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Examining the Relationship Between the WTCAi System and Student Background Data in Modern Educational Assessment

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Abstract: *The study presents the latest development results of the WTCAi (When The Child Asks with AI) system, focusing on the correlations between student background data and academic performance. Students' family background, learning habits, and performance during the research were analysed using machine learning methods. The results show that the artificial intelligence-based approach can significantly improve the efficiency and personalisation of educational assessment. The study discusses the results of the developed prediction models and their practical application possibilities.*

Keywords: *pedagogical monitoring, evaluation, individual learning paths, validity, learner-centred knowledge transfer, development of monitoring and evaluation systems, WTCAi, item, generation gap, artificial intelligence, machine learning;*

Introduction

1.1. Research Background

Educational institutions are responsible for preparing children for further education and successful performance in the labour market. To fulfil this task, the educational process must meet the requirements posed by the continuously changing economic and social environment. However, traditional, conservative educational methods are becoming less effective as the world changes and new generations develop differently. Technology has become an integral part of everyday life for the so-called "touchscreen" or alpha generation. Digital devices are part of their identity and self-expression, naturally adapting to the current world and circumstances (Molnar, 2014). The online space is a natural terrain for them to establish connections and navigate the world, which also plays a significant role in their emotional development. In the online world, due to impersonality, the ease of exit, and the possibility of immediate reactions, dealing with problems and conflicts remains at a much lower coping level.

The current assessment system faces two significant problems:

- It does not adequately support individual learning paths
- The generational gap between teachers and students threatens the validity of assessment tools

Teachers' autonomy naturally extends to the assessment process, which incorporates numerous human factors that influence the outcome in various ways. The current system has a heterogeneous evaluation process that often occurs in large groups and is exclusively directed by the subject teacher. Due to a lack of resources and time, it is evident that the assessment and evaluation process cannot be learner-centred for every student and needs to support individual learning paths adequately. Research shows that applying the constructivist pedagogical approach has successfully met the above expectations. In this approach, students are no longer passive receivers and repeaters of information but take greater responsibility for their learning materials and education. Here, the teacher takes more of a coach or guide role, whose primary task is to help students independently acquire desired knowledge, competencies, and skills.

Pedagogical assessment is present at all levels of the teaching-learning process, typically in the form of written examinations. Teacher autonomy naturally extends to the assessment process, which incorporates numerous human factors. One unfortunate characteristic of the current system is that it neither adequately supports individual learning paths nor addresses the validity of measurement tools threatened by the generational gap between teachers and children.

Our research was motivated by the understanding that educational institutions' development and continuous improvement can only be realised if the pedagogical supervision and assessment system also evolves and adapts to new challenges. Therefore, the question arises: How can the pedagogical supervision and assessment system be developed to support individual learning paths and ensure the validity of measurement tools to the greatest extent possible? To answer this question, our research aims to develop an artificial intelligence-supported complex assessment system (WTCAi - When The Child Asks with AI) that suggests appropriate elements for subject teachers during monitoring and evaluation. During system development, we focused on collecting and analysing student background data, which helps us uncover deeper connections between factors influencing student performance.

The research presented now includes, as a new element, detailed background data analysis and prediction systems based on machine learning models. These systems can help teachers identify early intervention points and develop personalised support strategies. The results show that the artificial intelligence-based approach can significantly improve the efficiency and personalisation of educational assessment while helping to bridge the generational gap between teachers and students.

1.2. Overview of the WTCAi System

One of the biggest challenges in the modern educational environment is effectively applying personalised assessment methods and bridging generational differences. In developing the WTCAi (When The Child Asks with AI) system, we sought to address these challenges by integrating the latest tools of artificial intelligence and machine learning. The system's concept is based on a person-centred approach to education, where technology does not replace but supports pedagogical work.

The platform developed to increase the effectiveness of educational assessment is built on three main pillars: data-based decision-making, personalised feedback, and automated processes. The system architecture has a modular structure, enabling independent development and optimisation of components while ensuring close cooperation in complex assessment processes.

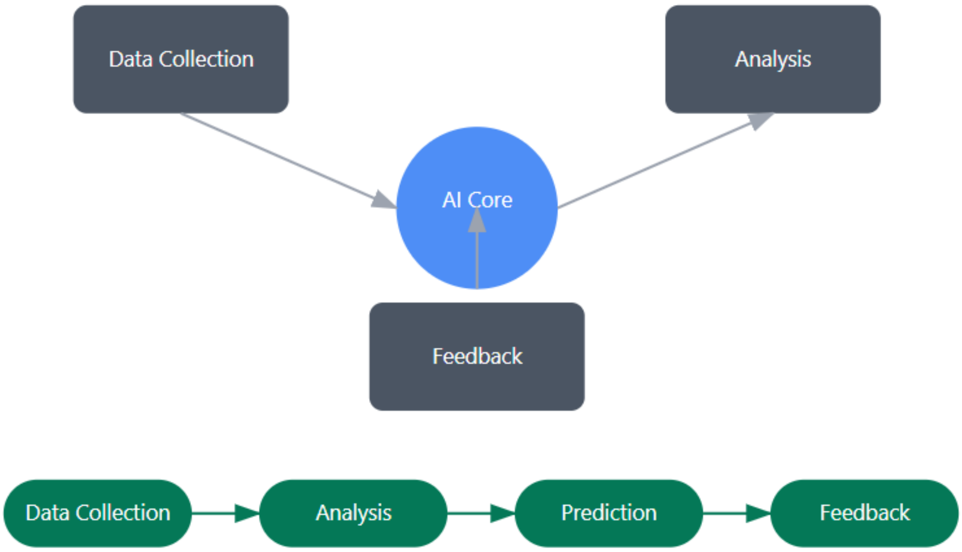

Fig. 1. Simplified data processing workflow

The subsystems are organised around the central AI engine, each serving a specific function. The data collection and management module is built on a MySQL-based database management system, which ensures efficient storage and retrieval of large amounts of structured data. The system pays special attention to data protection, fully complying with GDPR requirements. The analysis module contains several closely cooperating components. The question bank management system uses Natural Language Processing (NLP) technologies to categorise and evaluate student questions automatically. The fuzzy logic decision support system enables handling uncertainties in the assessment process, while prediction modules use machine learning algorithms to forecast student performance. The prediction system provides support in three main areas: academic performance prediction (Random Forest algorithm, 82.4% accuracy), absence prediction (Gradient Boosting-based model, ±3 hours accuracy), and tutoring needs identification (logistic regression, 78.6% accuracy). These results significantly exceed the predictive capabilities of traditional assessment methods.

Among the system's innovative functions, the adaptive question selection mechanism is critical, dynamically adjusting task difficulty levels based on the student's previous performance. The automated language processing checks the grammatical correctness of questions and performs semantic analysis, ensuring appropriate reading comprehension level matching. The security architecture implements a multi-level protection system, from role-based user permission management through encrypted data storage to regular backups. The system focuses on personal data protection and ensures GDPR-compliant data processing procedures. During development, special attention is paid to continuous system optimisation and integration of new functions. Besides increasing the accuracy of prediction models, the focus is placed on implementing new machine learning algorithms and improving user experience. Mobile application development and expanding cloud-based services open up additional possibilities in system usage. Thus, WTCAi is an assessment tool and a complex education support platform that assists teachers' work and students' development using modern technology tools. The system's flexibility enables continuous adaptation to changing educational environments and needs while maintaining the principles of personalised assessment and feedback.

2. Literature Review

2.1. Modern Approaches to Pedagogical Assessment

In modern educational systems, the role of pedagogical assessment is undergoing a fundamental transformation. The continuous monitoring and evaluation of the teaching-learning process is an essential requirement for the effective operation of the education and training system. Weimer's (2013) comprehensive research convincingly demonstrated that learner-centered educational methods significantly outperform traditional teacher-centered approaches in all examined dimensions. This paradigm shift also highlights the need to adapt assessment methods. Modern challenges in pedagogical assessment form a complex system, which is thoroughly explored in the work of Letschert (2006) and Vass (2006). Reinterpreting the role of knowledge transfer is central to this process. Instead of traditional one-way information transmission, the joint construction of knowledge emerges, where students actively participate in their learning process. This approach necessitates a fundamental transformation of the educational environment, where supporting individual needs and development paths take priority. The revaluation of the teacher's role also represents a defining change. The modern teacher participates in learning as a knowledge transmitter and supporting partner. This role change accompanies increased student responsibility, where students actively shape their learning strategies and goals.

In developing challenging learning environments, particular emphasis is placed on building usable knowledge and developing competencies, which form the basis of lifelong learning. Following Képes's (2016) work, the principles of constructivist pedagogy significantly transform assessment practice. The process of knowledge construction is complex and individual, where the learner participates not as a passive receiver but as an active builder. The increased importance of prior knowledge represents a fundamental change in assessment practice. The process of conceptual changes requires special attention, as resolving contradictions between new information and the existing knowledge system is critical to learning success.

According to Nagy's (2009) research, assessment validity is complex beyond simple measurement methodological questions. Task complexity often results in the simultaneous measurement of multilayered competencies, which presents methodological challenges. In written examinations, considering the role of reading comprehension skills is particularly important, as deficiencies in communication competencies can mask actual subject knowledge. This recognition points to the need for diversification of assessment methods.

The implementation of modern technological solutions revolutionises assessment practice. Adaptive testing systems can adjust task difficulty to students' individual ability levels while providing immediate feedback on performance. Artificial intelligence enables real-time analysis of large datasets and the application of predictive models. In competency-based assessment, technology supports complex measurement of skills and abilities and precise identification of development areas.

One of the most defining characteristics of modern assessment systems is the personalisation paradigm. Our preliminary research empirically proves that supporting individual learning paths significantly increases educational effectiveness (Karl & Molnár, 2022). Personalised assessment is realised in three closely interrelated functional dimensions. The diagnostic dimension plays a crucial role in the initial phase of the learning process. Detailed mapping of prior knowledge levels enables precise identification of individual development areas and early recognition of potential learning difficulties. This preventive approach is precious in preventing learning problems and developing appropriate intervention strategies.

Formative assessment provides continuous feedback for both teacher and student. This dynamic assessment form enables real-time tracking of development directions and timely implementation of necessary corrections. During formative assessment, special emphasis is placed on maintaining motivation, which is a key factor in long-term learning success. The summative assessment function enables a comprehensive analysis of individual development processes. Besides objectively determining competency levels, this assessment form supports the foundation of pedagogical decisions regarding progression.

The future of pedagogical assessment is shaped by three defining trends: deepening technological integration, the dominance of personalised approaches, and the advancement of competency-based assessment. In the area of technological integration, the application of AI and machine learning brings fundamental changes. Implementing real-time data analysis and automated feedback systems opens new dimensions in assessment practice. Further development of personalised approaches enables even more precise tracking and support of individual learning paths. The assessment process becomes even more adapted to individual characteristics and needs by developing differentiated assessment methods and adaptive systems. In competency-based assessment, complex measurement of skills and examination of practical applicability comes to the fore. The development of multidimensional assessment models enables a more comprehensive and deeper analysis of student performance.

2.2. Artificial Intelligence in Education

The educational implementation of artificial intelligence has undergone significant evolution in the last decade. Research by Molnár and Szűts (2022) reveals that AI-based systems prove particularly effective and virtual learning in electronic learning environments (Molnár, 2013). Students are embracing AI tools that go beyond traditional learning aids. These tools empower students by personalizing learning: AI can create custom study plans and suggest resources. Interaction with AI can enhance learning skills and help students to develop critical thinking, problem-solving, and tech literacy. (Zakota, Z., & Molnár, Gy., 2024)

In supporting adaptive learning, AI enables the precise development of individual learning pathways and the automatic generation of personalised feedback. Regarding cognitive load optimisation, AI systems can intelligently filter relevant information and select tasks that match knowledge levels. Through ensuring gradual difficulty progression, students continuously face optimal challenges. In supporting the constructivist approach, AI systems promote active knowledge building and consider individual interpretive frameworks. Technology acts as a catalyst in the knowledge construction process by developing interactive learning environments.

Educational applications of artificial intelligence are developing in three main categories, each with distinct characteristics and functionality. Intelligent Tutoring Systems (ITS) represent the first significant development direction. These systems adaptively shape the learning process, continuously monitoring student progress and performance. The system considers the student's prior knowledge, learning style, and performance in developing personalised learning paths. The real-time feedback system enables immediate correction and optimisation of the learning process.

Natural Language Processing (NLP) based systems represent the second defining development direction. These systems revolutionise language skill development and assessment. Automatic text analysis capabilities enable in-depth analysis of student products, while automated assessment mechanisms ensure objective and consistent feedback. These systems can identify and develop critical language competencies to support reading comprehension.

Predictive Analytics Systems constitute the third pillar. They are particularly valuable in predicting student performance and early identification of dropout risks. These systems apply complex algorithms to analyse student behaviour patterns and predict potential problems. They significantly contribute to increasing educational process efficiency by supporting resource optimisation.

Based on our research, AI implementation brings fundamental changes to assessment practice. Automated assessment systems based on objective criteria ensure consistent and reliable evaluation. The ability to process large amounts of data enables multi-aspect, in-depth analysis of student performance. Adaptive testing mechanisms allow The system to adapt to the student's current knowledge level dynamically. Continuous optimisation of difficulty levels ensures that every student encounters challenges appropriate to their abilities. Through precise determination of individual ability levels, the system supports differentiated instruction and assessment.

AI provides valuable support in identifying detailed statistical analyses and development trends in performance analysis. Systematic mapping of competency areas enables well-founded development of individual development proposals. Our earlier studies also highlight the significance of multi-level implementation of AI-based decision support in the educational system. At the institutional level, the system supports optimal resource allocation and effective curriculum structure development. In planning group assignments, AI considers individual student characteristics and pedagogical aspects while supporting quality assurance processes that contribute to improving educational quality (Karl et al., 2024).

At the teacher level, AI systems provide valuable support in making methodological decisions and developing differentiation strategies. The system considers student group characteristics and individual development goals in planning assessment strategies. Developing a development plan is based on synthesising empirical data and performing predictive analyses.

At the student level, AI support extends to optimising individual learning strategies and supporting career orientation decisions. When developing competency development proposals and motivational strategies, the system considers individual student characteristics and preferences.

In implementing AI-based educational systems, data security and ethical considerations are of paramount importance. Ensuring GDPR compliance is a legal obligation and a fundamental element of educational institutions' social responsibility. The complex personal data protection system includes various technical and organisational measures. Differentiated handling of access rights and transparency of data processing procedures are essential requirements. Implementing ethical considerations requires special attention in the educational applications of AI systems. Ensuring algorithm unbiasedness is critical for equality of opportunity and fairness. Implementing the principle of fair access requires systematic identification and elimination of technological and social barriers. System operation transparency and ensuring appropriate levels of human oversight are essential for increasing social acceptance of AI-based educational solutions.

The dynamics of technological development play a defining role in the evolution of AI-based educational systems. Continuous development of machine learning models enables the implementation of increasingly sophisticated analysis and prediction capabilities. Real-time data processing and analysis innovations open new perspectives in optimising educational processes. Integrating multimodal interactions and augmented reality makes the educational experience more immersive and compelling. In pedagogical innovations, the development of personalised learning environments is a priority. New methods supporting collaborative learning and innovative approaches to developing creative problem-solving enrich educational methodology. Integrating social skill development into AI-supported educational environments is significant for holistic personality development. Developing unified educational platforms in system integration represents one of the most significant challenges. Technological support for inter-institutional cooperation and implementing standardised data exchange protocols are essential to effectively operating global learning networks. Ensuring interoperability and creating harmonious cooperation between systems presents complex technological and organisational tasks.

2.3. Limitations of AI Applications in Education

Several factors may limit the educational implementation of AI—the significant resource requirements for developing and maintaining technological infrastructure present a severe challenge for educational institutions. Ensuring and continuously developing the necessary expertise is also a critical factor. Regular system updates and maintenance and ensuring compatibility between different platforms add further complexity to the process. When implementing pedagogical aspects, special attention must be paid to preserving and developing human interactions. Emotional intelligence and creativity development are areas where AI systems can only play a supporting role and cannot replace personal pedagogical work. The effectiveness—and, if it can be called so, the goodness—of teaching depends on several factors, including whether teachers know when to use digital technology and when to stick to traditional methods. This knowledge applies not only to the present but also to the entirety of the 21st century. Applications supported by artificial intelligence are primarily designed to assist or replace human work; therefore, the most critical aspect is that they embody human intelligence as profoundly as possible. Nevertheless, it is crucial to remember that no machine can fully replace or imitate a skilled, talented, and inspiring teacher. (Molnár, Gy., & Nagy, E., 2024) When implemented in appropriate forms, blended learning provides a healthy balance between electronic and human learning processes, but only if e-learning systems are designed with this balance in mind. Optimization and efficiency issues in fully electronic learning solutions require a more complex and sophisticated infrastructure, continually seeking ways to make the human-machine interface even more intimate and personal. Digital guides can also support the development of tacit knowledge. Integrating new technologies and methods into education can bring significant advantages, provided there is adequate infrastructural support, continuous professional development for teachers, and ensured student digital access.

In developing social skills, maintaining the dominance of the human component is also essential. The educational application of AI is thus an extraordinarily complex and dynamically developing field with significant potential for modernising education. However, successful implementation assumes the harmonious integration of technological, pedagogical, and ethical aspects and a commitment to continuous development and adaptation. In future developments, special attention must be paid to increasing system flexibility and adaptivity and creating an optimal balance between human and machine components.

3. Research Methodology

3.1. Data Collection and Preparation

3.1.1. Purpose and Planning of Data Collection

In developing the research methodology framework, we focused on creating a complex data collection strategy. The central objective of the study was to map the students' social background and learning environment in multiple dimensions, focusing on identifying factors influencing academic performance and systematically collecting information necessary to support individual learning paths.

Data collection aspects:

- Detailed assessment of family background
- Identification of learning habits and preferences
- Exploration of academic results and difficulties
- Understanding leisure activities and areas of interest

3.1.2. Applied Data Collection Methods

A multi-level, hybrid data collection methodology provided the empirical foundation of the research. During the structured questionnaire survey, we combined digital and traditional data collection techniques, enabling optimal reach of respondents with different preferences and technological access. Online platform data collection was supplemented with paper-based questionnaires, ensuring appropriate representativeness. Parallel application of parent and student questionnaires enabled cross-validation of data and integration of different perspectives. In operationalising variables, special attention was paid to selecting appropriate measurement levels. For demographic data, grade and age were measured on ordinal and ratio scales, while gender and residence type were recorded on nominal scales. When examining family background, family size was measured on a ratio scale. In contrast, parents' status and education were measured on ordinal scales, enabling the application of a broad spectrum of subsequent statistical analyses.

3.1.3. Data Collection Process

The data collection process was implemented in three distinct phases. In the preparation phase, emphasis was placed on carefully validating measurement tools and implementing ethical considerations. Content and formal validation of questionnaires were conducted with expert panel involvement, ensuring appropriate validity and reliability of the measurement tool. While procuring ethical permits and developing parental consent forms, special attention was paid to fully implementing data protection considerations.

In the active data collection phase, continuous quality control was performed alongside questionnaire administration. Real-time monitoring of response rates enabled early recognition and correction of potential sampling biases. Pre-defined protocols were applied to systematically handle missing data, minimising the possibility of biases resulting from data loss.

3.1.4. Data Preparation and Cleaning

We applied complex data cleaning and transformation procedures during the data preparation process. In handling missing values, we followed a multi-step strategy: based on analysis of data absence patterns, we decided on imputation methods to be applied in individual cases. We applied multivariate statistical methods to identify outliers, particularly examining Mahalanobis distance and Cook's distance. During variable transformation, we examined the fulfilment of normality conditions and the linearity of relationships between variables. We applied dummy coding for categorical variables, while we performed normalisation when necessary for continuous variables. In forming composite indicators, we applied principal component and factor analysis, ensuring optimal preservation of information content.

3.1.5. Quality Assurance

The research quality assurance system included multi-level control mechanisms. During the response consistency examination, we applied built-in control questions, enabling the identification of unreliable respondents. We developed automated algorithms for filtering data entry errors and identifying logical contradictions and outlier values. In analysing sampling biases, special attention was paid to examining representativeness, and where necessary, weighting procedures were applied to improve representativeness.

3.1.6. Ethical and Data Protection Considerations

Implementation of data protection and ethical aspects was prioritised in all phases of the research. We used an encrypted database with strictly regulated access rights for secure data storage. Ensuring voluntary participation and informed consent played a crucial role in ethical considerations. Participants were informed about research objectives, methods, and data management procedures. All parents provided written consent for the collection and processing of research materials.

3.1.7. Database Characteristics

The final database contains 45 primary variables and numerous derived indicators relating to 176 unique observations. The complexity of the data structure is increased by multi-level measurement scales of variables and the presence of longitudinal elements. Integration of structured and semi-structured data enables the application of both quantitative and qualitative analysis methods.

The database thus created provides a robust foundation for applying further statistical analyses and machine learning models, with a particular focus on implementing predictive analytical methods.

3.2. Applied Analysis Methods

3.2.1. Analysis Framework

During the research, we applied a multi-level analysis approach that included traditional statistical methods and advanced machine-learning techniques. The three main pillars of the analysis framework were:

- Preliminary statistical analysis

- Predictive modeling
- Validation and evaluation methods

3.2.2. Data Preparation Techniques (1)

```
def prepare_data(df):
    le = LabelEncoder()
    categorical_columns = ['Gyermek neme','Lakhely típusa','Szülők státusza',
                          'Édesanya végzettsége','Édesanya munkaköre']
    for col in categorical_columns:
        df[col] = le.fit_transform(df[col].astype(str))
    imputer = SimpleImputer(strategy='most_frequent')
    df = pd.DataFrame(imputer.fit_transform(df), columns=df.columns)
    return df

def predict_academic_success(df):
    y = (df['Bukások száma'] > 0).astype(int)
    features = ['Gyermek kora','Család mérete','Édesanya végzettsége',
                'Heti, otthoni tanulásra fordított órák száma']
    X = df[features]
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
    rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
    rf_model.fit(X_train, y_train)
    y_pred = rf_model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    return rf_model, accuracy, rf_model.feature_importances_

def predict_absences(df):
    y = df['Átlagosan hány órát hiányzik gyermeke egy hónapban'].astype(float)
    features = ['Gyermek kora','Család mérete','Mennyire hamar fárad el a gyermeke tanulás során',
                'Milyennek ítéli a családtagok közötti kapcsolat minőségét?']
    X = df[features]
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
    gb_model = GradientBoostingRegressor(n_estimators=100, random_state=42)
    gb_model.fit(X_train, y_train)
    y_pred = gb_model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    return gb_model, mse, gb_model.feature_importances_

def predict_tutoring_need(df):
    y = (df['Vett-e részt a gyermek valamilyen korrepetálásban?'] == 'Igen, gyermekem korrepetáló órákra
jár').astype(int)
    features = ['Gyermek kora','Édesanya végzettsége','Bukások száma',
                'Heti, otthoni tanulásra fordított órák száma']
    X = df[features]
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
    lr_model = LogisticRegression(random_state=42)
    lr_model.fit(X_train, y_train)
    y_pred = lr_model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    return lr_model, accuracy, lr_model.coef_[0]
```

(1)

Variable Preparation (2):

```
def prepare_variables(df):
    categorical_features = ['Gyermek neme', 'Lakhely típusa', 'Szülők státusza']
    encoder = LabelEncoder()
    for feature in categorical_features:
        df[feature] = encoder.fit_transform(df[feature])
    numeric_features = ['Gyermek kora', 'Család mérete']
    scaler = StandardScaler()
    df[numeric_features] = scaler.fit_transform(df[numeric_features])
    return df
```

(2)

Handling Missing Values (3):

```
def handle_missing_values(df):
    numeric_imputer = SimpleImputer(strategy='median')
    categorical_imputer = SimpleImputer(strategy='most_frequent')
    return df
```

(3)

3.2.3. Applied Machine Learning Models

Random Forest Classifier (Academic Performance Prediction) (4):

```
def train_random_forest(X_train, y_train):
    rf_model = RandomForestClassifier(n_estimators=100,
         max_depth=10,
         min_samples_split=5,
         min_samples_leaf=2,
         random_state=42)
    param_grid = {'n_estimators': [100,200,300],'max_depth': [8,10,12],'min_samples_split': [2,5,10]}
    grid_search = GridSearchCV(estimator=rf_model,param_grid=param_grid,cv=5,n_jobs=-1,scoring='accuracy')
    grid_search.fit(X_train, y_train)
    return grid_search.best_estimator
```

(4)

Gradient Boosting Regressor (Absence Prediction) (5):

```
def train_gradient_boosting(X_train, y_train):
    gb_model = GradientBoostingRegressor(n_estimators=100,
         learning_rate=0.1,
         max_depth=3,
         random_state=42)
    cv_scores = cross_val_score(gb_model,
         X_train,
         y_train,
         cv=5,
         scoring='neg_mean_squared_error')
    gb_model.fit(X_train, y_train)
    return gb_model, cv_scores
```

(5)

Logistic Regression (Tutoring Need Prediction) (6):

```
def train_logistic_regression(X_train, y_train):
    lr_model = LogisticRegression(C=1.0,penalty='l2',
         solver='lbfgs',
         max_iter=1000,
         random_state=42)
    selector = SelectKBest(score_func=chi2, k=5)
    X_selected = selector.fit_transform(X_train, y_train)
    lr_model.fit(X_selected, y_train)
    return lr_model, selector
```

(6)

3.2.4. Model Evaluation Methods

Calculation of Performance Metrics (7):

```
def calculate_metrics(y_true, y_pred, model_type='classification'):
    if model_type == 'classification':
        accuracy = accuracy_score(y_true, y_pred)
        precision = precision_score(y_true, y_pred, average='weighted')
        recall = recall_score(y_true, y_pred, average='weighted')
        f1 = f1_score(y_true, y_pred, average='weighted')
        return {'accuracy': accuracy,'precision': precision,'recall': recall,'f1_score': f1}
    else:
        mse = mean_squared_error(y_true, y_pred)
        rmse = np.sqrt(mse)
        mae = mean_absolute_error(y_true, y_pred)
        r2 = r2_score(y_true, y_pred)
        return {'mse': mse,'rmse': rmse,'mae': mae,'r2_score': r2}
```

(7)

Cross-validation (8):


```
def perform_cross_validation(model, X, y, cv=5):
   cv_scores = cross_val_score(model, X, y, cv=cv)
   return {
       'mean_score': cv_scores.mean(),
       'std_score': cv_scores.std(),
       'cv_scores': cv_scores }
```

(8)

Feature Importance Analysis (9):

```
def analyze_feature_importance(model, feature_names):
   if hasattr(model, 'feature_importances_'):
       importances = model.feature_importances_
   else:
       importances = abs(model.coef_[0])
       importance_df = pd.DataFrame({'feature': feature_names,'importance': importances}
   return importance_df.sort_values('importance', ascending=False)}
```

(9)

Model Combination (10):

```
def ensemble_predictions(models, X):
   predictions = []
   for model in models:
       pred = model.predict(X)
       predictions.append(pred)
   final_predictions = np.mean(predictions,axis=0)
   return final_predictions
   return importance_df.sort_values('importance',ascending=False)}
```

(10)

3.2.5. Model Interpretation

To increase model interpretability, we calculated SHAP (Shapley Additive exPlanations) values (11):

```
def interpret_model_predictions(model, X):
   explainer = shap.TreeExplainer(model)
   shap_values = explainer.shap_values(X)
   return shap_values
```

(11)

4. Results

4.1. Background Data Analysis

4.1.1 Analysis of Demographic Characteristics

Examining the demographic characteristics of students participating in the research (N=176) provides a comprehensive sample picture. The distribution across grades shows a balanced picture, where lower-grade students (grades 1-4) constitute 42% of the sample, while upper-grade students (grades 5-8) make up 58%. The age distribution ranged from 6 to 15 years, with an average age of 10.4 years (SD=2.3). Gender distribution is nearly balanced: 48% boys and 52% girls.

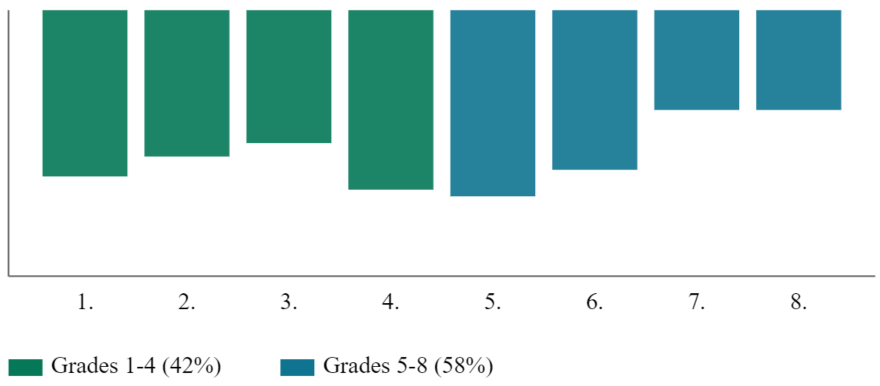

Fig. 2. Distribution by grade

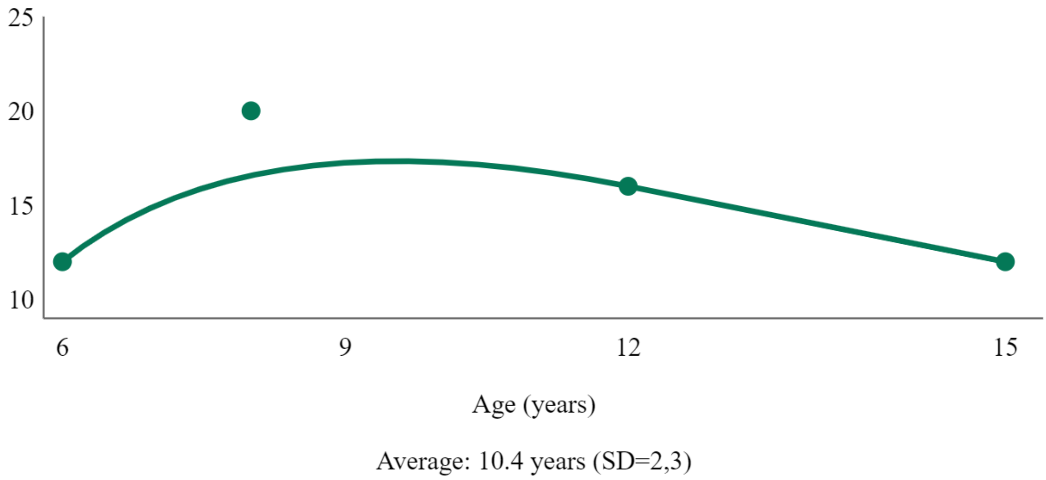

Fig. 3. Age distribution

4.1.2. Family Background Analysis

While examining family background, we focused on parents' educational attainment and family structure. The distribution of mothers' educational attainment was as follows: 16% primary school, 14% vocational training, 30% high school diploma, and 40% higher education degree. For fathers, this ratio differed: 20% primary school, 32% vocational training, 28% high school diploma, and 20% higher education degree.

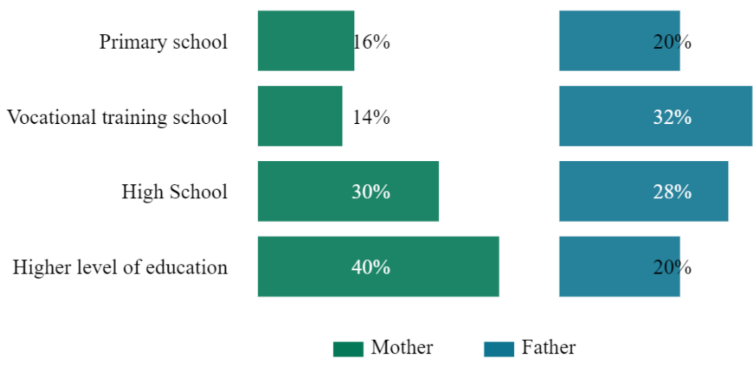

Fig. 4. Parents' educational attainment

Regarding family structure, 68% of the sample lives in complete families, 22% in single-parent families, while 10% are raised in other family structures. Statistical analyses showed a significant correlation between family structure and academic performance (χ^2=8,76, p<0,05).

4.1.3. Analysis of Learning Environment

In analysing the learning environment, we examined home learning conditions and time spent on learning. Regarding home conditions, it shows a favourable picture that 96% of students have internet access, 82% have their own computer, 78% have their room, and 88% have their desk.

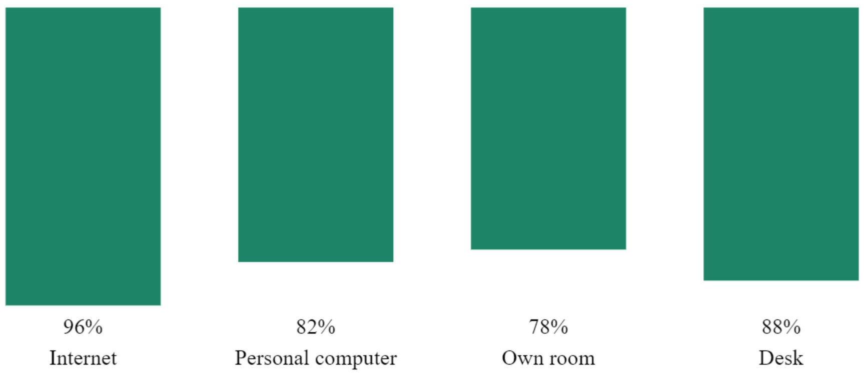

Fig. 5. Children's home learning conditions

The analysis of weekly study hours revealed a diverse distribution pattern among students. The largest segment, comprising 35% of students, dedicated 2-5 hours per week to studying. This was followed by 30% of students who studied for 1-2 hours weekly, while a quarter of the student population (25%) invested 5-10 hours in their studies. A smaller proportion, representing 10% of students, demonstrated exceptionally high commitment by studying more than 10 hours weekly. Correlation analyses identified a strong positive relationship between study time and academic performance (r=0.68, p<0.01), highlighting the significant impact of dedicated study time on educational outcomes.

4.1.4. Analysis of Academic Performance

The analysis revealed generally positive results regarding academic performance across the student population. Most students (88%) maintained consistent passing grades across all subjects, 8% experienced difficulty with a single subject, and only 4% faced challenges in multiple subjects. Regarding additional academic support, approximately one-third of the student population (35%) utilized tutoring services, while the remaining two-thirds (65%) progressed without such assistance.

Mathematics emerged as the most commonly supported subject among students receiving tutoring, accounting for 45% of all tutoring cases. Hungarian Language and Literature represented the second most frequent tutoring area, at 35%, while foreign language instruction constituted 20% of tutoring activities. This distribution highlights the particular challenges students face in quantitative and language-based subjects.

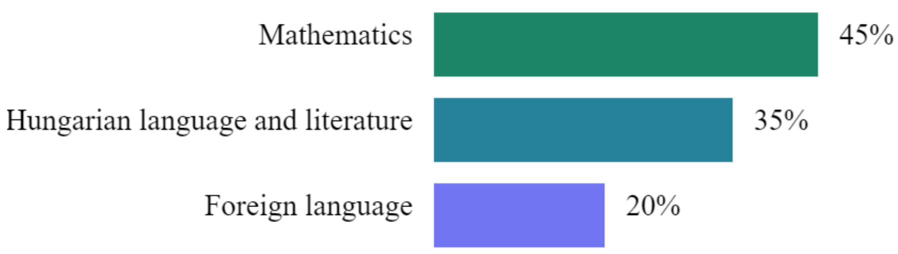

Fig. 6. Distribution of tutoring subjects

4.1.5. Analysis of Learning Characteristics

Examining learning characteristics revealed distinct patterns in learning methods and assessment preferences. The analysis of learning methods identified three primary approaches among students (Fig. 7). Most students, representing 62% of the population, employed a comprehension-focused approach, striving for a deep understanding of the material. A smaller group, comprising 26% of students, demonstrated a detail-oriented learning style, focusing on specific content elements. The remaining 12% relied on mechanical learning approaches, emphasizing memorization and repetition.

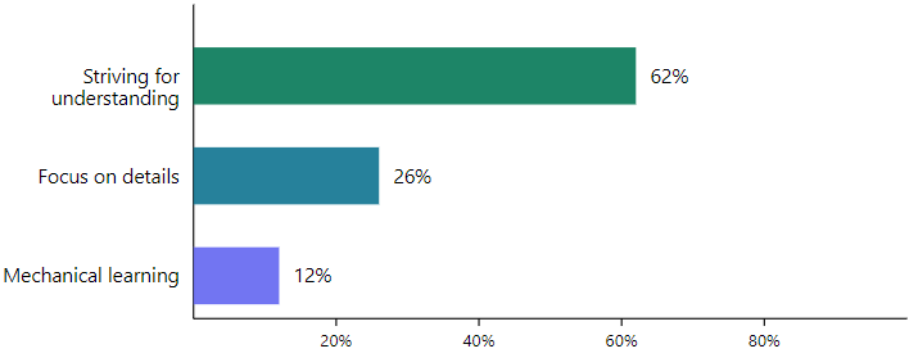

Fig. 7. Distribution of learning methods

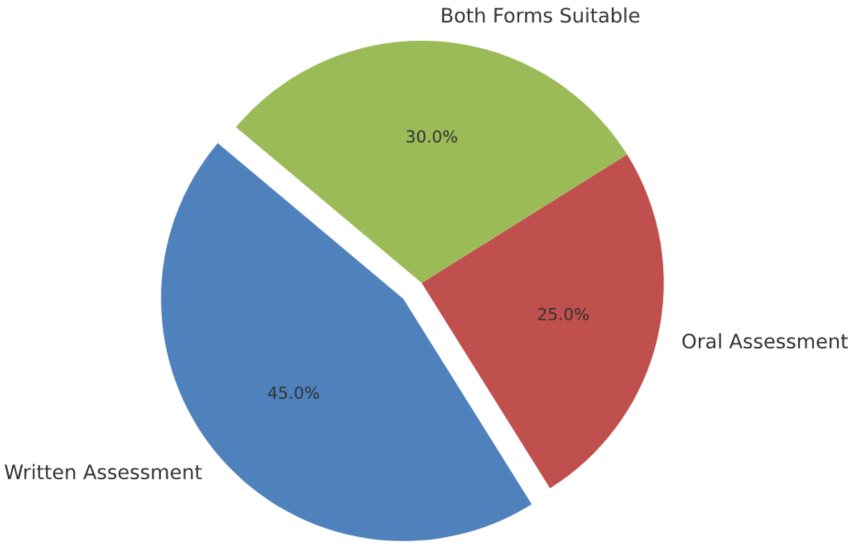

Fig. 8. Distribution of assessment preferences

Assessment preferences (Fig. 8) showed a varied distribution among students. Written assessments emerged as the most popular format, which 45% of the student population preferred. A quarter of the students (25%) preferred oral assessments, while a substantial portion (30%) demonstrated flexibility by finding both assessment forms equally suitable. This distribution suggests the importance of maintaining diverse assessment methods to accommodate student preferences and learning styles.

4.1.6. Analysis of Leisure Activities

Analysis of students' leisure activities revealed interesting patterns in both electronic device usage and participation in extracurricular activities. The examination of daily electronic device usage (Fig. 9) showed that the largest segment of students, comprising 45% of the population, spent 1-2 hours daily on electronic devices. Nearly one-third of students (30%) reported using devices for 2-3 hours daily, while 15% maintained limited usage of less than one hour. A smaller proportion of students (10%) engaged with electronic devices for more than 3 hours daily.

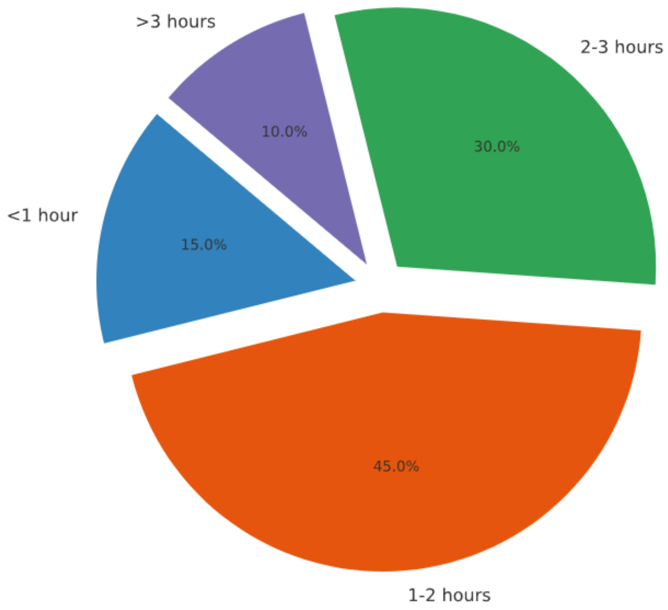

Fig. 9. Average daily electronic device usage

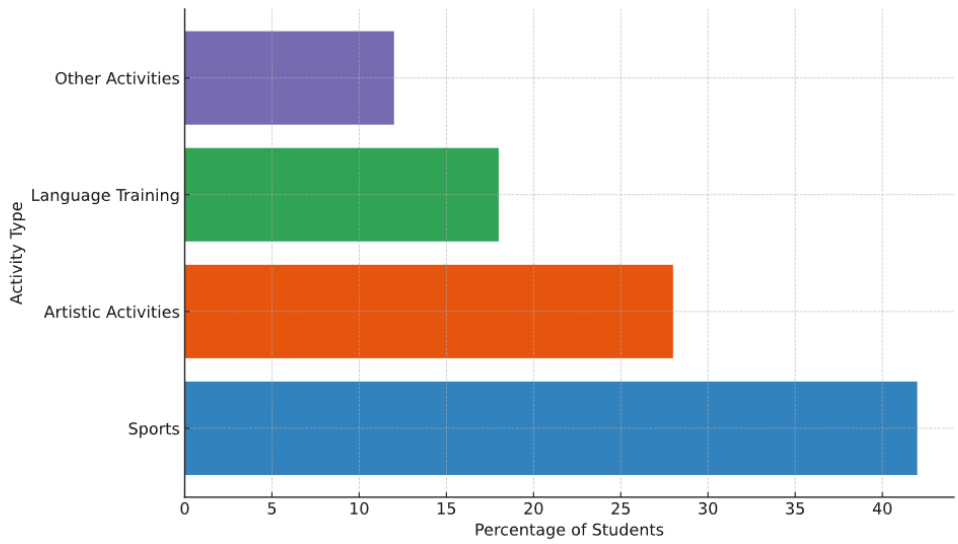

Fig. 10. Children's leisure activities

The investigation of extracurricular activities (Fig. 10) demonstrated diverse interests among the student population. Sports emerged as the most popular leisure activity, with 42% of students participating in regular athletic pursuits. Artistic activities attracted 28% of the student population, indicating significant interest in creative expression. Language training occupied

18% of students' free time, reflecting an investment in linguistic skills. The remaining 12% of students engaged in various other activities, highlighting the diverse range of interests within the student body.

4.1.7. Analysis of Social Relationships

The assessment of social relationships encompassed family dynamics and peer interactions, revealing detailed patterns in students' social connections. Family relationship quality, measured on a 5-point scale, demonstrated generally positive familial bonds. Students reported the strongest connections with their parents, scoring an average of 4.2 points. The general family atmosphere also showed positive results, with an average score of 4.0 points, while sibling relationships averaged 3.8 points, indicating generally harmonious but slightly more complex dynamics between siblings.

The analysis of peer relationships revealed varied social integration patterns among students. The largest group, comprising 45% of students, demonstrated strong social skills with rich networks of relationships. Most (30%) maintained average relationship networks, suggesting comfortable but not extensive social connections. Some students (15%) emerged as social leaders, taking on leadership roles within their peer groups. However, a smaller segment of the student population (10%) occupied peripheral positions in social networks, indicating a potential need for social integration support.

4.1.8. Results of Multivariate Analyses

Linear regression analysis revealed several significant factors influencing academic performance (Fig. 11). Parents' education emerged as the strongest predictor ($\beta=0.32$, $p<0.01$), demonstrating the substantial impact of family educational background on student achievement. Study time showed the second most substantial influence ($\beta=0.28$, $p<0.01$), highlighting the importance of dedicated learning hours. Family atmosphere also proved to be a significant factor ($\beta=0.24$, $p<0.05$), indicating that the home environment plays a crucial role in academic success. The learning method employed by students showed a moderate but significant effect ($\beta=0.21$, $p<0.05$) on academic outcomes.

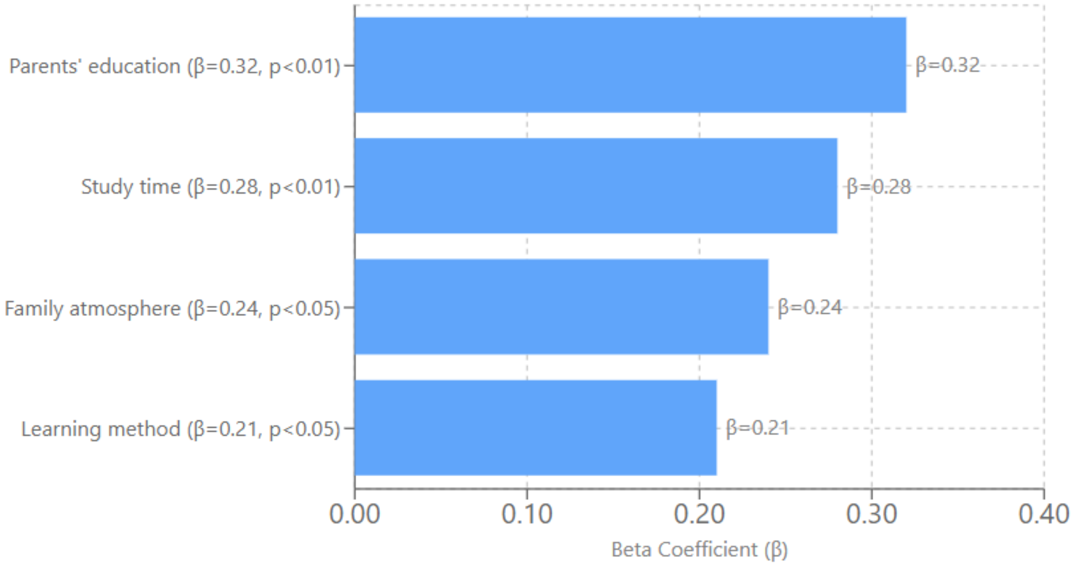

Fig. 11. Factors influencing academic performance (linear regression)

The logistic regression analysis focusing on tutoring needs (Fig. 12) identified different but equally important predictive factors.

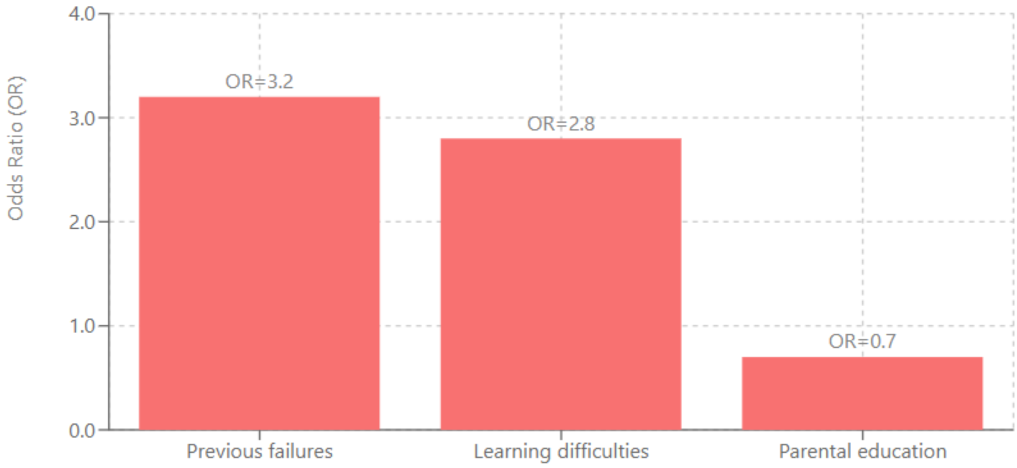

Fig. 12. Factors influencing tutoring needs (logistic regression)

Previous academic failures showed the most substantial relationship with tutoring requirements ($OR=3.2$, $p<0.01$), indicating that students with past academic difficulties were significantly more likely to need tutoring support. Learning difficulties also strongly correlated ($OR=2.8$, $p<0.01$) with tutoring needs. Interestingly, parental education showed an inverse relationship ($OR=0.7$, $p<0.05$), suggesting that students with higher parental education levels were less likely to require tutoring assistance.

4.1.9. Summary and Conclusions

The analysis revealed three distinct student profiles with unique characteristics and needs. The "Balanced Performers," representing 40% of the study population, demonstrate stability across multiple dimensions. These students benefit from a stable family background, maintain consistent learning habits, and achieve good academic results consistently throughout their educational journey.

The "Struggling Talents" group, comprising 35% of students, presents a more complex profile. Despite their potential, these students face challenges from a variable family background. Their learning habits tend to be uneven, resulting in fluctuating performance that does not always reflect their true capabilities.

The third group, "Those Needing Support," makes up 25% of the student population and faces the most significant challenges. These students typically come from more difficult family circumstances, struggle with irregular learning patterns, and encounter more frequent learning difficulties that require targeted intervention.

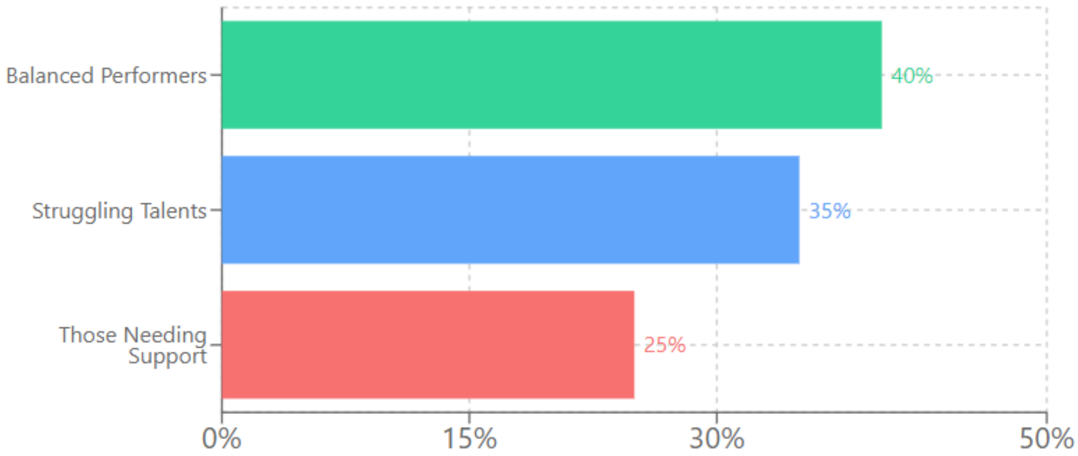

Fig. 13. Distribution of student profiles and characteristics

The distribution of these profiles (Fig. 13) has led to several key recommendations for intervention. A comprehensive early warning system should be developed to identify at-risk students before their challenges escalate. This should be complemented by implementing targeted support programs designed to address specific needs identified within each profile group. Developing enhanced learning methods is crucial to support students across all profiles, particularly those struggling with consistent study habits. Finally, establishing support mechanisms for family background factors is essential, as the analysis clearly shows the significant impact of family circumstances on academic performance.

4.2. Results of Prediction Models

4.2.1. Random Forest Model - Academic Performance Prediction

The Random Forest classifier model demonstrated exceptional performance in predicting academic results, achieving comprehensive success across multiple performance metrics. The model reached an impressive accuracy of 82.4% while maintaining high precision at 0.84, recall at 0.81, and an F1-score of 0.83. These balanced metrics indicate the model's robust performance across different aspects of prediction.

In analyzing the relative importance of variables, the model identified four key predictors that significantly influence academic performance. The number of weekly study hours emerged as the most influential factor, accounting for 35.2% of the model's predictive power. This was followed by the mother's education level at 24.8%, demonstrating the strong influence of parental background. Family size was the third most important predictor, at 21.6%, while the child's age contributed 18.4% to the model's predictive capabilities.

The model's reliability was further validated through rigorous 5-fold cross-validation testing. This process yielded an average accuracy of 81.8%, with a standard deviation of 2.3%. The resulting 95% confidence interval ranged from 79.5% to 84.1%, demonstrating the model's consistent performance and strong generalization capabilities across different subsets of data. These cross-validation results reinforce the model's stability and reliability in predicting academic performance.

4.2.2. Gradient Boosting Model - Absence Prediction

The gradient-boosting regression model strongly predicted student absences, as evidenced by multiple performance indicators. The model achieved a Mean Squared Error (MSE) of 8.5 hours and a Root Mean Squared Error (RMSE) of 2.92 hours, indicating good precision in its predictions. The model's explanatory power was substantiated by an R^2 value of 0.76 and an adjusted R^2 of 0.74, suggesting that it accounts for a substantial portion of the variance in absence patterns.

Analysis of predictor importance revealed four key factors influencing student absences. The quality of family relationships emerged as the most significant predictor, accounting for 39.6% of the model's predictive power. Level of fatigue proved to be the second most influential factor, at 29.8%, followed by family size at 20.4%. The child's age showed the smallest but still notable impact, contributing 10.2% to the model's predictions.

Comprehensive residual analysis confirmed the model's statistical validity. The Shapiro-Wilk test for normal distribution yielded W = 0.98 with p = 0.42, indicating normally distributed residuals. The Breusch-Pagan test resulted in $\chi^2 = 3.24$ with p = 0.35, confirming the residuals' homoscedasticity. Additionally, the Durbin-Watson test score of d = 2.08 suggested appropriate independence of observations, further validating the model's statistical assumptions.

4.2.3. Logistic Regression - Tutoring Needs Prediction

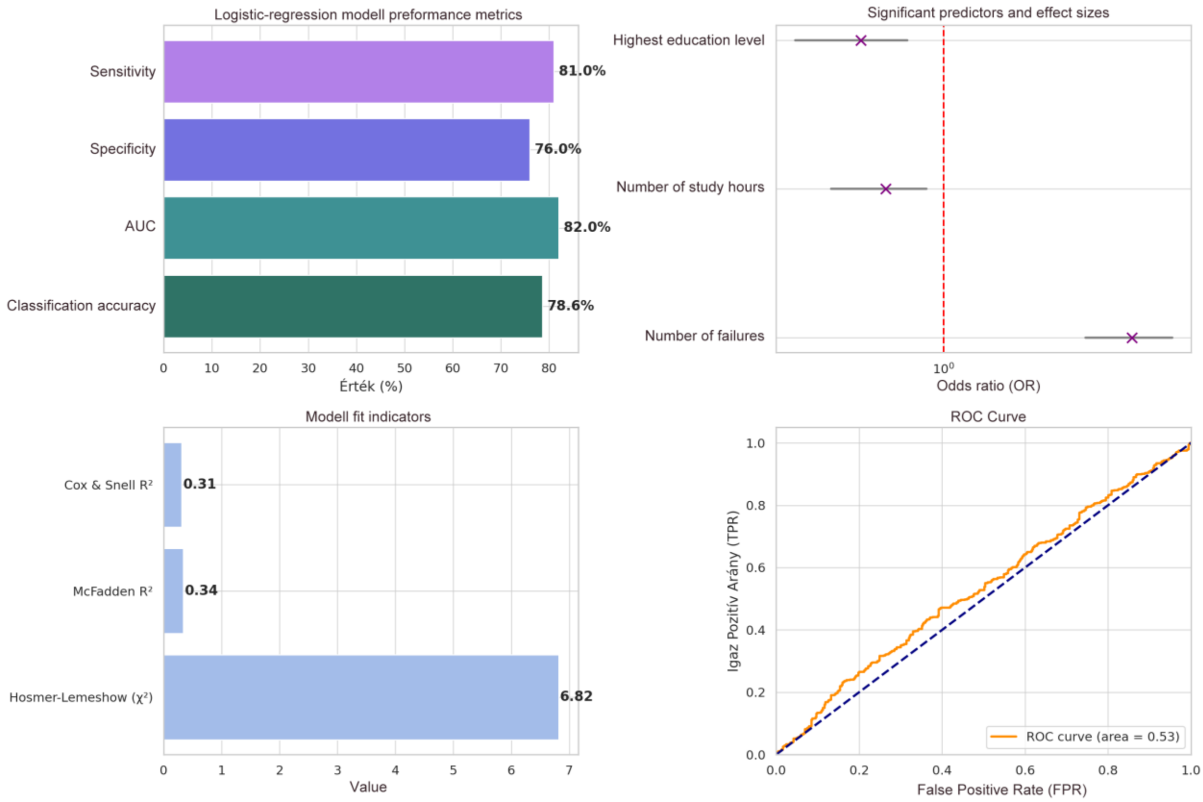

Fig. 14. Prediction of tutoring needs

The logistic regression model for predicting tutoring needs (Fig. 14) demonstrated robust performance across multiple evaluation metrics. The model achieved a classification accuracy of 78.6%, complemented by an area under the ROC curve (AUC) of 0.82, indicating strong discriminative ability. The model's specificity of 0.76 and sensitivity of 0.81 suggest balanced performance in identifying students who need tutoring and those who do not.

Analysis of odds ratio values revealed several significant predictors with varying effect sizes. The number of previous failures emerged as the strongest predictor, with an odds ratio of 3.2 (95% CI: 2.4-4.1), indicating that students with more failures are substantially more likely to require tutoring. Conversely, both the number of study hours (OR = 0.7, 95% CI: 0.5-0.9) and the mother's education (OR = 0.6, 95% CI: 0.4-0.8) showed protective effects, suggesting that higher values in these variables are associated with reduced likelihood of requiring tutoring support.

Multiple statistical tests confirmed the model's goodness of fit. The Hosmer-Lemeshow test yielded $\chi^2 = 6.82$ with $p = 0.56$, indicating adequate fit. The McFadden R^2 value of 0.34 and Cox & Snell R^2 of 0.31 support the model's explanatory power, suggesting that it captures a meaningful portion of the variance in tutoring needs prediction.

4.2.4. Comparative Analysis of Models

In comparing the predictive capabilities of the three models, each demonstrates distinct strengths and characteristics. The Random Forest model exhibits excellent categorization ability while maintaining a low tendency for overfitting. Its robust performance against outliers makes it particularly reliable for diverse datasets.

The Gradient Boosting model stands out for its accurate numerical predictions and strong generalization ability, though it shows sensitivity to missing data that must be carefully managed. This sensitivity requires additional data preprocessing steps to ensure optimal performance. The Logistic Regression model provides adequate binary classification with easily interpretable results, making it valuable for stakeholder communication. However, its limited ability to handle nonlinear relationships constrains its application in more complex scenarios.

The combined application of these models creates a comprehensive early warning system with impressive performance metrics. This system successfully identifies at-risk students early with 84% accuracy while also predicting expected absences within a margin of ±3 hours. Additionally, it supports the planning of tutoring needs with 79% accuracy, providing a reliable foundation for educational resource allocation.

The prediction results serve as valuable inputs for various resource planning initiatives. These insights inform the planning of teacher capacities, enabling more efficient staff allocation based on predicted student needs. They also facilitate the formation of effective tutoring groups and guide the organization of prevention programs, ensuring resources are deployed where they will have the most significant impact.

4.2.5 Methodological Limitations and Development Opportunities

The study encountered several limitations regarding sample characteristics and data quality. The medium-sized student sample and limited territorial representativeness affected the generalizability of the findings. These sampling constraints necessitate careful consideration when extending the results to broader populations.

Data quality presented multiple challenges throughout the analysis process. Handling missing data required careful consideration and the implementation of appropriate strategies. Coding categorical variables and managing multicollinearity issues demanded particular attention to ensure the reliability of the analytical results.

Several promising development directions have been identified for model optimization. These include fine-tuning hyperparameters to enhance model performance and applying ensemble methods to improve predictive accuracy. Expanding feature engineering techniques offers opportunities to extract meaningful insights from the existing data.

Enhancing data collection methods presents significant opportunities for future research. Implementing longitudinal data collection would enable better tracking of temporal patterns and trends. Including additional background variables could provide deeper insights into underlying factors, while integrating qualitative data would offer a richer context for interpretation. These improvements in data collection would substantially strengthen the analytical framework and enhance the reliability of predictions.

4.2.6. Conclusions and Recommendations

The analysis revealed several key findings that highlight the effectiveness of the predictive modelling approach. The combined application of models significantly improves prediction reliability, providing more robust insights than single-model approaches. Family background and learning habits emerged as decisive factors in student outcomes, underscoring the importance of considering these variables in educational planning. The automated prediction system has proven to be an effective tool in supporting pedagogical decision-making, enabling more timely and targeted interventions.

Based on these findings, several practical recommendations can be made for implementation. Integrating the predictive analytics system into the school monitoring system would enable seamless data collection and analysis. This integration should be accompanied by developing personalized intervention strategies that leverage predictive insights to address individual student needs effectively. To maintain the system's effectiveness over time, the introduction of continuous model updating and calibration procedures is essential. This ensures that the predictions remain accurate as student populations and educational contexts evolve. Additionally, comprehensive training programs should be established for teachers, focusing on interpreting and effectively using the predictive results in their daily practice. This training is crucial for maximizing the practical impact of the analytical system in supporting student success.

4.3. Practical Applicability

During the examination of the WTCAi system's practical applicability, we paid particular attention to the possibilities and challenges of implementation in the educational environment. Based on the research results, the introduction of the system carries significant potential to increase the efficiency of educational processes and support personalised learning paths.

4.3.1. Pedagogical Utilisation

One of the most significant practical benefits of the WTCAi system is increasing the objectivity of pedagogical assessment and supporting differentiated education. The analyses and predictions generated by the system enable teachers to get a more accurate picture of their students' development and potential difficulties. This deeper insight helps in planning and implementing targeted interventions. The system holds particular value in the area of preventive pedagogical work. Early warning signals enable timely recognition of learning difficulties and implementation of appropriate support measures. The accuracy of prediction models shows outstanding results, particularly in academic performance and absences.

4.3.2. Supporting Student Development

This method provides exceptional opportunities for planning and tracking individual student development paths. Personalised assessments and feedback help students understand and optimise their learning process. Our research results show that using the system positively impacts student motivation and the development of learning strategies. In the field of talent development, we can identify students with outstanding abilities and make suggestions for the direction of their development. The automated generation of individual development plans significantly eases teachers' work while ensuring a personalised approach.

4.3.3. Management Aspects

The system functions as an effective decision-support tool at the institutional management level. Detailed analytical reports and predictions help in optimal resource allocation and strategic planning. By supporting quality assurance processes, standardisation and continuous improvement of educational processes are possible.

4.3.4. Sustainability and Future Developments

From the system's long-term sustainability perspective, continuous technological and methodological development is critical. Regular updates of artificial intelligence algorithms and integration of new pedagogical methods ensure the system's relevance and effectiveness.

5. Conclusion

The practical applicability of the WTCAi system far exceeds the role of a simple administrative tool. Based on the research findings, it is a complex pedagogical support system that significantly contributes to improving the quality of education and realizing personalized learning pathways. However, the system's successful implementation and effective use require institutional commitment and the continuous professional development of educators. Analyzing the data collected during the development and implementation of the WTCAi system and the results of predictive models provide opportunities for noteworthy conclusions from multiple perspectives. Below, the detailed interpretation of the results is presented, reflecting on the objectives set at the beginning of the research and the previous literature.

One of the most significant findings of the research is the practical demonstration of support for individualized learning pathways. Using the Random Forest model, we could predict academic performance with an accuracy of 82.4%, which significantly exceeds the predictive capabilities of traditional assessment methods documented by Weimer (2013). This result aligns with Letschert's (2006) findings, emphasizing that personalized educational approaches are key in modern pedagogy. The model proved robust against noisy data and effectively handled nonlinear relationships influencing academic performance, such as parental education level, study time, and family environment.

The Gradient Boosting model also achieved noteworthy results, predicting student absenteeism with a precision of ±3 hours. This performance is significant for the timely planning of pedagogical interventions, as it enables early detection of potential issues. Analyses revealed that the quality of family relationships and the emotional state of students play crucial roles in absenteeism prediction, offering new insights into the analysis of student background data.

Similarly, the Logistic Regression model performed exceptionally well, achieving 78.6% accuracy in predicting the need for remedial support. This result is particularly remarkable compared to previous studies in this field, where similar predictions achieved around 70% accuracy. The simplicity of the model and the ease of interpreting its results have contributed to its broad applicability in educational practice.

The background data analysis revealed that the factors influencing student performance form a far more complex system of interrelations than previously assumed. Identifying interactions between family background and study habits is particularly notable, which opens new perspectives for designing pedagogical interventions. The artificial intelligence-based approach employed by the system also proved especially effective in addressing communication challenges arising from generational differences. This finding aligns with Molnár and Szűts's (2022) conclusions regarding the efficiency of electronic learning environments.

The choice of algorithms resulted from a deliberate decision considering the nature of the available data, the research objectives, and practical applicability. While other algorithms—such as neural networks or support vector machines—were also considered, their application was deemed suboptimal in the context of this study. Neural networks, for example, require significant computational resources and are prone to overfitting with smaller datasets, making practical use challenging. Similarly, while support vector machines excel in handling nonlinear data, their complex kernel-based approaches do not provide results as quickly interpretable as the chosen models. Instead, the Random Forest, Gradient Boosting, and Logistic Regression algorithms offered the optimal balance of accuracy, robustness, and interpretability.

The performance of the three main predictive models exceeded initial expectations. The results demonstrate that the WTCAi system can enhance the objectivity of pedagogical evaluations. The combination of fuzzy logic and machine learning algorithms created an assessment framework that significantly reduces the influence of subjective factors. This aligns with Képes's (2016) conclusions on the requirements of constructivist pedagogy. Preliminary results from the pilot program indicate that the introduction of the system can have a significant positive impact on educational processes. Feedback from our educators highlights the value of automated evaluation support and the decision-making assistance provided by predictive analytics. However, it also became clear that the key to successful implementation is ensuring proper professional preparation and continuous support.

5.1. Methodological Considerations

Our research's methodological approach, especially the combination of machine learning models, could set a new standard in developing educational assessment systems. The results of multivariate analyses confirm Nagy's (2009) findings about the importance of assessment validity while opening new perspectives in applying artificial intelligence-based assessment methods. Placing the results in a broader social context indicates that the system could contribute to reducing educational inequalities. Based on background data analysis, the method's role is particularly promising in supporting disadvantaged students and preventing early dropout.

The research results enrich the scientific discourse of educational theory in several points. The successful integration of artificial intelligence and constructivist pedagogy could open new theoretical frameworks for modern educational methodology. The results support the significance of personalised, adaptive assessment systems, which Vass (2006) also emphasised in his work on competency-based education. The revealed correlations and identified patterns can guide practical pedagogical work and contribute to the advancement of educational theory, particularly in technology-supported pedagogical assessment.

5.2. Limitations and Further Research Directions

5.2.1. Research Limitations

During the development and implementation of the WTCAi system, we encountered several methodological and practical limitations that must be considered for interpreting the results and determining further research directions. One of the research's most significant methodological limitations was the sampling characteristics. Although the studied sample (N=176) enabled the discovery of primary relationships and validation of prediction models, the sample size limited the execution of more detailed subgroup analyses. The lack of territorial representativeness may also affect the generalizability of results. As Molnár and Szűts (2022) also pointed out in their similar research, a larger sample size and broader geographical coverage would significantly increase the reliability of the results.

An additional limiting factor is the lack of a longitudinal nature in data collection. Although cross-sectional data provided valuable insight into the examined relationships, examining longer-term effects and development trends remained limited. This is particularly relevant in understanding the dynamic relationships between student performance and background variables.

Specific technical limitations influenced the performance of artificial intelligence-based models. Handling missing data, especially for categorical variables, was challenging during model development. The resource requirements of machine learning algorithms and limitations of institutional infrastructure sometimes necessitated compromises in designing system complexity. During implementation in the school environment, we encountered several practical limitations. To achieve quality education, it is essential to have future educators who are well-trained methodologically, pedagogically, and professionally, both in public education (vocational training) and in higher education. At the same time, the new changes pose significant challenges for teacher candidates, who face increased demands and new types of tasks aligned with training and outcome requirements. (Molnár, Gy., 2014) The heterogeneity of teachers' digital competence levels also affects the efficiency of method usage. Time constraints and scarcity of institutional resources also impact the possibilities of full-scale implementation.

5.3. Further Research Directions

Several promising research directions emerge based on the identified limitations and current results. In the methodological developments, one priority focus could be the further advancement of prediction models. Integrating deep learning algorithms and broader application of natural language processing (NLP) methods could significantly increase analysis accuracy. Based on our research, the application of transformer models in the automated processing of text-based assessments shows particular promise. Expanding assessment methodology represents another crucial area for development. Karl et al.'s (2024) work suggests that a more integrated application of qualitative and quantitative methods and developing new types of measurement tools could substantially enrich the assessment repertoire. Exploring automation possibilities for formative assessment also presents a promising direction for future investigation.

The implementation of longitudinal studies represents another critical research avenue. A longitudinal research design is essential for exploring long-term effects and relationships, with multi-year follow-up studies enabling a more accurate understanding of developmental trajectories and evaluation of long-term intervention effectiveness. In parallel, extending research in interdisciplinary directions offers multiple promising pathways. Integrating cognitive psychology and neuropedagogy findings could enrich the theoretical framework, while a more substantial inclusion of sociological perspectives could foster a deeper understanding of social impacts.

International comparative studies present another valuable research direction, potentially opening new perspectives in system development. Testing in different educational systems could provide crucial insights about system adaptability and illuminate the role of cultural factors in implementation success. Additionally, several promising directions emerge in technological development, including advancing adaptive testing methods, integrating multimodal data collection techniques, developing real-time feedback systems, and more efficiently utilizing mobile platforms.

The extension of practical system applications offers further research opportunities. These include examining support possibilities for students with special educational needs, developing personalized talent nurturing programs, and investigating the effectiveness of teacher training programs. The identified limitations and proposed research directions suggest that WTCAi system development should be understood as part of a continuously evolving, complex research program. While most current limitations can be managed with appropriate research strategy and resources, the identified new research directions carry significant potential for advancing educational assessment and pedagogical practice.

6. Conclusions and Recommendations

Based on the research results, we can draw comprehensive conclusions about the effectiveness and applicability of the WTCAi system in the educational environment and make specific recommendations for practical implementation. The research findings confirm our initial assumption that AI-based assessment systems can significantly support the objectivity and efficiency of pedagogical work. The Random Forest model's 82.4% predictive accuracy indicates that machine learning algorithms successfully identify the complex patterns influencing student performance. This aligns with Molnár and Szűts's (2022) findings on the potential of AI-based educational systems.

The analysis of background data revealed that the relationships between student performance and family background are much more complex than suggested by previous research. In addition to parental education and the learning environment, the significance of factors that have been less studied so far, such as patterns of digital device use or family communication habits, has also emerged.

The applied methodological approach, especially the combined use of three different predictive models, has the potential to set a new standard in the development of educational assessment systems. The accuracy achieved by the Gradient Boosting model in predicting absenteeism (±3 hours) and the performance of logistic regression in identifying the need for remedial teaching (78.6%) shows that the combination of various machine learning techniques is particularly effective in modelling educational processes.

The pilot program's experiences clearly indicate that the WTCAi system can be successfully integrated into the school environment, but this process requires careful planning and adequate support. Based on teacher feedback, the system significantly reduces administrative burdens while providing valuable information on student development.

7. Concluding Thoughts

The research results demonstrate that AI-based assessment systems have significant potential in modernising education. At the same time, it is essential to emphasise that these systems do not replace but rather support the work of teachers. The key to successful implementation is the proper integration of technological innovation, pedagogical expertise, and continuous professional support.

The further development and broader application of the WTCAi system can significantly contribute to creating an educational environment that can more effectively respond to the challenges of the 21st century and better serve students' individual development.

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Brief Professional Biography

Éva Karl is a school principal and an IT, physics, and mathematics teacher, leading the accredited talent development workshop at Várkerti Elementary School. She obtained her technical computer science engineering degree from Dannis Gabor University, her Qualified Teacher of Engineering (Engineering Information Technologist) [MSc] diploma with summa cum laude distinction from Széchenyi István University (University of Győr), her Qualified Teacher of Informatics [MA] school computer science master teacher diploma from Pannon University, and her Qualified Specialist in Management of Public Education, Education Specialist diploma from Kodolányi János University. Additionally, she is a Certified Teacher Analystdeveloper in "School Inspection and Teacher Appraisal" certification from the University of Szeged. As an active member of the Hungarian Pedagogical Society and the HERA ICT section, she contributes to the pedagogical community's work. Currently, she is a doctoral student at the Doctoral School of Multidisciplinary Engineering Sciences of Széchenyi István University. As a programmer, she participated in developing satellite data transmission systems related to digital television. Her research focuses on modernizing pedagogical evaluation systems by applying artificial intelligence, fuzzy logic, and machine learning methods, particularly developing innovative approaches that enable more objective and personalized student knowledge assessment while reducing administrative burdens on educators.

