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Research paper

Development of Models, Methods, and Algorithms for An Auto-Mated Rating System in Professional Education

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Abstract

This study aims to develop tools for constructing an automated rating system to objectively assess vocational education quality in the Kyrgyz Republic. It led to the creation of a conceptual model for an automated rating system, identification of key evaluation criteria, and development of a framework for component interaction. Methods for automated data collection were developed, including database integration via a software interface, electronic questionnaires, and web scraping. Processes for data cleaning, normalisation, and weighting were established to prepare information for analysis. Algorithms were implemented to integrate quantitative and qualitative indicators in assessing educational institutions' performance. The conceptual model reflects the specific features of vocational education and the regional environment. Key methods include data cleaning, normalisation, assigning weights to criteria, and analysing institutional effectiveness. Algorithms for automated data collection via software interfaces and web scraping ensure access to up-to-date information from educational portals. Prohierarchycessing algorithms, such as data cleaning and normalisation, ensure high-quality data preparation. Quality assessment algorithms, based on hierar-chy analysis and efficiency evaluation methods, objectively incorporate qualitative and quantitative indicators like teaching quality, student performance, scientific publications, and material resources.

***Keywords**: Assessment Efficiency; Data Analysis; Indicator Normalisation; Information Processing; Quality of Education.*

1. Introduction

Vocational education is a critical component of the education system, aimed at training skilled personnel for various industries. The quality of education is evaluated through a range of indicators, including the knowledge and skills of graduates, the effectiveness of educational programmes, alignment with current labour market demands, and the availability of material and technical resources. Objective analysis of vocational education quality employs various approaches, such as evaluating teaching effectiveness, student academic achievements, the level of scientific activity, and the collaboration between educational institutions and employers. In the context of rapid technological progress and global transformations in education, there is an increasing need to enhance assessment mechanisms to ensure objectivity and transparency in the development of institutional ratings. This issue is particularly relevant in developing countries like Kyrgyzstan, where there is an urgent need to improve education quality to address contemporary social and economic challenges.

Assessing the quality of vocational education is a challenging task due to the absence of unified approaches for determining its effectiveness, particularly within multi-level educational systems. The lack of transparent and objective methods for forming institutional ratings complicates the evaluation of educational activities, leading to risks such as uneven resource distribution and insufficient motivation to enhance education quality. Without open and standardised evaluation processes, educational institutions lack dependable standards for evaluating their performance (Vishnikina et al., 2024; Kozhevnikova & Kozhevnykov, 2024). This uncertainty establishes a disincentive framework in which institutions fail to recognise definitive criteria or competitive pressures to improve educational quality. In the absence of data-driven information about comparable performance, neither internal stakeholders (such as teachers and administrators) nor external stakeholders (including policymakers and employers) can adequately recognise advancements or rectify deficiencies. Consequently, the motivation for participating in systematic quality enhancement diminishes. In this situation, formative assessment lowers its institutional value since it does not contribute to a comprehensive, comparable evaluation system that may encourage strategic improvements. Consequently, the establishment of an automated, objective grading system is not just a technological enhancement but also an essential structural pre-requisite for augmenting incentive and institutional responsibility. In Kyrgyzstan, these issues are further compounded by the limited digitalisation of educational processes and the difficulty of integrating existing data from diverse sources to draw objective conclusions. There is an urgent need for a comprehensive approach to automate the collection, processing, and analysis of information, ensuring the accuracy and adaptability of assessment systems to the specific characteristics of regional educational institutions.

For example, a study by Karazakova & Sheranova (2023) highlighted the importance of introducing internal rating systems in higher educational institutions in Kyrgyzstan. The authors emphasised that a university's ranking significantly impacts the quality of education and contributes to national development. Similarly, Zhou & Asipova (2024) analysed higher education in the Kyrgyz Republic, focusing on its harmonisation with international standards. They noted key advancements such as the introduction of a credit-modular system, enhanced collaboration with employers, and a growing number of exchange programmes for students and teachers. Furthermore, Kyshtoobaeva (2023) underscored the role of computer technologies in the educational process. The author observed that modern information and communication technologies facilitate rapid knowledge acquisition and adaptation to societal changes, meeting the educational demands of an information-driven society.

The study conducted by Ananth et al. (2022) presented mathematical models for intelligent career guidance systems, highlighting the importance of automating these models to enhance decision-making efficiency and incorporate fuzzy knowledge into vocational education. In another study, Pi et al. (2024) found that professional identity plays a critical role in the development of teachers, while social support helps mitigate the negative effects of low self-esteem on their professional growth. These findings can inform the development of effective strategies for assessing and improving vocational education systems. The research of Wei et al. (2024) examined the challenges of integrating innovation and entrepreneurship education into vocational education, underlining its importance for cultivating students' professional skills. The authors proposed practical methods for reforming educational programmes in higher vocational colleges to better align with these objectives. Additionally, the study by Zhang & Hu (2024) highlighted the transformative potential of natural language processing (NLP) technologies in education. Applications such as automated grammar checking, text scoring, and interactive dialogue systems were shown to significantly enhance language skills development. The results demonstrate the considerable potential of NLP technologies in education.

On the other hand, Wang (2024) proposed an evaluation system for integrating innovation and entrepreneurship into vocational education, based on the Kirkpatrick model. By employing Delphi methods and the Analytic Hierarchy Process (AHP), he developed an index system with four levels: reaction, learning, behaviour, and achievement. Zhang & Meng (2024) introduced a professional certification system for higher vocational education institutions. They proposed a tool to support the analysis of achievements, manage training programmes, courses, and graduates, thereby contributing to the enhancement of education quality and vocational training. Finally, the study by Villegas (2024) explored the impact of evaluation systems on teachers' professional growth in education. The author highlighted that transparency, fairness, and the practical utility of evaluations are key factors that significantly influence teacher development, fostering a culture of continuous improvement.

While these studies address various aspects of educational systems, they do not adequately tackle the challenge of creating an integrated, automated rating system capable of providing an objective assessment of vocational education quality. This article investigates the development of a comprehensive model, methods, and algorithms for an automated system designed to process data effectively and integrate both internal and external assessment criteria. The objectives of this study include analysing contemporary approaches to assessing the quality of vocational education, developing a conceptual model for an automated rating system, and defining the methods and algorithms required for data collection and processing.

2. Materials and methods

At the first stage of the study, the key criteria for inclusion in the model were identified, focusing on both qualitative and quantitative indicators of the effectiveness of educational institutions. A conceptual diagram was developed to illustrate the interaction of components within the automated rating system. This system comprises four main blocks: input, processing, analysis, and results. Separate logical-structural models were created for each block, detailing the functional relationships between their respective elements. The input data block diagram defines the structure of the parameters collected from educational portals and databases. The data processing block diagram outlines the processes of data cleaning, normalisation, and preliminary clustering. The analytical module is responsible for generating the rating based on predefined criteria. The results block produces reports in various formats, designed for use by relevant stakeholders.

In the subsequent stage, methods were developed to enable the functionality of the rating system. Data collection employed methods such as automatic import via Application Programming Interfaces (APIs), electronic questionnaires, document import and export, and web scraping. The data processing methods included cleaning erroneous values, normalising indicators, analysing missing values, and preliminary clustering. Weighting criteria were assigned to each parameter influencing the rating's formation. The evaluation methods incorporated a multi-criteria approach, including the AHP method, statistical analysis, weighted average indicators, and the Data Envelopment Analysis (DEA) method. To demonstrate the practical application of these methods, examples of their use within relevant subsystems of the rating model were provided, using educational institutions in the Kyrgyz Republic as case studies.

The final stage of the research centred on developing and implementing algorithms essential for the operation of the main methods and processes of the automated rating system. All algorithms were demonstrated using the C# programming language, ensuring flexibility, scalability, and ease of use. An algorithm was specifically developed to integrate the system with national databases via APIs, enabling queries, retrieval, and processing of information on key parameters of educational institutions. For websites lacking API access, a web scraping algorithm was designed to automate data collection from educational portals by parsing the HyperText Markup Language (HTML) code.

Special emphasis was placed on data cleaning and normalisation algorithms, which addressed missing values, duplicates, and anomalies. These algorithms also standardised variables to a single scale, facilitating accurate analysis. For the multi-criteria assessment of educational institutions, AHP algorithms were implemented to assign weights to criteria and determine their relative importance. Additionally, DEA algorithms were employed to evaluate institutional efficiency, optimising resource usage and calculating efficiency coefficients. The developed algorithms, methods, and models aim to create an integrated and adaptive system that ensures a transparent and objective evaluation of vocational education quality in Kyrgyzstan. This system is designed to address modern educational challenges and meet the specific needs of the region.

3. Results

3.1 Conceptual design of a model for automating rating assessment in vocational education

Modelling is a critical tool in the development of automated systems that address complex analysis and evaluation tasks. In the context of vocational education, automating the rating evaluation process is an essential step towards ensuring the objectivity, transparency, and adaptability of evaluation systems. A conceptual model serves as the foundation for developing software that performs tasks such as collecting, processing, and analysing data related to the quality of educational services.

Automation of rating evaluation in vocational education must consider the specific characteristics of this educational domain. Vocational education focuses on training specialists with practical skills, necessitating the integration of diverse assessment criteria (Derevianko & Shovkaliuk, 2023; Onyshchenko & Serdiuk, 2025). These include the quality of the educational process, the professional competence of teachers, the alignment of educational programmes with labour market demands, and the availability of a modern material and technical base (Tytarenko, 2023).

The main criteria that should be incorporated into the model of an automated rating system are as follows:

- Criterion “Conditions for Quality Education” – 27 indicators.
- Criterion “Employability of Graduates by Employers” – 4 indicators.
- Criterion “Level of Research Activity” – 17 indicators.
- Criterion “University Brand” – 4 indicators.

The model of an automated rating system for vocational education can be structured around the interaction of three key components such as input data, main system functions (data processing and analysis), as well as output data (results) (Fig. 1). These components collectively enable the collection, processing, and presentation of data in the form of a comprehensive final rating.

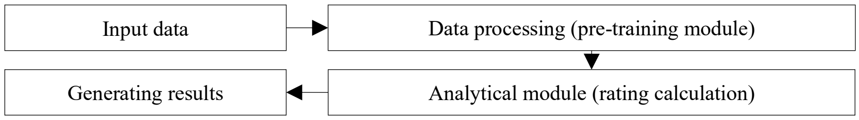

Fig. 1: Conceptual diagram of the interaction of components of the automated rating system for vocational education

Source: created by the authors.

The logical-structural model of the automated rating system for vocational education outlines the sequence of operations and relationships between system components, from data entry to the generation of final results. This model is designed to ensure the efficiency, accuracy, and transparency of the assessment process. Initially, the user – whether an administrator, analyst, or representative of an educational institution – enters the required information using established formats (e.g., via a web interface). Data is then automatically imported from relevant databases or documents. This is followed by a validation process to ensure the format’s compliance, data integrity, and completeness, as well as to detect and address errors or duplicate records.

Next, the significance of various indicators is weighted, allowing the system to account for the impact of each parameter on the overall rating. Subsequently, data normalisation is conducted to standardise the format, facilitating efficient processing and analysis. The system then applies algorithms to calculate rating indicators, leveraging structured and normalised data to produce objective results. The output is an aggregated result, such as institutional ratings or an analysis of the strengths and weaknesses of each educational institution. The final stage involves the generation of reports, which are presented in user-friendly formats, such as tables, graphs, or diagrams. These reports simplify the interpretation of results and provide actionable recommendations based on the analysed data, aiding in informed decision-making.

To ensure maximum objectivity and efficiency in assessing the quality of educational services, a detailed model must encompass all major stages of the system: from collecting initial data to producing final ratings and recommendations. This model should address the specific characteristics of vocational education, integrating information from various sources for comprehensive processing. The developed structure will include the following key components: input data module, processing module, analytical module, and result generation module. The interconnection of these components ensures consistency and transparency in the system’s operation.

The main advantage of the proposed automated grading system is its modular design, allowing for adaptation to many educational situations outside of vocational institutions in Kyrgyzstan. Each core module, data intake, processing, analysis, and output, can be individually adjusted to meet the distinct needs of national or institutional stakeholders. In higher education systems prioritising research output, the weighting scheme may highlight publication metrics and academic cooperation, but in practice-oriented institutions, factors such as graduate employment and industrial collaborations may be prioritised. The system facilitates the integration of many data sources, such as institutional databases, government registries, certification organisations, and labour market analytics, which enable context-sensitive assessment. This modularity guarantees that the system is both scalable and configurable, providing a flexible framework that can adapt to varying educational goals, legal requirements, and infrastructure capabilities across different areas and nations.

Input data is gathered from a variety of sources, including educational institution databases, labour market statistics, and external peer reviews. This data encompasses information on students, faculty, educational programmes, infrastructure, and external factors (Fig. 2).

Input data			
Students:			
Academic achievements	Ratings	Portfolio	Participation in projects
Teachers:			
Qualification	Academic degrees	Publications	Participation in seminars
Educational programmes:			
Compliance with standards	Accreditation	Topicality	
Infrastructure:			
Laboratories condition	Access to information resources	Libraries	
Labor market:			
Graduate employment data	Employers' reviews		
External sources:			
National standards	Regulatory requirements		

Fig. 2: Diagram of the input data block of the automated rating system model

Source: created by the authors.

Data processing involves formatting, cleaning, and normalising information to ensure consistency. It also includes data collection, validation, and filtering to maintain accuracy and reliability (Fig. 3).

Data processing (pre-training module)		
Data collection:		
Automatic import from database	Manual input via user interface	
Data verification:		
Formatting	Error detection	Removing duplications
Normalisation:		
Unification of formats	Scaling metrics	
Filtration:		
Selection of relevant data	Removing outdated or incorrect information	

Fig. 3: Diagram of the data processing block of the automated rating system model

Source: created by the authors.

In addition, the analytical module employs algorithms to calculate rating indicators by applying weighting factors to various criteria. This module also handles data aggregation (Fig. 4). The analytical module uses several algorithms to compute rating indicators, using multi-criteria decision-making methodologies such as the AHP and DEA. These algorithms provide weighting variables to assessment criteria, such as graduate employability, research production, and educational infrastructure, according to their relative significance, facilitating a systematic and objective integration of many qualitative and quantitative indicators.

The results generation module produces easy-to-interpret outputs, such as rating tables, graphs, and charts. It also provides recommendations for improving educational services (Fig. 5). Thus, the proposed model encompasses all stages of the operation of an automated rating system for vocational education.

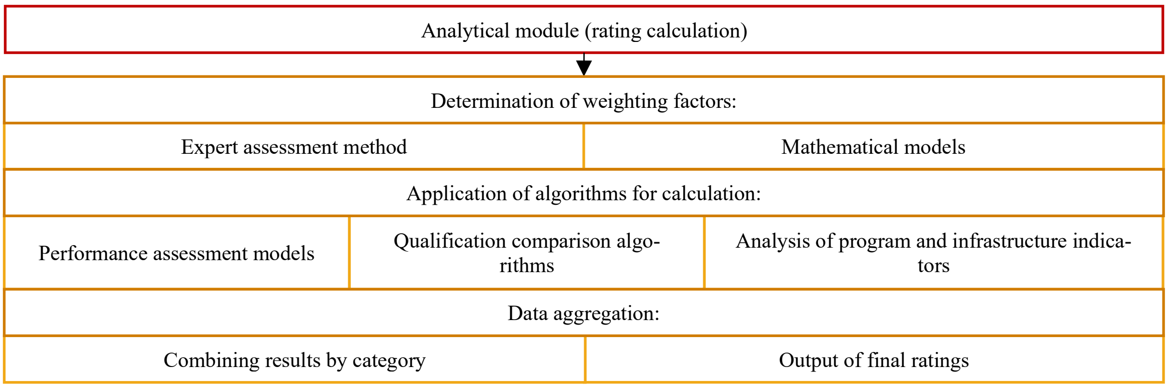

Fig. 4: Diagram of the analytical module of the automated rating system model

Source: created by the authors.

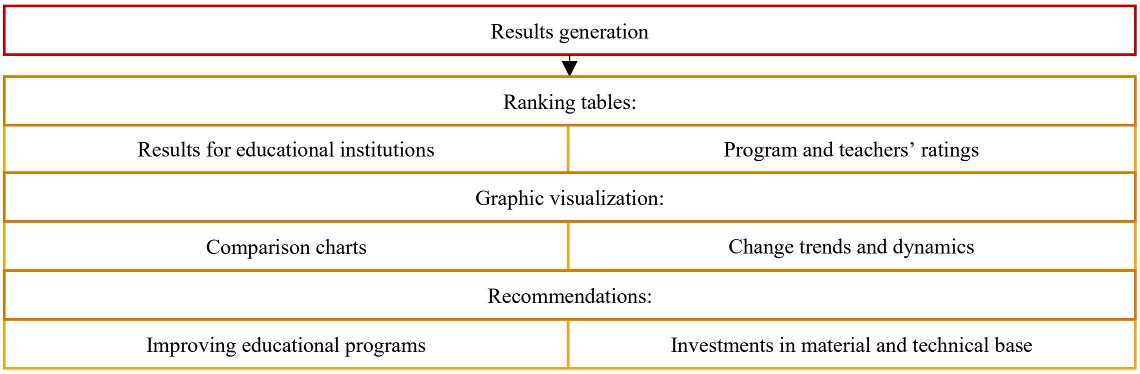

Fig. 5: Diagram of the results generation block of the automated rating system model

Source: created by the authors.

Overall, this model offers a systematic approach to analysing the quality of vocational education. It enhances the transparency and objectivity of the assessment process, enabling informed decision-making based on data. Such an approach has the potential to serve as an effective tool for managing the quality of educational services and improving their competitiveness.

3.2 Development of methods for implementing rating system functionality

The methods utilised in the automated rating system for vocational education determine how the system collects, analyses, and processes information to provide an objective rating of educational institutions or programmes (Table 1). These methods can be categorised into data collection methods (Table 2), data processing methods (Table 3), and evaluation methods (Table 4). The effectiveness of these methods directly influences the objectivity of the evaluation results, simplifies the tasks for system users, ensures adaptability to evolving conditions in the vocational education sector, and supports management decisions based on accurate and reliable data.

Table 1: Methods of automated rating system for vocational education

Method category	Methods
Data collection methods	Automatic import from database Integration via API Electronic questionnaire Export/import of documents Web scraping
Data processing methods	Data cleaning (removal of errors, duplications, gaps) Data normalization Missing value analysis Pre-clustering Weighting criteria
Evaluation methods	AHP method Expert assessment method Statistical analysis Weighted average method DEA method

Source: created by the authors.

Automatic import from a database involves establishing a direct connection to internal or external databases using standardised information exchange protocols, such as Structured Query Language (SQL) or Representational State Transfer (REST) API. This process automates the retrieval of data from various sources, including internal university information systems and government registries. For Kyrgyzstan, this may involve retrieving data from systems that manage student information, assessments, teacher records, and programme accreditation. The automation of data collection eliminates the need for manual entry, significantly reducing the likelihood of errors and increasing the speed and efficiency of data acquisition (Bisenovna et al., 2024; Uludag, 2023). A critical component of this process is the periodic updating of data, ensuring its relevance and accuracy for the assessment process.

Integration via API enables automated assessment systems to seamlessly connect to external data sources for efficient information exchange (Trofymchuk et al., 2019; Bezshyyko et al., 2008). For example, this could include connecting to government platforms, such as employment monitoring systems, to retrieve data on graduate employment. Such integration allows for automatic access to critical information about how effectively higher education institutions prepare their students for professional careers. The use of APIs facilitates rapid data retrieval, minimising the need for manual collection and enabling more precise evaluation of the effectiveness of educational programmes (Amelina & Tarasenko, 2024; Dudko, 2024).

A crucial practical factor for implementing the suggested automated grading system is the degree of network connection accessible to educational institutions, especially in rural and remote regions of the Kyrgyz Republic. The system's design, which depends on automated data input via APIs, electronic surveys, and web scraping, assumes stable and dependable internet connectivity. However, infrastructure inequalities between urban and rural areas may impede comprehensive system integration. Numerous rural vocational institutions may be deficient in high-bandwidth connectivity or contemporary IT infrastructure, hence complicating the implementation of real-time data sharing, cloud-based analytics, and secure data transfer (Kerimkhulle et al., 2021; 2023). Consequently, the effective implementation of the concept necessitates simultaneous investments in digital infrastructure and perhaps the creation of offline-compatible modules with asynchronous data upload capabilities.

Electronic surveys are an essential method for collecting data from educational stakeholders, such as students and alumni (Pan & Chekal, 2024; Bendo et al., 2025). This approach enables direct feedback from current and former students regarding their experiences and acquired competencies. Graduates can be surveyed online to assess their satisfaction with educational programmes, the relevance of the knowledge gained, and its impact on their career prospects. In the Kyrgyz Republic, electronic surveys can be conducted using platforms that support the Kyrgyz language and are compatible with local technological capabilities, such as Google Forms or specialised survey systems.

The document export/import method allows data to be transferred in structured formats, such as Excel, Comma-Separated Values (CSV), or eXtensible Markup Language (XML). For instance, student exam results can be imported into a rating system for streamlined data analysis. In the Kyrgyz Republic, this method can be employed to integrate state exam results and convert them into a format suitable for further analysis, eliminating the need for manual data entry.

Web scraping, on the other hand, automates the collection of information from websites containing critical data for evaluating the quality of vocational education. This may include gathering information on programme accreditations, course descriptions, announcements, and other publications from Kyrgyz universities and educational organisations. Web scraping is particularly useful for updating system databases and collecting supplementary information not readily accessible through official APIs or databases (Teremetskyi et al., 2024; Varanitskyi et al., 2024).

Table 2: Examples of using automated rating system data collection methods

Methods	Examples
Automatic import from database	Reading data about students and teachers from the Moodle learning system used in universities in Kyrgyzstan
Integration via API	Connecting to the API of the state employment monitoring system to obtain data on graduate employment in Kyrgyz Republic
Electronic questionnaire	Online survey of graduates on the level of acquired competencies, conducted through platforms that support Kyrgyz language
Export/import of documents	Import of data on student exam results from the Electronic Journal system in Excel format
Web scraping	Collection of information about study programs and their accreditations from the official websites of universities in Kyrgyzstan to update the ranking

Source: created by the authors.

Data cleaning is a critical step in information processing, focused on eliminating errors, duplications, or incomplete records (Pavlova et al., 2024; Horbatiuk & Kabak, 2022). For example, duplicate records for the same student may exist across different databases, such as those of universities, government agencies, or private organisations. This often occurs when a student registers on multiple platforms or progresses through different stages of education. Data cleaning involves identifying and resolving such issues to ensure the accuracy and reliability of rating results (Ronzhes, 2023).

Data normalisation, in turn, is the process of standardising data from different formats or measurement systems to a unified scale, enabling comparability. In the Kyrgyz Republic, this may involve converting grades from different educational institutions – such as a 4.0 scale used by some universities and a 5.0 scale used by others – into a common scale to ensure accurate performance comparisons. Normalisation simplifies data analysis and makes the results more objective.

The missing value analysis method addresses datasets with incomplete information. For example, missing student scores can be imputed using the average value for the respective group or predictive algorithms designed to estimate missing data. In Kyrgyzstan, where continuous data collection may not always be feasible, this method helps maintain data quality and prevents missing values from negatively impacting rankings.

Pre-clustering is used to group similar elements prior to further processing. In the context of vocational education, this method can classify educational programmes into distinct categories (e.g., technical, humanities, medical), facilitating the analysis of programme effectiveness within individual groups. Clustering simplifies the comparison and evaluation of universities or other educational institutions in Kyrgyzstan by organising them into manageable and comparable subsets.

Criteria weighting is a method that assigns specific weights to evaluation criteria based on their relative importance (Povidaichyk & Bartosh, 2025; Yuriychuk & Dadak, 2024). These criteria may include factors such as student success, graduate employment rates, international partnerships, infrastructure quality, and other aspects relevant to vocational education in Kyrgyzstan. By applying criteria weighting, the assessment process becomes more accurate and balanced, reflecting the diverse dimensions of institutional performance.

Table 3: Examples of using data processing methods of an automated rating system

Methods	Examples
Data cleaning	Elimination of duplicate records about one student in different databases (for example, in national and university databases)
Data normalisation	Converting scores from different scoring systems into a single scale to ensure comparability
Missing value analysis	Filling in missing student grades with the group average or using prediction methods
Pre-clustering	Clustering of educational programs by areas to simplify comparison of universities by different categories
Weighting criteria	Establishing greater weight for the criterion of “graduates’ employment” in the ranking for higher education institutions in Kyrgyzstan

Source: created by the authors.

Moreover, the AHP method facilitates the resolution of complex decision-making problems by prioritising criteria based on expert assessments. This method can be applied to evaluate the importance of factors such as the quality of educational programmes and the infrastructure of educational institutions in Kyrgyzstan, enabling the development of a more accurate model for an automated rating system.
The expert assessment method involves engaging qualified specialists or employers to evaluate qualitative aspects of educational programmes and the graduates of educational institutions. This approach considers local conditions and the specific needs of the Kyrgyz labour market, making it essential for forming objective ratings based on the insights of those who directly interact with graduates.
Statistical analysis is used to evaluate collected data through various statistical methods, including averages, variances, and correlations. For instance, this could involve calculating the average student success scores or comparing the performance efficiency of different universities in Kyrgyzstan based on statistical indicators.
The weighted average method calculates university ratings by combining weighted averages of various indicators, such as student success, graduate employment rates, and the availability of international programmes. This method provides a more accurate representation of the actual state of the education system in Kyrgyzstan.
The DEA method assesses the efficiency of various units (e.g., universities) by analysing the ratio of input to output indicators. For instance, it can be used to evaluate the efficiency of universities in Kyrgyzstan by examining metrics such as the ratio of the number of teachers to the level of student success. This approach helps identify the most efficient educational institutions.

Table 4: Examples of using automated rating system evaluation methods

Methods	Examples
AHP method	Determining the priority of the criteria “quality of educational programs” and “level of infrastructure” based on surveys of experts in the field of education in Kyrgyzstan
Expert assessment method	Involving employers in assessing the competencies of university graduates, especially regarding the level of training for specific professions
Statistical analysis	Determining the average score of students’ performances in different institutions in Kyrgyzstan to compare the overall effectiveness of educational programs
Weighted average method	Calculation of the university rating based on the weighted average of student success indicators, quality of education and employment
DEA method	Assessment of university efficiency based on the ratio of the number of teachers and the level of student success, which allows determining the optimal resources to achieve high results

Source: created by the authors.

Therefore, the use of these methods creates a powerful basis for the development of an objective and adaptive rating system that can effectively assess the quality of vocational education in Kyrgyzstan. They allow for a high level of accuracy, relevance and flexibility in the process of collecting, processing and analysing data, which is critically important for meeting modern requirements for educational systems. Using these methods, it is possible not only to improve the process of evaluating educational institutions, but also to provide support for making informed management decisions in the field of vocational education, which has a positive impact on the development of the educational environment in the country and in other regions.

3.3 Utilising algorithms to assess the quality of vocational education

Although automated systems for assessing the quality of vocational education are gaining popularity, it remains essential to develop and implement specific algorithms to perform the system’s core operations, including data collection, processing, and the generation of educational institution ratings (Kuznietsov & Kuznietsova, 2024). The primary objectives of these algorithms are to ensure the reliability, accuracy, and adaptability of the assessment process.
Data collection is the initial stage of the automated assessment process (Chavez, 2025; Matkivskyi & Taras, 2024). It involves retrieving data from a variety of sources, including databases, APIs, and the websites of educational institutions or organisations. Algorithms designed to perform API queries are particularly useful for automated data collection from national or university databases. Such APIs enable the retrieval of up-to-date information on various parameters of educational institutions, such as student enrolments, financial metrics, and institutional ratings. An example of an algorithm for retrieving data via API is as follows:

```
import requests

# API data collection feature
def fetch_data_from_api(api_url, params):
    response = requests.get(api_url, params=params)
    if response.status_code == 200:
        return response.json()
    else:
        return None

# Example of use
api_url = ‘https://api.education.kz/v1/schools’
params = {‘region’: ‘Bishkek’}
data = fetch_data_from_api(api_url, params)
print(data)
```

The result of this algorithm:

```
[
    {
        “id”: 1,
        “name”: “Bishkek High School 1”,
        “region”: “Bishkek”,
```

```
        "students": 500,
        "rating": 4.5
    },
    {
        "id": 2,
        "name": "Bishkek High School 2",
        "region": "Bishkek",
        "students": 300,
        "rating": 4.0
    }
]
```

This code demonstrates an algorithm for retrieving data from an external API using Hypertext Transfer Protocol (HTTP) requests. It includes a function that takes the Uniform Resource Locator (URL) of the API and the request parameters, sends the request, verifies the response status code, and returns the retrieved data in JavaScript Object Notation (JSON) format. The algorithm produces a structured list of objects containing information about institutions, such as their names, regions, student populations, and ratings. For websites that do not provide an API, the web scraping method is employed. This method enables the extraction of information from web pages by parsing their HTML code. An example of an algorithm for implementing the web scraping method is as follows:

```
from bs4 import BeautifulSoup
import requests

# Web scraping data collection feature
def fetch_data_from_website(url):
    response = requests.get(url)
    soup = BeautifulSoup(response.text, 'html.parser')
    # Parsing specific site elements
    data = soup.find_all('div', class_='rating')
    return data

# Example of use
url = 'https://education-portal.kg/schools'
data = fetch_data_from_website(url)
print(data)
```

The result of this algorithm:

```
['School 1: Rating 4.5', 'School 2: Rating 4.0', 'School 3: Rating 4.2']
```

This program utilises the BeautifulSoup library to collect data from a website using the web scraping method, enabling the extraction of information from the HTML code of the page. The algorithm sends an HTTP request to the specified URL, retrieves the HTML code of the response, and processes it to identify elements containing information about the ratings of educational institutions. Upon execution, the program generates a list of HTML elements containing data on the institutions' ratings, which can be further processed to extract clean text with the results.

After collecting the data, processing is required for subsequent analysis. This stage involves data cleaning, normalisation, and clustering. Data cleaning focuses on identifying and correcting errors, such as missing values, duplicates, or anomalies, within the collected dataset. Normalisation enables the adjustment of variables to a uniform range, improving comparability among various indicators. However, the selection of a normalisation method, such as min-max scaling or z-score standardisation, can affect the distribution and interpretability of the data, necessitating careful consideration of its statistical characteristics and contextual significance. An example of a data cleaning and normalisation algorithm is as follows:

```
import pandas as pd
from sklearn. preprocessing import MinMaxScaler

# Data cleaning
def clean_data(df):
    df = df.dropna()
    return df

# Data normalisation
def normalize_data(df):
    scaler = MinMaxScaler()
    df[['score', 'rating']] = scaler.fit_transform(df[['score', 'rating']])
    return df

# Example of use
data = pd.DataFrame({'score': [70, 80, 85, 90], 'rating': [3, 4, 5, 2]})
cleaned_data = clean_data(data)
normalized_data = normalize_data(cleaned_data)
print(normalized_data)
```

The result of the algorithm:

```
   score  rating
0   0.0    0.0
1   0.5    0.5
2   0.75   0.75
3   1.0    1.0
```

The program initially cleans the dataset (e.g., grades and ratings) by removing rows with missing values. It then normalises the data using a method that scales the values to a range between 0 and 1. As a result, the dataset is cleaned of empty values and transformed to a standardised scale. An essential aspect of data processing involves addressing missing values. Gap-filling methods, such as imputation by the mean value or the use of predictive algorithms to estimate missing data, can be applied to resolve this issue effectively.

Following data processing, the next step is the assessment of the quality of education, performed using various mathematical and statistical methods. The AHP method facilitates the evaluation of the importance of each criterion in the assessment process. To achieve this, specialised algorithms are employed to perform pairwise comparisons of elements and determine the weight assigned to each criterion. An example of an algorithm for implementing the AHP method is as follows:

```
from numpy import array, dot
from numpy.linalg import inv

# Algorithm for assessing the importance of criteria using the AHP method
def ahp(matrix):
    eigenvalues, eigenvectors = np.linalg.eig(matrix)
    principal_eigenvector = eigenvectors[:, np.argmax(eigenvalues)]
    weights = principal_eigenvector / np.sum(principal_eigenvector)
    return weights

# Example of use
criteria_matrix = array([1, 3, 5], [1/3, 1, 2], [1/5, 1/2, 1]])
weights = ahp(criteria_matrix)
print(weights)
```

The result of this algorithm:

```
[0.56568542 0.3236068 0.11070778]
```

This code implements the AHP method to evaluate the importance of various criteria. First, the program calculates the eigenvalues and eigenvectors of the matrix. It then identifies the principal eigenvector, which is normalised to derive the weights of the criteria. The results indicate that the first criterion holds the largest weight (approximately 56%), the second criterion has 32%, and the third criterion accounts for 11%. These weights represent the relative importance of each criterion. For instance, if the criteria used to evaluate the quality of vocational education include “teaching quality”, “student performance”, and “infrastructure”, the AHP method can identify the most significant criterion in forming the overall rating. In this example, the first criterion (e.g., “teaching quality”) has the largest weight, signifying its dominant influence on the overall rating.

The DEA method, meanwhile, is used to assess the efficiency of educational institutions. This method allows for the comparison of multiple alternatives based on several criteria. An example of algorithmic code implementing the DEA method is as follows:

```
import numpy as np
from scipy.optimize import linprog

# Algorithm for DEA method
def dea(input_data, output_data):
    num_units = input_data.shape[0]

    # Formulation of a linear problem for DEA
    c = np.ones(num_units)

    # Input data (resources) limitations
    A_ub = np.hstack([input_data, -np.ones((num_units, 1))])
    b_ub = np.zeros(num_units)

    # Output data (results) limitations
    A_eq = np.hstack([output_data, np.zeros((num_units, 1))])
    b_eq = np.ones(num_units)

    # Linear programming
    res = linprog(c, A_ub=A_ub, b_ub=b_ub, A_eq=A_eq, b_eq=b_eq, method=‘highs’)

    return res

# Example of use
input_data = np.array([[30, 40], [50, 60], [70, 80]])
```

```
output_data = np.array([[200, 300], [250, 350], [300, 400]])

# Calling on DEA to gain efficiency
efficiency = dea(input_data, output_data)
print(efficiency)
```

Algorithm code result:

```
message: The optimization terminated successfully and determined that the problem is feasible.
success: True
status: 0
fun: 1.0
x: [ 1.0, 0.0, 0.0]
nit: 4
lower: [0.0, 0.0, 0.0]
upper: [1.0, 1.0, 1.0]
residual: 0.0
```

This program implements the DEA method using linear programming for data analysis, utilising the scipy.Optimize library. It optimises the efficiency of units by comparing their outputs (results) to their input resources. Upon successful optimisation, the program outputs a message confirming that the task was solved without errors, along with the optimisation value for each unit. The results include efficiency coefficients for each unit, with the first unit receiving a coefficient of 1.0, indicating its optimal use of resources compared to others. One practical example of using algorithms to automate the evaluation process is the implementation of the weighted average method to generate an overall rating.

Thus, the algorithms discussed for data collection, processing, and evaluation form the foundation of an adaptive, efficient, and objective rating system for assessing the quality of vocational education in Kyrgyzstan and other countries. These methods enable the processing of large datasets, their adjustment for further analysis, and a high level of accuracy in generating institutional ratings. The presented algorithms exhibit flexibility and technical effectiveness in controlled conditions. Nonetheless, their deployment in various institutional settings may encounter several hurdles. A primary challenge is the variability of local technological infrastructures, which may restrict the steady functioning of algorithmic components, especially in institutions with obsolete hardware, inadequate processing capacity, or unreliable internet connectivity. Furthermore, the effective implementation of algorithms like AHP and DEA needs precise, consistent, and comprehensive input data. In practical settings, particularly within rural institutions, data deficiencies, inconsistent reporting, or mismatched system formats can impede the automatic calculation of ratings. Another challenge involves algorithm maintenance and version control since updates to institutional databases or changes in indicator definitions may need frequent recalibration to ensure output validity. To overcome these challenges, it is important to set up technical support, create flexible algorithms, and provide ongoing training at the institution to ensure the system works reliably and lasts over time.

As the system gathers and evaluates potentially sensitive data, such as academic records, institutional performance metrics, and graduate employment statistics, it is crucial to include suitable protections. While the model emphasises efficiency and impartiality, the next advancements should include data security measures, including secure access protocols, encryption, and anonymisation techniques. Such improvements will enhance user trust and ensure adherence to national and international data governance norms, ultimately bolstering the legitimacy and ethical integrity of the rating system.

4. Discussion

The results of this study are aimed at developing tools for an automated rating system that provides an objective assessment of the quality of vocational education. The proposed model integrates key indicators such as student success, teaching quality, the number of scientific publications, and the level of material support. The methods and algorithms developed enable efficient data collection, processing, and analysis, enhancing transparency and accuracy in the formation of ratings (Rexhepi et al., 2023; Maulenov et al., 2023). These findings complement the research of Tran Minh (2024), which focuses on the professional development of teachers within the framework of Education 5.0, particularly through continuous learning, personalised approaches, and mentoring. While the work emphasises enhancing pedagogical skills, the current study contributes to improving the system for assessing education quality, which in turn supports the strategic development of vocational education in addressing modern challenges. This study demonstrates methods for integrating automated tools to assess the effectiveness of vocational education, considering the impact of innovative approaches on the quality of the educational process. Similarly, the authors Soares et al. (2024) explored the prospects and challenges of professional development for teachers, highlighting the necessity of continuous learning to adapt to the evolving educational environment. Thus, the obtained results complement the findings of Soares et al. (2024), offering practical tools for evaluating educational innovations in vocational education. These tools enable the identification of strengths and weaknesses in pedagogical methods.

This study focuses on developing a model for an automated rating system to assess the quality of vocational education, incorporating both internal and external criteria to provide an objective approach to evaluation at regional and international levels. Unlike the work of Kudaibergenova & Serikkaliyeva (2024), which emphasises criteria for academic excellence within the framework of international university rankings, this study proposes a more adaptive model. The model accounts for the unique characteristics of vocational education and enables the creation of transparent ratings at various levels, particularly for local educational institutions. Additionally, this work centres on developing methods and algorithms for the automated assessment of vocational education quality, tailored to the specifics of national educational systems, particularly in Kyrgyzstan. In contrast, the study by Wang et al. (2024) explores the development of professional identity among teachers in China, examining key relationships between professional identity, work engagement, social support, and professional development agency. The present study complements the research of Wang et al. (2024), which emphasises the human potential factor and its role in enhancing education quality, by providing tools for systematic analysis and optimisation of educational processes. These tools include methods for data collection and normalisation, contributing to the development of an objective evaluation system for vocational education.

While this study focused on the automation of vocational education quality assessment, including data collection algorithms and criteria weighting, Guerra Hahn et al. (2021) explored automated assessment tools in online education, highlighting their role in scaling learning platforms. Unlike the pedagogical focus of Guerra Hahn et al. (2021), the current work examines complex indicators for analysing institutional effectiveness, thereby broadening the scope of automation to enhance transparency and objectivity. Moreover, this study addresses the automation of assessment with an emphasis on multi-criteria analysis of vocational education data. In comparison, the study by Gao et al. (2024) conducted a systematic review of automated assessment systems for text-based tasks in higher education, with a particular focus on artificial intelligence and NLP models. While Gao et al. (2024) concentrated on automating text-based assessments in teaching practice, the latter study proposes an approach for collecting, processing, and evaluating a broader range of criteria, thereby improving transparency and adaptability in vocational education.

The results of this study demonstrated the critical role of automation, particularly in the context of vocational education and the development of rating systems. In contrast, the work of Li (2023) focused on an automated assessment system for text writing, integrating teacher feedback to improve students' skills. While the study of Li (2023) concentrated on text-based tasks, the present research proposes a model and algorithms for the multi-criteria analysis of educational institutions' indicators. Both studies underscore the effectiveness of automated systems in enhancing education quality, but this work highlights the broader application of automation in assessing the quality of educational services. Additionally, this study emphasised the integration of technologies into the educational process, particularly in automating rating systems. Similarly, Yangiboev (2024) highlighted the importance of incorporating new technologies into training junior specialists, including information technologies, innovative methods, and teaching approaches. The research of Yangiboev demonstrated how such innovations improve education quality and align with modern requirements for teachers' professional competencies. These aspects are closely related to the current study, as both works propose technological solutions that enable objective assessments of education quality using algorithms and automated data analysis methods.

This study examined the role of technology in assessing the quality of vocational education, focusing on the development of adaptive methods and algorithms for automated assessment systems. This aligns with the work of Luo (2024), whose findings demonstrated the impact of technology on the professional development of teachers through the integration of the Internet and education. The work also highlighted how external factors significantly influence teachers' professional development via internal factors, emphasising the need to integrate new technologies to enhance the quality of vocational training. Y. Luo's conclusions confirm the obtained results by underscoring the importance of modern technology integration for effective quality assessment in vocational education. Furthermore, the results of this study, which highlight the automation of assessment processes and the use of algorithms to improve accuracy and efficiency, are consistent with the findings of Dimari et al. (2024). The research explored the application of artificial intelligence in automated assessment within the context of open examinations, which is becoming increasingly popular in higher education. Their study presented a system that employs machine learning algorithms and NLP to automate assessments, aiming to enhance objectivity and efficiency. The current study's results reinforce these findings, demonstrating that automation reduces human error and provides more accurate and fair evaluations. These methods can be effectively applied to assess the quality of training in vocational education, further supporting the integration of advanced technologies in the education sector.

As in this study, the research conducted by Akhatov et al. (2021) highlights the pivotal role of automated systems in enhancing the accuracy of educational quality assessments. The research stressed the importance of automating assessment processes to ensure transparency and efficiency in education. Both studies emphasise the necessity of using mathematical models to calculate ratings, enabling objective student evaluation and effective management of employment processes based on ratings. However, the latter research delves deeper into the algorithms and automation methods, which not only support student assessment but also provide flexibility in generating ratings based on various criteria. Messer et al. (2024) underscore the significance of automated assessment and feedback tools within the educational process. The researchers examined key methods for assessing programme tasks, particularly dynamic and static analysis methods. In contrast, the current study proposes a broader range of methods for automating assessment in vocational education. These include the application of mathematical models and a multi-criteria approach, offering a more precise and adaptable assessment of teaching quality.

In general, this study focuses on automating the assessment of vocational education quality through the use of algorithms for data processing and rating generation. This approach establishes conditions for objective evaluations and enhances the transparency of the educational process. By contrast, the study by Aida-zade et al. (2024) developed algorithms and software for the automated generation of class schedules within the credit-module system. Their system ensures adherence to hard constraints, such as teacher and classroom availability, while optimising soft requirements, such as the comfort of participants in the educational process. The present study offers a more comprehensive approach, focusing on the automated assessment of educational institution quality by integrating both quantitative and qualitative indicators. Furthermore, this work developed methods for the automated assessment of education quality, particularly through the use of multi-criteria algorithms such as AHP and DEA. Additionally, the study by Baral et al. (2024) demonstrated the effectiveness of using large language models for automated assessment in mathematics, ensuring accuracy and personalised learning experiences. However, the current study focuses on integration with national databases and adaptation to the specific needs of vocational education in Kyrgyzstan, thereby broadening its scope and applicability.

While this research focuses on automated assessment systems to improve the quality of education, with a particular emphasis on a rating system for vocational education in Kyrgyzstan, Rahat et al. (2024) demonstrated that purposeful learning enhances students' understanding of infrastructural equity. The current study extends the findings of the researchers by automating the processes for assessing vocational education quality, thereby increasing the objectivity and effectiveness of rating systems in education. It also aligns with the work of Gomez et al. (2022), which demonstrated how assessment and rating systems can stimulate quality improvement in educational programmes. The researchers found that participation in such systems led to higher overall quality ratings and improvements in structural components of education. In contrast, the latter study emphasises vocational education and the use of algorithms to automate assessment processes. Furthermore, the study by Aydın-Karaca & Kılınç (2024), like the present research, highlights the importance of objective assessments through well-defined criteria. The researchers developed a teacher rating scale to assess gifted students based on analytical, practical, and creative abilities. However, the current study specifically focuses on automating data collection and the rating process for vocational education.

Finally, this work focuses on a model for a rating system in vocational education, integrating multi-criteria analysis methods to create adaptive ratings. This can be compared to the work of Wei (2024), which explored the application of technology to objectively assess educational achievements. The researcher proposed a novel learning model based on data mining algorithms, analysing student behaviour and outcomes to personalise learning and optimise resource management. However, the obtained results extend this approach by concentrating on an adaptive rating system for evaluating the quality of education at the institutional level, incorporating both internal and external factors. The present research emphasises tools for an automated rating system to assess vocational education quality, employing algorithms for data analysis and multi-criteria evaluation. In contrast, Gebreyes & Abajemal (2024) focused on formative assessment practices and their impact on students' academic achievement, revealing a strong link between assessment and motivation to learn. Their study highlighted the importance of quality assessment in improving educational outcomes. In this context, the current work underscores the need for automated systems capable of conducting objective assessments and generating student ratings. This study builds on these concepts by implementing data analysis algorithms and multi-criteria evaluation methods, ensuring the transparency and adaptability of the rating system for vocational education.

Moreover, the research takes into account the specific educational environment of Kyrgyzstan and other regional characteristics, addressing unique challenges in these contexts. Unlike other studies that focus on continuous professional development for teachers, the integration of new technologies, or the assessment of academic performance, this research proposes specific automation methods. These include data collecting algorithms, criteria weighting, and multi-criteria analysis, which together form the foundation of an effective and objective automated rating system for vocational education.

5. Conclusion

During the research, a conceptual model of an automated rating system for assessing the quality of vocational education was developed, tailored to the specific challenges and characteristics of the educational environment in Kyrgyzstan. The model comprises four main functional blocks: input, processing, analytical, and output, which collectively ensure efficient data processing while maintaining system transparency and adaptability. The developed methods – such as automatic data import via API, electronic questionnaires, web scraping, and techniques for data cleaning, normalisation, and criteria weighting – facilitate the effective and objective collection and processing of information. Multi-criteria analysis algorithms, particularly the AHP and DEA methods, enable a comprehensive evaluation of both qualitative and quantitative indicators, forming the foundation for the proposed rating system. The results confirm that the proposed tools are effective for the automated assessment of vocational education quality in Kyrgyzstan. By employing advanced methods and algorithms, the study demonstrates a high level of integration between diverse data sources, providing objective information for the creation of ratings. The strengths of the study are the provision of tools for a system that can handle large amounts of data and adapt to changes in vocational education requirements. However, there are also limitations, including the limited set of assessment criteria, the difficulties in ensuring full integration with national databases due to technical or organisational issues, and the need to further adapt the algorithms to different educational contexts.

For further research, it is proposed to expand the set of assessment criteria to include new factors, such as the impact on the labour market. It is also necessary to improve the methods of data integration with various national and international databases. In addition, it is important to fully develop an automatic rating system and conduct its pilot implementation in several educational institutions to test its effectiveness in practice. The next step could be to develop methods for predicting rating changes based on historical data. It is also worth exploring the possibilities of using artificial intelligence to improve the accuracy of assessments and forecasts.

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