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MATHEMATICAL MODELING COMPETITION METHODS AND EXPERIENCE SHARING: IN-DEPTH ANALYSIS BASED ON MULTIPLE CONTEST PROBLEMS

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Abstract: As a highly comprehensive discipline competition, the mathematical modeling contest integrates mathematical theory, computer technology, and practical problem-solving skills, providing a broad interdisciplinary practice platform for students. This paper selects typical problems from three competitions—the 2024 "Jindi Cup" Shanxi Province College Students Mathematical Modeling Contest, the Third National College Students Big Data Analysis Technology Skills Competition, and the 10th Digital Dimension Cup International Collegiate Mathematical Modeling Challenge—as research objects. This paper conducts a deep analysis of the methods and practical experience in mathematical modeling competitions, detailing specific approaches for key stages such as data processing, model construction/selection, and result optimization/verification. A comprehensive and systematic analysis is performed on the non-awarded work "Evaluation of Urban Resilience and Sustainable Development Capacity," providing reflections on deficiencies in data quality, model design, and paper composition. These insights aim to offer directions for improvement to future participants, thereby enhancing their comprehensive abilities and competition performance.
Keywords: Mathematical contest in modeling; Methodology; Experience summary; Model ealuation; Competition strategy

1 INTRODUCTION

As an important vehicle for interdisciplinary education, mathematical contest in modeling (MCM) originated in the United States in the 1980s. After over 40 years of development, it has become one of the world's most influential academic competitions, attracting participants from more than 100 countries [1]. The competition integrates mathematical theory with practical challenges in engineering, social economics, and other fields, significantly enhancing students' innovative thinking and practical abilities. However, with the rapid advancement of artificial intelligence, big data, and other technologies, the complexity of competition problems has increased exponentially, involving scenarios such as multi-objective optimization and high-dimensional data analysis [2]. The traditional "experience-driven" modeling approach is increasingly inadequate to meet these challenges, necessitating the establishment of a scientific methodological framework.

Current research primarily focuses on optimizing models for individual competitions or improving specific components like data cleaning and feature engineering. For instance, existing path planning studies mainly address enhancements to genetic algorithms or ant colony algorithms [3]. However, there is a lack of systematic exploration into integrating dynamic programming with clustering algorithms [4]. Models such as Lasso regression and gradient-boosted regression (GBR) are widely applied in prediction tasks [5], yet theoretical gaps remain in practical implementations of multi-model fusion. Additionally, few reflective studies have been conducted on non-award-winning submissions, and no reproducible improvement framework has been established [6].

This paper investigates three representative problems: soil survey path planning, red wine quality score prediction, and urban housing price forecasting. For the first time, a holistic methodological framework of 'data-driven modeling—model fusion—dynamic verification' is proposed in this paper. Specifically, this study evaluates a collaborative optimization model combining dynamic programming and K-means clustering [7], which addresses computational complexity in traditional path planning algorithms. A Lasso-Ridge-GBR fusion model is analyzed for its prediction accuracy improvement mechanism [8]. Through a comparative analysis of the non-award-winning submission Evaluation of Urban Resilience and Sustainable Development Capacity, this paper identifies structural flaws in data collection, index weighting, and report presentation. Based on these analytical insights, a "three-dimensional improvement strategy" is proposed as a reference framework for future competitions [9]. The aim of this research is to provide participants with systematic solutions from problem analysis to result presentation, thereby advancing theoretical innovation and practical applications in mathematical contest methodology [10].

2 ANALYSIS OF THE DEVELOPMENT COURSE AND FUTURE PROSPECT OF MATHEMATICAL MODELING

2.1 Development of Mathematical Contest in Modeling

Mathematical contest in modeling (MCM) originated in the United States in the 1980s. It was originally held jointly by the Mathematical Association of America (MAA) and the Society for Industrial and Applied Mathematics (SIAM). At that time, the competition aimed to stimulate college students' interest in mathematics and cultivate their ability to apply mathematical knowledge to practical problems. Competition topics typically involved simple real-world challenges such as population forecasting, resource allocation, and other similar scenarios. Teams were required to complete model formulation, solution, and report writing within a specified timeframe.

With the competition's continuous development and global promotion, its influence has expanded worldwide. An increasing number of countries and regions have initiated similar competitions, including China's National College Mathematical Contest in Modeling and the European Mathematical Contest in Modeling. These competitions provide practical platforms for students to apply mathematical knowledge to real-world problems, thereby strengthening the integration of mathematics with practical applications.

In China, the National College Mathematical Contest in Modeling has grown significantly since its establishment in 1992, evolving into one of the nation's largest and most influential academic competitions for undergraduates. Competition topics have become increasingly complex and diverse, covering fields such as environmental protection, economic and financial analysis, engineering, and other interdisciplinary areas. This trend imposes higher demands on participants' comprehensive capabilities.

2.2 Research Status of Mathematical Contest in Modeling

2.2.1 Data processing method

In mathematical modeling contests, data processing is a critical step whose quality directly influences the accuracy and reliability of the model. Researchers are dedicated to exploring effective data processing strategies for competitions, including data cleaning, feature selection, and feature engineering. For example, some scholars have proposed a deep learning-based feature selection method that can automatically identify the most relevant features for model prediction from large datasets. This approach not only enhances model efficiency and accuracy but also mitigates the impact of data noise. Additionally, studies focus on addressing issues such as missing data and outliers to ensure data integrity and consistency.

2.2.2 Model construction method

Model building lies at the core of mathematical modeling, with researchers focusing on constructing more efficient mathematical models. This process encompasses model selection, integration, optimization, and other related aspects. With advancements in machine learning and artificial intelligence, deep learning-based mathematical models have garnered increasing attention. These models can automatically extract complex patterns and relationships from data, thereby enhancing their predictive capabilities. For instance, some scholars have proposed convolutional neural networks (CNN) for processing image data, demonstrating effectiveness in tasks such as target recognition and image classification. Meanwhile, other researchers have applied recurrent neural networks (RNNs) to time-series prediction, achieving favorable outcomes. Concurrently, traditional mathematical models are undergoing continuous optimization to adapt to increasingly complex problems and evolving data characteristics.

2.2.3 Result optimization and verification method

Result optimization and validation are critical steps to ensure the accuracy and reliability of model outcomes. Researchers have explored strategies for optimizing model results, including multi-index evaluation, cross-checking, and result adjustment. For instance, some scholars have proposed a results optimization method based on machine learning, which automatically adjusts model parameters to enhance prediction accuracy. Through iterative refinement, the model can achieve superior performance across diverse datasets. Additionally, studies focus on constructing a comprehensive evaluation metrics system to objectively assess model performance, ensuring that results truly reflect the underlying patterns of real-world problems.

2.3 Proposition Trend of Mathematical Contest in Modeling

2.3.1 Interdisciplinary integration

With the increasing complexity of problems, competition topics are integrating knowledge and methods from mathematics, computer science, physics, biology, economics, and other disciplines. This interdisciplinary trend imposes higher demands on participants' comprehensive application capabilities. For example, in environmental protection, researchers may need to combine ecological, meteorological, and mathematical modeling approaches to investigate the impact of climate change on ecosystems. In finance, integrating knowledge of economics, statistics, and mathematical modeling is often necessary for analyzing market risks and investment strategies. Participants require interdisciplinary knowledge backgrounds and collaborative skills to effectively address such complex cross-disciplinary challenges.

2.3.2 Model innovation

The competition encourages participants to propose innovative mathematical models and methods to enhance prediction accuracy and model applicability. With the rapid advancements in science and technology and the increasing complexity of data, traditional mathematical models often fail to meet real-world demands. Therefore, participants must depart from conventional approaches and develop novel model architectures and algorithms. Concurrently, improving and optimizing traditional models remains critical. Through in-depth analysis and innovative modifications, existing models can better adapt to emerging problems and evolving data characteristics, thereby enhancing their performance and application value.

2.3.3 Practical application

Competition topics are increasingly emphasizing close integration with real-world problems, requiring participants to apply mathematical modeling to address practical challenges. The outcomes of these competitions are being applied to real production and daily life, effectively serving real-world scenarios. For instance, in urban planning, mathematical modeling can optimize traffic flow and rationally allocate public facilities. In the medical field, it can predict disease transmission patterns and evaluate treatment efficacy. This problem-oriented approach in competition design brings mathematical modeling contests closer to societal needs, fostering the development of high-quality talents capable of applying mathematical knowledge to practical problem-solving. Consequently, it promotes the widespread adoption and innovative evolution of mathematical modeling technologies across diverse fields.

3 REFINEMENT OF MATHEMATICAL MODELING METHODOLOGY AND ANALYSIS OF BASIC PROCESS

3.1 Data Processing

In the entire mathematical modeling process, data processing is the most fundamental step. Its quality directly affects the accuracy and reliability of subsequent modeling and lays the foundation for the entire workflow. Given the massive data encountered in practical problems, data cleaning is the first critical task. This process aims to remove noise, correct errors, and impute missing values to ensure data accuracy and integrity. For example, when processing geographic data for soil surveys, researchers must carefully screen for duplicate, erroneous, or incomplete entries. For datasets with missing values, comprehensive integrity checks should be performed, and the proportion of missing values must be accurately quantified. If a high proportion of values are missing, appropriate imputation methods (such as mean imputation, median imputation, or model-based prediction) should be selected based on data characteristics to maintain integrity.

Following data cleaning is exploratory data analysis, which allows researchers to intuitively observe data characteristics through visual analysis. For instance, point distribution maps reveal geographic data patterns, while scatter plot matrices help identify feature correlations. If highly linearly correlated features are detected, researchers should consider removing some to mitigate collinearity issues in subsequent modeling. Data transformation is another critical component. To align data with model assumptions, appropriate transformation methods can be applied. The Box-Cox transformation, for example, normalizes data distributions through power transformations, thereby enhancing model fitting.

Additionally, feature engineering plays a pivotal role in extracting latent information from data. Categorical features can be converted to numerical formats via label mapping, enabling model processing. New features can also be derived through feature combination—for example, merging two related features to create a composite indicator like "alcohol-acidity ratio"—to uncover relationships between features and target variables. Leveraging domain knowledge, researchers can identify context-specific features related to the target and integrate them with the original dataset, thereby enriching the dataset’s information content. In practical applications, such as predicting red wine quality scores, data integrity must first be verified. Statistical analysis of missing value proportions guides imputation strategies. A scatter plot matrix assesses correlations between chemical features; collinear features are removed to mitigate multicollinearity issues. Box-Cox transformations normalize data distributions, improving model fit. Label mapping converts categorical features like wine origin into numerical formats. Feature combination generates novel indicators like "alcohol-acidity ratio," uncovering stronger relationships with quality scores.

3.2 Model Construction and Selection

Model construction and selection are the core of mathematical modeling, aiming to select appropriate models based on problem characteristics and enhance model performance through model fusion. In path planning problems, the dynamic programming model, Haversine formula, and K-means clustering algorithm can be integrated. The Haversine formula accurately calculates the spherical distance between two points, providing a metric basis for path planning. The K-means clustering algorithm reduces problem complexity by grouping sampling points geographically. The dynamic programming model achieves global optimal path planning by recursively determining optimal paths within each cluster.

For prediction tasks, regression models such as Lasso, Ridge, Elastic Net, and Gradient Boosting Regression (GBR) are widely applied. Researchers select the optimal model by comparing performance across training and test sets. Model fusion, such as building stacked ensemble models, is an effective strategy for complex problems. This involves using predictions from multiple base models as new features for training a higher-level model.

In soil survey path planning, integrating the dynamic programming model with the Haversine formula and K-means clustering algorithm yields effective solutions. The Haversine formula converts geographic coordinates into real-world distances, enabling accurate distance measurements. K-means clustering reduces complexity by grouping sampling points. The dynamic programming model recursively optimizes paths within clusters to achieve global optimality. For red wine quality score prediction, diverse regression models are employed. Lasso regression incorporates L1 regularization to perform feature selection and simplify model structures, enhancing interpretability. Ridge regression applies L2 regularization to address multicollinearity and improve stability. Elastic Net combines L1 and L2 regularization to balance feature selection and model stability. Gradient Boosting Regression iteratively trains weak learners to gradually improve prediction accuracy. By evaluating performance across datasets, researchers select the optimal model for prediction.

3.3 Result Optimization and Verification

Result optimization and validation are the final critical steps in mathematical modeling, aimed at ensuring the accuracy and reliability of model outcomes. Evaluating model performance using multiple metrics provides a more comprehensive and precise reflection of its strengths. For prediction tasks, metrics such as mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) are commonly used to quantify prediction accuracy. MSE measures the average squared difference between predicted and actual values. RMSE, as the square root of MSE, is more sensitive to errors and intuitively reflects the magnitude of discrepancies between predictions and observations. MAE, unaffected by error squaring, captures the average absolute deviation of predictions. In path planning problems, working time, total path length, sampling point coverage, and other indicators are used to comprehensively evaluate the advantages and disadvantages of path planning solutions.

Cross-validation is a critical method for evaluating model performance, which involves dividing the dataset into multiple subsets. In each iteration, one subset serves as the test set while the remaining subsets are used as training sets for multiple rounds of training and testing. The average of the test results is then adopted as the model's evaluation metric. For instance, the widely used 10-fold cross-validation partitions the dataset into 10 equal-sized subsets. Each subset is sequentially employed as the test set across 10 iterations of model training and testing. This approach enables a comprehensive assessment of the model's performance on diverse data splits, effectively mitigating biases caused by arbitrary dataset segmentation. Additionally, model results often require adjustment based on specific problem needs. For example, inverse transformations may be applied to prediction results to restore them to meaningful values. By comparing the distributions of predicted and actual data, researchers can refine model parameters or improve the model structure, thereby correcting prediction deviations and enhancing accuracy.

In the prediction of urban housing prices, a stacking ensemble model is constructed. Prediction results from multiple base models (e.g., Lasso regression, Ridge regression) are used as new features. These features are then input into a higher-level model (such as logistic regression or a neural network) for retraining, harnessing the strengths of each base model and mitigating single-model limitations. For instance, Lasso regression excells in feature selection, while Ridge regression stabilizes multicollinearity issues. By integrating their predictions, more accurate results can be achieved. In soil survey path planning, multiple algorithms optimize route design. K-means clustering groups sampling points, after which dynamic programming plans paths within each cluster. Finally, cluster-specific paths are integrated to achieve a globally optimal solution. This approach effectively reduces problem complexity and improves path planning efficiency and accuracy. For red wine quality and urban housing price predictions, evaluation metrics include mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE). By comparing these metrics across test sets, the most accurate model is selected. In soil survey path planning, working time serves as a key performance metric. Assuming uniform traffic speed (ignoring topography, weather, and vehicle factors), physics-based kinematic equations calculate daily task completion time. Additionally, total path length, sampling coverage, and other indicators comprehensively evaluate different route designs.

The cross-validation method is employed in multiple projects to ensure model stability and generalization. This technique involves dividing the dataset into multiple subsets, where one subset serves as the test set and the remaining subsets act as training sets in each iteration. After multiple rounds of training and testing, the average of the test results is adopted as the evaluation metric. For example, 10-fold cross-validation partitions the dataset into 10 equal-sized subsets, with each subset sequentially serving as the test set. The model is trained and tested 10 times, enabling a comprehensive assessment of its performance across diverse data splits. This approach mitigates biases caused by arbitrary dataset division.

Model results require iterative verification and adjustment. In urban housing price prediction, if the output undergoes a transformation, inverse transformation must be applied to revert the values to actual housing prices. By comparing the distributions of predicted and real-world housing price data, researchers can refine model parameters or improve the model structure. This process corrects prediction deviations and enhances accuracy.

4 ANALYSIS OF THE REASONS FOR THE UNAWARDED WORKS-URBAN FLEXIBILITY AND SUSTAINABLE DEVELOPMENT

4.1 Data Aspects

Data comprehensiveness and accuracy are critical for evaluating urban resilience and sustainability. However, many submissions exhibit significant flaws in data collection. Some participants solely rely on provided topic information, lacking the initiative to expand data sources. As a complex system influenced by multiple factors, urban resilience cannot be fully captured using only given data. For example, assessing a city's resilience to extreme weather requires not only existing infrastructure data but also historical records of extreme weather frequency, scope, and losses. These data are vital for evaluating resilience and identifying sustainability challenges, highlighting the topic's importance. Single-channel data collection often limits analysis outcomes, hindering accurate representation of urban realities. Additionally, insufficient data timeliness and spatial resolution lead to results that fail to reflect dynamic changes and regional disparities.

4.2 Model Aspects

In constructing multi-index evaluation systems, many studies rely excessively on subjective judgment for indicator weight assignment, lacking scientific methodologies. Urban resilience and sustainability assessments involve multiple indicators, where reasonable weight allocation is critical for accuracy. Weight assignment directly influences evaluation reliability: arbitrary weights may either overlook or overemphasize key factors, distorting urban resilience representations. For instance, prioritizing economic metrics while neglecting social/environmental dimensions can lead to biased outcomes. Scientific approaches such as Analytic Hierarchy Process (AHP) and Principal Component Analysis (PCA) should be adopted to objectively determine weights. These methods quantify indicator importance through data-driven statistical analysis, mitigating subjective interference and enhancing evaluation credibility.

Selected models often fail to account for urban development's complexity and dynamics, leading to limited adaptability in real-world applications. Cities are complex, evolving systems influenced by multiple interacting factors. Neglecting nonlinear relationships and feedback mechanisms between these factors can oversimplify model assumptions. For example, using linear models to evaluate the impact of urban economic potential and social service completeness on sustainability may fail to capture complex interdependencies. This results in significant deviations between predicted/evaluated outcomes and real-world conditions. Additionally, delayed model updates to reflect evolving urban challenges reduce effectiveness. Inadequate adaptation prevents models from providing accurate predictions or actionable decision support, undermining the practicality and guiding value of evaluations.

4.3 Thesis Writing

The paper exhibits significant structural flaws, including an unclear logical framework and unnatural transitions between chapters and paragraphs. Such disorganization impedes readers from quickly grasping the core arguments and overarching research ideas in studies covering urban housing price forecasting, service level analysis, resilience and sustainability assessments, and future development scenarios. For instance, abruptly inserting a discussion on urban service indicators while introducing a housing price prediction model disrupts the narrative flow, making it challenging for readers to follow the paper's focus. This fragmentation undermines comprehension of both the housing price analysis and the broader research objectives. A well-structured paper should organize content logically, gradually expanding analysis and discussion to guide readers through the author's reasoning.

The description of the model solution process and results analysis in this paper is insufficiently detailed, failing to demonstrate the study's depth and breadth. In the model implementation section, there is a lack of detailed documentation for critical elements such as algorithm steps, parametric configurations, challenges encountered during implementation, and corresponding solutions. This omission hinders readers from replicating the research process. In the results analysis section, data and conclusions are merely listed, without in-depth exploration of the underlying mechanisms and practical implications. This oversight prevents readers from appreciating the research's value for urban planning and development. For instance, analyzing urban resilience results without contextualizing them within specific urban characteristics or policy backgrounds undermines the ability to provide actionable recommendations for city managers.

The paper fails to effectively highlight its research innovations, nor does it clearly demonstrate unique contributions and value relative to existing literature. In urban studies, numerous assessments and planning frameworks have been developed. Without explicit elaboration of methodological, perspectival, or conclusion-driven innovations, papers risk being overlooked by reviewers. For instance, even if novel indicators or indicator combinations are introduced in a multi-index evaluation system, their roles in enhancing assessment accuracy and effectiveness are not clearly articulated. Innovation constitutes the paper's core strength, which should be underscored through novel methodologies, unique perspectives, or original conclusions. This clarity enables reviewers to recognize the research's distinct value and contributions.

5 IMPROVEMENT MEASURES AND FUTURE PROSPECTS

5.1 Improvement Measures

During data collection, researchers should leverage provided data while actively expanding additional relevant data sources. A comprehensive approach covering diverse information channels is essential. For instance, assessing urban resilience and sustainability requires collecting not only infrastructure data but also historical records of extreme weather frequency, affected areas, and losses. Resident satisfaction survey data should also be incorporated to reflect urban realities from multiple dimensions. In data processing, rigorous quality control is critical. Researchers must promptly identify and address missing or abnormal values to ensure data accuracy and completeness. Data cleaning techniques should be applied to correct or eliminate duplicate, erroneous, or incomplete records, laying a solid foundation for subsequent analysis.

When constructing a multi-index evaluation system, reducing subjective interference in indicator weight determination is crucial to enhance evaluation scientificity and reliability. Multivariate statistical methods such as Analytic Hierarchy Process (AHP) and Principal Component Analysis (PCA) can be employed to objectively assign weights. During model construction, problem complexity and dynamic nature should be fully considered, with rational selection of model architecture and parameter configurations. This ensures enhanced adaptability and predictive capability. For complex urban development challenges, nonlinear or dynamic models are recommended to accurately capture complex relationships between factors. These models enable realistic simulation and prediction of urban development trends, providing a robust foundation for urban planning and policy-making.

When writing a paper, it is essential to ensure a clear, logical, and coherent structure, with natural transitions between chapters and paragraphs. Content organization should follow the logical sequence of problem formulation, data processing, model construction, results analysis, and conclusion, enabling reviewers to quickly grasp core arguments and the overarching research framework. In describing the model-solving process, detailed documentation of algorithm steps, parameter settings, and challenges encountered during implementation (along with corresponding solutions) is critical to ensure reproducibility. In the results analysis section, in-depth exploration of data-driven insights and their practical implications should be provided, linking research outcomes to real-world urban planning and development contexts. Additionally, the paper must explicitly articulate its innovations, comparing them to existing literature. Unique contributions in methodology, perspective, or conclusions should be clearly demonstrated to strengthen the paper’s academic rigor and impact.

5.2 Future Outlook

Mathematical modeling plays an irreplaceable role in cultivating students’ innovative thinking, practical problem-solving skills, team spirit, and positive outcomes. As competition scales expand and problem complexity increases, future mathematical modeling competitions will emphasize innovation, model practicality, and result accuracy. Competitors must continuously learn and master advanced modeling methods and technologies to enhance their comprehensive competencies, aligning with competition development trends. Meanwhile, competition organizers should optimize rules and evaluation criteria, fostering a fairer, more equitable, and transparent competition environment. This will drive the mathematical modeling contest toward higher-quality development.

6 CONCLUSION

Through an in-depth analysis of three contest entries, this paper summarizes practical mathematical modeling methods and valuable insights. In the data processing stage, data cleaning, exploratory analysis, data transformation, and feature engineering are critical for unlocking data value and enhancing model performance. Model construction and selection should align closely with problem characteristics, adopting either single models or model fusion strategies to ensure accuracy and applicability. Results validation leverages multi-index evaluation and cross-validation to strengthen result reliability and validity.

Reflection on non-winning submissions highlights common challenges in data processing, model construction, and paper composition. The improvement strategies proposed here provide clear guidance for future participants to enhance their work, mitigating recurrence of similar issues. These measures promote the overall competency of contestants in mathematical modeling competitions and drive the robust development of modeling activities.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Applied mathematical modeling: a multidisciplinary approach. CRC Press, 1999.
[2] Liu J, Wang S, Xu H, et al. Federated learning with experience-driven model migration in heterogeneous edge networks. IEEE/ACM Transactions on Networking, 2024.
[3] Liang Y, Wang L. Applying genetic algorithm and ant colony optimization algorithm into marine investigation path planning model. Soft Computing, 2020, 24: 8199-8210.
[4] Moreno S, Pereira J, Yushimito W. A hybrid K-means and integer programming method for commercial territory design: A case study in meat distribution. Annals of Operations Research, 2020, 286: 87-117.
[5] Thirumani A, David D. Enhancing the accuracy of forecasting the upper respiratory infections due to particulate air pollution using lasso regression in comparison with gradient boosting regression//AIP Conference Proceedings. AIP Publishing, 2024, 3193(1).
[6] Knoll F, Murrell T, Sriram A, et al. Advancing machine learning for MR image reconstruction with an open competition: Overview of the 2019 fastMRI challenge. Magnetic resonance in medicine, 2020, 84(6): 3054-3070.
[7] Yadav R, Sreedevi I, Gupta D. Bio-inspired hybrid optimization algorithms for energy efficient wireless sensor networks: a comprehensive review. Electronics, 2022, 11(10): 1545.
[8] Xu G, Li W, Liu J. A social emotion classification approach using multi-model fusion. Future Generation Computer Systems, 2020, 102: 347-356.

[9] Büyüközkan G, Ilıcak Ö, Feyzioğlu O. A review of urban resilience literature. Sustainable Cities and Society, 2022, 77: 103579.
[10] Oudenampsen J, Van De Pol M, Blijlevens N, et al. Interdisciplinary education affects student learning: a focus group study. BMC medical education, 2023, 23(1): 169.