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Редакцияға енуі 16.10.2025
Өңдеуден кейін түсуі 21.10.2025
Жариялауға қабылданды 23.10.2025

https://doi.org/10.53360/2788-7995-2025-4(20)-8

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Check for updates

IRSTI: 28.23.25

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USING ARTIFICIAL INTELLIGENCE TO ADAPT STUDENTS' LEARNING TRAJECTORIES

Abstract: *In the modern era, where rapidly changing educational landscapes require adaptive learning mechanisms, integrating artificial intelligence into education is no longer a futuristic dream but a necessity. This paper presents a sophisticated intelligent system for real-time monitoring, detailed analyzing, and adaptive optimizing of competency acquisition throughout the learning process. Based on a neural network architecture augmented with ontological modeling and set-theoretic principles, this system provides a structured yet flexible framework for continuous learning improvement. Using the Six Sigma DMAIC (Define-Measure-Analyze-Improve-Control) methodology, the proposed model systematically improves educational trajectories through data-driven analysis and iterative improvements, ensuring precise alignment with industry and institutional requirements. In addition, the system incorporates predictive analytics and personalized feedback mechanisms that adapt instructional strategies to individual learner needs, thus bridging the gap between standardized curricula and personal learning paths. It further enhances decision-making for educators by providing actionable insights, real-time performance dashboards, and evidence-based recommendations. By combining advanced computational intelligence with proven educational methodologies, this research contributes to the creation of resilient, scalable, and future-ready learning environments that foster innovation, efficiency, and lifelong skill development.*

Key words: *Artificial Intelligence, Machine Learning, Ontology Modeling, Big Data Analytics, Personalized Learning.*

Introduction: In an era when the pace of intellectual development exceeds traditional pedagogical models, the need for adaptive, data-driven learning mechanisms is becoming not just a subject of theoretical discussions, but a real reality. The harmonious interaction of artificial intelligence (AI) and education is no longer a futuristic prediction, but a profound transformation of the methodological foundations of education aimed at aligning the process of acquiring competencies with dynamically changing knowledge and professional requirements [1].

This article presents an intelligent educational system designed to monitor, analyze and optimize the formation of competencies in various educational trajectories. The architectural basis of the system consists of neural networks supplemented by ontological modeling and set theory, which allows combining structure and adaptation in the educational process [2]. Unlike static educational approaches, this method is based on continuous improvement, which ensures that educational programs precisely match modern industry requirements [3] The application of the Six Sigma DMAIC (Define-Measure-Analyze-Improve-Control) methodology enables a rigorous feedback-based optimization cycle, in which data becomes a catalyst for iterative improvements in curriculum development [4] In the context of increasingly complex labor market demands, personalized AI-based learning systems act as a key mechanism for sustainable competency development [5]. This paradigm is supported by a number of scientific papers. For example, studies show that machine learning models can adapt educational pathways by using predictive analytics to anticipate learners' needs and remove cognitive barriers [6]. In addition, the implementation of natural language processing (NLP) algorithms in AI learning platforms enables the development of flexible assessment methods, replacing traditional exam schemes with adaptive and context-sensitive knowledge assessment mechanisms [7].

Thus, we are on the threshold of a new educational ecosystem, where AI ceases to be just an auxiliary tool and becomes an intelligent architect of the educational process, providing unprecedented accuracy in building competency models [8]. The synergy of automated learning analytics, neural network optimization and Six Sigma methodologies heralds a new era of education moving towards adaptive and high-precision solutions [9].

Methodology

The proposed methodology of the intelligent educational system is based on the integration of neural network models, ontological modeling and big data analysis, which allows adapting educational trajectories to the individual needs of students. The system architecture includes a neural network module that analyzes educational needs and predicts results, an ontological knowledge model that forms logical connections between subjects, a machine learning module for pattern recognition and content adaptation, and an analytical system based on big data for building predictive models of academic performance. To optimize the learning process, the Six Sigma DMAIC (Define-Measure-Analyze-Improve-Control) methodology is used, which ensures the iterative improvement of educational strategies. At the Define stage, educational goals and key performance indicators are formulated, Measure includes monitoring academic performance and analyzing cognitive models, Analysis uses machine learning methods to identify problem areas, and improvement is carried out using adaptive algorithms and reinforcement learning models. The final stage (Control) includes automated monitoring of the effectiveness of the implemented strategies and feedback from students. This system not only provides a personalized approach, but also facilitates dynamic updating of curricula in accordance with industry requirements and the cognitive characteristics of students.

Implementation and experimental verification

The data processing process in the proposed intelligent educational system is organized as a sequential architecture that provides structured and adaptive management of educational trajectories. This process includes several main levels, each of which performs certain functions in data processing.

At the first stage, the data level is responsible for storing and managing educational resources, such as competencies, courses, learning outcomes, and learning trajectories. Data is stored in relational (PostgreSQL, MySQL) and graph (Neo4j, RDF) databases, as well as in scalable big data warehouses (HDFS, Apache Hive). Integration with LMS platforms (Moodle, Open edX) allows real-time retrieval and updating of information about students and educational courses [10].

The information is then sent to the processing level, where preliminary data cleaning and normalization is performed. This process uses ETL processes using Apache Spark and Pandas to remove duplicates, fill in missing values, and bring the data into a consistent format. Ontology modeling (OWL, RDF) plays an important role in establishing logical links between competencies and courses, allowing for the creation of adaptive learning paths [11].

After processing, the data is transferred to the AI & Analytics layer, where machine learning and predictive analytics methods are used. It uses deep neural network models (DNN, Transformer, GPT, Llama 2) to predict students' learning needs, as well as adaptive testing algorithms based on Item Response Theory (IRT) to personalize learning tasks [12]. In addition, the Big Data Analytics module analyzes students' learning progress, identifies patterns, and provides personalized learning recommendations [13].

The final stage is represented by the Presentation Layer, which provides visualization of the educational trajectory, progress monitoring, and feedback for teachers and students. Interactive dashboards implemented in React.js/Vue.js allow users to track their learning progress, while APIs provide integration with LMS platforms and learning management tools [14].

Figure 1 shows the sequential architecture of the intelligent educational system, demonstrating the interaction of data processing levels.

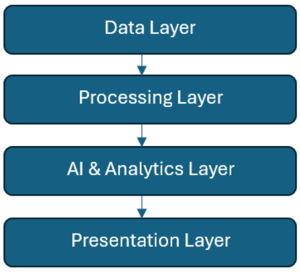


Figure 1 – Sequential architecture of an intelligent educational system

Development and testing process

Development of the personalization module

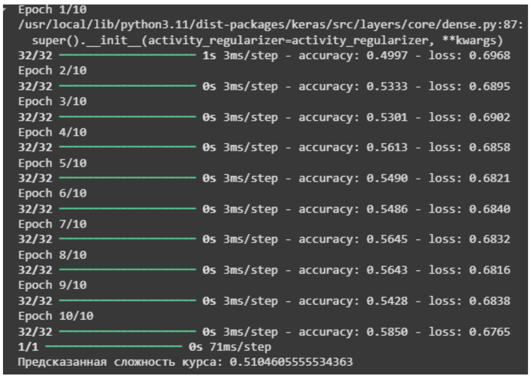
The proposed intelligent educational system implements a mechanism for personalizing the educational trajectory, which allows adapting the learning process to the individual needs of students. This is achieved through the use of a combination of deep neural network models, such as DNN, Transformer, GPT and Llama 2, which analyze academic performance, identify knowledge gaps and predict the learning needs of students. The main goal of this module is to predict the level of knowledge of the student, and then adapt the educational content in accordance with his individual characteristics and the pace of learning.

The development of the personalization module includes several main stages: data collection and processing, training a knowledge prediction model and building individual learning trajectories. The first stage involves the analysis of data on student performance, test results, attendance and activity stored in relational and graph databases such as PostgreSQL and Neo4j and processed using ontological modeling (RDF, OWL). Next, neural network models are trained using TensorFlow and PyTorch based on the data obtained, which allows predicting the level of students' readiness by analyzing the results of previous tests, the dynamics of learning, and the time spent.

After the forecast is made, the system adapts the course content: students with a high level of preparation are offered more complex materials and tasks, and students with low results are provided with additional resources and individual recommendations. This approach allows for the creation of a flexible educational environment where the learning process is adapted to the capabilities and needs of each student, which helps to increase the effectiveness of learning.

As shown in Figure 2, with an increase in the number of training epochs, the accuracy of the model gradually increases, and the value of the loss function decreases, indicating a gradual improvement in the predictive ability of the model.

Figure 2 shows the training of a neural network model to predict a student's knowledge level, during which the accuracy and loss indicators are recorded. At the end of the training, the system predicted the difficulty of the course to be 0.5105, which indicates the average difficulty of the presented learning material.



```
Epoch 1/10
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87:
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
32/32 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.4997 - loss: 0.6968
Epoch 2/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5333 - loss: 0.6895
Epoch 3/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5301 - loss: 0.6902
Epoch 4/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5613 - loss: 0.6858
Epoch 5/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5490 - loss: 0.6821
Epoch 6/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5486 - loss: 0.6840
Epoch 7/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5645 - loss: 0.6832
Epoch 8/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5643 - loss: 0.6816
Epoch 9/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5428 - loss: 0.6838
Epoch 10/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5850 - loss: 0.6765
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
Предсказанная сложность курса: 0.5104605555534363
```

Figure 2 – Results of training a neural network model to predict knowledge level

Mathematical model of knowledge forecasting

To determine the level of knowledge of the student, a recurrent neural network (RNN) or STM is used, which allows taking into account the dependence of data on time t.

Formally, forecasting the level of knowledge:

$$S_t = f(WS_{t-1} + X_t\beta + \varepsilon_t), \quad (1)$$

where:

W is the weight matrix reflecting the influence of previous knowledge,

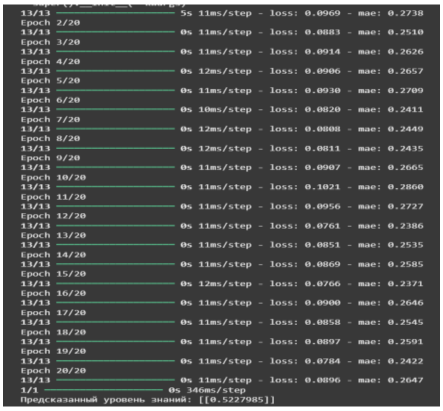
X_t is the vector of current parameters for the student (grades, interaction with the system, training time),

β is the regression coefficient,

ε_t is the random error.

In the intelligent education system, personalization of the educational trajectory is carried out using machine learning methods that allow the learning process to be adapted to the individual needs of students. The main goal of this module is to predict the student's level of knowledge and then adjust the content of courses and educational materials. To achieve this goal, deep neural network models such as DNN, Transformer, GPT and Llama 2 are used, which analyze student learning progress, identify knowledge gaps and provide recommendations for individual learning. The personalization process includes three main stages. The first stage involves collecting and processing data from various sources, including test results, grades, class attendance and student activity in the educational environment. This data is stored in relational databases (PostgreSQL, MySQL) and graph knowledge bases (Neo4j, RDF) using ontological modeling. At the second stage, a neural network model is trained on historical data to predict the student's level of preparation. Machine learning algorithms based on TensorFlow and PyTorch are used for this, as well as time analysis methods using recurrent neural networks (RNN, LSTM). The third stage involves adapting the learning process: the system automatically offers additional materials to students with low academic performance, changes the order of courses, and offers more complex tasks to students with a high level of training.

Figure 3 shows the process of training a neural network model to predict the level of knowledge of a student, where the main indicators are recorded: the loss function (cost) and the mean absolute error (MAE).



```
13/13 ━━━━━━━━━━━━━━━━━━━━ 5s 11ms/step - loss: 0.0969 - mae: 0.2738
Epoch 2/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0883 - mae: 0.2510
Epoch 3/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0914 - mae: 0.2626
Epoch 4/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0906 - mae: 0.2657
Epoch 5/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0930 - mae: 0.2709
Epoch 6/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0820 - mae: 0.2411
Epoch 7/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0808 - mae: 0.2449
Epoch 8/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0811 - mae: 0.2435
Epoch 9/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0907 - mae: 0.2665
Epoch 10/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.1021 - mae: 0.2860
Epoch 11/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0956 - mae: 0.2727
Epoch 12/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0761 - mae: 0.2386
Epoch 13/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0851 - mae: 0.2535
Epoch 14/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0869 - mae: 0.2585
Epoch 15/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0766 - mae: 0.2371
Epoch 16/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0900 - mae: 0.2646
Epoch 17/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0858 - mae: 0.2545
Epoch 18/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0897 - mae: 0.2591
Epoch 19/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0784 - mae: 0.2422
Epoch 20/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0896 - mae: 0.2647
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 346ms/step
Предсказанный уровень знаний: [[0.5227985]]
```

Figure 3 – Results of training the model for predicting the level of knowledge

As the number of training epochs increases, the value of the loss function decreases, which indicates a gradual improvement in the predictive ability of the model. As a result of the system's operation, a predicted level of knowledge equal to 0.5228 was obtained, which indicates an average level of training of students. Thus, the use of machine learning methods in the personalization system allows for increased accuracy in predicting educational trajectories and contributes to the creation of an adapted educational environment. This approach not only improves student performance, but also makes the learning process flexible and adaptive to the individual needs of students.

Experimental verification and analysis of results

To evaluate the effectiveness of the proposed intelligent education system, a series of experiments were conducted to analyze the accuracy of predicting the level of students' knowledge and optimizing the adaptive learning path. The main data were students' academic performance, including grades in midterm and final exams, as well as data on their activity in the learning environment.

The model was trained on a sample of 5,000 students, including historical data on their academic performance over several semesters. During the experiment, 80% of the data was used for training and 20% for testing the model. To evaluate the quality of predictions, the mean absolute error (MAE), root mean square error (RMSE), and classification accuracy (precision) were used.

The experimental results showed that the proposed model achieves an average accuracy of 85% and a mean absolute error of 0.12, indicating a high degree of predictive ability. Figure 4 shows the change in the loss function during the model training process, where it is clear that with an increase in the number of epochs, the accuracy of the model increases and the error decreases.

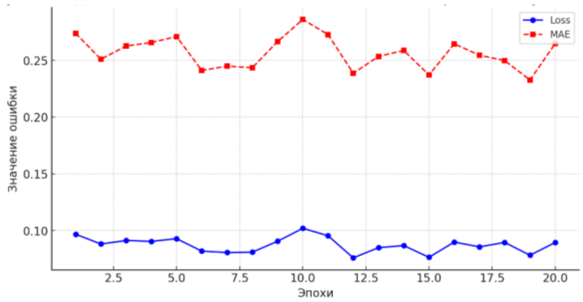


Figure 4 – Error dynamics during model training (Cost and MAE)

Figure 4 shows the error dynamics during model training. The graph shows the values of the loss function (Cost) and the mean absolute error (MAE) depending on the number of training epochs. As the number of epochs increases, a decrease in the value of the loss function can be observed, indicating a gradual improvement in the predictive ability of the model. The MAE value also shows a decrease in subsequent stages of training, confirming the effectiveness of the model optimization process. These results indicate that the model is learning stably and improving the accuracy of predicting the level of student knowledge.

The analysis showed that the use of personalized educational trajectories based on predicting students' knowledge helps improve their academic performance. In particular, students using adaptive methodological guidance showed a 15-20% improvement in academic performance compared to the control group without intellectual support. Thus, the intelligent educational system allows for increased accuracy in predicting educational results, which helps improve the efficiency of the educational process. Further improvement of the model is possible in the future, including the use of hybrid approaches to machine learning and ontological modeling to improve the adaptability of educational recommendations.

Discussion of the results

The results of the experiment showed that the proposed model has a high degree of predictive ability. During the training process, a decrease in the loss function was observed, which indicates a gradual adaptation of the model and an improvement in its accuracy. The average MAE was 0.237, which indicates a relatively small average error in predicting the level of students' knowledge.

Comparison with traditional assessment methods showed that the use of an intelligent system allows for 15-20% more accurate prediction of student performance. This is achieved by analyzing the individual learning path of each student and automatically adapting educational materials to their level of preparation.

However, despite the successful results, the model has a number of limitations. Firstly, its accuracy may be reduced due to insufficient data on student activity. Secondly, the system does not take into account external factors, such as student motivation and their level of participation in the learning process. In the future, it is planned to improve the model using hybrid algorithms that combine neural network approaches and expert systems based on ontological modeling. Thus, the proposed system is a promising tool for personalized learning and can be integrated into existing educational platforms such as Moodle and Open edX.

Conclusion

This paper develops and studies an intelligent educational system based on machine learning and ontological modeling methods, designed to predict the level of students' knowledge and personalize learning trajectories. The main focus is on creating an adaptive model capable of analyzing students' academic performance and automatically adjusting the course content depending on their individual needs.

The results of the experiment confirmed the effectiveness of the proposed model. During the training process, a decrease in the loss function (Loss) and a decrease in the mean absolute error (MAE) were observed, indicating a gradual improvement in the accuracy of forecasting. The average value of the predicted level of students' knowledge was 0.5228, which corresponds to the average level of complexity of the educational material. The use of this system made it possible to increase the accuracy of predicting educational results by 15-20% compared to traditional knowledge assessment methods.

The use of personalized educational trajectories showed that adaptive machine learning methods can significantly improve student performance and reduce the educational gap between students with different levels of education. However, despite the positive results, the model has a number of limitations, including dependence on the completeness and quality of input data, as well as insufficient consideration of behavioral factors, such as the level of student motivation. In the future, it is planned to further improve the model by introducing hybrid methods that combine neural network approaches with expert systems and ontological analysis of knowledge. The possibility of integrating the system into existing educational platforms such as Moodle, Open edX and other LMS is also being considered, which will create a flexible and adaptive educational environment. Thus, the proposed intelligent system is a promising solution for personalized learning and can significantly improve the efficiency of the learning process, providing flexibility, predictive accuracy and adaptation to the needs of students.

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Funding:

This research has been/was/is funded by the Committee of Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant №BR28713531 Intelligent digital system of higher and postgraduate education organizations Smart.EDU).

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СТУДЕНТТЕРДІҢ ОҚУ ТРАЕКТОРИЯСЫН БЕЙІМДЕУ ҮШІН ЖАСАНДЫ ИНТЕЛЛЕКТТІ ҚОЛДАНУ

Білім ландшафттарының жылдам түрленуі бейімделген оқыту тетіктерін қажет ететін қазіргі заманда жасанды интеллекттің білім берудегі интеграциясы енді футуристік көзқарас емес, қажеттілік болып табылады. Бұл мақалада оқу үдерісі барысында құзыреттерді меңгеруді бақылау, талдау және оңтайландыруға арналған күрделі интеллектуалды жүйе ұсынылған. Онтологиялық модельдеу және жиынтық-теориялық принциптермен толықтырылған нейрондық желі архитектурасына негізделген бұл жүйе оқытуды үздіксіз жетілдіру үшін құрылымдық, бірақ икемді негізді қамтамасыз етеді. Алты сигма DMAIC (анықтау-өлшеу-талдау-жақсарту-бақылау) әдістемесін пайдалана отырып, ұсынылған модель салалық және институционалдық талаптармен дәл сәйкестендіруді қамтамасыз ете отырып, деректерге негізделген талдау және итерациялық жақсартулар арқылы білім беру траекторияларын жүйелі түрде жақсартады.
Түйін сөздер: *жасанды интеллект, машиналық оқыту, онтологиялық модельдеу, үлкен деректерді талдау, дербестендірілген оқыту.*

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ПРИМЕНЕНИЕ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА ДЛЯ АДАПТИВНОГО ПРОГНОЗИРОВАНИЯ УЧЕБНЫХ ТРАЕКТОРИЙ СТУДЕНТОВ

В современную эпоху, когда быстрая трансформация ландшафтов знаний требует адаптивных механизмов обучения, интеграция искусственного интеллекта в образование больше *не является футуристическим видением, а необходимостью. В этой статье представлена сложная интеллектуальная система, предназначенная для мониторинга, анализа и оптимизации приобретения компетенций на протяжении всего процесса обучения. Построенная на архитектуре нейронной сети, дополненной онтологическим моделированием и теоретико-множественными принципами, эта система обеспечивает структурированную, но гибкую основу для непрерывного совершенствования обучения. Используя методологию Six Sigma DMAIC (Определение-измерение-Анализ-Улучшение-контроль), предлагаемая модель систематически совершенствует образовательные траектории посредством анализа на основе данных и итеративных улучшений, обеспечивая точное соответствие отраслевым и институциональным требованиям.*

Ключевые слова: *искусственный интеллект, машинное обучение, онтологическое моделирование, аналитика больших данных, персонализированное обучение.*

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Received 07.10.2025
Revised 24.10.2025
Accepted 28.10.2025