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# INTELLIGENT SYSTEM FOR SELF-STUDY OF MATHEMATICS

# МАТЕМАТИКАНЫ ӨЗДІГІНЕН ОҚЫТУҒА АРНАЛҒАН ИНТЕЛЛЕКТУАЛДЫ ЖҮЙЕ

# ИНТЕЛЛЕКТУАЛЬНАЯ СИСТЕМА ДЛЯ САМОСТОЯТЕЛЬНОГО ОБУЧЕНИЯ МАТЕМАТИКЕ

***Abstract.*** *The abrupt shift toward remote learning has compelled digital education creators to reexamine learning tool design. A core priority is enhancing quality and efficacy amid this transition [1]. When developing digital learning centers, accounting for digital-native learners' needs is crucial. This analysis proposes realigning didactic principles to boost self-directed mathematics proficiency.*

*DLRs now constitute primary, not auxiliary, learning instruments. Their creation should focus on nonlinear, multifaceted architectures enabling personalized content [2]. DLRs can potentially be transformed via cognitive-focused, modular, inverted, and gamified approaches.*

*This study explores optimal machine learning techniques to implement artificial intelligence-based systems aimed at raising math instruction effectiveness for both online and offline contexts. Core principles for developing intelligent self-directed resources to teach mathematical problem-solving and assess retention are discussed.*

*The suggested methods foster creating next-generation DLRs with unified, learner-adaptive structures. Applying these techniques also upholds individualization, critical for distance learning. Overall, the approaches aim to produce intelligent systems tailored for Generation Z's at-home self-study needs. The analysis provides initial examples of DLRs embracing these approaches.*

***Keywords:*** *mental approach, transformer textbook, inverted textbook, computational primitive, mental schemes, gamification.*

***Аңдатпа***. *Қашықтықтан оқытуға көшу сандық білім беруді жасаушыларды оқу құралдарының дизайнын қайта қарауға мәжбүр етті. Осындай көшу жағдайында оқытудың сапасы мен тиімділігін арттыру негізгі басымдық болып табылады [1]. Цифрлық оқу орталықтарын әзірлеу кезінде «цифрлық аборигендердің» қажеттіліктерін есепке алу өте маңызды. Осы талдауда математиканы өз бетінше меңгерудің тиімділігін арттыру үшін дидактикалық қағидаттарды қайта құруды ұсынады.*

*ДОР қазір негізгі оқыту құралдарының, емес қосалқы құралдарының рөлін атқарады. Оларды жасау кезінде сызықтық емес, көптеген форматтарға негізделген ақпараттық салаларға назар аударған жөн [2]. ДОР ми қабылдауға бағытталған, модульдік, кері, және геймификацияланған* *тәсілдер арқылы өзгертілуі мүмкін.*

*Бұл зерттеу онлайн және офлайн мәнмәтіндерде математика оқытудың тиімділігін арттыруға бағытталған жасанды интеллект негізіндегі жүйелерді енгізудің оңтайлы машиналық оқыту тәсілдерін зерделейді. Математикалық есептерді шешуге үйрету және білімді бақылау үшін интеллектуалды өзін-өзі оқытатын ресурстарды дамытудың негізгі қағидалары талқыланады.*

*Ұсынылған әдістер келесі буын ДОР жасауға, олардың бірыңғай, оқытушыға бейімделген құрылымдарын дамытуға ықпал етеді. Бұл тәсілдерді қолдану қашықтан оқыту үшін маңызды жеке оқыту қағидатын сақтауға мүмкіндік береді. Жалпы алғанда, осы тәсілдер Z ұрпақтың үйде өзін-өзі оқыту қажеттіліктеріне бағдарланған интеллектуалды жүйелер жасауға бағытталған. Талдауда осы тәсілдерді пайдаланатын DLR-дің алғашқы мысалдары келтірілген.*

***Түйін сөздер:*** *психикалық тәсіл, трансформаторлық оқулық, инверттелген оқулық, есептеу примитиві, психикалық схемалар, геймификация.*

***Аннотация.*** *Резкий переход к дистанционному обучению заставил создателей цифрового образования пересмотреть дизайн учебных пособий. Основным приоритетом является повышение качества и эффективности обучения в условиях такого перехода [1]. При разработке цифровых учебных центров крайне важен учет потребностей «цифровых аборигенов". В данном анализе предлагается изменить дидактические принципы для повышения уровня самостоятельного освоения математики.*

*В настоящее время ЦОРы являются основными, а не вспомогательными средствами обучения. Их создание должно быть ориентировано на нелинейные, многогранные архитектуры, позволяющие персонализировать контент [2]. Потенциально DLR могут быть преобразованы с помощью когнитивно-ориентированного, модульного, инвертированного и геймифицированного подходов.*

*В данном исследовании рассматриваются оптимальные методы машинного обучения для реализации систем на основе искусственного интеллекта, направленных на повышение эффективности обучения математике как в онлайн, так и в офлайн-контекстах. Обсуждаются основные принципы разработки интеллектуальных самонаправляемых ресурсов для обучения решению математических задач и оценки усвоения материала.*

*Предложенные методы способствуют созданию РСУ нового поколения с унифицированной, адаптивной к учащимся структурой. Применение этих методов также способствует индивидуализации, что очень важно для дистанционного обучения. В целом подходы направлены на создание интеллектуальных систем, адаптированных к потребностям поколения Z в домашнем самообучении. В анализе приведены первые примеры DLR, использующих эти подходы.*

***Ключевые слова:*** *ментальный подход, учебник-трансформер, перевернутый учебник, вычислительный примитив, ментальные схемы, геймификация*

*Introduction.* During the pandemic of widespread forced adoption of distance learning, the question of the quality and effectiveness of this format of learning has become urgent. From both research and experience, the principles and quality of the digital learning resources used in distance learning play a major role. While a proliferation of digital learning resources exists, evidence indicates many are not optimized for self-directed education despite their prevalence. The emerging «cognitive revolution» in education points to the need to accommodate students' individual thinking styles and mental frameworks in the learning process [1, 2]. However, the mindsets of today's Generation Z students, shaped by digital immersion, can conflict with traditional knowledge sources and learning formats [3]. Previously, the educational focus was on broad expertise transfer based on a «knowledge for knowledge's sake» rationale. In contrast, digital native students tend to use technology to access networked information to solve problems as needed, embodying a «just-in-time knowledge» mentality. This generational shift calls for realigning educational resources with how this cohort prefers to gather and apply knowledge [4].

Modern educational tools are rapidly evolving as a synthesis of theoretical frameworks and empirical findings from teaching practice. This research builds on the influential conception of mental textbooks incorporating mental maps, originally proposed by Professor N.I. Pak of Krasnoyarsk State Pedagogical University [5]. Additionally, the search for optimal techniques in digital education has been extensively developed in the work of scholars such as Zakharova, Lapchik, Ragulina, Robert, Blinov, and Henner. Their research has brought greater clarity to defining core concepts and models related to pedagogical innovation as education undergoes a transition to digital platforms [6, 7]. The integration of robust theoretical foundations with evidence-based insights from instructional design continues to advance the development of modern education tools.

Contemporary educational standards at both the secondary and university levels imply a transition in instructional priorities toward cultivating students' personal qualities and competencies. Given this shift, core objectives of computer science, computer engineering, and information technology curricula now emphasize nurturing algorithmic thinking capabilities. To fulfill these goals, designing an innovative cognitive learning platform could effectively enhance students' cognitive skillsets and algorithmic mindsets [7, 8]. This represents a move away from concept-focused teaching toward directly developing the analytical and computational thinking patterns that underpin success in technology-oriented fields. Mental algorithmic patterns play a big role in thinking. Any professional or any other daily human activity requires modeling, accumulation and analysis of learning information followed by development of algorithm of actions. Individual ability of an individual to develop and apply such algorithm forms the basis for algorithmic thinking [6]. The need has arisen to develop a new generation of digital tools for interactive learning, creative development, synchronous and asynchronous distance learning, etc. In their research paper, Andrew S., E. Waters emphasized important advantages of organizing the learning process using intelligent computer-based educational systems such as individual approach to the learner, taking into account his characteristics and interests; the possibility of organizing distance learning; independence of classroom time, etc. [7].

To date, there are a large number of educational intelligent systems in the world. One of the most successful ones is «PARIS - École 42» by Nicolas Sadirac. «PARIS – École 42» has an analogue in Kazakhstan, which is called «Alem school». In this system the learning process is built on the «peer to peer» model, which allows effectively giving theoretical knowledge and applied practical skills, but without taking into account the formation of fundamental knowledge and scientific component, which is very important for further professional development of the student. The peer-to-peer model lacks self-learning capabilities and expert systems based on this model are simple. A solution to this problem is proposed in this study.

Approaches to New Generation DER Development

In the course of the study, the authors identified approaches to the transformation of DER adequate to the mentality of today's Z-generation learners, in order to increase the efficiency of independent home learning.

A Cognitive-Focused Approach

The cognitive-focused approach conceptualizes learning as a process of shaping and evolving students' mental models and knowledge structures through informational exchanges with their environment [8]. This learner-centered perspective emphasizes the cumulative development of internal cognitive schemas, frameworks, and patterns as the foundation of meaningful learning. The cognitive approach places priority on engaging and enhancing students' existing mental models rather than imposing external frameworks.

Employing a cognitive approach involves two core stages. First, foundational sensory mental schemas of the subject area are constructed through conceptual models. Next, the images, models, and concepts are systematized and integrated using language and terminology. This delineates learning into intuitive and systematic phases. The initial intuitive learning stage focuses on forming connections between sensory representations and their abstract models. Learners develop an experiential grasp of the concepts. The second stage contextualizes this intuitive knowledge within the formal conceptual and semantic system of the subject area. Here, the intuitive experience is crystallized and consolidated using official vocabulary and concepts (Figure 1). This staged development sequentially builds up learners' cognitive faculties and integrative capacities.

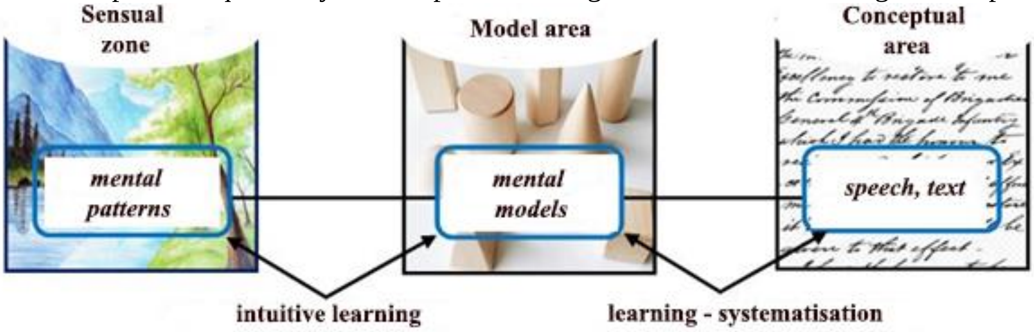


**Figure 1.** Staging the mental approach to learning

During the initial intuitive learning phase, presenting concepts through mental maps can provide an accessible starting point [8]. At the systematic consolidation stage, hands-on problem solving helps cement theoretical knowledge.

Research shows learning is most effective when learners actively construct their own mental frameworks, rather than passively receiving pre-fabricated schemes [9]. Accordingly, the cognitive approach focuses on facilitating the organic emergence and evolution of students' understanding, rather than imposing external models.

Mental textbooks allow intuitive, modeling, and theoretical stages to be integrated, moving from visual-figurative to conceptual forms. Visual knowledge mapping techniques aid intuitive comprehension by illustrating connections and causal relationships. Both conventional visualization methods (e.g., charts, diagrams) and innovative techniques like hyperbolic trees are applicable. In particular, mind mapping has become a popular cognitive design approach.

A Modular Approach

An additional model for learner-adaptive e-textbooks involves an interactive, modular framework where content is presented based on users' preferences and changing needs. This transformative style of textbook allows customizable structuring [10, 11, 12]. Creating such modular textbooks requires extensive development efforts. Consequently, developing a software shell to facilitate authoring modular textbooks could provide useful capabilities. Potential software foundation’s include: (figure 2)

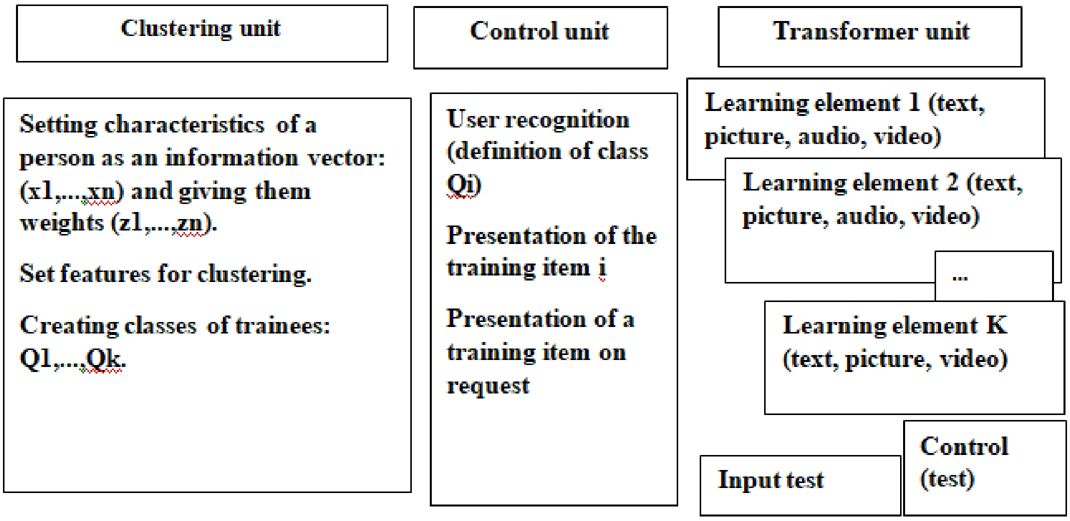


**Figure 2.** Structure of the construction of a textbook-transformer

This modular approach enables dynamic textbook architectures that can rearrange content elements to align with individual learners' cognitive profiles and evolving mastery levels. The software infrastructure to power such books simplifies implementation for creators.

The modular textbook architecture contains three core components:

A profiling interface clusters learners based on criteria like cognitive style, skill level, memory, attention span, and reading pace. This enables personalization.

The transformer block houses a array of learning objects for each topic area tailored to the learner groups identified by the profiling engine.

An interactive control module lets users provide feedback to select the most appropriate content elements.

This structured approach empowers learners to essentially customize materials to fit their unique needs and preferences. The modular components work together to adapt resources to individual learners' capacities and interests.

Inverted Learning Tools

The notion of an "inverted e-textbook" ties indirectly to the flipped classroom model [13]. This inversion overturns the conventional linear content structure. Instead, an inverted format employs a nonlinear, networked architecture driven by inquiry-based nodes. Students explore core questions to propel their learning pathways through the material (figure 3). This inquiry-led approach aims to actively engage learners in analyzing and constructing knowledge rather than passively receiving instruction. The inverted model challenges traditional transmissive teaching methods in favor of discovery-based, learner-driven resource architectures.

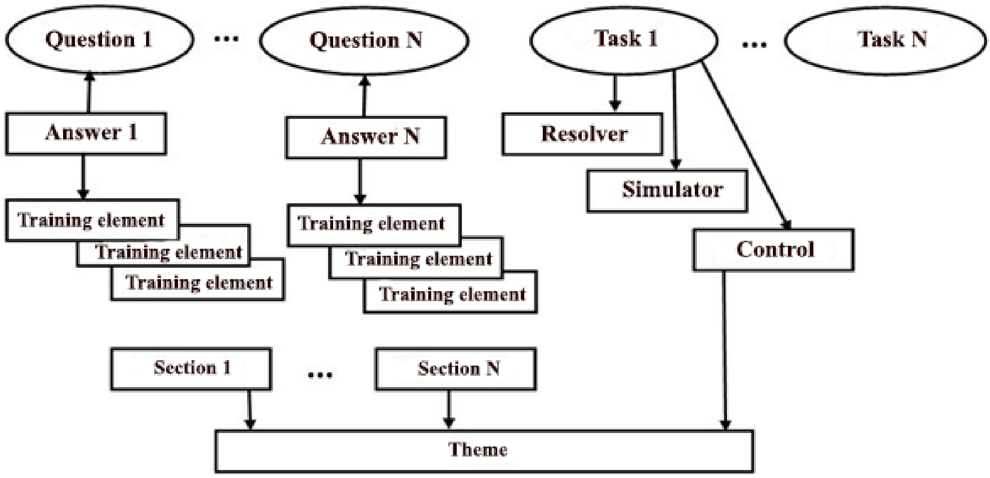


**Figure 3.** Structure of a flipped e-textbook

Gamified Learning Tools

Gaming principles are widely recognized as valuable for engaging learners and promoting knowledge retention. Integrating game elements into e-learning tools can motivate students and stimulate interactivity [14].

Gamification typically involves applying game-inspired mechanics like point systems, challenges, and rewards to traditionally non-game contexts [15, 16]. For example, an interactive software environment could use gamification to structure independent work developing students' computational thinking and problem-solving abilities. Gamefic interfaces prompt active learning and discovery through incentive-driven participation.

Overall, leveraging gamification techniques in digital learning resources represents a promising approach to captivating learners' interest and imagination within educational settings. Playful, game-inspired systems create opportunities for self-directed learning and mastery attainment.

*Results.* In this study, an intelligent learning system model based on sparse matrix factorization (SMF) is constructed. This method is a key component in many machine learning problems and there are many applications to solve real world problems such as, recommendation systems, missing value estimation, gene expression modelling, intelligent learning systems (ITSs) etc.

There are various approaches to solve the SMF problem based on linear algebra and probability theory. In system design, an incomplete binary matrix of learner performance for a set of questions assessing the probability of success or failure on unanswered questions is of interest. This problem is solved using maximum likelihood estimation (MLE), which leads to a binary convex optimization problem (this formulation is based on SPARFA [MM]). This results in a complex optimization problem which is difficult to handle due to the existence of many local minima.

On the other hand, when the learner matrix size increases, the existing algorithms are not successful, so an efficient algorithm for large matrices is required to solve this problem. This study uses a parallel algorithm (i.e., a parallel version of SPARFA) developed to solve the binary convex optimization problem and tested with a series of generated matrices.

Researchers note that there is a significant shift from traditional methods of learning mainly through textbooks, lectures, etc. to artificial intelligence-based systems that are adapted to each learner individually [6]. Personalized Learning Systems (PLSs) and Intelligent Learning

Systems (ITSs) are two more well-known examples of such newly developed learning systems. In intelligent learning systems (ITSs), performance evaluation, decision making and outputs (knowledge/skills) and debriefing are controlled in simulations. Intelligent Tutoring Systems (ITSs) by adapting instructions to tasks including a «Learner Model» simulates the teacher. In such systems, the student's learning is assessed based on the analysis of their previous work. The model implementation provides a two-convex maximum likelihood-based solution to the sparse factor analysis problem (SPARFA). However, the scalability of SPARFA when the number of questions and students increases significantly has not yet been explored.

The creation of an intelligent learning system is based on the following model.

Let Y denote a binary set of data about the performance of N students on Q questions; hence, Y is a matrix of size $Q \times N$ with the notation $Y_{ij} = 1(0)$ if student j answers question i correctly. The Y matrix is very sparse because there are many questions which are not answered, leading to incomplete data. One way to estimate the missing values in Y is to decompose Y into matrices W, C and M so that the function WC+M can estimate the values of Y. Assume that the set of questions is associated with a small number of abstract concepts represented by W, where the weight $W_{ik}$ ($\forall i = 1, ..., Q$ and $k = 1, ..., K$) indicates the degree to which question i includes concept k, and K is the number of hidden abstract concepts. Let $C_{kj}$($\forall k = 1, . . ., K$ and $j = 1, . . ., N$) denote student j's knowledge of concept k (C equals the matrix version of $C_{kj}$). M-matrix $Q \times N$ representing the intrinsic complexity of each question.

It is assumed that K Q, N, thus W becomes a high, narrow matrix $Q \times K$ and C will be a short, wide matrix $K \times N$.

The study implements the described model.

The developed intelligent system incorporates a bank of math tutorial questions and collects learner performance data through machine learning networks.

The task module utilizes an AI tutor model with three components: Solver, Simulator, and Controller. The Solver enables students to tackle problems, view explanations, and see the step-by-step work. The Simulator generates personalized practice problems and provides feedback or guidance as needed. The Controller covers administrative functions and adds visualization capabilities.

Additional psychological and pedagogical principles can be programmed into the system architecture along with user-friendly interfaces. Overall, the aim is to create a responsive intelligent platform that adapts to individual learners' evolving needs and comprehension. By leveraging AI technologies, the system can continually refine instructional strategies based on performance patterns.

*Conclusion*

Today's societal challenges alongside the distinct learning needs of students necessitate rapidly developing new frameworks and models for education. Independent self-directed learning activities tailored for at-home use are becoming essential. Consequently, digital learning resources (DLRs) require robust psychological, pedagogical, and didactic design principles.

Rather than supplemental materials, DLRs now represent primary learning tools. Their architecture should focus on nonlinear, flexible formats enabling personalized learning pathways responsive to individual needs. As discussed, DLRs can be transformed through cognitive-focused, modular, inquiry-based, and gamified approaches.

The techniques outlined here facilitate creating intelligent systems that holistically account for Generation Z's characteristics to deliver customized self-learning. This analysis has provided initial examples of DLR implementations utilizing these methods. Further innovation in this direction has the potential to enrich independent learning while empowering learner agency over individual education journeys. These insights may hold value for DLR developers seeking to heighten personalization and outcomes in self-directed education models. Increasingly, creators must align emerging tools with the cognitive and developmental needs of the students using them.

References


1. Pak N.I., Stepanova T.A., Bazhenova I.V., Gavrilova I.V. Multidimensional algorithmic thinking development on mental learning platform. Journal of the Siberian Federal University. Series: Humanities. V. 12. No. 6. 2019. pp.1072-1087.
2. S. Natasha Lee,B. Brian, J. Martin Bach, M. Thomas B., T. Janus Laust. Machine learning in general practice: a scoping review of administrative task support and automation. BMC Primary Care, V. 24, No. 1, 2023, https://doi.org/10.1186/s12875-023-01969-y.
3. Robert I. V. Digital Transformation of Education: Challenges and Opportunities for Improvement // Informatization of Education and Science. № 3(47). 2020. C. 3-17.
4. Didactic concept of digital professional education and training / P.N. Bilenko, V.I. Blinov, M.V. Dulinov, E.Y. Esenina, A.M. Kondakov, I.S. Sergeev; Ed. I. Blinov, 2020, 98 p.
5. Arthur S. Grasser, Mark W. Conley, and Andrew Olney, Intelligent learning systems., 2012, 237 p.
6. Andrew S. Lan, Andrew E. Waters, Christoph Studer, and Richard G. Baranyuk, Sparse Factor Analysis for Learning and Content Analytics, Journal of Machine Learning Research, V.15, No 1, 2014, pp.1959-2008.
7. Asaulenko E.V. Artificial intelligence from the position of mental schemas. Open Education, No. 4, 2014, pp. 50 54.
8. M. Ilbeigi, D. Bairaktarova, A. Morteza. Gamification in Construction Engineering Education: A Scoping Review. Journal of Civil Engineering Education, V.149, No.21, 2023, No.04022012.
9. West, Darrell M. Using Technology to Personalize Learning and Assess Students in Real-Time. Darrell M. West. - Washington: Center for technology innovations at Brookings, 2011, pp.19.
10. Pak N.I., Potupchik E.G., Hegai L.B. The concept of transformational and inverted electronic textbooks. RUDN Bulletin, Education Informatization Series, Vol.17, No.2, 2020, pp.153-168.
11. C.Eoghan,J.Jennifer, P.Karen A., P.Daryl, S.Cassy. Motivating youth to learn STEM through a gender inclusive digital forensic science program. Smart Learning Environments. – V. 10. – No. 1, 2023, https://doi.org/10.1186/s40561-022-00213-x
12. Kogel A.S., Fenyuk A.N. Gamification as a marketing tool: the psychological aspect .Skif. Voprosy student's science, № 9(37), 2019, C.56-60.
13. Pakhomova T.E. The use of gamification elements in the educational process. Informatics in school, №4(107), 2015. – P. 17 23.
14. Pak N.I., Asaulenko E.V. Personification of students' independent work on the formation of the ability to solve calculation problems on the basis of an automated training and diagnostic system.Informatics and Education. – № 8(297), 2018. – P. 26-31.
15. ShagaiegSahebi, Yoon Huang, and Peter Brusilovsky, Predicting Student Performance in Parametrized Exercise Solutions, Intelligent Learning Systems, Springer, 2014. – Pp. 496-503.
16. B.Nauryzbayev, S.Baygamitova; Zh.Akhmetova, N.Pak, A.Karipzhanova, K.Urazbaeva. Using Machine Learning to Analyze the Learning Process for Solving Mathematical Problems. International Journal of Interactive Mobile Technologies Vol. 16. – No. 21. – Pp. 114-124, 2022.


Список литературы


1. Pak N.I., Stepanova T.A., BazhenovaI. V., GavrilovaI. V. Multidimensional algorithmic thinking development on mental learning platform. Journal of the Siberian Federal University. Series: Humanities..V. 12. – No. 6.. 2019. – Pp. 1072-1087.
2. S. Natasha Lee, B.Brian, J. Martin Bach, M. Thomas B., T. Janus Laust. Machine learning in general practice: scoping review of administrative task support and automation. BMC Primary Care, V. 24, No. 1, 2023, https://doi.org/10.1186/s12875-023-01969-y
3. Роберт И.В. Цифровая трансформация образования: вызовы и возможности совершенствования // Информатизация образования и науки. – № 3(47). – 2020. – С. 3-17.
4. Дидактическая концепция цифрового профессионального образования и обучения / П.Н. Биленко, В.И. Блинов, М.В. Дулинов, Е.Ю. Есенина, А.М. Кондаков, И.С. Сергеев; под науч. ред. В.И. Блинова, 2020. – 98 с.
5. Артур С. Грэссер, Марк У. Конли и Эндрю Олни, Интеллектуальные системы обучения., 2012, 237 с.

6. Andrew S. Lan, Andrew E. Waters, Christoph Studer, and Richard G. Baranyuk, Sparse Factor Analysis for Learning and Content Analytics, Journal of Machine Learning Research, V.15, No 1, 2014, pp.1959-2008.
7. Асауленко Е.В. Искусственный интеллект с позиции ментальных схем. Открытое образование, № 4, 2014, стр. 50-54.
8. M.Ilbeigi, D.Bairaktarova, A. Morteza. Gamification in Construction Engineering Education: A Scoping Review. Journal ofCivil Engineering Education, V.149, No.21, 2023, №04022012.
9. West, Darrell M. Using Technology to Personalize Learning and Assess Students in Real-Time. Darrell M. West. – Washington: Center of technology innovations at Brookings, 2011, pp.19.
10. Пак Н.И., Потупчик Е.Г., Хегай Л.Б. Концепция трансформационных и перевернутых электронных учебников. Вестник РУДН, Серия «Информатизация образования», Том 17, № 2, 2020, С.153-168.
11. C.Eoghan ,J.Jennifer, P.Karen A., P.Daryl, S.Cassy. Motivating youth to learn STEM through a gender inclusive digital forensic science program. Smart Learning Environments, V. 10, No. 1, 2023, https://doi.org/10.1186/s40561-022-00213-x
12. Когель А.С., Фенюк А.Н. Геймификация как маркетинговый инструмент: психологический аспект. Скиф. Вопросы студенческой науки, №9(37), 2019, С.56-60.
13. Пахомова Т.Е. Использование элементов геймификации в образовательном процессе. Информатика в школе, №4(107), 2015, С.17-23.
14. Пак Н.И., Асауленко Е.В. Персонификация самостоятельной работы студентов по формированию умения решать расчетные задачи на основе автоматизированной обучающе-диагностической системы.Информатика и образование, №8 (297), 2018. – С. 26-31.
15. Shagaieg Sahebi, Yoon Huang, and Peter Brusilovsky, Predicting Student Performance in Parametrized Exercise Solutions, Intelligent Learning Systems, Springer, 2014, pp. 496-503.
16. B. Nauryzbayev, S.Baygamitova; Zh.Akhmetova, N.Pak, A.Karipzhanova, K.Urazbaeva. Using Machine Learning to Analyze the Learning Process for Solving Mathematical Problems. International Journal of Interactive Mobile Technologies Vol. 16, No. 21. – Pp. 114-124, 2022.