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RISK ASSESSMENT SCALE FOR MONITORING RISKS IN MYOCARDIAL INFARCTION

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Abstract. Myocardial infarction (MI) remains one of the leading causes of mortality and disability worldwide, which necessitates accurate and timely assessment of the risk of adverse outcomes. Modern clinical practice uses a number of prognostic scales, including TIMI, GRACE, PURSUIT, and HEART, each of which has proven effectiveness but also certain limitations related to narrow focus, complexity of calculation, or lack of dynamic reassessment of the patient's condition.

This paper presents an extended analysis of existing risk assessment scales for myocardial infarction, compares them, and proposes a scoring scale—the Myocardial Infarction Grading Scale (MIGS)—that integrates clinical, symptomatic, laboratory, and instrumental indicators. A mathematical model based on a weighted sum of risk factors with logistic transformation has been developed for MIGS, allowing quantitative assessment of the likelihood of complications and fatal outcomes. Examples of scoring calculations for various clinical scenarios are presented, as well as a graphical visualization of the dependence of the probability of complications on the total MIGS score.

It is shown that the scale has advantages over traditional tools due to its comprehensive approach, dynamic monitoring capabilities, and integration into digital clinical systems. The results obtained indicate the feasibility of using MIGS in inpatient and emergency cardiology practice to improve the accuracy of risk stratification and personalization of treatment tactics.

Keywords: myocardial infarction; risk stratification; prognostic scales; TIMI; GRACE; PURSUIT; HEART; scoring scale; mathematical model; probability of complications; clinical prediction; digital cardiology.

Introduction

The high frequency of complications after MI, such as heart failure, recurrent infarction, and sudden cardiac death, requires effective risk monitoring [1, 8]. Assessment scales allow standardizing the prediction process, identifying high-risk groups, and making informed clinical decisions.

Despite the widespread use and clinical significance of existing risk assessment scales for myocardial infarction, such as TIMI [2, 9], GRACE [3, 10], PURSUIT, and HEART [4, 11], their practical application reveals a number of methodological and functional limitations. These scales were developed at different times, on different patient populations, and using heterogeneous statistical approaches, which accounts for differences in both the composition of the parameters assessed and the principles of interpreting the final risk.

For example, the TIMI and PURSUIT scales are primarily focused on rapid risk stratification in acute coronary syndrome, but they use a fixed scoring system without taking into account the relative significance of individual factor blocks [9, 12]. The GRACE scale,

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which has high prognostic value, requires calculation based on more complex formulas and is often unsuitable for dynamic monitoring of the patient's condition in clinical practice [10, 13]. The HEART scale, on the contrary, is simple and accessible, but is characterized by limited depth of analysis and does not cover the entire spectrum of laboratory and instrumental indicators that affect the prognosis [4, 11].

A common limitation of the scales listed above is their predominantly threshold nature, whereby patients are assigned to a specific risk category without a quantitative assessment of the likelihood of developing adverse complications. This makes it difficult to personalize treatment strategies, conduct dynamic monitoring, and integrate the scales into modern clinical decision support systems.

In this regard, it seems relevant to develop an integrated assessment model that combines the clinical interpretability of classical scales with the possibility of mathematical risk prediction.

Materials and methods. The MIGS scoring scale is designed to overcome these limitations through its modular structure, weighting of key risk factor blocks, and subsequent conversion of the total score into the probability of complications using a logistic function.
MIGS consists of five blocks (Fig. 1) [17]:

1. Clinical block: age, concomitant diseases (diabetes mellitus, hypertension, CHF).
2. Symptomatic block: pain severity, signs of acute heart failure.
3. Laboratory block: troponin, creatine phosphokinase, natriuretic peptides.
4. Instrumental block: ECG changes, echocardiography parameters (LV ejection fraction, chamber dimensions).
5. Dynamic block: possibility of re-evaluation after 24-48 hours to adjust treatment.
6.

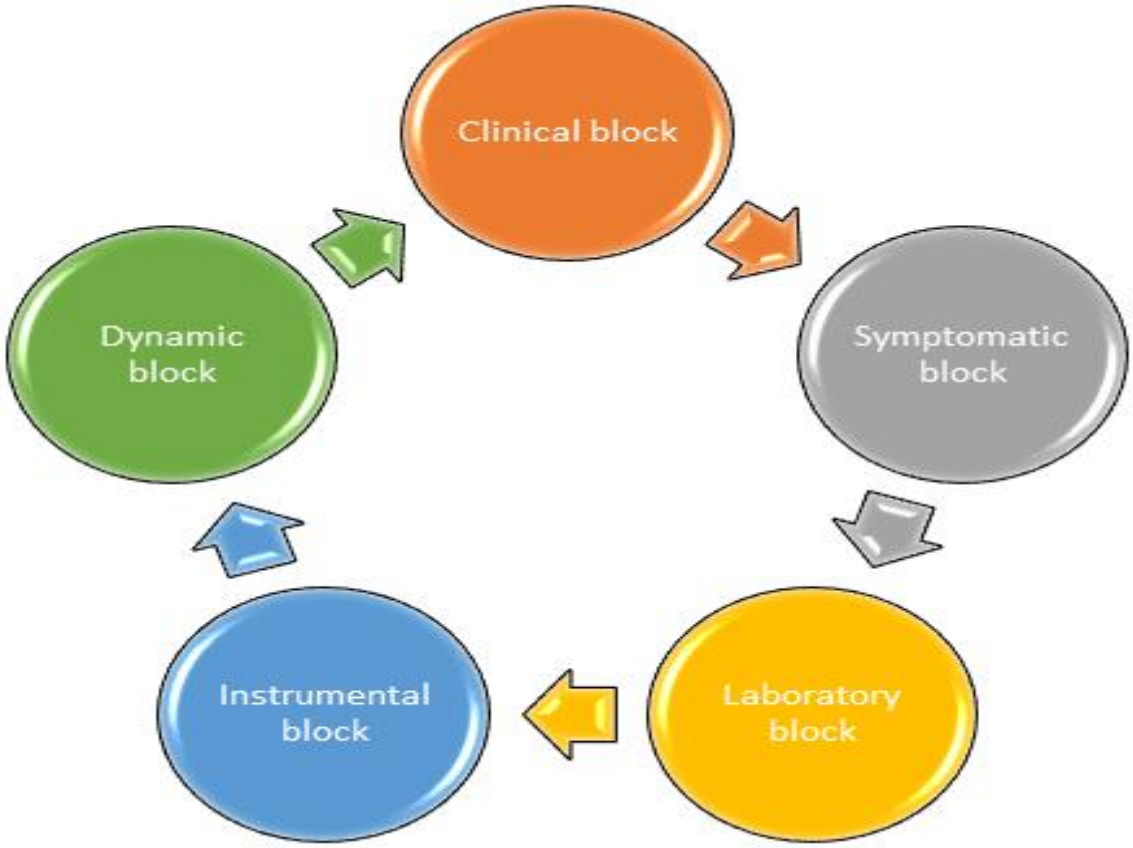

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Fig. 1. MIGS scale blocks

Each parameter is assigned a score from 0 to 3, where 0 is no risk and 3 is high risk. Total score = sum of all blocks.

Table 1. MIGS scale scoring

Block	Parameter	Points (0–3)
Clinical	Age >75	3
Clinical	SD, GB, CHF	1-3 (for each factor)
Symptomatic	Intense pain, shortness of breath	2–3
Laboratory	Troponin >3x normal	3
Laboratory	NT-proBNP >400 pg/ml	2
Instrumental	STEMI/stenosis ≥70%	3
Instrumental	LVEF <40%	3

Interpretation:

- 0-8 points - low risk;
- 9-15 points - medium risk;
- 15 points - high risk of complications.

The scores for each MIGS parameter were determined based on an analysis of:

1. Scientific publications and clinical studies confirming the statistical significance of risk factors for myocardial infarction [1].
2. The risk grading principle used in the classic TIMI, GRACE, PURSUIT, and HEART scales, where each factor is assigned points depending on its degree of influence on an adverse outcome [2].
3. The practical experience of clinicians and expert consensus, taking into account the local characteristics of the patient population and the availability of instrumental and laboratory tests.

Principles of scoring

1. Clinical block (age, comorbidities)
    - Age >75 years: 3 points, as age is the strongest independent predictor of mortality after MI [3].
    - DM, AH, CHF: 1-3 points for each factor, depending on their number and clinical severity, since the presence of comorbidities increases the risk of complications and death [1].
2. Symptomatic block (pain, dyspnea)
    - Mild angina: 1 point; severe pain with dyspnea: 3 points.
    - Rationale: the severity of symptoms correlates with the extent of myocardial damage and the likelihood of acute heart failure [4].
3. Laboratory block (troponin, NT-proBNP)
    - Troponin >3x normal: 3 points; 1-3x normal: 1 point.
    - NT-proBNP >400 pg/ml: 2 points.
    - Rationale: troponin and NT-proBNP are independent predictors of heart failure and mortality [20].
4. Instrumental block (ECG, LV ejection fraction)
    - STEMI or stenosis ≥70%: 3 points, as a high degree of ischemia directly increases the risk of complications.

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- LVEF <40%: 3 points, as a reduced ejection fraction is associated with high in-hospital and post-hospital mortality.

5. Dynamic block
   - The ability to recalculate scores after 24-48 hours allows the initial assessment to be adjusted depending on changes in the patient's condition and the effectiveness of therapy.

Assessment structure and interpretation

- Total score = sum of scores for all blocks.
- 0-8 points - low risk;
- 9-15 points - medium risk;
- 15 points - high risk.

This approach ensures objective risk assessment, integrates different types of data (clinical, laboratory, instrumental), and allows for dynamic adaptation of therapy.

Mathematical model of the scoring scale (MIGS)

The scoring scale (MIGS) can be formalized as a weighted sum of risk factors, followed by conversion into the probability of an adverse outcome (complication or mortality).

Let each MIGS block have several parameters x_i with scores b_i . Then the total score B is calculated as:

$$B=\sum_{i=1}^{n} b_i$$

where:

- n is the total number of parameters (clinical, symptomatic, laboratory, instrumental);
- b_i - score assigned to each parameter (0-3).

To improve the accuracy of the prediction, weights can be assigned to the blocks w_j reflecting their relative significance:

$$B_{\text{знач}}=\sum_{j=1}^{m} w_j \cdot \sum_{i=1}^{n_j} b_{ij}$$

where:

- m - number of blocks (clinical, symptomatic, laboratory, instrumental, dynamic);
- n_j - number of parameters in block j;
- b_{ij} - score of parameter i in block j;
- w_j - block weight (0-1, sum of all weights = 1).

Example of weights:

- Clinical: 0.25
- Symptomatic: 0.15
- Laboratory: 0.30
- Instrumental: 0.25
- Dynamic: 0.05

To assess the probability of an adverse outcome P, a logistic function can be used, which is widely used to predict binary events (event/non-event) [6]:

$$P=\frac{1}{1+e^{-(\alpha+\beta \cdot B_{\text{знач}})}}$$

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where:

- P - probability of complications or mortality;
- α -offset (intercept), reflects the baseline risk;
- β-slope coefficient, reflects the sensitivity of risk to an increase in points;
- B_{sign} -weighted MIGS score.

Interpretation:

- Low B_{signif}values → P close to 0 (low risk);
- Medium values → P is around 0.5 (medium risk);
- High values → P close to 1 (high risk).

The dependence of the probability of complications on the weighted MIGS score is nonlinear and is described by a logistic function (Fig. 2), which allows us to clearly distinguish between low, medium, and high risk zones:

- Green zone (B ≤ 8) - low risk;
- Yellow zone (B = 9–15) - medium risk;
- Red zone (B > 15) - high risk.

The graph visualizes how an increase in MIGS scores increases the likelihood of complications and allows for a quick assessment of the degree of risk for each patient.

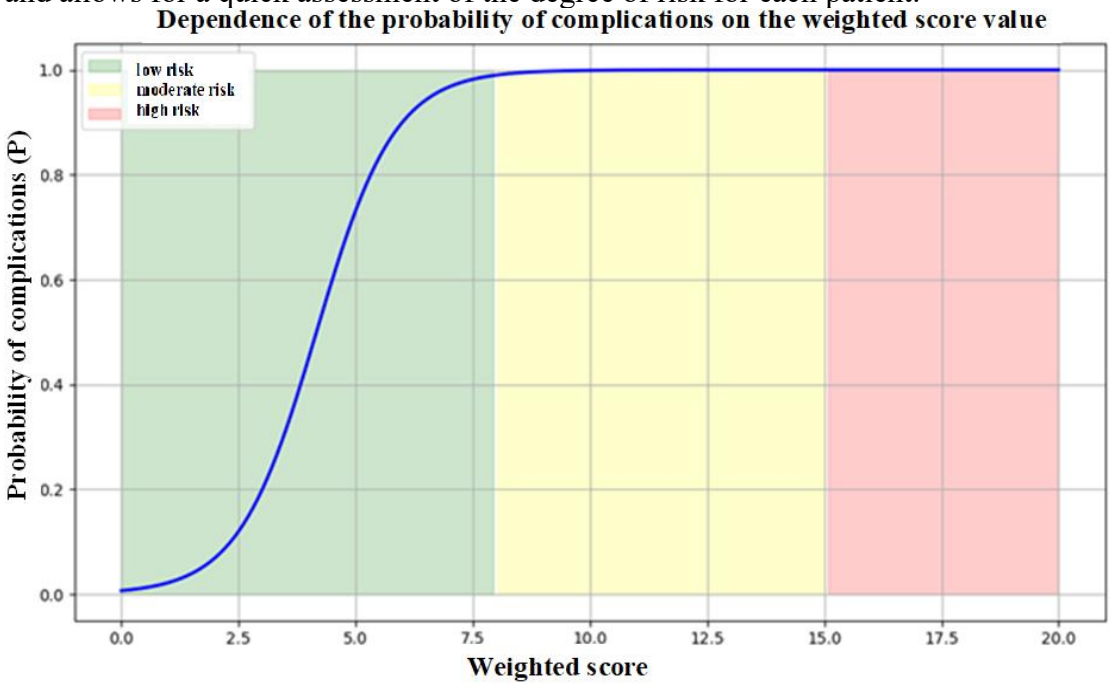

Fig. 2. Dependence of the probability of developing adverse complications of myocardial infarction P on the weighted total score of the $B_{significance}$scoring scale. Low, medium, and high risk zones are marked.

Example: Suppose a patient has the following scores:

- Clinical block: 5
- Symptomatic block: 3
- Laboratory block: 6
- Instrumental block: 4
- Dynamic block: 1

Weighted score:

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B_{value}= 0.25 × 5 + 0.15 × 3 + 0.30 × 6 + 0.25 × 4 + 0.05 × 1 = 1.25 + 0.45 + 1.8 + 1.0 + 0.05 = 4.55

With the given coefficients of the logistic function α = -5, β = 1.2:

$$P=\frac{1}{1+e^{-(-5+1.2\cdot 4.55)}}=\frac{1}{1+e^{-0,46}}\approx 0,61$$

That is, the probability of complications for this patient is 61%, which corresponds to a high risk.

Fig. 3 shows the logistic dependence of the probability of developing adverse complications of myocardial infarction P on the weighted total score of the scoring scale $B_{significance}$. The curve has an S-shape characteristic of logistic risk models, reflecting the nonlinear increase in the probability of complications with an increase in the total severity of risk factors.

A separate point on the graph marks the patient in question with a weighted score B_{sign} =4.55, which corresponds to a calculated probability of complications P≈61% [17].

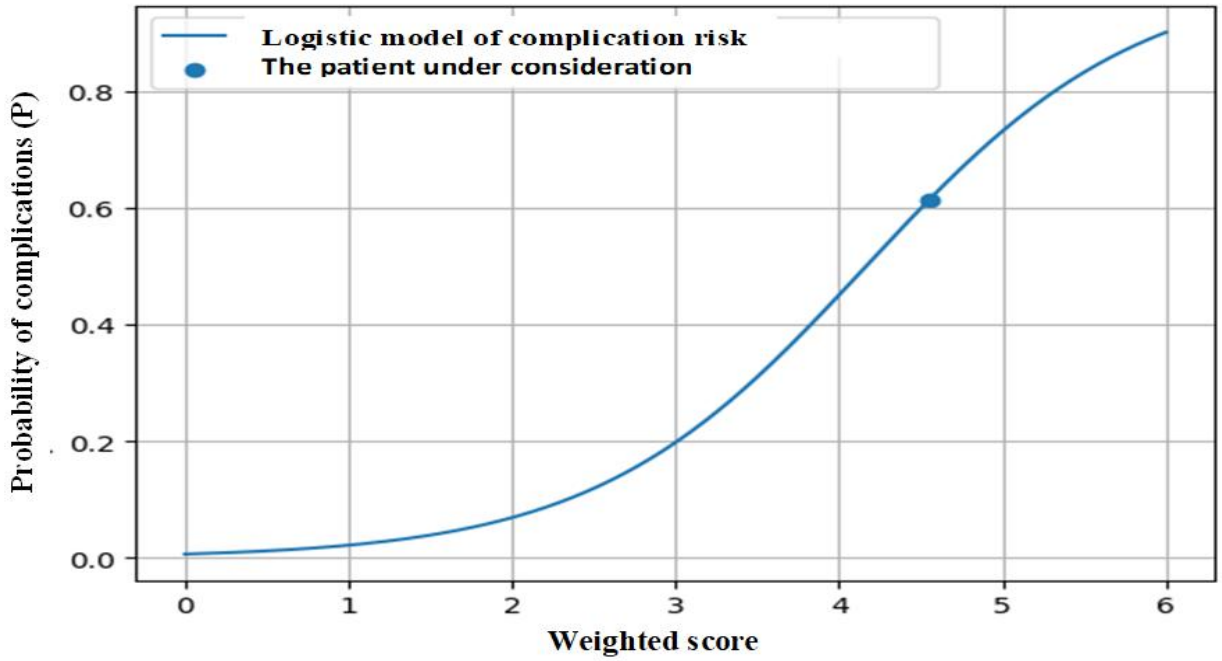

Fig. 3. Dependence of the probability of developing complications of myocardial infarction P on the weighted total score of the scoring scale $B_{significance}$. The point marks the position of a patient with a high risk of complications.

Thus, looking at the clinical picture of the graph, we see that:

- At low values of B_{sign} ≈ (0–2), the probability of complications remains minimal, which corresponds to the low-risk zone.
- In the range B_{sign} ≈ (3–4), there is a sharp increase in the curve, reflecting the transition zone of medium risk, where even a small increase in points significantly worsens the prognosis.
- When B_{sign}>4, the curve reaches a plateau of high probability values corresponding to a high risk of complications.

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A patient with $B_{significance}$= 4.55 is located at the top of the ascending segment of the curve, indicating a high probability of an unfavorable outcome and the need to intensify monitoring and treatment tactics.

Advantages of the MIGS mathematical model

1. **Objectivity:** conversion of qualitative and quantitative parameters into a single numerical score.
2. **Dynamic adaptation:** the probability can be recalculated as the patient's condition changes.
3. **Integration with AI:** the model is easy to use in electronic medical systems for automatic risk calculation.
4. **Comparability:** allows direct comparison of patients with each other and with classic scales such as TIMI or GRACE.

So, let's compare the existing TIMI, GRACE, PURSUIT, and HEART scales with the MIGS scoring scale in terms of structure, prognostic accuracy, clinical applicability, and integration capabilities into digital medical systems.

Table 2. Comparative characteristics of the MIGS scale with other scales

Scale	Prediction period	Focus	Scoring system	Features
TIMI	30 days	NSTEMI/STEMI	0	Simple, but limited to a short period
GRACE	Hospital-based, 6 months	All ACS	0–372	Integration of clinical and laboratory data, high accuracy
PURSUIT	Hospital	NSTEMI	0–100	Main focus on mortality, less accurate for recurrent MI
HEART	6 weeks	Acute chest pain	0–10	Convenient for ED, quick decision-making
MIGS	Hospital + dynamic	ACS	0–20	Combines all factors, possibility of dynamic reassessment, integration of laboratory and instrumental indicators

Thus, MIGS combines the advantages of all the listed systems, adding dynamic reassessment and an expanded laboratory and instrumental component [5, 16, 22].

Results. Here are some examples of MIGS score calculations

Table 3. Patient 1 (MIGS = 7 - low risk)

Parameter	Value	Points
Age	62	1
SD/GB	No	0
Pain	Mild angina	1
Troponin	1.5x normal	1

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NT-proBNP	150 pg/ml	0
STEMI	No	0
LVEF	55	0
Amount		7

Table 4. Patient 2 (MIGS = 17 - high risk)

Parameter	Value	Points
Age	78	3
SD/GB	Yes/Yes	2
Pain	Severe, shortness of breath	3
Troponin	4x normal	3
NT-proBNP	500 pg/ml	2
STEMI	Yes	3
LVEF	35	3
Amount		17

Discussion. The comparative analysis of existing risk assessment scales for myocardial infarction (TIMI, GRACE, PURSUIT, and HEART) presented in the table shows that each of them has certain advantages, but at the same time is characterized by a number of methodological limitations. Differences in the composition of the assessed parameters, scoring principles, and methods of interpreting the final risk determine the heterogeneity of their clinical applicability, especially in conditions requiring dynamic monitoring of the patient's condition [2, 9–11].

The data obtained allow us to conclude that there is currently no universal scale that can be applied equally effectively at all stages of managing patients with myocardial infarction. This circumstance necessitates a transition from static, threshold risk assessment models to integrated approaches that combine clinical interpretability with the ability to quantitatively predict adverse outcomes.

In this context, the MIGS scoring scale, developed with the identified limitations of existing tools in mind, is of particular interest. The modular structure of the scale, which includes clinical, symptomatic, laboratory, instrumental, and dynamic blocks, as well as the use of risk factor weighting, allows the model to be adapted to the individual characteristics of the patient and their current clinical condition.

To assess the practical applicability and prognostic capabilities of MIGS, clinical examples of weighted score calculation and the corresponding probability of complications are provided below. The analysis of specific scenarios clearly demonstrates how the integration of heterogeneous data is transformed into a quantitative risk assessment and contributes to informed clinical decision-making.

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Based on the examples presented and the calculations obtained, the concluding part of the work formulates conclusions about the diagnostic and prognostic significance of the author's scale, as well as determines the prospects for its implementation in clinical practice and medical decision support systems.

Thus, the results of a comparative analysis of existing risk assessment scales for myocardial infarction, as well as the clinical examples of the application of the scoring scale presented at , demonstrate the advisability of transitioning from static threshold models to integrated probabilistic approaches. The use of a weighted total score and its conversion into a quantitative probability of complications not only improves the accuracy of risk stratification, but also ensures a personalized interpretation of clinical data [7, 16, 21].

The results obtained create the prerequisites for generalizing the main provisions of the study and formulating conclusions that reflect the diagnostic, prognostic, and practical significance of the proposed model, i.e.:

1. An analysis of modern risk assessment scales for myocardial infarction (TIMI, GRACE, PURSUIT, and HEART) showed that, despite their widespread clinical use, they have a number of limitations related to the threshold nature of the assessment, the lack of risk factor weighting, and limited capabilities for dynamic monitoring of the patient's condition.
2. The developed MIGS scoring scale is based on a modular principle and includes clinical, symptomatic, laboratory, instrumental, and dynamic blocks, which ensures comprehensive consideration of key determinants of prognosis in myocardial infarction.
3. The use of a weighted total score allows for the different prognostic significance of individual risk factor groups to be taken into account, which increases the sensitivity of the model to clinically significant changes in the patient's condition.
4. The use of a logistic function to convert the weighted score into the probability of complications ensures the transition from qualitative risk stratification to quantitative prediction of adverse outcomes.
5. The clinical examples presented confirm the practical applicability of MIGS and demonstrate its ability to identify patients at high risk of complications who require intensified monitoring and correction of treatment tactics.
6. A comparative analysis showed that the MIGS scoring system does not replace existing risk assessment tools, but rather complements them, expanding the possibilities of personalized medicine and integration into digital medical decision support systems.

Conclusion

This study proposes and justifies a MIGS scoring scale for monitoring risks in myocardial infarction, combining the clinical interpretability of traditional assessment systems with the mathematical apparatus of probabilistic forecasting. The principle of weighting risk factors and the use of a logistic model allow the risk assessment to be adapted to the individual characteristics of the patient and the dynamics of the clinical process.

The results obtained indicate the high potential value of the proposed scale for clinical practice, especially in conditions where it is necessary to identify patients with an unfavorable prognosis at an early stage and optimize treatment and diagnostic tactics. The model can be considered as a basis for further clinical research, statistical validation on expanded samples, and implementation in automated medical decision support systems.

In the future, the development and adaptation of MIGS using machine learning and big data analysis methods may contribute to improving the accuracy of prognosis and further developing a personalized approach to the treatment of patients with myocardial infarction [22, 23].

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