UDC 004.8:61

**Igilikov Adilkhan Igilikovich**
Master's student, 2nd year
**Scientific supervisor:** Lamasheva Zhanar Beibutovna
PhD, Assistant Professor
School of Artificial Intelligence and Data Science
Astana IT University
(Astana, Kazakhstan)

# PRE-TRAINED REPRESENTATIONS OF PRIOR-ADMISSION HISTORY IMPROVE ONE-YEAR, BUT NOT IN-HOSPITAL, MORTALITY PREDICTION IN ICU PATIENTS WITH CHRONIC DISEASE: A MIMIC-IV STUDY

**Abstract:** ICU patients with chronic disease usually have a record of earlier hospital stays, but ICU risk models seldom use it. We tested whether a small transformer encoder, pre-trained on diagnosis codes of earlier admissions, improves prediction made at hour 24 of the ICU stay, and whether the answer depends on the prediction horizon. From MIMIC-IV 3.1 we selected 38 734 first ICU stays of adults with type 2 diabetes, chronic kidney disease stage 3-5, heart failure, chronic obstructive pulmonary disease or hypertension. Two outcomes were fixed in advance: in-hospital mortality (10.9%) and death within one year of discharge among survivors (34 517 stays, 18.5%). The encoder (six layers, 1.6 million parameters) was pre-trained by masked code modelling on 184 575 patients, using only admissions before the index stay. Its patient vector was added to XGBoost on 24-hour physiological summaries and to a temporal convolutional network (TCN). For one-year mortality the pre-trained vector raised the ROC-AUC of XGBoost from 0.809 to 0.821 (mean of five seeds, significant for each seed) and by 0.029 in patients with prior admissions. An untrained encoder of the same size added 0.004, and indicators of the 200 most frequent codes added 0.007. In patients with prior admissions the hybrid TCN gained 0.025 over the physiology-only TCN, yet it stayed level with XGBoost. For in-hospital mortality no representation of history improved XGBoost (ROC-AUC 0.884). Pre-trained history helps with long-term risk in patients who have a history, whereas early in-hospital death is predicted by current physiology.

**Keywords:** electronic health records, MIMIC-IV, chronic disease, mortality prediction, transformer, self-supervised pre-training, XGBoost, temporal convolutional network

## Introduction

Noncommunicable diseases cause about three quarters of deaths worldwide, and cardiovascular disease, chronic respiratory disease and diabetes are among the main contributors [1]. Patients with these conditions are often admitted to intensive care, and many of them die in the year after discharge. The severity scores used in the ICU (SOFA, SAPS-II, OASIS, APS-III) [2-5] describe the physiology of the first day. They were

designed for death during the current admission and ignore what earlier encounters say about the patient.

Electronic health records keep this history as sequences of diagnosis codes. Transformer models from natural language processing [6, 7] can be pre-trained on such sequences without labels and reused for prediction. Med-BERT [8], BEHRT [9], CEHR-BERT [10] and related models [11] improved disease prediction, most of all when labelled data were scarce, and recent generative models forecast ICU outcomes from MIMIC-IV timelines [12]. A review of more than 80 clinical foundation models found, however, that most were evaluated on tasks with unclear value for health systems [13]. Gradient-boosted trees also remain hard to beat on tabular data [14-16], and on ICU benchmarks deep models give at best small gains [17]. It is therefore an open question whether a pre-trained history encoder adds anything to a well-tuned model of current physiology, and for which outcomes.

The study is part of a master's project on a big medical data analytics system for chronic disease prediction. The system has a cloud data layer, physiological and history representations, risk models, and evaluation of discrimination, calibration and subgroup performance. Here we test its central component on the public MIMIC-IV database [18]. We ask (1) whether a pre-trained representation of prior-admission diagnoses improves mortality prediction at hour 24 of the ICU stay over physiology alone; (2) whether the gain comes from pre-training itself, which we check against an untrained encoder and against plain code indicators; (3) whether the benefit depends on the prediction horizon. Both outcomes and the main comparisons were fixed before the experiments, and the report follows TRIPOD+AI where it applies [19].

**Materials and methods**

**Data and cohort.** MIMIC-IV 3.1 contains de-identified records of patients treated at Beth Israel Deaconess Medical Center (Boston, USA) in 2008-2022 [18, 20, 21]. We queried it in Google BigQuery under the PhysioNet credentialed data use agreement, and only aggregate results left the database. We took the first ICU stay of each adult, required a stay of at least 24 hours and survival to hour 24, and kept patients with at least one target chronic disease coded in ICD-9 or ICD-10: type 2 diabetes, chronic kidney disease stage 3-5, heart failure, chronic obstructive pulmonary disease or essential hypertension (Fig. 1). Predictions are made at hour 24 of the ICU stay.

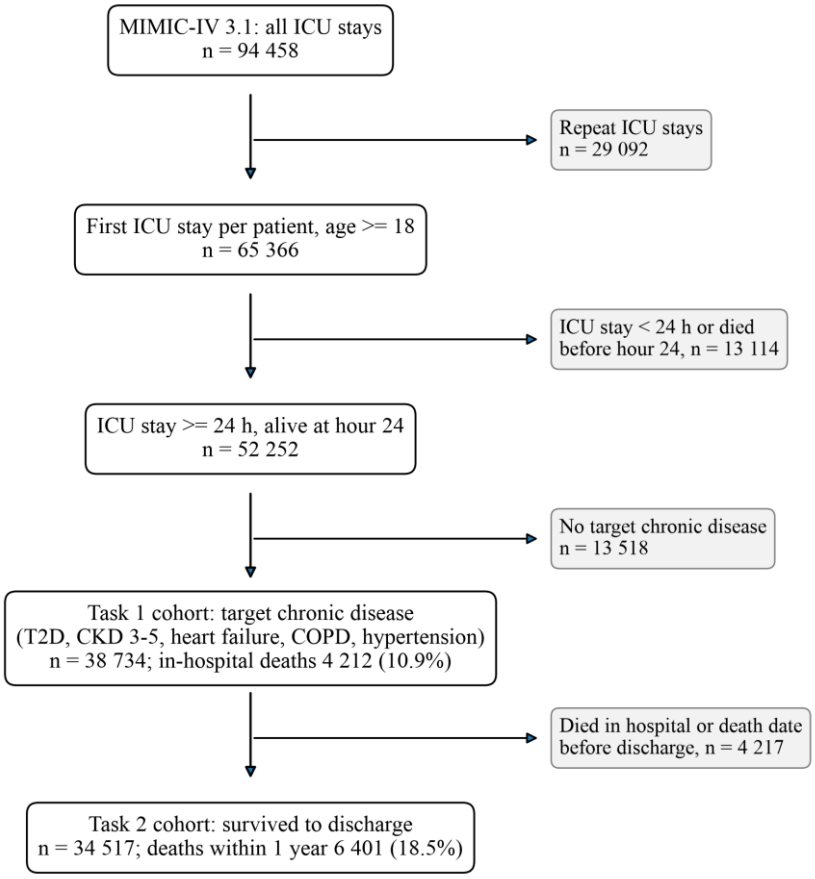



Figure 1 – Cohort selection for the two prediction tasks

**Outcomes.** Task 1 is in-hospital death after hour 24. Task 2 is death within 365 days of discharge among patients discharged alive. MIMIC-IV links out-of-hospital deaths from state records for up to one year after the last discharge [20], which sets this horizon. Stays with a recorded date of death before discharge were excluded from Task 2. Patients were split into training (70%), validation (15%) and test (15%) sets by a hash of the patient identifier, stratified by in-hospital outcome, so that no patient appears in two sets. Model selection, early stopping, recalibration and threshold choice used the validation set, and the test set was scored once.

**Physiology of the first 24 hours.** We took 33 hourly variables from the MIMIC-IV derived tables [22]: vital signs, Glasgow Coma Scale, urine output, blood chemistry, blood count, blood gases, coagulation and liver enzymes. Values outside the 1st-99th percentiles of the training set were clipped. For tree and linear models each variable was summarised by its mean, minimum, maximum, last value and number of hours measured; with age, sex and the number of prior admissions this gives 168 features. For neural models the hourly 33 × 24 matrix was forward-filled, imputed with training medians, standardised and paired with a binary observation mask.

**Prior-admission history.** For each patient we collected the diagnosis codes of all admissions that ended before the index admission. Codes of the index admission were left

out because they are assigned at discharge and are unknown at hour 24. Each code was cut to its ICD version and three-character category (for example, ICD-10 I50); categories seen at least five times form a vocabulary of 2 385 tokens. A history is the sequence [CLS] visit 1 [SEP] visit 2 … truncated to the 256 most recent tokens, and patients without history get a [NOHIST] token. Some history was present in 35.8% of the cohort.

**History encoder and pre-training.** The encoder follows Med-BERT [8] at a smaller scale: six transformer layers, hidden size 192, six attention heads, feed-forward size 64, 1.6 million parameters. A token embedding is the sum of a code, a visit-index and a position embedding. The encoder was pre-trained by masked code modelling [7] (15% of code tokens; 80% replaced by [MASK], 10% by a random code, 10% unchanged) on the code histories of 184 575 MIMIC-IV patients, with 9 714 held out for monitoring. Validation and test patients of the cohort were removed from the pre-training corpus, and for training patients only admissions before the index stay were used. Training took 10 epochs with AdamW (learning rate $5 \cdot 10^{-4}$, one-cycle schedule) on an NVIDIA T4 GPU in Google Colab. The 192-dimensional [CLS] output is the patient's history vector.

**Models.** Baselines were logistic regression, random forest and XGBoost [14] on the 168 summary features, and the four clinical scores mapped to probabilities by logistic regression on the training set. In XGBoost we compared three ways to add history: binary indicators of the 200 codes most frequent in training patients' histories, the frozen [CLS] vector of the pre-trained encoder, and the [CLS] vector of an untrained encoder of the same size. The neural model is a causal temporal convolutional network (TCN) [23] with kernel 3, dilations 1, 2, 4 and 8 and 64 channels, so its receptive field covers 24 hours; age, sex and the logarithm of prior admissions enter before the output layer. In the hybrid model the [CLS] vector is projected to 33 values, repeated over the 24 hours and concatenated with physiology and mask before the TCN, and the encoder is fine-tuned with a three times lower learning rate. The ablation compares five configurations: TCN on physiology, history encoder alone (untrained or pre-trained) and hybrid (untrained or pre-trained). Neural models were trained with class-weighted cross-entropy and AdamW, with early stopping on validation ROC-AUC (patience 8, at most 40 epochs).

**Evaluation.** Predicted probabilities were recalibrated on the validation set by Platt scaling [24]. We report ROC-AUC and the area under the precision-recall curve (AUPRC) with 95% bootstrap confidence intervals (1 000 resamples of the test set), the Brier score and the calibration slope [25]. Paired ROC-AUC values were compared with the DeLong test [26]. Every comparison was repeated with five random seeds (42, 1, 2, 3, 4), which change model initialisation and sampling but keep the patient split and the pre-trained weights. The pre-specified subgroups were patients with and without prior admissions. To check fairness we also compared age groups, sexes and the five chronic diseases, with paired bootstrap intervals for the difference in ROC-AUC. Hypertension was present in 68% of the cohort, so a sensitivity analysis removed stays in which it was the only target disease. Feature contributions of the final XGBoost model were computed with TreeSHAP [27], with the 192 history dimensions pooled into one group. The analysis code is available from the author on request.

## Results

**Cohort.** The cohort included 38 734 ICU stays, and 4 212 patients (10.9%) died in hospital. Of the 34 517 patients discharged alive, 6 401 (18.5%) died within one year (Table 1). Compared with one-year survivors, these patients were older (median 76 vs 68 years), more often had prior admissions (46.4% vs 33.2%) and heart failure (45.8% vs 29.9%), more often had COPD or chronic kidney disease, and had higher severity scores on the first day.

**Table 1 – Characteristics of the cohort**

| | Full cohort | Survived to discharge | Died within 1 year | Alive at 1 year |
|---|---|---|---|---|
| N | 38 734 | 34 517 | 6 401 | 28 116 |
| Age, years, median (IQR) | 70 (60-80) | 69 (60-79) | 76 (66-85) | 68 (59-77) |
| Female sex, n (%) | 16 407 (42.4%) | 14 455 (41.9%) | 2 929 (45.8%) | 11 526 (41.0%) |
| Any prior admission, n (%) | 13 883 (35.8%) | 12 293 (35.6%) | 2 969 (46.4%) | 9 324 (33.2%) |
| Prior admissions, median (IQR) | 0 (0-1) | 0 (0-1) | 0 (0-2) | 0 (0-1) |
| Hypertension, n (%) | 26 345 (68.0%) | 23 863 (69.1%) | 3 806 (59.5%) | 20 057 (71.3%) |
| Type 2 diabetes, n (%) | 14 647 (37.8%) | 13 017 (37.7%) | 2 595 (40.5%) | 10 422 (37.1%) |
| Heart failure, n (%) | 13 154 (34.0%) | 11 326 (32.8%) | 2 929 (45.8%) | 8 397 (29.9%) |
| COPD, n (%) | 6 939 (17.9%) | 5 969 (17.3%) | 1 619 (25.3%) | 4 350 (15.5%) |
| CKD stage 3-5, n (%) | 4 144 (10.7%) | 3 537 (10.2%) | 1 067 (16.7%) | 2 470 (8.8%) |
| SOFA, median (IQR) | 4 (2-6) | 4 (2-6) | 4 (3-7) | 4 (2-6) |
| SAPS-II, median (IQR) | 36 (28-44) | 35 (28-43) | 40 (33-49) | 33 (27-41) |
| OASIS, median (IQR) | 31 (26-37) | 31 (25-36) | 33 (27-38) | 30 (25-35) |
| APS-III, median (IQR) | 40 (30-53) | 38 (29-50) | 46 (36-58) | 36 (28-48) |
| In-hospital death, n (%) | 4 212 (10.9%) | - | - | - |
| Death within 1 year of discharge, n (% of survivors) | 6 401 (18.5%) | 6 401 (18.5%) | - | - |

IQR – interquartile range; COPD – chronic obstructive pulmonary disease; CKD – chronic kidney disease. Severity scores are computed for the first ICU day.

**Baselines.** XGBoost was the strongest baseline for both tasks (Table 2). For in-hospital mortality it reached ROC-AUC 0.886 (95% CI 0.873-0.899), against 0.711-0.762

for the clinical scores. For one-year mortality XGBoost reached 0.812 (0.797-0.826), and the scores fell to 0.572-0.676. Scores built for acute in-hospital risk say little about survival after discharge.

**Table 2 – Discrimination and calibration of baseline models on the test set**

| Model | ROC-AUC (95% CI) | AUPRC (95% CI) | Brier |
|---|---|---|---|
| ***In-hospital mortality*** | | | |
| Logistic Regression | 0.858 [0.843-0.871] | 0.461 [0.428-0.495] | 0.076 |
| Random Forest | 0.854 [0.841-0.867] | 0.431 [0.398-0.467] | 0.078 |
| XGBoost | 0.886 [0.873-0.899] | 0.532 [0.498-0.572] | 0.069 |
| SOFA | 0.711 [0.689-0.733] | 0.277 [0.251-0.308] | 0.088 |
| SAPS-II | 0.748 [0.727-0.768] | 0.286 [0.258-0.318] | 0.088 |
| OASIS | 0.727 [0.708-0.747] | 0.261 [0.236-0.291] | 0.089 |
| APS-III | 0.762 [0.741-0.781] | 0.320 [0.290-0.355] | 0.086 |
| ***1-year mortality*** | | | |
| Logistic Regression | 0.800 [0.785-0.815] | 0.483 [0.452-0.513] | 0.121 |
| Random Forest | 0.805 [0.791-0.820] | 0.474 [0.445-0.506] | 0.121 |
| XGBoost | 0.812 [0.797-0.826] | 0.482 [0.454-0.515] | 0.120 |
| SOFA | 0.572 [0.553-0.592] | 0.223 [0.210-0.239] | 0.149 |
| SAPS-II | 0.676 [0.659-0.695] | 0.290 [0.273-0.314] | 0.143 |
| OASIS | 0.595 [0.575-0.614] | 0.246 [0.230-0.266] | 0.147 |
| APS-III | 0.660 [0.641-0.677] | 0.271 [0.255-0.291] | 0.145 |

Seed 42. In-hospital mortality: 5 811 test stays, 632 deaths; one-year mortality: 5 178 test stays, 953 deaths. Scores are mapped to probabilities by logistic regression on the training set.

**Prior-admission history in XGBoost.** For one-year mortality the pre-trained history vector raised the mean ROC-AUC over five seeds from 0.809 to 0.821 (difference +0.012, range +0.008 to +0.016), and the difference was significant for every seed (Table 3). In patients with prior admissions the gain was +0.029 (from 0.787 to 0.816), and the smallest gain over seeds was +0.025. The untrained encoder added +0.004 (significant for two of five seeds) and the 200 code indicators added +0.007; the pre-trained vector beat the code indicators at every seed. For in-hospital mortality all three history representations lowered the ROC-AUC slightly, by 0.003-0.004.

**Table 3 – XGBoost with representations of prior-admission history, test set, five seeds**

| Model | ROC-AUC, mean ± SD | ROC-AUC with prior admissions | Δ vs XGBoost (range) | Seeds with p<0.05 (all / prior adm.) |
|---|---|---|---|---|
| ***In-hospital mortality*** | | | | |
| XGBoost | 0.884 ± 0.001 | 0.850 ± 0.002 | - | - |
| XGBoost + code multi-hot | 0.882 ± 0.002 | 0.841 ± 0.003 | -0.003 (-0.005 to +0.000) | 1/5, 3/5 |
| XGBoost + encoder (pre-trained) | 0.881 ± 0.001 | 0.846 ± 0.002 | -0.004 (-0.005 to -0.002) | 1/5, 0/5 |

| Model | ROC-AUC, mean ± SD | ROC-AUC with prior admissions | Δ vs XGBoost (range) | Seeds with p<0.05 (all / prior adm.) |
|---|---|---|---|---|
| XGBoost + encoder (random) | 0.881 ± 0.002 | 0.845 ± 0.004 | -0.004 (-0.006 to -0.000) | 1/5, 0/5 |
| ***1-year mortality*** | | | | |
| XGBoost | 0.809 ± 0.003 | 0.787 ± 0.003 | - | - |
| XGBoost + code multi-hot | 0.816 ± 0.002 | 0.801 ± 0.003 | +0.007 (+0.003 to +0.011) | 4/5, 4/5 |
| XGBoost + encoder (pre-trained) | 0.821 ± 0.002 | 0.816 ± 0.003 | +0.012 (+0.008 to +0.016) | 5/5, 5/5 |
| XGBoost + encoder (random) | 0.812 ± 0.002 | 0.792 ± 0.005 | +0.004 (-0.002 to +0.008) | 2/5, 1/5 |

Mean ± standard deviation over seeds 42, 1, 2, 3, 4; Δ – difference in ROC-AUC from XGBoost of the same seed; significance by DeLong test. Patients with prior admissions: 2 068 (in-hospital) and 1 842 (one-year) test stays.

Fig. 2 shows ROC and calibration curves for one-year mortality. After Platt scaling both XGBoost models were well calibrated (slope 1.06-1.07), and the history vector lowered the Brier score from 0.120 to 0.117.

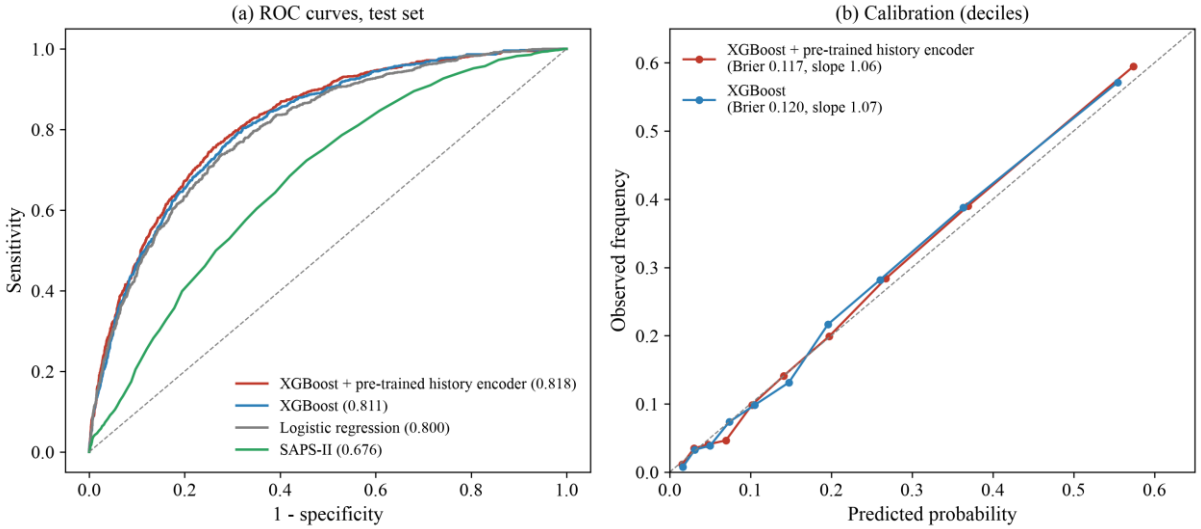



Figure 2 – One-year mortality: ROC curves (a) and calibration (b) on the test set, seed 42

**Subgroups and sensitivity.** The gain came from patients who had a history (Fig. 3): +0.027 (95% CI 0.011-0.042) with prior admissions and -0.002 (-0.008 to 0.004) without them. Among the chronic diseases the largest gain was in heart failure (+0.020, 0.007-0.032). The gain was also significant at age 65-79, in men and in patients with hypertension; in women, at other ages and in the other diseases the intervals included zero, and no subgroup was harmed. With stays where hypertension was the only target disease removed (22 811 stays left), the direction held: 0.788 vs 0.796 overall (p = 0.06) and 0.773 vs 0.790 in patients with prior admissions (p = 0.046).

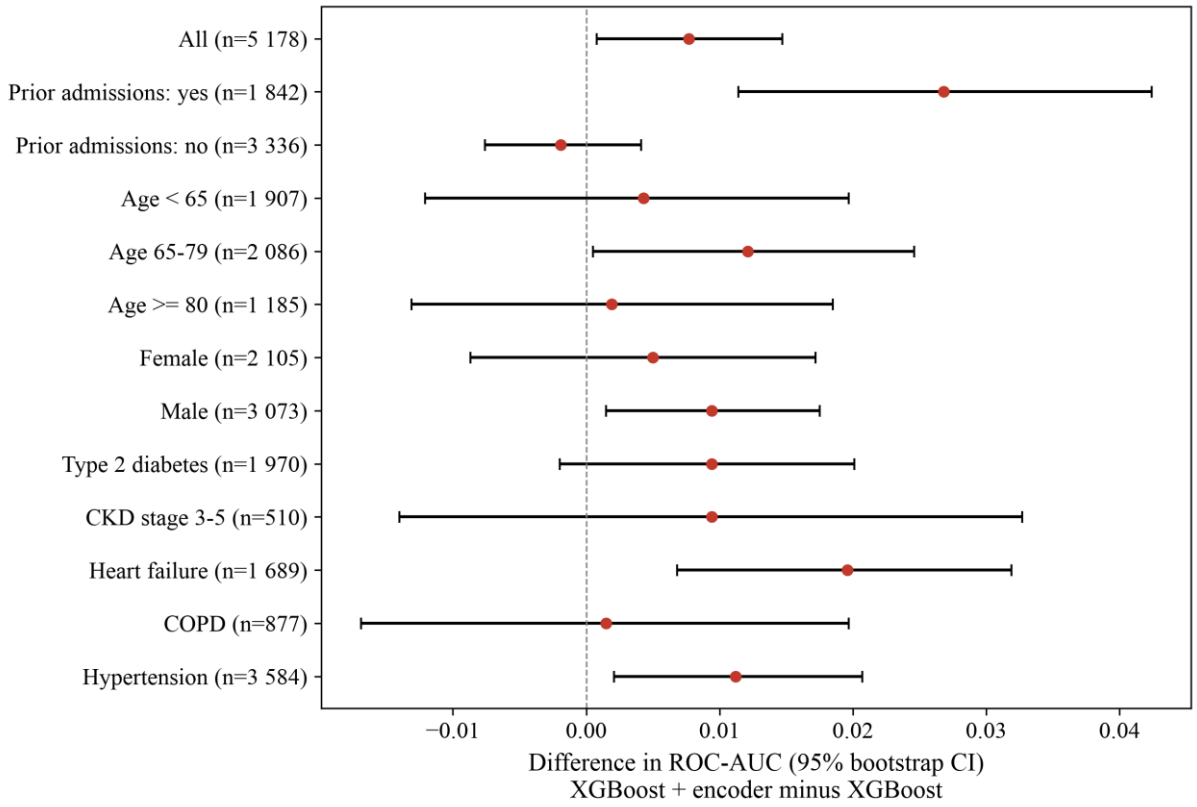



Figure 3 – Difference in ROC-AUC between XGBoost with and without the pre-trained history vector by subgroup, one-year mortality

**Neural models.** For in-hospital mortality the hybrid model matched the TCN (0.860-0.864 vs 0.862; p ≥ 0.43), and the history encoder alone reached 0.62-0.64 (Table 4). For one-year mortality the pre-trained hybrid was better than the TCN on average (0.809 vs 0.803 over five seeds; +0.006, significant for two seeds) and clearly better in patients with prior admissions (0.810 vs 0.785; +0.025, positive for every seed). The hybrid with an untrained encoder scored the same as the TCN (0.803). The history encoder alone reached 0.72, and 0.74-0.75 in patients with prior admissions. No neural model beat XGBoost (DeLong p 0.06-0.94 for the pre-trained hybrid).

**Table 4 – Ablation of the hybrid model, ROC-AUC on the test set**

| Model | In-hospital: ROC-AUC | In-hospital: with prior adm. | 1-year: ROC-AUC | 1-year: with prior adm. |
|---|---|---|---|---|
| TCN (physiology) | 0.862* | 0.822* | 0.803 ± 0.002 | 0.785 ± 0.003 |
| Codes (random init) | 0.621* | 0.611* | 0.720* | 0.741* |
| Codes (pre-trained) | 0.641* | 0.660* | 0.717* | 0.747* |
| Hybrid (random init) | 0.864* | 0.827* | 0.803* | 0.783* |
| Hybrid (pre-trained) | 0.860* | 0.824* | 0.809 ± 0.005 | 0.810 ± 0.005 |

Mean ± standard deviation over five seeds; * – single seed (42). All models use the same physiology input, static covariates and training protocol.

**Feature contributions.** In XGBoost with history, age had the largest mean absolute SHAP value, followed by the pooled history vector, oxygen tension, haemoglobin, blood urea nitrogen and the Glasgow Coma Scale (Fig. 4). The number of prior admissions, one of the baseline features, fell out of the top twenty once the history vector was added. A group of 192 dimensions collects importance more easily than a single feature, so Fig. 4 describes the model; the evidence of benefit is the controlled comparison in Table 3.

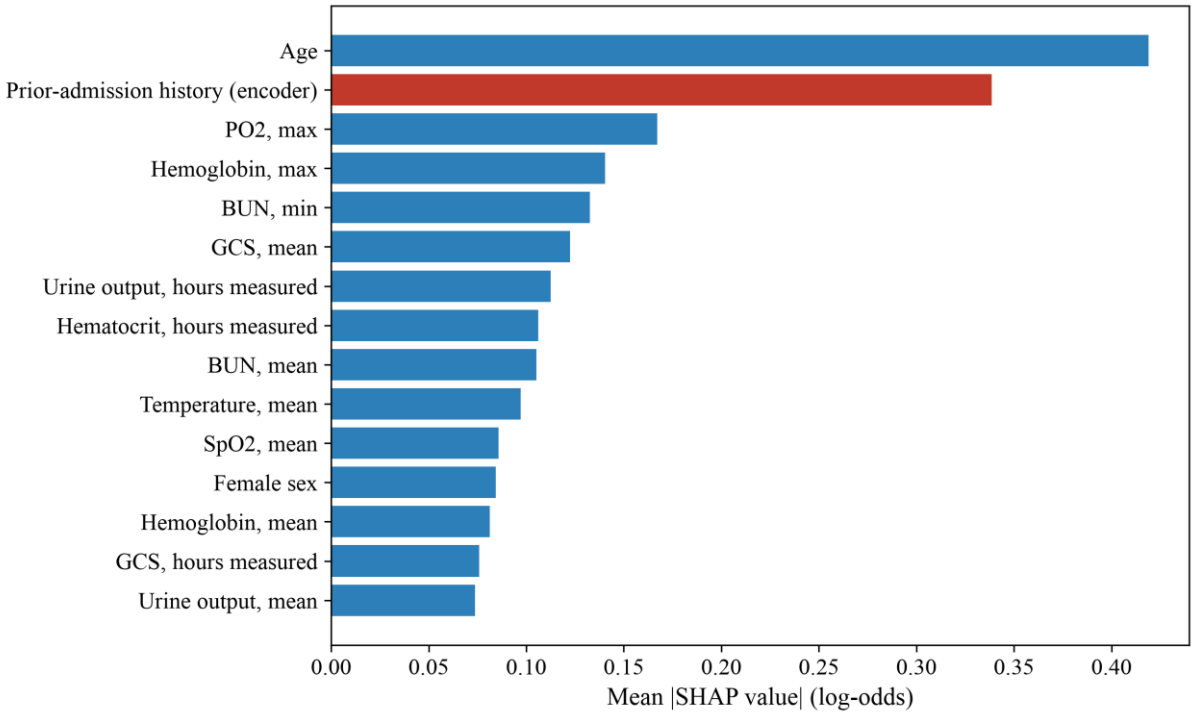



Figure 4 – Mean absolute SHAP values of the 15 most important features, XGBoost with the pre-trained history vector, one-year mortality

## Discussion

The value of a patient's prior-admission history depended on the prediction horizon. For death during the current admission, the first 24 ICU hours carried nearly all of the signal, and no representation of history improved a strong XGBoost model. For death within a year of discharge, the pre-trained history vector gave a consistent gain, about three times larger in patients who had a history. Long-term survival with heart failure or chronic kidney disease depends on the course of the disease, which earlier admissions record, more than on the first ICU day. Heart failure, a disease with frequent readmissions, showed the largest subgroup gain.

The gain needed pre-training. An encoder of the same architecture with random weights added almost nothing, and plain indicators of the same codes helped less than the pre-trained vector at every seed. Masked code modelling on about 185 thousand patients seems to capture co-occurrence patterns that the tree model cannot read from sparse

indicators. Med-BERT and BEHRT reported the largest benefit of pre-training for small cohorts [8, 9]. Our corpus and encoder are much smaller (1.6 million parameters), and pre-training took ten minutes on one free GPU.

The hybrid TCN did not beat XGBoost, which agrees with earlier comparisons on tabular and ICU data [15-17]. The best and simplest design in our data has two stages: pre-train the encoder once, then feed its frozen output to a gradient-boosted model. This design fits the analytics system the project builds. History vectors can be computed once per patient in the cloud data layer and stored next to other features, and outcome models can be retrained cheaply for new targets or sites. The evaluation used in this study (calibration, seed variation, subgroup checks by age, sex and disease) can serve as the acceptance test for such models, and no subgroup was harmed by adding history. Deployment would still need local validation, governance of patient data and an interface that shows clinicians the factors behind each risk estimate.

The study has limitations. All data come from one centre, and external validation, for example on the eICU database, is still needed. Chronic diseases were identified from diagnosis codes, including codes of the index admission; they define the cohort and are not model inputs. History was limited to three-character diagnosis categories, and procedures, medications and laboratory results of earlier admissions may add information. One-year deaths come from linked state records and may miss deaths elsewhere. The overall gain of about 0.01 in ROC-AUC is modest, and its clinical value should be assessed with decision-analytic measures.

**Conclusion**

In 38 734 ICU patients with chronic disease from MIMIC-IV, a small transformer pre-trained on diagnosis codes of earlier admissions improved the prediction of death within one year of discharge. The gain held across random seeds and was largest in patients with prior admissions and in heart failure. The same history did not improve the prediction of in-hospital death. The improvement required pre-training and was obtained most simply by adding the frozen patient vector to XGBoost. For a chronic disease analytics system this suggests using pre-trained history representations for long-term risk and current physiology for acute in-hospital risk.

**References:**

1. World Health Organization. Noncommunicable diseases : fact sheet [Electronic resource]. – URL: https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases (accessed: 27.10.2026).

2. Vincent J.-L., Moreno R., Takala J. et al. The SOFA (Sepsis-related Organ Failure Assessment) score to describe organ dysfunction/failure // Intensive Care Medicine. – 1996. – Vol. 22, No. 7. – P. 707–710.

3. Le Gall J.-R., Lemeshow S., Saulnier F. A new Simplified Acute Physiology Score (SAPS II) based on a European/North American multicenter study // JAMA. – 1993. – Vol. 270, No. 24. – P. 2957–2963.

4. Johnson A.E.W., Kramer A.A., Clifford G.D. A new severity of illness scale using a subset of Acute Physiology And Chronic Health Evaluation data elements shows

comparable predictive accuracy // Critical Care Medicine. – 2013. – Vol. 41, No. 7. – P. 1711–1718.

5. Knaus W.A., Wagner D.P., Draper E.A. et al. The APACHE III prognostic system: risk prediction of hospital mortality for critically ill hospitalized adults // Chest. – 1991. – Vol. 100, No. 6. – P. 1619–1636.

6. Vaswani A., Shazeer N., Parmar N. et al. Attention is all you need // Advances in Neural Information Processing Systems 30 (NIPS 2017). – 2017. – P. 5998–6008.

7. Devlin J., Chang M.-W., Lee K., Toutanova K. BERT: pre-training of deep bidirectional transformers for language understanding // Proceedings of NAACL-HLT 2019. – Minneapolis, 2019. – P. 4171–4186. – DOI: 10.18653/v1/N19-1423.

8. Rasmy L., Xiang Y., Xie Z., Tao C., Zhi D. Med-BERT: pretrained contextualized embeddings on large-scale structured electronic health records for disease prediction // npj Digital Medicine. – 2021. – Vol. 4. – Art. 86. – DOI: 10.1038/s41746-021-00455-y.

9. Li Y., Rao S., Solares J.R.A. et al. BEHRT: transformer for electronic health records // Scientific Reports. – 2020. – Vol. 10. – Art. 7155. – DOI: 10.1038/s41598-020-62922-y.

10. Pang C., Jiang X., Kalluri K.S. et al. CEHR-BERT: incorporating temporal information from structured EHR data to improve prediction tasks // Proceedings of Machine Learning for Health. – PMLR, 2021. – Vol. 158. – P. 239–260.

11. Steinberg E., Jung K., Fries J.A., Corbin C.K., Pfohl S.R., Shah N.H. Language models are an effective representation learning technique for electronic health record data // Journal of Biomedical Informatics. – 2021. – Vol. 113. – Art. 103637.

12. Renc P., Jia Y., Samir A.E. et al. Zero shot health trajectory prediction using transformer // npj Digital Medicine. – 2024. – Vol. 7. – Art. 256. – DOI: 10.1038/s41746-024-01235-0.

13. Wornow M., Xu Y., Thapa R. et al. The shaky foundations of large language models and foundation models for electronic health records // npj Digital Medicine. – 2023. – Vol. 6. – Art. 135. – DOI: 10.1038/s41746-023-00879-8.

14. Chen T., Guestrin C. XGBoost: a scalable tree boosting system // Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. – San Francisco, 2016. – P. 785–794. – DOI: 10.1145/2939672.2939785.

15. Grinsztajn L., Oyallon E., Varoquaux G. Why do tree-based models still outperform deep learning on typical tabular data? // Advances in Neural Information Processing Systems 35 (NeurIPS 2022), Datasets and Benchmarks Track. – 2022.

16. Shwartz-Ziv R., Armon A. Tabular data: deep learning is not all you need // Information Fusion. – 2022. – Vol. 81. – P. 84–90.

17. Harutyunyan H., Khachatrian H., Kale D.C., Ver Steeg G., Galstyan A. Multitask learning and benchmarking with clinical time series data // Scientific Data. – 2019. – Vol. 6. – Art. 96. – DOI: 10.1038/s41597-019-0103-9.

18. Johnson A.E.W., Bulgarelli L., Shen L. et al. MIMIC-IV, a freely accessible electronic health record dataset // Scientific Data. – 2023. – Vol. 10. – Art. 1. – DOI: 10.1038/s41597-022-01899-x.

19. Collins G.S., Moons K.G.M., Dhiman P. et al. TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods // BMJ. – 2024. – Vol. 385. – Art. e078378. – DOI: 10.1136/bmj-2023-078378.

20. Johnson A., Bulgarelli L., Pollard T. et al. MIMIC-IV (version 3.1) [Electronic resource] // PhysioNet. – 2024. – DOI: 10.13026/kpb9-mt58.

21. Goldberger A.L., Amaral L.A.N., Glass L. et al. PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals // Circulation. – 2000. – Vol. 101, No. 23. – P. e215–e220.

22. Johnson A.E.W., Stone D.J., Celi L.A., Pollard T.J. The MIMIC Code Repository: enabling reproducibility in critical care research // Journal of the American Medical Informatics Association. – 2018. – Vol. 25, No. 1. – P. 32–39. – DOI: 10.1093/jamia/ocx084.

23. Bai S., Kolter J.Z., Koltun V. An empirical evaluation of generic convolutional and recurrent networks for sequence modeling [Electronic resource] // arXiv. – 2018. – arXiv:1803.01271. – URL: https://arxiv.org/abs/1803.01271 (accessed: 27.10.2026).

24. Platt J. Probabilistic outputs for support vector machines and comparisons to regularized likelihood methods // Advances in Large Margin Classifiers. – Cambridge : MIT Press, 1999. – P. 61–74.

25. Van Calster B., McLernon D.J., van Smeden M. et al. Calibration: the Achilles heel of predictive analytics // BMC Medicine. – 2019. – Vol. 17. – Art. 230. – DOI: 10.1186/s12916-019-1466-7.

26. DeLong E.R., DeLong D.M., Clarke-Pearson D.L. Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach // Biometrics. – 1988. – Vol. 44, No. 3. – P. 837–845.

27. Lundberg S.M., Erion G., Chen H. et al. From local explanations to global understanding with explainable AI for trees // Nature Machine Intelligence. – 2020. – Vol. 2, No. 1. – P. 56–67. – DOI: 10.1038/s42256-019-0138-9.

# МАЗМҰНЫ – СОДЕРЖАНИЕ – CONTENT

## ӘЛЕУМЕТТІК-ЭКОНОМИКАЛЫҚ ЖӘНЕ ҚҰҚЫҚ ҒЫЛЫМДАРЫ - СОЦИАЛЬНО-ЭКОНОМИЧЕСКИЕ И ЮРИДИЧЕСКИЕ НАУКИ - SOCIO-ECONOMIC AND LEGAL SCIENCES

Төлегенов Тимур Сейфуллаулы
**ДИНАМИКА ТУРИСТСКИХ ПОТОКОВ И ЭФФЕКТИВНОСТЬ ИНФРАСТРУКТУРЫ ТУРКЕСТАНА: ОТ ЭКСТЕНСИВНОГО РОСТА К СМАРТ-УПРАВЛЕНИЮ ..... 12**

Alexander Gorevoy
**WHICH INEQUALITY STATISTICS SURVIVE AN ADMINISTRATIVE BOUNDARY CHANGE? EVIDENCE FROM KAZAKHSTAN, 2010–2023 ..... 16**

Rakhimov Djalil
**DOES THE SHIFT TO CASHLESS PAYMENTS GO TOGETHER WITH FASTER GROWTH IN HOUSEHOLD CREDIT? EVIDENCE FROM THE REGIONS OF KAZAKHSTAN, 2023-2025 ..... 28**

Kazhgerey Asan
**HOW MANY FOOD BASKETS DOES AN AVERAGE WAGE BUY? WAGES AND FOOD PRICES IN THE 20 REGIONS OF KAZAKHSTAN, 2024-2026 ..... 39**

Tagimova Alua
**WHO WAS LEFT BEHIND? EDUCATION AND FINANCIAL INCLUSION IN KAZAKHSTAN AND THREE CENTRAL ASIAN NEIGHBOURS, 2021-2024 ..... 46**

Wei Wei, Mynzhanova Gulzhakan, Niyetalina Gaukhar
**DIGITAL–PHYSICAL INTEGRATION AND ECONOMIC PERFORMANCE IN INDUSTRIAL INTEGRATED ENERGY SYSTEMS: A SCENARIO-BASED ANALYSIS OF SMART GRID CONTROL, BATTERY ENERGY STORAGE, AND DIGITAL TWINS ..... 53**

Xu Fumin, Wei Wei, Ruziyeva Elvira, Moldabekova A.
**FROM CULTURAL RESOURCES TO GLOBAL CONSUMER VALUE: THE BRIDGE–IMC MODEL AND THE INTERNATIONALIZATION OF BLACK MYTH: WUKONG UNDER THE BELT AND ROAD INITIATIVE ..... 66**

Ibraimkhan Alikhan
**WHICH CRIMES CAN A 14-YEAR-OLD BE TRIED FOR? THE LIST IN ARTICLE 15 OF KAZAKHSTAN'S CRIMINAL CODE COMPARED WITH 30 OTHER JURISDICTIONS ..... 82**

Yerboluly Madi
**DID IMPORTED CARS REALLY GET CHEAPER? CHINESE CARS AND THE AVERAGE CUSTOMS VALUE OF PASSENGER CARS IMPORTED INTO KAZAKHSTAN, 2015-2025 ..... 93**

Салимбаев Ербол Аманжолович
**АНАЛИЗ ИНВЕСТИЦИОННОЙ АКТИВНОСТИ КАК ИНДИКАТОР ИЗМЕНЕНИЙ ПОТЕНЦИАЛЬНОГО СПРОСА НА КОНСАЛТИНГОВЫЕ УСЛУГИ ..... 101**

Rambergenov Ramil
**REGIONAL NEW-FIRM FORMATION IN UZBEKISTAN AFTER THE 2017 REFORMS: PERSISTENCE IN SCALE, CONVERGENCE IN INTENSITY, AND RECOMPOSITION TOWARD TRADE ..... 109**

Abdesh Dinara
**FROM A WOMEN'S LEAD TO A MEN'S LEAD: THE GENDER GAP IN DIGITAL PAYMENTS IN KAZAKHSTAN AND THREE CENTRAL ASIAN NEIGHBOURS, 2021-2024 ..... 118**

Amangeldi Aidana
**DID SMALL BUSINESS IN KAZAKHSTAN REALLY SHRINK IN 2026? THE NEW TAX CODE, REGIONAL TAX RATES AND THE FALL IN THE NUMBER OF INDIVIDUAL ENTREPRENEURS ..... 126**

Cheng Che
**BUILD, BUY, OR PARTNER? ENTRY MODE SELECTION AND RISK GOVERNANCE FOR WIND POWER INVESTMENT IN KAZAKHSTAN** ..... **135**

Wang Liang
**FROM CAPACITY EXPANSION TO SYSTEM VALUE: COORDINATED DEVELOPMENT OF RENEWABLE ENERGY, GRID FLEXIBILITY AND ENERGY STORAGE IN KAZAKHSTAN** ..... **148**

Chen Jun
**CONSTRUCTION-PERIOD CREDIT RISK MANAGEMENT FOR LARGE INFRASTRUCTURE PROJECT FINANCE IN KAZAKHSTAN** ..... **161**

Alniyaz Danial
**HOW MUCH FUEL DOES A HYBRID REALLY SAVE? A SAME-MODEL COMPARISON OF HYBRID AND GASOLINE CARS IN US FUEL ECONOMY** ..... **175**

Assem Yergali, Maral Assanova
**DIGITAL TRANSFORMATION AND SUSTAINABLE BUSINESS MODEL INNOVATION IN SMALL AND MEDIUM-SIZED ENTERPRISES: A SYSTEMATIC REVIEW OF DYNAMIC CAPABILITIES, VALUE CREATION, AND THE CREDIBILITY GAP IN EMERGING ECONOMIES** ..... **182**

Бейбіт Инара Алибекқызы, Едилов Саназар
**ВОДА ИЗ ТУМАНА ИЛИ ВОДА ИЗ МОРЯ: ПОРОГОВАЯ СТОИМОСТЬ, ПРИ КОТОРОЙ ТУМАНОУЛОВИТЕЛИ КОНКУРЕНТОСПОСОБНЫ В МАНГИСТАУСКОЙ ОБЛАСТИ** ..... **195**

Zhenisbekova Aknur
**DID A TENGE DEPOSIT OR THREE KAZAKHSTANI SHARES PROTECT SAVINGS FROM INFLATION? REAL RETURNS OF BANK DEPOSITS, KAZATOMPROM, KEGOC AND KASPI.KZ, 2020-2025** ..... **207**

Абилдаева Аселя
**ОРГАНИЗАЦИОННАЯ ГОТОВНОСТЬ ВУЗОВ КАЗАХСТАНА К ВНЕДРЕНИЮ ЭНДАУМЕНТ-ФОНДОВ: КОНЦЕПТУАЛЬНАЯ РАМКА НА ОСНОВЕ ОБЗОРА ЛИТЕРАТУРЫ И АНАЛИЗА ДОКУМЕНТОВ** ..... **215**

Yang Juntao
**DIGITAL ESG GOVERNANCE AND NEXT-GENERATION DIGITAL COMPETENCY AS DRIVERS OF SUCCESSION IN FAMILY AGRICULTURAL ENTERPRISES: A CONCEPTUAL FRAMEWORK** ... **229**

Kairbek Mariya Islamkyzy, Kylbaev Erlan Serikovich
**STATE SUPPORT FOR THE DIGITALIZATION OF MANUFACTURING IN THE REPUBLIC OF KAZAKHSTAN: AN ANALYSIS OF ITS COVERAGE OF MARKETING AND SALES ACTIVITIES** ..... **242**

Tilep Aiaru
**WHEN DID IT EXPORTS TAKE OFF? ICT SERVICE EXPORTS OF KAZAKHSTAN, ARMENIA, GEORGIA AND THREE NEIGHBOURS, 2015-2024** ..... **255**

Anuarbek Murager
**DID THE TENGE STOP FOLLOWING OIL? BRENT PRICES AND THE TENGE-DOLLAR RATE BEFORE AND AFTER FEBRUARY 2022** ..... **266**

Kaiyrbek Zhanadil
**HOW ACCURATELY CAN OBSERVABLE LISTING DATA ESTIMATE FAIR PRICES FOR USED CARS IN KAZAKHSTAN? A HEDONIC MODEL OF 2,546 ONLINE LISTINGS** ..... **276**

Wen Yali
**PERCEIVED ORGANIZATIONAL SUPPORT AND TURNOVER INTENTION AMONG KNOWLEDGE WORKERS IN A CHINESE PRIVATE TRAINING INSTITUTION: THE MEDIATING ROLE OF AFFECTIVE ORGANIZATIONAL COMMITMENT** ..... **289**

Құрманалиева Дана
**ИСТОЧНИКИ ФИНАНСИРОВАНИЯ ИННОВАЦИОННЫХ ПРОЕКТОВ И КРИТЕРИИ ВЫБОРА ФИНАНСОВОЙ МОДЕЛИ** ..... **300**

## ТЕХНИКАЛЫҚ ҒЫЛЫМДАР - ТЕХНИЧЕСКИЕ НАУКИ - TECHNICAL SCIENCE

Nurmakhan Almira
**ADVANTAGES OF FIBER OPTIC COMMUNICATION OVER TRADITIONAL COPPER CABLES** ..... **307**

Kozhabai Bereke
**SECURITY CHALLENGES IN IOT-BASED TELECOMMUNICATION NETWORKS** ..... **315**

Azamatuly Yerassyl
**WHY AI-GENERATED CODE FAILS A BENCHMARK: A FAILURE ANALYSIS OF THREE OPEN LANGUAGE MODELS ON 30 HUMANEVAL+ TASKS** ..... **324**

Nurzhan Sanzhar
**A FEW SHELLS, A FEW OPERATORS: WHERE LOW EARTH ORBIT IS CROWDED IN AN ALTITUDE-INCLINATION MAP OF 16,620 ACTIVE SATELLITES** ..... **333**

Askarbek Nurislam
**CAN THE WEATHER TELL WHICH DAYS IN ASTANA WILL BE POLLUTED? CLASSIFYING PM2.5 EXCEEDANCE DAYS WITH MACHINE LEARNING AND CHECKING THE DATA AGAINST A GROUND MONITOR** ..... **339**

Iliyas Arman
**SHOOTING ON THE MOVE: HOW MUCH AIM A ROBOT LOSES BY IGNORING ITS OWN VELOCITY, AND WHETHER A VIRTUAL-TARGET CORRECTION RECOVERS IT** ..... **350**

Ануар Әлімжан Бахытжанұлы, Сексенбаева Айша Курманбековна
**СРАВНИТЕЛЬНЫЙ АНАЛИЗ СТАНДАРТОВ И МЕТОДИК ОБУЧЕНИЯ КИБЕРБЕЗОПАСНОСТИ: NICE FRAMEWORK, ECSF И ПРАКТИКО- ОРИЕНТИРОВАННЫЕ ТЕХНОЛОГИИ** ..... **356**

Mukhamedzhan Yerganat
**GROWTH OF GITHUB DEVELOPER COMMUNITIES IN KAZAKHSTAN, UZBEKISTAN AND KYRGYZSTAN, 2020-2026: EVIDENCE FROM THE GITHUB INNOVATION GRAPH** ..... **366**

Kashkinov Alden
**WHAT DECIDES HOW LONG A LANDER WORKS ON ANOTHER WORLD? SURFACE LIFETIMES OF 55 LANDERS ON THE MOON, VENUS, MARS, TITAN AND SMALL BODIES IN THE GCAT CATALOGUE, 1966-2025** ..... **378**

Kenesbek Miras
**HOW MANY HERONIAN TRIANGLES HAVE A GIVEN LONGEST SIDE? A COMPLETE COUNT UP TO 2000 AND THE RIGHT TRIANGLES HIDDEN INSIDE** ..... **390**

Amirlan Seitkadyrov, Akezhan Omashev
**AUTOMATIC MULTIPLE-CHOICE QUESTION GENERATION USING ARTIFICIAL INTELLIGENCE** ..... **401**

Idrissov Amirzhan
**WHERE DO SMALL OPEN LANGUAGE MODELS BREAK ON OLYMPIAD MATHEMATICS? DOMAIN, DIFFICULTY AND MODEL SIZE ON OMNI-MATH** ..... **410**

Маматаева Рамина Адилгазыевна, Бидуәлі Алмат Алматұлы
**ОБЗОР И СРАВНЕНИЕ ПОПУЛЯРНЫХ КРОССПЛАТФОРМЕННЫХ ФРЕЙМВОРКОВ ДЛЯ РАЗРАБОТКИ МОБИЛЬНЫХ ПРИЛОЖЕНИЙ** ..... **415**

Қасен Ғауһар Ғалымжанқызы, Алкеева Дана Мирасовна
**КОМПЬЮТЕРЛІК КӨРУДІ ПАЙДАЛАНЫП,МЕХАНИКАЛЫҚ ДЕНЕ ЗАҢЫН АНЫҚТАУ АЛГОРИТМДЕРІН ӘЗІРЛЕУ** ..... **421**

Khalilzade Seymur Fazil oglu
**ASSESSING THE IMPACT OF ELECTRIC VEHICLES ON ENERGY DEMAND IN HIGH-RISE RESIDENTIAL BUILDINGS** ..... **434**

Igilikov Adilkhan Igilikovich
**PRE-TRAINED REPRESENTATIONS OF PRIOR-ADMISSION HISTORY IMPROVE ONE-YEAR, BUT NOT IN-HOSPITAL, MORTALITY PREDICTION IN ICU PATIENTS WITH CHRONIC DISEASE: A MIMIC-IV STUDY** ..... **449**

Nurgali Dias, Nurgali Miras, Akashov Aslan
**PREDICTIVE TRAFFIC MANAGEMENT: EXPLORING SOLUTIONS TO TRAFFIC CONGESTION IN ASTANA, KAZAKHSTAN** ..... **461**

**ПӘНДЕР АРАЛЫҚ ҒЫЛЫМДАР – МЕЖДИСЦИПЛИНАРНЫЕ НАУКИ – INTERDISCIPLINARY SCIENCES**

Albiyev Asser
**HOW MUCH OF AN ARTICLE COUNT IS HUMAN WORK? DECOMPOSING THE CREATION OF FIVE WIKIPEDIAS, 2010–2025** ..... **467**

Amangeldy Nurbolat
**HOW MUCH OF KAZAKHSTAN'S URBAN BUILT STOCK PREDATES ITS SEISMIC CODES, AND WHERE DOES THAT STOCK SIT RELATIVE TO HAZARD?** ..... **477**

Torekhan Sabrina
**WHERE ALMATY WALKS ITS OWN WAY: INFORMAL SHORTCUTS IN OPENSTREETMAP AND THE DETOURS THEY AVOID** ..... **483**

Ailan Salybekova
**PARENTAL SUPPORT, PARENTAL CONTROL, STRESS AND EARLY ALCOHOL USE IN ADOLESCENT GIRLS: A NARRATIVE REVIEW WITH A FOCUS ON KAZAKHSTAN** ..... **488**

Yerboluly Madi
**WHY IS KAZAKHSTAN'S GENDER GAP AT THE TOP OF CHESS SO SMALL? A BIRTH-COHORT COMPARISON ON THE FIDE RATING LIST** ..... **496**

Omashev Akezhan
**REGIONAL HEALTH AND SOCIAL INDICATOR PATTERNS AND PCA- BASED MORTALITY MODELING IN KAZAKHSTAN, 2011–2024. A TWO- PART EXPLORATORY ECOLOGICAL ANALYSIS** ..... **501**

Мадиярова Жанел Биржановна
**ДИПФЕЙК ТЕХНОЛОГИЯСЫНЫҢ ҚОҒАМДЫҚ ПІКІРГЕ ЫҚПАЛЫ ЖӘНЕ ОНЫ ҚҰҚЫҚТЫҚ РЕТТЕУ ТӘЖІРИБЕСІ** ..... **511**

Bolatov Sanzhar
**HOW MUCH DOES KAZAKH SPEECH RECOGNITION LOSE WHEN THE MODEL GETS SMALLER? KAZAKH AGAINST 82 LANGUAGES IN THE PUBLISHED WHISPER RESULTS** ..... **521**

Ilya Tsoy
**WHO PAYS MORE TOKENS FOR THE SAME SENTENCE? RUSSIAN, KOREAN AND ENGLISH IN FOUR LANGUAGE MODEL TOKENIZERS ON 1,012 FLORES-200 SENTENCES** ..... **530**

Assan Ramazan
**WHICH NAME DO READERS STILL USE? FORMER NAMES OF RENAMED KAZAKHSTANI CITIES IN RUSSIAN AND KAZAKH WIKIPEDIA PAGE VIEWS, 2015–2026** ..... **543**

Nigmadilova Zhasmin
**WHAT REPLACES PARABENS? THE PARABEN-FREE LABEL ACROSS PRODUCT CATEGORIES IN THE OPEN BEAUTY FACTS DATABASE** ..... **556**

**ӘЛЕУМЕТТІК ЖӘНЕ ГУМАНИТАРЛЫҚ ҒЫЛЫМДАР - СОЦИАЛЬНО-ГУМАНИТАРНЫЕ НАУКИ - SOCIAL SCIENCES AND HUMANITIES**

Мұқатаева Айзат Амантайқызы, Стамбекова Жанат Байғазықызы, Слямханова Гүлім Болатқызы, Қызырбек Аяулым Ерболқызы
**ЖАСАНДЫ ИНТЕЛЛЕКТ ДӘУІРІНДЕГІ ҒЫЛЫМИ ТАНЫМ: ПОППЕР, КУН ЖӘНЕ ЛАКАТОС ИДЕЯЛАРЫ ТҰРҒЫСЫНАН ТАЛДАУ** ..... **561**

Мұқатаева Айзат Амантайқызы, Сапарханова Мадина Төлегенқызы, Окенова Аружан Муратхановна, Тұрсынғазыева Ақерке Ерболатқызы
**ШӘКӘРІМ ФИЛОСОФИЯСЫНДАҒЫ ЕРКІНДІК ЖӘНЕ МОРАЛЬДЫҚ ТАҢДАУ МӘСЕЛЕСІ** ..... **571**

Komekova Saida
**DO UNHAPPY REVIEWERS MIX IN MORE RUSSIAN? STAR RATINGS AND KAZAKH-RUSSIAN CODE-SWITCHING IN 175,002 ONLINE REVIEWS** ..... **580**

Zhumagali Yerbol
**DOES A BIGGER MODEL CLOSE THE GAP? KAZAKH-LANGUAGE ACCURACY ON KAZAKHSTAN-SPECIFIC VERSUS UNIVERSAL SCHOOL SUBJECTS IN SMALL OPEN-WEIGHT LANGUAGE MODELS** ..... **593**

Abdrakhmanova Madina
**DOES A MEDAL BUY ATTENTION? WIKIPEDIA VIEWS OF KAZAKHSTAN'S ATHLETES BEFORE AND AFTER THE PARIS 2024 OLYMPIC** ..... **597**

**ПЕДАГОГИКАЛЫҚ ЖӘНЕ ПСИХОЛОГИЯЛЫҚ ҒЫЛЫМДАР – ПЕДАГОГИЧЕСКИЕ И ПСИХОЛОГИЧЕСКИЕ НАУКИ – PEDAGOGICAL AND PSYCHOLOGICAL SCIENCES**

Kaldarbek Mergen
**FAMILY OR SCHOOL? SOCIOECONOMIC COMPOSITION AND MATHEMATICS ACHIEVEMENT IN KAZAKHSTAN, PISA 2022 AND 2025** ..... **605**

Zhenis Adilzhan
**WHICH OLYMPIAD PROBLEMS DO STUDENTS TAKE TO THE BOARD? CHOICES AND DEFENCES IN THE 8TH-GRADE LEAGUE OF KARAGANDY MATHBATTLES 2026** ..... **612**

Базарбаева Айнур Бектуровна
**ДЕТСКИЙ ФОЛЬКЛОР И ПОДВИЖНЫЕ ИГРЫ КАК ИНСТРУМЕНТЫ ФОРМИРОВАНИЯ ОСНОВ ПРАВОВОЙ КУЛЬТУРЫ У ДЕТЕЙ СТАРШЕГО ДОШКОЛЬНОГО ВОЗРАСТА** ..... **619**

**БИОЛОГИЯ ҒЫЛЫМДАР - БИОЛОГИЧЕСКИЕ НАУКИ - BIOLOGICAL SCIENCES**

Bazhenova Diana
**GROWTH DYNAMICS OF STERLET (Acipenser ruthenus L.) REARED IN A RECIRCULATING AQUACULTURE SYSTEM** ..... **622**

**ТУРИСТИЧЕСКИЕ И СПОРТИВНЫЕ НАУКИ - ТУРИСТІК ЖӘНЕ СПОРТ ҒЫЛЫМДАРЫ - TOURISM AND SPORTS SCIENCES**

Төлеп Жазира Маратқызы
**ГАСТРОНОМИЯЛЫҚ ФЕСТИВАЛЬДЕРДІҢ ТУРИСТІК ДЕСТИНАЦИЯ ТАРТЫМДЫЛЫҒЫН ҚАЛЫПТАСТЫРУДАҒЫ РӨЛІ МЕН ДАМУ ҮРДІСТЕРІ** ..... **629**

## ЕСТЕСТВЕННЫЕ НАУКИ - ЖАРАТЫЛЫСТАНУ ҒЫЛЫМДАРЫ - NATURAL SCIENCES

Нургельдина Асель Ермековна, Серикбаева Жанерке Алимжановна
**ШЕКАРАСЫЗ ФИЗИКА: ӘР ЕЛДЕГІ ФИЗИКАЛЫҚ БІЛІМДІ САЛЫСТЫРУ** ..... **636**

Torekhan Sabrina
**IS ALMATY A 15-MINUTE CITY? WALKING ACCESS TO SIX EVERYDAY PLACES FROM 170,838 BUILDINGS IN THE CITY'S EIGHT DISTRICTS** ..... **643**

Онгарбек Махабат Саятқызы
**CU-PT ЖӘНЕ NI-PT ҚОРЫТПАЛАРЫНЫҢ ФИЗИКАЛЫҚ ҚАСИЕТТЕРІНЕ РЕТТЕЛУ ҮДЕРІСІНІҢ ЖӘНЕ ҚҰРЫЛЫМДЫҚ ӨЗГЕРІСІНІҢ ӘСЕРІН РЕТТЕУ** ..... **651**

Нургельдина Асель Ермековна, Әбдуәлі Мерей Ералықызы
**ҮЙКЕЛІС КҮШІНІҢ ТАБИҒАТТАҒЫ РӨЛІ** ..... **659**

Ossipov Vladislav
**MANY REPORTS, WEAK EVIDENCE? EVIDENCE LEVELS FOR MICROBIAL PLASTIC DEGRADATION IN THE 2,535 RECORDS OF PLASTICDB** ..... **664**

Нургельдина Асель Ермековна, Кабдулаева Жанель Батырбековна
**РАДИОАКТИВТІЛІК. АЛЬФА, БЕТА, ГАММА СӘУЛЕЛЕРІНІҢ ТЕГІ МЕН ЗАҢДЫЛЫҚТАРЫ. ЯДРОЛЫҚ РЕАКЦИЯ ЖӘНЕ ЖАРТЫЛАЙ ЫДЫРАУ ПЕРИОДЫ** ..... **673**

Kashkinov Alden
**DOES AN ACTIVE SUN BRING SATELLITES DOWN SOONER? SOLAR ACTIVITY AND THE RE-ENTRY OF UNCONTROLLED OBJECTS IN LOW EARTH ORBIT, 1990-2025** ..... **678**

Demin Mark
**HOW MUCH LESS OXYGEN CAN THE WARMING CASPIAN SEA HOLD? THE LOSS OF OXYGEN SOLUBILITY IN THE NORTHERN, MIDDLE AND SOUTHERN CASPIAN, 1982-2022** ..... **684**