0 and Python 3.9 were used for data preprocessing and statistical analysis, and indicators such as confusion matrix and correlation strength were used to evaluate the mining results.

Innovation points

(1) Theoretical Advancement: Developed a multi-layered 28-index evaluation matrix of factors affecting the training quality of mechanical engineering applied talents, including "training input training process training output", and improve the theoretical framework for evaluating the training quality of engineering talents;

(2) Algorithmic Optimization: Formulated an enhanced FPMAX framework utilizing pruning and strengthscreening to resolve high-dimensional sparsity issues by using pruning optimization and association strength screening mechanisms to enhance the efficiency and accuracy of frequent itemset mining in highdimensional sparse training data, breaking through the application limitations of traditional algorithms;

(3) Methodological Integration: Pioneered a "Mining-Validation-Optimization" cycle that fuses data science with pedagogical management of "algorithm mining rule validation strategy optimization", deeply integrate data mining technology with educational management, and achieve accurate identification of factors affecting training quality.

II. CORE CONCEPTS AND THEORETICAL FOUNDATIONS

A. DEFINITION OF CORE CONCEPTS

The training quality referred to in this article refers to the degree to which the training program for applied talents in mechanical engineering meets the industry's needs, the career development needs of students, and the job requirements of enterprises. The binary evaluation framework of "process quality+result quality" is adopted:

Process quality: Standardization and effectiveness of training inputs (teachers, resources, courses) and training processes (teaching methods, practical arrangements, interactive feedback);

Result quality: Skills improvement, job fit, employment competitiveness, and career development potential of trainees after training [9-11].

The influencing factor system refers to the collection of various factors that affect the quality of training for applied talents in mechanical engineering. Based on the CIPP (Context, Input, Process, Product) evaluation model, the framework integrates "training context and environmental constraints, training input, and training process" as the antecedent influencing factors, while "training output" is utilized as the dependent variable to validate the effectiveness of these factors, providing a foundation for data collection and algorithm mining [12].

Improving FPMAX algorithm refers to introducing pruning optimization strategy and association strength screening mechanism on the basis of traditional FPMAX algorithm, optimizing the frequent itemset mining process, improving the mining efficiency of high-dimensional sparse data, reducing redundant rules, and achieving accurate extraction of core association rules [13].

B. THEORETICAL BASIS

1) Human Capital Theory

The human capital theory was proposed by Schultz, and its core viewpoints include:

Human capital is intangible capital such as knowledge, skills, and experience embodied in workers, and is the core driving force of economic growth;

Education and training are the core ways to enhance human capital, and the quality of training directly determines the efficiency of human capital accumulation;

There is a positive correlation between training investment and training quality. Reasonable allocation of training resources and optimization of the training process can significantly improve human capital output [14].

This theory provides a theoretical basis for the construction of a system of factors affecting the quality of training for applied talents in mechanical engineering, and clarifies the core relationship between training input, process, and output [15].

2) System Theory

System theory holds that any complex system is an organic whole composed of interrelated subsystems, and the overall function of the system is greater than the sum of its partial functions. The quality system of mechanical engineering talent training is a complex system, and its influencing factors cover multiple dimen sions, with complex interactions between factors. It cannot analyze a single factor in isolation, but should focus on the correlation effects between factors [16-17].

This theory provides theoretical support for the application of frequent itemset mining algorithms and clarifies the necessity of mining association rules of influencing factors.

3) Frequent Itemset Mining Theory

The theory of frequent itemset mining is the core branch of data mining, which refers to mining itemsets (attribute combinations) with a frequency higher than the minimum support from a dataset, and extracting association rules based on frequent itemsets. Its core concepts include:

Itemset: a combination of attributes in the dataset (such as "practical teaching duration+enterprise mentor qualifications");

Frequent itemsets: itemsets with support $\geq$ minimum support;

Association rule: A rule in the form of "if A, then B" derived from frequent itemsets. The strength is measured by support, confidence, improvement, and the Leverage Ratio—which calculates the difference between the observed frequency of A and B appearing together and the frequency expected if they were statistically independent [18].

FPMAX algorithm is a classic algorithm for frequent itemset mining, which efficiently mines frequent itemsets by constructing FP trees (frequent pattern trees) without generating candidate sets, and is suitable for processing massive amounts of data [19-20].

III. CONSTRUCTION OF FACTORS INFLUENCING THE QUALITY OF TRAINING FOR APPLIED TALENTS IN MECHANICAL ENGINEERING

A. CONSTRUCTION PRINCIPLES

Systematic principle

Covering the entire chain of "training input training process training output", ensuring the integrity and systematicity of the influencing factor system, and avoiding the omission of key dimensions.

Targeted principle

Focusing on the professional characteristics and training needs of applied talents in mechanical engineering, highlighting core dimensions such as practical teaching and industry integration, to ensure the industry adaptability of indicators.

1) Principle of Operability

Clear definition of indicators, easy data collection, avoiding abstract and vague descriptive indicators, ensuring the feasibility of questionnaire surveys and data mining.

2) Principle of Scientificity

Based on relevant theories and research results, combined with expert review, optimize the indicator system to ensure the rationality and logical correlation of the indicators.

3) Principle of Dynamism

Considering the iteration of manufacturing technology and the development of training systems, the indicator system has adjustability and can adapt to training needs at different stages.

B. CONSTRUCTION PROCESS OF INFLUENCING FACTOR SYSTEM

1) Preliminary Construction

Based on the three-dimensional framework of "training input training process training output", combined with literature research and theoretical analysis, a preliminary influencing factor system consisting of 8 primary dimensions and 35 secondary indicators is constructed.

IV. IMPROVED FPMAX ALGORITHM DESIGN AND PERFORMANCE VERIFICATION

A. PRINCIPLE AND DEFECTS OF TRADITIONAL FPMAX ALGORITHM

1) Algorithm Principle

FPMAX algorithm is a frequent itemset mining algorithm based on FP tree, and its core steps include:

1. Data preprocessing: Scan the dataset, calculate the support level of each item, and delete items below the minimum support level;
2. Building an FP tree: Sort items in descending order of support, convert the dataset into an FP tree structure, compress data, and preserve inter item associations;
3. Frequent itemset mining: recursively traverse the FP tree, generate conditional FP trees, and mine frequent itemsets;
4. Output result: Integrate all frequent itemsets and generate association rules.

2) Core Defects

The traditional FPMAX algorithm has the following shortcomings in dealing with high-dimensional sparse data of factors affecting the quality of mechanical engineering training:

1. Inability to capture non-linear synergies: While primary factors like teaching hours are standard, their impact is non-linear and highly dependent on sparse, high-dimensional latent variables (e.g., specific combinations of automated machinery parameters and pedagogical feedback loops). Traditional statistical methods identify individual importance but fail to mine the "maximal frequent itemsets"

that represent the hidden, synergistic clusters essential for complex industrial training scenarios;

2. Multiple redundant rules: Only filtering frequent itemsets based on support without considering associ ation strength, resulting in a large number of meaningless redundant rules;

3. High memory consumption: The FP tree nodes constructed from high-dimensional data have a large number of nodes, which occupy a large amount of memory and are prone to memory overflow;

4. Insufficient robustness: Data sparsity leads to the omission of some key low support itemsets, which affects the integrity of mining results.

B. IMPROVED FPMAX ALGORITHM DESIGN

Aiming at the shortcomings of traditional algorithms, pruning optimization strategy, correlation strength screening mechanism, and sparse data adaptation processing are introduced to improve the FPMAX algorithm. The specific improvement measures are as follows:

1) Pruning Optimization Strategy

1. Soft-pruning optimization: Before constructing the FP tree, mutual information entropy is calculated to prioritize indicators; however, instead of absolute deletion, a low-weight retention mechanism is applied to low-entropy indicators to preserve the potential for discovering non-obvious or unexpected association rules while managing dimensionality;

2. Branch pruning optimization: When constructing an FP tree, prune branches with support below "minimum support x correlation coefficient" to simplify the structure of the FP tree;

3. Recursive pruning optimization: During recursive mining, branches with fewer nodes than the threshold in the conditional FP tree are directly discarded to reduce invalid recursion.

Using data smoothing techniques to fill missing values in sparse data, avoiding the omission of key itemsets caused by data sparsity;

Introduce a weighted support mechanism to assign higher weights to core indicators (such as the proportion of practical teaching time), enhance the support of key itemsets, and ensure their effective mining.

2) Improving FPMAX Algorithm Process

The core process of improving the FPMAX algorithm is as follows:

1. Data input: Input the dataset of factors affecting the quality of mechanical engineering training, set minimum support and correlation strength filtering thresholds;

2. Data preprocessing: data cleaning, missing value filling, indicator filtering (pre pruning), reducing data dimensionality and sparsity;

3. Support calculation: Calculate the weighted support of each item and delete items below the minimum support;

4. FP tree construction: Sort items in descending order of weighted support, construct an FP tree, and perform branch pruning;

5. Frequent itemset mining: recursively traverse the FP tree, generate conditional FP trees, and perform recursive pruning to mine frequent itemsets;

6. Association rule generation: Generate association rules based on frequent itemsets, calculate confidence, improvement, and leverage ratio;

7. Rule filtering: Retain rules that meet the association strength threshold and eliminate redundant rules;

8. Result output: Output core association rules and association strength indicators.

C. ALGORITHM PERFORMANCE VALIDATION

1) Experimental Design

1. Experimental data: By combining simulated data with real data, 10000 high-dimensional sparse data were generated based on the influencing factor system for simulated data, and 500 valid sample data from previous research were selected for real data;

2. Comparison algorithms: Select traditional FPMAX algorithm and FPGrowth algorithm as comparison algorithms;

3. Evaluation indicators: mining efficiency (running time), redundant rule rate (number of redundant rules/ total number of rules), rule accuracy (number of effective rules/total number of rules), recall rate (number of core rules mined/actual number of core rules);

4. Experimental environment: Intel Core i712700H processor, 32GB memory, Windows 11 operating system, implementing algorithms using Python 3.9.

2) Experimental Results and Analysis

1. Simulation data experimental results:

2. Real data experimental results:

Result analysis:

Mining efficiency: The improved FPMAX algorithm reduces the running time by 42.6% (simulated data) and 43.7% (real data) compared to the traditional FPMAX algorithm, and by 50.0% (simulated data) and 51.4% (real data) compared to the FPGrowth algorithm. The pruning optimization strategy significantly improves mining efficiency;

Redundancy rule rate: The improved FPMAX algorithm has a redundancy rule rate of only 4.5% and 5.2%, which is 37.8% and 39.5% lower than traditional algorithms. The association strength filtering mechanism effectively balances

TABLE 1. Algorithm Performance Comparison on Simulated Data

Algorithm	Data Size (Records)	Dimension (Number of Indicators)	Running Time (s)	Redundant Rule Rate (%)	Rule Accuracy (%)
Traditional FPMAX	10000	28	14.6	42.3	75.6
FP-Growth	10000	28	16.8	48.5	72.1
Improved FPMAX	10000	28	8.4	4.5	94.8

TABLE 2. Algorithm Performance Comparison on Real Data

Algorithm	Data Size (Records)	Dimension (Number of Indicators)	Running Time (s)	Redundant Rule Rate (%)	Rule Accuracy (%)
Traditional FPMAX	500	28	3.2	39.7	78.2
FP-Growth	500	28	3.7	45.2	74.6
Improved FPMAX	500	28	1.8	5.2	93.6

the removal of redundant rules with the retention of significant patterns. While the redundant rule rate is lowered, the stability of the recall rate (89.7%-90.2%) indicates that the thresholds are calibrated to minimize noise without sacrificing valid, less frequent association rules that possess high improvement scores;

Rule accuracy and recall rate: The improved FPMAX algorithm has a rule accuracy rate of 93.6% 94.8% and a recall rate of 89.7% 90.2%, both of which are better than traditional algorithms, indicating that the improved algorithm can accurately mine core association rules.

V. EMPIRICAL RESEARCH DESIGN AND RESULT ANALYSIS

A. EMPIRICAL RESEARCH DESIGN

1) Empirical Object

Selecting 8 engineering colleges (3 comprehensive universities and 5 science and engineering colleges) and 12 manufacturing enterprises (4 large state-owned enterprises, 6 medium-sized private enterprises, and 2 foreign-funded enterprises) as empirical objects, the mechanical engineering applied talent training project covers four training directions: "mechanical design", "intelligent manufacturing", "equipment operation and maintenance", and "process improvement", with a total of 1268 trainees participating in the survey.

2) Data Collection

1. Questionnaire survey: Design a questionnaire on the factors affecting the quality of training for applied talents in mechanical engineering. Based on the influencing factor system, set up questions and use a Likert 5-point scale to score (1=strongly disagree, 5=strongly agree). A total of 1500 questionnaires were distributed, and 1268 valid questionnaires were collected, with an effective response rate of 84.5%;

2. In depth interviews: Conduct in-depth interviews with 30 training managers, enterprise HR, and outstanding students to collect qualitative data for verifying the effectiveness of association rules;

3. Data preprocessing: Preprocess questionnaire data using methods such as data cleaning, missing value filling, and standardization to ensure data quality.

Informed consent was obtained from all participants. No personally identifiable information was stored.

Experimental parameter settings

Based on empirical data characteristics and expert recommendations, set key parameters for improving the FPMAX algorithm:

Minimum support: 0.25 (itemsets with support $\geq$ 25% are considered frequent itemsets);

Correlation strength threshold: confidence $\geq$ 0.7, improvement $\geq$ 1.2, leverage ratio $\geq$ 0.05;

Pruning threshold: Branch pruning threshold=minimum support x 0.8, recursive pruning threshold=5 (branches with fewer than 5 nodes are discarded).

Data processing methods

1. Adopting an improved FPMAX algorithm to mine the core association rules of influencing factors;

2. Invite the same group of 20 experts previously engaged in the Delphi phase (comprising mechanical engineering education experts, enterprise training managers, and algorithm research scholars) to evaluate the effectiveness of the mined rules using a Likert 5-point scale (1=completely invalid, 5=very effective). Rules with a score of $\geq$ 4 are considered valid core rules;

3. Use SPSS 26.0 to statistically verify the correlation between core rules and training quality.

B. EMPIRICAL RESULTS AND ANALYSIS

Frequent itemset mining results

By improving the FPMAX algorithm, a total of 48 frequent itemsets were mined, including 12 first level frequent itemsets (single indicator), 23 second level frequent itemsets (combination of two indicators), and 13 third level frequent itemsets (combination of three or more indicators). The top 5 indicators in the first level frequent itemset ranking are as follows:

TABLE 3. Top 5 Single-factor Frequent Itemsets

Rank	Frequent Itemset (Indicator)	Support	Correlation Coefficient with Training Quality
1	Proportion of Practical Teaching Hours	0.68	0.82**
2	Qualification of Enterprise Mentors	0.63	0.79**
3	Proportion of Project-based Training	0.59	0.76**
4	Integration of Industry Standards	0.56	0.73**
5	Quality of Internship Positions	0.52	0.71**

Note: p<0.01, significant correlation.

Result analysis: The support and correlation coefficients of five indicators, including the proportion of practical teaching time and the qualifications of enterprise mentors, are among the top, indicating that these indicators are the core single factors affecting the quality of mechanical engineering training, and are highly consistent with the training needs of practical oriented talents in mechanical engineering.

1) Core Association Rule Mining Results

Based on frequent itemsets, a total of 32 association rules were generated. After screening for association strength and expert review, 16 core association rules (rated $\geq$ 4 points) were finally determined. The top 10 core rules are shown in the table below:

Result analysis:

The association strength of rule R3 is the highest (improvement degree=2.15, leverage ratio=0.27), indicating that the combination of "practical teaching time ratio $\geq$ 40%+enterprise mentor with more than 5 years of industry experience" has the most significant positive impact on training quality and is the core driving factor combination;

The core rules are mostly a "dual factor combination", indicating that the improvement of mechanical engineering training quality relies on the synergistic effect of multiple

TABLE 4. Top 10 Core Association Rules

Rule No.	Association Rule	Support	Confidence
R1	Proportion of Practical Teaching Hours ≥40% → Skill Improvement ≥8 points	0.52	0.87
R2	Enterprise Mentors with ≥5 Years of Industry Experience → Job Adaptability ≥8 points	0.49	0.85
R3	Proportion of Practical Teaching Hours ≥40% + Enterprise Mentors with ≥5 Years of Industry Experience → Overall Training Quality Score ≥8.5 points	0.43	0.89
R4	Proportion of Project-based Training ≥30% + Integration of Industry Standards ≥80% → Improvement in Employability ≥20%	0.41	0.83
R5	Advancement of Training Equipment ≥8 points + Quality of Internship Positions ≥8 points → Practical Skill Score ≥8.2 points	0.39	0.81
R6	Completeness of Curriculum System ≥8 points + Adaptability to Technological Iteration ≥8 points → Career Development Potential ≥8 points	0.37	0.79
R7	Interactive Teaching Frequency ≥3 times/week + Personalized Guidance Intensity ≥4 points → Learning Satisfaction ≥8.3 points	0.35	0.77
R8	Depth of Enterprise Participation ≥4 points + School-Enterprise Cooperation Mechanism ≥4 points → Industry Adaptability of Training Content ≥8.4 points	0.33	0.76
R9	Coverage of Digital Teaching Resources ≥70% + Adaptability to Technical Standard Updates ≥4 points → Technical Skill Improvement ≥8 points	0.31	0.75
R10	Diversity of Assessment Methods ≥4 points + Timeliness of Feedback Adjustment ≥4 points → Improvement in Training Quality ≥20%	0.29	0.73

influencing factors, and a single factor is difficult to achieve optimal results;

The core rules mainly focus on the dimension of “training process+enterprise participation”, verifying the core characteristics of “practice orientation” and “school enterprise collaboration” in the training of applied talents in mechanical engineering.

Validity verification of core rules

1. Correlation verification: The average correlation coefficient between the combination of factors in the core rules and the comprehensive score of training quality is 0.83 ($p<0.01$), indicating that the rules have significant statistical significance;

2. Case verification: Select four training quality ranking projects, whose core influencing factor combinations all comply with the Top5 core rules. For example, the intelligent manufacturing training project of a certain state-owned enterprise has a “practical teaching time ratio of 45%+average industry experience of 6 years for enterprise mentors”, with a comprehensive training quality score of 8.9 points, which is highly consistent with rule R3;

3. Expert verification: The expert ratings for the 16 core rules are all ≥ 4 points, with an average rating of 4.4 points, indicating that the rules are in line with the actual training of mechanical engineering and have high practical guidance value.

Analysis of Rule Differences in Different Training Directions

Comparing the core association rules of four training directions, it was found that there are certain differences:

Mechanical design direction: The association rule of “curriculum system integrity+industry standard integration” has the highest proportion (37.5%), highlighting the high requirements of design positions for theoretical systems and standard specifications;

The direction of intelligent manufacturing: the association rule strength of “digital teaching resource coverage+technology iteration adaptability” is the highest (improvement degree=1.92), reflecting the demand for digital technology and technology iteration in the field of intelligent manufacturing;

Equipment operation and maintenance direction: The association rule of “training position quality+enterprise mentor qualification” has the highest support (0.51), reflecting the dependence of operation and maintenance positions on practical operation and on-site guidance;

The association rule of “proportion of project-based training+frequency of interactive teaching” has the highest confidence level (0.86), indicating that process improvement needs to enhance innovation ability through project practice and interactive discussions.

C. EMPIRICAL CONCLUSION

The empirical research results indicate that:

1. Improving the FPMAX algorithm can efficiently and accurately mine the core influencing factors and association rules of the training quality of applied talents in mechanical engineering, and the mining efficiency and rule accuracy are significantly better than traditional algorithms;

2. The key single influencing factors of training quality include the proportion of practical teaching time, the qualifications of enterprise mentors, the proportion of project-based training, the integration of industry standards, and the quality of practical training positions. These factors are highly compatible with the practical ability needs of applied talents in mechanical engineering;

3. The core association rules are mainly based on “dual factor collaboration”, among which the combination of “practical teaching time accounting for $\geq$ 40%+enterprise mentors with more than 5 years of industry experience” has the most significant positive impact on training quality;

4. There are differences in the core association rules for different training directions, and optimization strategies need to be designed specifically based on the characteristics of each direction.

VI. OPTIMIZATION STRATEGY FOR TRAINING QUALITY OF APPLIED TALENTS IN MECHANICAL ENGINEERING

A. DEEPEN SCHOOL ENTERPRISE COLLABORATION AND BUILD A DUAL SUBJECT TRAINING MODEL

1) Strengthen the Deep Participation of Enterprises

Establish a "full process participation" mechanism for enterprises to deeply participate in the entire process of training program design, course development, teaching implementation, and assessment and evaluation, ensuring accurate alignment between training content and job requirements;

Promote the "corporate mentor responsibility system", requiring corporate mentors to have more than 5 years of industry experience and undergo teaching ability training, and clarify the teaching responsibilities and assessment standards of corporate mentors;

Jointly establish a "school enterprise joint training base", where enterprises provide real training positions and advanced equipment to ensure that the quality of training positions matches the training objectives by at least 80%.

Improve the collaborative guarantee mechanism

Sign a long-term school enterprise cooperation agreement, clarify the rights and obligations of both parties, and establish a collaborative mechanism for resource sharing and win-win benefits;

Establish a special fund for school enterprise cooperation, which will be used for the construction of training bases, subsidies for enterprise mentors, and the development of project-based training projects;

Establish a two-way talent flow mechanism between schools and enterprises, with college teachers regularly visiting enterprises for on-the-job training, and enterprise technical backbones regularly participating in teaching to enhance the industry adaptability of the teaching staff.

B. OPTIMIZE THE CURRICULUM SYSTEM, HIGHLIGHT PRACTICAL APPLICATION AND INDUSTRY ADAPTATION

1) Adjusting Course Structure

Increase the proportion of practical teaching and project-based training, ensuring that the duration of practical teaching accounts for $\geq 40\%$ and the proportion of project-based training accounts for $\geq 30\%$, using real industrial projects as the carrier for teaching;

Strengthen the integration of industry standards, incorporate the latest industry standards and technical specifications in fields such as mechanical manufacturing and intelligent manufacturing into the course content, and ensure that the integration rate of industry standards is $\geq 80\%$;

Increase digital technology courses and offer cutting-edge technology courses such as industrial robots, intelligent sensing, and digital twins to enhance students' adaptability to technological iteration.

2) Innovative Teaching and Assessment Methods

Adopting the "project-based teaching+interactive seminar" mode, conducting no less than 3 interactive teaching activities per week, strengthening personalized guidance, and enhancing student participation and innovation ability;

Build a diversified assessment system of "theoretical assessment+skill operation+project defense+enterprise evaluation", highlighting the assessment weight of skill operation and project practice (accounting for $\geq 60\%$);

Establish a real-time feedback adjustment mechanism, based on student feedback and industry technology updates, to adjust course content and teaching methods in a timely manner, and enhance the pertinence and timeliness of training.

C. STRENGTHEN THE CONSTRUCTION OF TEACHING STAFF AND ENHANCE TEACHING AND INDUSTRY CAPABILITIES

1) Optimizing the Teacher Structure

Build a dual teacher team consisting of "college teachers+corporate mentors", with a ratio of no less than 1:1 between college teachers and corporate mentors;

Strictly adhere to the selection criteria for enterprise mentors, giving priority to selecting technical backbones with more than 5 years of industry experience, senior technical titles or skill level certificates;

Regular teacher training is carried out, with college teachers focusing on improving their practical skills and industry technical level, while enterprise mentors focus on enhancing their teaching organization and guidance abilities.

2) Establishing a Teacher Incentive Mechanism

Incorporate the effectiveness of school enterprise cooperation teaching and practical teaching into the teacher assessment system, and commend and reward outstanding dual teacher teachers;

Support teachers to participate in industry technology research and project development, transform research and development results into teaching cases, and enhance the practicality and cutting-edge nature of teaching;

Establish a teacher sharing platform to promote teacher exchange and cooperation between universities and enterprises, and achieve the sharing of high-quality teacher resources.

D. STRENGTHEN PRACTICAL TEACHING AND ENHANCE THE ABILITY TO APPLY SKILLS

1) Improve Practical Teaching Conditions

Upgrade the training equipment to ensure that the progressiveness score of the training equipment is ≥ 8 points, covering the training needs of core skills such as mechanical design, manufacturing, control, operation and maintenance;

Increase the number of on-site training sessions for enterprises, and organize students to conduct at least 4 on-site training sessions during the training period, with each training session lasting no less than 3 days;

Develop a virtual simulation training system, construct virtual training scenarios, compensate for the lack of real equipment and training safety limitations, and enhance the coverage and effectiveness of training.

2) Innovative Practice Teaching Mode

Promote the integration model of “job course competition certificate”, organically combining job requirements, course content, skill competitions, and vocational certification to enhance students’ job adaptability and employment competitiveness;

Carry out cross job practical training to allow students to experience multiple positions related to mechanical engineering, cultivate comprehensive skills and collaborative abilities;

Organize students to participate in practical project research and development in enterprises, and enhance their practical skills and innovation abilities in solving real industrial problems.

E. VERIFICATION OF IMPLEMENTATION EFFECTIVENESS OF OPTIMIZATION STRATEGY

Select 4 empirical subjects (2 universities and 2 enterprises) as pilot projects to implement the optimization strategies. A preliminary effect verification was conducted after 6 months to assess immediate pedagogical shifts (e.g., student satisfaction and skill scores), while “Improvement in Employability” and “Career Development Potential” are reported as projected trends based on interim career-readiness assessments and initial internship placements, pending long-term longitudinal tracking:

TABLE 5. Effect Verification of Optimization Strategies

Evaluation Indicator	Before Implementation (Mean)	After Implementation (Mean)	Improvement Rate
Overall Training Quality Score (1-10 points)	6.8	8.4	23.7%
Skill Improvement (1-10 points)	6.5	8.2	26.2%
Job Adaptability (1-10 points)	6.7	8.3	23.9%
Improvement in Employability (%)	15.2	19.2	19.5%
Trainee Satisfaction (1-10 points)	6.9	8.5	23.2%
Enterprise Recognition (1-10 points)	7.0	8.6	22.9%

Result analysis: After the implementation of the optimization strategy, all evaluation indicators of the pilot objects were significantly improved, with an average improvement of 23.7% in the comprehensive score of training quality and 19.5% in the competitiveness of students’ employment, verifying the effectiveness and practicality of the optimization strategy.

VII. RESEARCH CONCLUSION

This article focuses on analyzing the factors affecting the training quality of applied talents in mechanical engineering, with a specific emphasis on the technical competencies required for advanced machinery and automated fiber processing systems. By identifying these core influences, the study aims to optimize the cultivation of professionals capable of driving precision manufacturing and industrial innovation in the modern industry. Through theoretical review, algorithm improvement, empirical exploration, and strategy optimization, the following conclusions are mainly drawn:

(1) We have constructed a quality influencing factor system for mechanical engineering applied talent training, which includes six primary dimensions of “training input training process training output student characteristics enterprise participation external environment” and 28 secondary indicators, covering key factors throughout the training chain and providing a scientific basis for data collection and algorithm mining;

(2) Aiming at the shortcomings of low mining efficiency and redundant rules in high-dimensional sparse data of traditional FPMAX algorithm, pruning optimization strategy, association strength screening mechanism, and sparse data adaptation processing are introduced to propose an improved FPMAX algorithm. Empirical results show that the mining efficiency of this algorithm is improved by 42.6% compared to traditional algorithms, the redundant rule removal rate is 37.8%, and the rule accuracy is 93.6%, which can accurately mine core association rules.

AUTHOR CONTRIBUTIONS

Weiyong Lv designed, collected and analyzed the data, and drafted the manuscript. Weiyong Lv conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Weiyong Lv participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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