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MACHINE LEARNING ASSESSMENT OF DIGITAL WORKS IN FUTURE TEACHER COMPETENCY MAPPING

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Abstract. In the context of educational digitalization, the level of professional training of future teachers is increasingly reflected in their academic work. Presentations, infographics, and visual materials are becoming not only a form of reporting but also indicators of the formation of key competencies among students enrolled in teacher education programs. In this regard, the relevance of their systematic analysis and evaluation is growing. The study involves the use of machine learning methods to analyze the digital academic work of students in teacher education programs. The empirical base consisted of 112 student digital works. The experiment was conducted across four dimensions: digital literacy, visualization, creativity, and pedagogical orientation. Random Forest and AI-based models were used for data processing, allowing simultaneous analysis of structural metadata and visual characteristics of the works. The results demonstrated a high level of correspondence between expert evaluations and machine-generated predictions, particularly in the domains of digital literacy and pedagogical orientation. The assessment of creativity proved to be less precise, confirming the difficulty of algorithmic interpretation of original solutions.

The results do not suggest that machine learning can replace expert judgement. Yet they clearly show that it may function as an additional analytical layer, helping to make the evaluation process more consistent and less dependent on purely subjective interpretation.

Keywords: *machine learning, digital literacy, competency assessment, future teachers, educational analytics.*

Introduction

Modern education, when viewed not only through large-scale reforms but also through the quiet routines of everyday academic practice, is becoming increasingly intertwined with the digital environment. This transformation often unfolds gradually, almost imperceptibly. It can be noticed in the way students search for information, structure visual materials, or rely more confidently on images and mixed media rather than exclusively textual explanations.

Such tendencies become particularly visible in the preparation of future teachers. Digital tools in teacher education are no longer perceived merely as auxiliary instruments. They function more as a working environment in which students simultaneously assume the roles of designer, communicator, and future educator. Presentations, infographics, visual lesson plans, and multimedia assignments increasingly reflect not only the completion of academic tasks but also the gradual formation of professional competencies.

In many cases, these digital works reveal aspects of pedagogical thinking that remain less visible in traditional written assignments. Through visual composition, structuring of information, and stylistic decisions, students implicitly demonstrate how they interpret educational content and how they imagine interaction with future learners. Their work may contain early signs of methodological reasoning, aesthetic awareness, and professional self-expression. In this sense, digital artifacts can be viewed as indicators of emerging pedagogical identity rather than simply as assessment materials.

At the same time, this shift toward visual and multimodal forms of academic expression presents a methodological challenge. Conventional assessment systems, largely designed for text-based tasks and standardized evaluation criteria, often struggle to capture the complex structure of competencies embedded in digital educational products. Aesthetic choices, technical execution, conceptual clarity, and pedagogical intent are frequently intertwined, making evaluation both multidimensional and partially subjective.

Researchers increasingly note that the expansion of digital learning environments requires corresponding changes in diagnostic approaches. Selwyn [1] emphasizes that the digitalization of higher education not only diversifies forms of learning but also intensifies the need for more flexible

and analytically sensitive assessment systems. As digital artifacts become an integral part of students' academic activity, the question of how to interpret and evaluate them acquires particular significance.

Over the past decade, attempts to modernize competency assessment have taken various forms. Learning analytics and educational data mining have demonstrated that digital traces left by students in online environments can provide valuable insights into learning processes. Siemens [2] argues that such traces often reflect not only final outcomes but also patterns of engagement, shifts in strategy, and emerging conceptual difficulties. Nevertheless, these approaches remain less developed in fields where visual and creative outputs dominate, including art-pedagogical and design-oriented teacher education.

This situation creates a noticeable paradox. The most visually rich and conceptually layered educational artifacts are often produced in those disciplines where automated analytical tools are least frequently applied. As noted in recent studies [3], the integration of artificial intelligence into competency assessment remains uneven, with creative and pedagogically oriented fields still relying predominantly on expert judgement.

At the same time, contemporary research increasingly views artificial intelligence not as a substitute for expert evaluation but as a complementary analytical resource. Aggarwal [4] suggests that AI systems are capable of identifying subtle patterns in educational materials that may remain unnoticed within routine assessment practices. These include recurring compositional structures, stylistic tendencies, and implicit organizational principles that reflect how students interpret and present pedagogical content.

In recent years, interest in machine learning as an instrument for educational diagnostics has grown substantially. Holmes [5] demonstrate that machine learning models can predict aspects of student performance using digital artifacts as input data. Vasich et all [6] emphasize the potential of AI-supported assessment in improving consistency and scalability, particularly in contexts involving large volumes of student work. Within Kazakhstan, the relevance of such approaches is also increasing. OECD recommendations [7] points out that the development of objective and transparent diagnostic tools remains one of the unresolved challenges of educational digitalization.

Against this background, the present study explores the possibility of applying machine learning methods to the analysis of digital academic works created by students in teacher education programs. The working assumption is that algorithmic models, while not replacing expert judgement, may approximate it with sufficient accuracy to serve as an additional analytical layer. Such an approach allows for a more structured interpretation of visual and multimodal educational materials and reduces dependence on purely subjective evaluation.

It is important to note that the intention of the study is not to propose full automation of assessment. Rather, the focus lies on examining whether machine learning can function as a supportive diagnostic instrument capable of identifying patterns in digital works that correspond to expert evaluations. The central objective of the research is therefore to develop and test a model that can detect meaningful features in student digital artifacts and relate them to key professional competencies.

In practical terms, the study seeks to determine to what extent algorithmic analysis can reproduce the logic of expert judgement and whether such tools can contribute to greater consistency and transparency in competency assessment within teacher education. Addressing this question becomes especially relevant in art-technological training contexts, where evaluation traditionally relies on experiential expertise and qualitative interpretation.

Materials and methods

The empirical basis of this study was formed from digital academic works created by students enrolled in pedagogical programs at Zhetysu University named after I. Zhansugurov. These materials were collected over a two-year period (2022–2024) and represent authentic outcomes of students' academic and creative activity within the university's learning management system.

In total, 112 digital artifacts were selected for analysis. The dataset included presentation slides prepared for methodological courses, infographic posters developed as part of creative assignments, visual lesson materials created using graphic editors, and several project-based

compositions produced during teaching practice. Such diversity of formats proved methodologically valuable. It allowed observation of how professional competencies manifest not only in structured academic tasks but also in more experimental visual and hybrid forms.

Before analysis, all materials underwent a thorough anonymization procedure. Any identifying elements – including student names, group identifiers, metadata, comments, and visual references that could reveal personal identity – were removed. Each file was converted into a neutral format and assigned a random alphanumeric code. Because the research relied exclusively on depersonalized educational materials and did not involve sensitive personal data, the study complied with international ethical standards governing the use of anonymized learning artifacts and did not require formal institutional ethical approval.

To establish a reliable reference framework for machine learning training and validation, expert evaluation of all artifacts was conducted. The assessment model was based on the European framework for digital competence of educators (DigCompEdu), proposed by Redecker [9], which emphasizes the integrated evaluation of digital literacy, visual communication, and pedagogical functionality.

Five experienced faculty members specializing in art-pedagogical education participated as expert raters. Prior to evaluation, the experts jointly discussed and refined the rubric to ensure a shared understanding of criteria. Each artifact was assessed independently by all experts across four competency domains:

- digital literacy**,** including structural clarity, technical correctness, and appropriate use of digital tools;
- visual culture, encompassing compositional balance, color logic, and aesthetic coherence;
- creativity, reflecting originality of ideas, diversity of visual solutions, and the use of non-standard approaches;
- pedagogical orientation, indicating alignment with lesson objectives, clarity of didactic intent, and appropriateness for school-age learners.

All competencies were evaluated using a five-point scale, enabling differentiation of achievement levels across student works. To ensure objectivity, a double-blind evaluation procedure was applied: experts did not have access to the identities of students or to the scores assigned by their colleagues. After completion of the annotation process, inter-rater agreement was calculated. Kendall's coefficient of concordance reached 0.79, indicating a high level of consistency among expert evaluations and confirming the reliability of the reference dataset.

The multi-criteria approach used in the assessment of digital competence corresponds with the position of Zakirova [10], who emphasizes the necessity of applying structured evaluation tools that consider several interconnected competency domains simultaneously.

Data processing and analysis were carried out using the Python programming environment, including the libraries scikit-learn, Tensor Flow, and Keras. Google Colab was used to provide cloud-based computational resources. Quantitative parameters extracted from the digital works included the number of slides, text density, number of visual elements, and the proportion of textual and graphical content.

Random Forest algorithms were applied to analyze structured numerical indicators, while a convolutional neural network (CNN) architecture was employed to examine visual characteristics such as composition, layout, color distribution, and placement of graphic elements. The dataset was divided into training and testing subsets using a 70/30 ratio. Model performance was evaluated using standard metrics including accuracy, precision, recall, F1-score, and Cohen's kappa coefficient to determine agreement between model predictions and expert assessments.

In addition, Spearman's rank correlation coefficient was used to examine the degree of correspondence between the ranking of competencies produced by the machine learning model and those established by expert evaluators.

The overall research procedure unfolded in four consecutive stages. The first stage involved the collection and anonymization of digital artifacts. The second stage focused on expert annotation and formation of a benchmark dataset. During the third stage, the machine learning model was trained and tested on separate subsets of data. The fourth stage consisted of a

comparative analysis of expert evaluations and algorithmic predictions in order to determine the degree of correspondence between them.

The methodological design, combining quantitative indicators with content-visual analysis, made it possible to obtain a more comprehensive understanding of how professional competencies are reflected in students' digital academic work.

Results and discussion

The testing of the developed model demonstrated a generally high level of correspondence between machine-generated predictions and expert evaluations. In several competency areas this alignment appeared stronger than initially expected, particularly in relation to digital literacy and pedagogical orientation. These domains are characterized by relatively clear structural and didactic indicators, which makes them more accessible for algorithmic interpretation.

The effectiveness indicators of the model are presented in Table 1.

Table 1 – Performance indicators of the ML model in assessing competencies

Competency	Overall areaaccuracy	Prediction precision	Sensitivity (recall)	Balanced F1 indicator	Agreement with (Cohen's kappa)
Digital literacy	0,86	0,84	0,83	0,83	0,78
Visual culture	0,81	0,79	0,77	0,78	0,72
Creativity	0,74	0,70	0,69	0,69	0,63
Pedagogical orientation	0,85	0,83	0,82	0,82	0,76
Mean value	0,82	0,79	0,78	0,78	0,72

The data presented in Table 1 indicate that the proposed machine learning model demonstrates the highest performance in assessing digital literacy (0.86) and pedagogical orientation (0.85). Slightly lower, yet still stable results were obtained for visual culture (0.81). The lowest performance is observed in the assessment of creativity (0.74).

This distribution of indicators appears logically consistent. Competencies such as digital literacy and pedagogical orientation are typically expressed through observable structural features – clarity of formatting, alignment between content and lesson objectives, and logical organization of material. These characteristics can be detected and quantified with relative precision by algorithmic systems.

Creativity, by contrast, represents a far more complex and less formalized dimension. Its evaluation depends not only on visible structural parameters but also on originality of ideas, contextual relevance, and stylistic experimentation. Such qualities resist strict formalization and often require interpretive judgement. As Kaufman and Beghetto note, assessments of creativity inevitably contain a subjective component, even when conducted by experienced experts [11].

At the same time, comparative analysis revealed that machine learning is capable of identifying certain structural patterns that are not always explicitly articulated within expert evaluation criteria. For example, the model consistently associated high digital literacy with visual balance, restrained color palettes, and limited font variation. Interestingly, these parameters were not always consciously considered by experts during manual evaluation, yet they appeared as stable indicators within algorithmic analysis.

The overall level of agreement between expert and machine assessments reached a Cohen's kappa value of 0.74, indicating substantial consistency. This suggests that the model can reproduce the general logic of expert evaluation with a fairly high degree of reliability. Nevertheless, the issue of interpretability remains unresolved. Despite accurate predictions, machine-generated assessments do not always provide transparent explanations for their decisions. Similar concerns are emphasized in UNESCO recommendations, which underline the necessity of maintaining human oversight when artificial intelligence is applied in educational assessment [12].

The use of machine learning methods in educational analytics is gradually moving beyond the stage of experimentation and is increasingly becoming part of the tools used to assess learning outcomes. Kipper and Rüütmann [13] note that algorithmic analysis of students' academic materials makes it possible to identify stable structural patterns and enhance the consistency of expert evaluation.

In a review study, Zawacki-Richter and colleagues [14] emphasize that artificial intelligence in higher education is primarily applied to the analysis of educational data and automated assessment of learning outcomes. However, creative and pedagogically oriented fields of training remain less represented in such research.

Chen et al. [15], examining the development of AI technologies in education, highlight the need to integrate technological capabilities with pedagogical theories of competency formation. At the same time, Kirschner and De Bruyckere [16] warn against overestimating students' digital skills and stress the importance of objective diagnostic tools. Anderson and Dron [17], analyzing the evolution of digital learning, argue that the contemporary educational environment requires analytical approaches capable of capturing not only outcomes but also the dynamics of students' professional development.

Taken together, these studies confirm the relevance of applying machine learning methods for a more systematic analysis of the digital academic work of future teachers.

The correlation between expert and machine-based evaluations across competencies is presented in Table 2.

Table 2 – Correlation between expert and ML-based assessments across competencies

Competency	**Spearman's ρ**	**p-value**
Digital literacy	0,78	<0.01
Visual culture	0,72	<0.01
Creativity	0,63	<0.05
Pedagogical orientation	0,76	<0.01
Average	0,72	—

As shown in Table 2, the strongest correlation between expert judgments and algorithmic predictions was identified for digital literacy ($\rho = 0.78$) and pedagogical orientation ($\rho = 0.76$), with both correlations statistically significant at $p < 0.01$. These results indicate that the model reliably captures structural and pedagogically meaningful characteristics embedded in students' digital work.

A slightly lower, yet still stable correlation was observed for visual culture ($\rho = 0.72$). The lowest correspondence was identified in the assessment of creativity ($\rho = 0.63$), which appears consistent with the inherently interpretive nature of this competency. Creativity rarely follows predictable patterns and often manifests through unconventional visual or conceptual solutions that challenge standardized evaluation criteria.

In this context, the discrepancies between expert and automated assessments should not be interpreted solely as model limitations. Rather, they reflect the broader methodological difficulty of formalizing creative expression. Even among human evaluators, agreement in assessing originality and novelty is not always complete.

A number of illustrative discrepancies between expert scores and model predictions are presented in Table 3.

Table 3 – Examples of discrepancies between expert and ML assessments

Artifact type	**Expert evaluation (score)**	**ML prediction (score)**	**Comment**
Infographic poster with complex color scheme	Creativity = 5	Creativity = 3	The model underestimated originality, likely due to focus on structural balance rather than novelty.

Artifact type	Expert evaluation (score)	ML prediction (score)	Comment
Lesson slide with minimalistic design	Digital literacy = 3	Digital literacy = 5	The model overrated clarity, interpreting simplicity as correctness.
Visual project with rich illustrations but weak structure	Pedagogical orientation = 2	Pedagogical orientation = 4	The model prioritized visual richness, overlooking weak alignment with lesson goals.
Presentation with innovative layout and bold colors	Visual culture = 4	Visual culture = 2	The model penalized unconventional color use, whereas experts valued creative expressiveness.

The cases summarized in Table 3 demonstrate that the model tends to underestimate works characterized by unconventional visual solutions and overestimate those with technically correct but conceptually limited structures. Such tendencies highlight the model's sensitivity to formal parameters and its comparatively weaker responsiveness to expressive or experimental elements.

The distribution of model accuracy across competencies is visually presented below Figure 1.

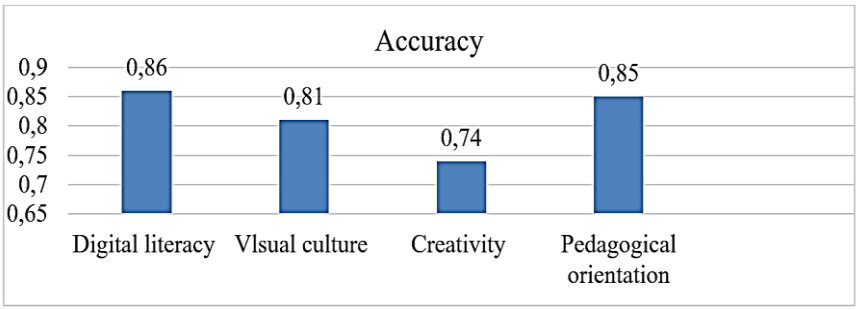

Figure 1 – Comparison of ML model accuracy across competencies

The diagram shows that the highest level of accuracy is achieved in diagnosing digital literacy and pedagogical orientation. These competencies rely on structured and measurable features that can be consistently recognized by algorithmic systems. Lower accuracy in the assessment of creativity once again confirms the complexity of formalizing originality and stylistic innovation within automated evaluation frameworks.

The relationship between expert and machine-based assessments is illustrated in the following diagram Figure 2.

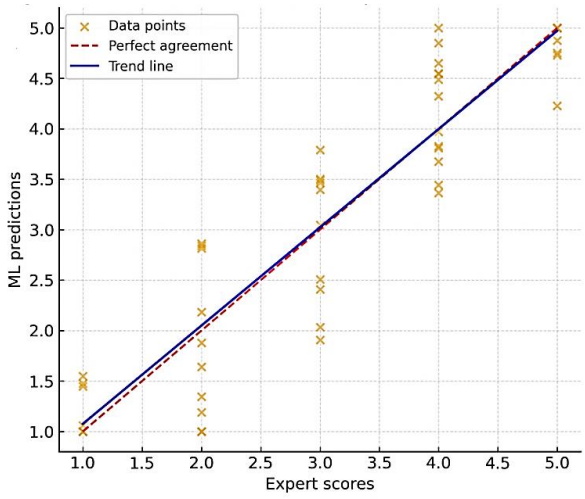

Figure 2 – Correlation between expert and ML assessments

A generally strong positive correlation between expert and algorithmic evaluations can be observed. At the same time, several deviations remain visible, particularly in the upper ranges of creativity scores. These deviations suggest that the model may interpret unconventional visual decisions as structural inconsistencies rather than deliberate creative choices.

Additional discrepancies are illustrated in the confusion matrix.

A more detailed representation of these discrepancies is provided in the confusion matrix shown in Figure 3.

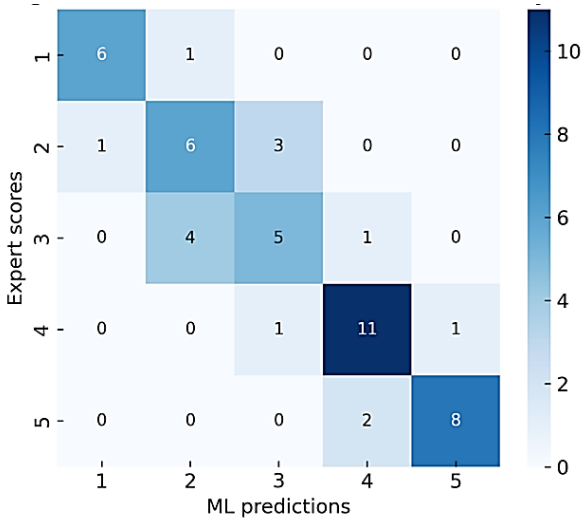

Figure 3 – Confusion matrix for Creativity

The matrix demonstrates that the model most accurately classifies works with moderate levels of creativity, while predictions at the highest and lowest ends of the scale remain less stable. This once again indicates that the evaluation of originality and novelty remains the most challenging area for automated systems.

Overall, the results of the study indicate that machine learning can serve as an effective supportive analytical instrument within competency assessment. It enables the identification of recurring structural patterns, accelerates preliminary evaluation procedures, and provides an additional layer of diagnostic information. At the same time, the findings clearly show that algorithmic assessment should not be interpreted as a replacement for expert judgement. Rather, its greatest value lies in complementing human evaluation and enhancing consistency within complex, visually oriented educational contexts.

Conclusion

The results of the present study suggest that the use of machine learning in the analysis of students' digital academic work is gradually moving beyond the stage of a purely technical experiment. Rather than being perceived as a replacement for expert evaluation, it begins to function as a methodological instrument capable of supporting and structuring the assessment process.

The developed model demonstrated a consistently high level of agreement with expert evaluations, particularly in those competency domains where professional qualities are expressed through clearly structured and pedagogically grounded decisions. Digital literacy and pedagogical orientation proved to be the most accessible for algorithmic interpretation, as both rely on features that can be observed, measured, and compared with relative precision.

At the same time, the comparatively lower accuracy in assessing creativity once again highlights the complex and multidimensional nature of evaluative judgement in art-technological education. Creativity rarely manifests through stable or easily quantifiable indicators. It often appears through unconventional visual solutions, stylistic experimentation, and context-dependent interpretation. These characteristics inevitably introduce a degree of subjectivity into assessment and explain the divergence between expert and automated evaluations.

Nevertheless, the findings indicate that machine learning can be effectively employed as a complementary analytical layer within competency diagnostics. Its primary value lies in the ability to identify recurring structural patterns, reduce evaluative variability, and provide preliminary analytical insights that support expert judgement. In this sense, algorithmic analysis does not simplify assessment but rather adds an additional dimension to it, enabling a more consistent interpretation of complex digital educational materials.

From a practical perspective, the integration of such models into learning management systems may assist instructors in several ways. Automated preliminary analysis can help identify general tendencies in student work, monitor the development of competencies over time, and support large-scale evaluation procedures where manual assessment alone becomes difficult to sustain. At the same time, the implementation of machine learning tools in pedagogical practice requires careful methodological consideration and a clear understanding of the limits of automation.

The study also reveals several directions for further research. Expanding the dataset, incorporating additional modalities such as textual and interactive components, and refining algorithms capable of interpreting creative variability may significantly enhance the accuracy and interpretability of automated assessment systems. As digital forms of academic expression continue to evolve, analytical approaches designed to interpret them must evolve accordingly.

Overall, the research demonstrates that the integration of machine learning into competency assessment within teacher education is both feasible and pedagogically meaningful. When combined with expert evaluation, such tools can contribute to greater objectivity, transparency, and scalability of diagnostic procedures, while preserving the interpretive depth that remains essential in assessing complex educational outcomes.

In this sense, the study contributes to the emerging methodological dialogue on how artificial intelligence can be responsibly integrated into pedagogical diagnostics without diminishing the role of professional expertise.

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БОЛАШАҚ ПЕДАГОГТЕРДІҢ КӘСІБИ ҚҰЗЫРЕТТЕРІН КАРТАЛАУ ҮДЕРІСІНДЕ ЦИФРЛЫҚ ЖҰМЫСТАРДЫ МАШИНАЛЫҚ ОҚЫТУ НЕГІЗІНДЕ БАҒАЛАУ

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Аңдатпа. Білім беруді цифрландыру жағдайында болашақ мұғалімдердің кәсіби даярлық деңгейі олардың оқу жұмыстарында айқын көрініс табуда. Презентациялар, инфографикалар және түрлі визуалды материалдар тек есеп беру нысаны ғана емес, сонымен қатар педагогикалық білім беру бағдарламаларында білім алатын студенттердің негізгі құзыреттерінің қалыптасу көрсеткішіне айналып келеді. Осыған байланысты оларды жүйелі түрде талдау мен бағалаудың өзектілігі арта түсуде.

Зерттеуде педагогикалық бағытта білім алатын студенттердің цифрлық оқу жұмыстарын талдау үшін машиналық оқыту әдістерін қолдану қарастырылады. Эмпирикалық база ретінде білім алушылардың 112 цифрлық жұмысы пайдаланылды. Эксперимент төрт бағыт бойынша жүргізілді: цифрлық сауаттылық, визуализация, креативтілік және педагогикалық бағыттылық. Деректерді өңдеу үшін Random Forest модельдері мен жасанды интеллект алгоритмдері қолданылып, жұмыстардың құрылымдық метадеректері мен визуалдық сипаттамаларын қатар талдауға мүмкіндік берілді.

Нәтижелер сарапшылар бағалары мен машиналық оқыту модельдерінің болжамдары арасында жоғары деңгейдегі сәйкестікті көрсетті, әсіресе цифрлық сауаттылық пен педагогикалық бағыттылық бойынша. Креативтілікті бағалау дәлдігі төмендеу болды, бұл бірегей шешімдерді алгоритмдік тұрғыдан интерпретациялаудың күрделілігін дәлелдейді.

Зерттеу нәтижелері машиналық оқытудың сараптамалық бағалауды толықтай алмастыра алмайтынын көрсетеді. Дегенмен, оны бағалау үдерісінің бірізділігін арттырып, субъективті түсіндіруге тәуелділікті азайтатын қосымша аналитикалық құрал ретінде қолдануға болатынын дәлелдейді.

Кілт сөздер: *машиналық оқыту, цифрлық сауаттылық, құзыреттерді бағалау, болашақ мұғалімдер, білім беру аналитикасы.*

ОЦЕНКА ЦИФРОВЫХ РАБОТ НА ОСНОВЕ МАШИННОГО ОБУЧЕНИЯ В КАРТИРОВАНИИ ПРОФЕССИОНАЛЬНЫХ КОМПЕТЕНЦИЙ БУДУЩИХ ПЕДАГОГОВ

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Аннотация. В условиях цифровизации образования уровень профессиональной подготовки будущих учителей всё чаще отражается в их учебных работах. Презентации, инфографика и визуальные материалы становятся не только формой отчётности, но и показателями сформированности ключевых компетенций студентов педагогических образовательных программ. В связи с этим возрастает актуальность их системного анализа и оценки.

В исследовании рассматривается применение методов машинного обучения для анализа цифровых учебных работ студентов педагогических направлений. Эмпирическую базу составили 112 цифровых работ обучающихся. Эксперимент проводился по четырём направлениям: цифровая грамотность, визуализация, креативность и педагогическая направленность. Для обработки данных использовались модели Random Forest и алгоритмы искусственного интеллекта, что позволило одновременно анализировать структурные метаданные и визуальные характеристики работ.

Полученные результаты показали высокий уровень соответствия между экспертными оценками и прогнозами, сформированными моделью машинного обучения, особенно в областях цифровой грамотности и педагогической направленности. Оценка креативности оказалась менее точной, что подтверждает сложность алгоритмической интерпретации оригинальных решений.

Результаты исследования не свидетельствуют о том, что машинное обучение способно заменить экспертную оценку. Вместе с тем они показывают, что его можно рассматривать как дополнительный аналитический инструмент, способствующий повышению согласованности оценивания и снижению зависимости от субъективной интерпретации.

Ключевые слова: *машинное обучение, цифровая грамотность, оценка компетенций, будущие учителя, образовательная аналитика.*

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