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Выявление предикторов риска отторжения зубных имплантатов в раннем послеоперационном периоде

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АННОТАЦИЯ

Обоснование. Современная модель здравоохранения требует изменения парадигмы мышления руководителей здравоохранения, врачей и пациентов. Персонализированный подход, выявление этиопатогенеза заболеваний и профилактики любого рода патологий — слагаемые успешного и качественного оказания медицинской помощи в нашей стране. Стоматология — та отрасль, в которой ЗП-медицина (профилактическая, превентивная, персонализированная) является неотъемлемой частью лечения пациентов. Одной из важных задач современной цифровой стоматологии представляется поиск показателей, которые позволили бы прогнозировать развитие осложнений дентальной имплантации. Решением этой проблемы может стать создание системы поддержки принятия врачебных решений, позволяющей предсказать исход до проведения имплантации.

Цель исследования — выявить статистически значимые предикторы риска раннего (до 6 мес) отторжения зубного имплантата за счёт применения иерархических байесовских моделей анализа выживаемости.

Материалы и методы. В качестве информационной базы рассматривались собранные ретроспективно данные пациентов, которым в период с 2013 по 2022 год были установлены зубные имплантаты. Данные сформированы на основе результатов многоцентровых обследований, полученных из центров дентальной имплантологии Ставрополя, Москвы, Пензы. Общее количество наблюдений составило 1472 случая. В качестве кандидатов на предикторы риска рассматривали группу определённых факторов, а в качестве модели выявления предикторов риска использовали байесовскую иерархическую модель Кокса (Gsslasso Cox).

Результаты. После сбора необходимой информации на основе ретроспективного анализа, отсева неполных и некачественных данных общий объём базы составил 39 переменных (факторов) по 1472 наблюдениям (имплантатам). В результате мультивариантного анализа получили следующие предикторы риска раннего отторжения зубного имплантата: мужской пол (HR=2,388; 95% CI: 1,345–4,240; $p=0,003$), возраст на момент имплантации, лет (HR=1,034; 95% CI: 1,008–1,041; $p=0,011$), гигиена полости рта (индекс Силнес–Лоу) (HR=2,439; 95% CI: 1,205–4,701; $p=0,051$), наличие остеопороза (HR=5,512; 95% CI: 3,684–8,248; $p<0,001$), ширина кости в миллиметрах (HR=0,823; 95% CI: 0,716–0,944; $p=0,006$), тип анестезии (местная) (HR=0,469; 95% CI: 0,234–0,944; $p=0,034$), локализованный пародонтит (HR=2,024; 95% CI: 1,452–2,821; $p=0,039$), низкий фестончатый, толстый биотип десны (HR=0,485; 95% CI: 0,358–0,658; $p=0,0104$).

Заключение. Проведённое исследование показывает возможность выявления предикторов риска отторжения зубного имплантата отдельно в раннем послеоперационном периоде (до 6 мес) за счёт применения иерархических байесовских моделей анализа выживаемости, так как в этом периоде выявляются предикторы риска, отличные от предикторов риска отторжения имплантата в более отдалённом периоде.

Ключевые слова: профилактическая, превентивная, персонализированная медицина; ЗП-медицина; дентальные имплантаты; система поддержки принятия врачебных решений; СППВР; отторжение имплантатов; предикторы риска; мультивариантный анализ.

Как цитировать

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Identification predictors of risk of dental implant rejection in the early postoperative period

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ABSTRACT

BACKGROUND: The modern model of healthcare requires a paradigm shift in the thinking of healthcare managers, doctors, and patients. A personalized approach, identification of possible causes of diseases, and prevention of pathologies are the components of successful and quality healthcare delivery in our country. Dentistry is a field in which preventive, prophylactic, and personalized medicine is an integral part of patient care. One of the important tasks of modern digital dentistry is to find indicators that allow for predicting dental implant complications. The solution to this problem could be the creation of a medical decision support system that allows predicting outcomes before implant surgery.

AIMS: To reliably identify predictors of early (up to 6 months) risk of dental implant rejection by applying hierarchical Bayesian survival analysis models.

METHODS: Data collected retrospectively for patients who underwent dental implant placement between 2013 and 2022 were considered information bases. Data were generated from multicenter surveys conducted in dental implant centers in Stavropol, Moscow, and Penza. The total number of observed cases was 1472. A group of defined factors was considered candidate risk predictors, and the Bayesian hierarchical Cox model (Gsslasso Cox) was used to identify risk predictors.

RESULTS: After retrospective analysis of the collected data and screening out incomplete and poor-quality information, the database included a total of 39 variables (factors) for 1472 observations (implants). The multivariate analysis yielded the following predictors of risk of early dental implant rejection: male sex (hazard ratio [HR] 2.388, 95% confidence interval [CI] 1.345; 4.240, $p=0.003$), age at implantation (years; HR 1.034, 95% CI 1.008–1.041, $p=0.011$), oral hygiene (Silnes–Low index; HR 2.439, 95% CI 1.205–4.701, $p=0.051$), osteoporosis (HR 5.512, 95% CI 3.684–8.248, $p<0.001$), bone width (mm; HR 0.823, 95% CI 0.716–0.944, $p=0.006$), anesthetic type (local; HR 0.469, 95% CI 0.234–0.944, $p=0.034$), localized periodontitis (HR 2.024, 95% CI 1.452–2.821, $p=0.039$), and low-festooned, thick gingiva (HR=0.485; 95% CI: 0.358–0.658; $p=0.0104$).

CONCLUSIONS: This study shows that predictors of risk of dental implant rejection can be identified separately in the early postoperative period (up to 6 months) by using hierarchical Bayesian survival analysis models, and risk predictors different from those in the longer term are identified in this period.

Keywords: preventive, prophylactic, personalised medicine; 3P medicine; dental implants; decision support system; DSS; implant rejection; risk predictors; multivariate analysis.

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BACKGROUND

One of the important tasks of modern digital dentistry is to find indicators that allow predicting the development of dental implant complications [1]. According to studies, the percentage of biological complications in implant treatment leading to implant rejection is quite high, ranging from 2 to 5% of removed implants in the first year of treatment [2]. The solution to this problem could be the creation of a medical decision support system to predict the outcome prior to implantation surgery. Such a system should be based on an adequate model that takes into account the many influencing factors on possible adverse outcomes. However, there are currently no multicentre studies in Russia analysing all the key factors (somatic, biological, anatomical, technical, medical) that influence the osseointegration of dental implants. This means that there is currently no unified protocol for taking into account the factors affecting engraftment, combined with a methodology for early risk assessment of complications, monitoring of osseointegration processes and control of functional load. Implant rejection in the early loading period, during the first 3 years, is usually the result of biological complications due to underestimation of general and local risk factors at the surgical planning stage. Globally, there are studies that have attempted to identify predictors of implant repair risk in the early postoperative period (up to 6 months). The vast majority of these studies use non-parametric statistical analysis, or classical statistical models. For example, Nathalia de Faria Schimunda et al. (2021) [3] applied Kruskal-Wallis tests to estimate differences between groups and tested a number of hypotheses using correlation analysis. Feher B. et al. (2020) [4] evaluated linear regression using the LASSO method on data from 2413 implantation cases. This study has a significant drawback, as the method does not allow for time-dependent covariates (risk predictors), which may affect unbiased estimates. However, due to the widespread use of machine learning algorithms, there have been a number of studies using these approaches to estimate the probability of implant rejection. For example, in Liu C.H. et al. (2018) [5] uses a large set of machine learning tools, such as decision tree, support vector machine, naive Bayesian classifier, to estimate the probability of implant rejection. Chiang H.J. et al. (2013) [6] applied a decision tree algorithm, which allows us to rank factors according to the significance of their influence on the final implant outcome. The study conducted by Vysotskaya E.V. et al. (2018) [7] relies on the application of logistic regression to estimate the prediction of implant rejection: the authors claim a prediction accuracy of 96%, but this figure was obtained by them on the entire sample involved in model training, which means there was no confirmation of the claimed prediction accuracy in blind validation, which does not exclude model overtraining. The work of Chinese colleagues Yang Y. et al. (2021) [8] investigates early risk factors for implant loss using a logistic regression model trained on a sample of 2053 implants.

In a study by Ha S.R. et al. (2018) [9] applied two machine learning tools to estimate the prediction regarding implant osseointegration: a support vector machine and a decision tree. In a sample of 667 implant cases, both algorithms produced similar results. A significant disadvantage of all the above studies is that they attempt to predict the loss of the implant, but each patient may have an individual period from implantation to loss, and the length of this period may be affected by various factors, and it cannot be excluded that these factors may themselves be time dependent. Survival analysis models [10] use the period from the start of follow-up to the time at which the (usually adverse) event occurred as the output (target) variable. A special advantage of these models is their interpretability due to the calculation of the risk ratio that an adverse event will occur. There is work by Moayeri R.S. et al. (2016) [11] that estimates the prediction of implant engraftment survival up to one year using one of the survival analysis models, namely the Cox proportional hazards model. Despite the obvious advantages of these models, their accuracy has not been great up to a certain point. The main problem with these models, particularly the Cox model, is that the condition of proportional risk must be satisfied, and the bias in the estimates of model coefficients can be derived from the correlation of risk predictors with each other. These problems can be solved by applying a hierarchical Bayesian estimation approach to the parameterisation of the survival model [12].

The aim of the study is to reliably identify predictors of early (up to 6 months) dental implant rejection by applying hierarchical Bayesian survival analysis models.

METHODS

Data collected retrospectively for patients who underwent dental implants between 2013 and 2022 were considered as an information base. The data were generated from multicentre surveys from dental implant centres in Stavropol, Moscow and Penza. The total number of cases was 1,472, with 52 cases (3.5%) of rejection after implant placement within 6 months.

The following group of factors were considered as candidates for risk predictors: demographics (gender and age of the patient), presence of periodontal disease, gingival biotype, bone density, width and height, history of implants, status of the adjacent medial tooth, time of placement after tooth extraction, oral hygiene, degree of alveolar ridge, load and type of anaesthetic.

A Bayesian hierarchical Cox model was used as a model for identifying risk predictors (Gsslasso Cox), taking the following form:

$$h(t|x) = \exp(x\beta) h_0(t),$$

where β is a vector of regression coefficients for predictor variables of implant rejection risk, x — vector of explanatory

risk factors (risk predictors), and $h_0(t)$ — baseline implant rejection risk function, t — time.

In the classical Cox model, however, the logarithmic partial likelihood function must be maximised in order to be calculated:

$$LL(\beta) = \sum_{i=1}^n d_i \log(\exp(x_i \beta) / \sum_{i' \in R(t_i)} \exp(x_{i'} \beta)),$$

where $R(t_i)$ — the set of indices of patients who are under observation but have not yet had a case of implant rejection by the i -th point in time, d_i — a censored variable with zero.

But for correlated or multivariate data, Bayesian hierarchical modelling using a double exponential a priori distribution over the coefficients is used:

$$\beta_j | y_j, s_0, s_1 \sim de(0, (1 - y_j)s_0 + y_j s_1) = 1 / ((1 - y_j)s_0 + y_j s_1) \exp(-|\beta_j| / ((1 - y_j)s_0 + y_j s_1)),$$

where s_0, s_1 — scale parameters (y_j) is the indicator variable.

Cox's Bayesian hierarchical model relates the level of risk for individual patients to the value of the rejection risk predictor x_i with the baseline risk level. The results of the implant rejection modelling were therefore interpreted on the basis of the risk ratio:

$$HR(x_i) = h(t|x_i) / h_0(t) = \exp(x_i \beta).$$

The model is based on the assumption that the underlying implant rejection risk function depends on time t , but the predictors are not time dependent. This assumption is also called the proportional risk assumption, which says that the ratio of risks of implant reparation does not change over time for each patient.

The primary data analysis was performed by comparing the rates for the group of patients who did not experience implant rejection within 6 months and the group of patients who did. Comparisons for continuous features were performed by testing the null hypothesis of no difference using the Wald-Wolfowitz test, for the null hypothesis of no difference in the frequency of nominal features using the χ^2 criterion with plausibility adjustments. The choice in favour of using appropriate hypotheses is related to the strong difference between groups in the number of observations, differences were considered proven at $p < 0.05$.

In addition, single-factor (univariate) models, in which only one factor of the possible risk of implant rejection was taken into account, were constructed to preliminarily analyse the selection of predictors of implant reparation risk. Based on this analysis, risk predictors with a significance of $p < 0.05$ were identified.

A generalised model was then constructed for the selected statistically significant features in the univariate analysis, and a 95% confidence interval was calculated for each odds ratio risk factor. The following quality metrics were examined for the model, suggesting the model's predictive value:

- 1) Measure of explained randomness (MER). The measure of explained randomness [13] is calculated using the following formula:

$$R^2_{mer} = 1 - \exp((2/m)L_0 - L_1),$$

where L_0 and L_1 are the values of the likelihood function for the null and saturated models, and m is the number of observed events.

- 2) Measure of explained variation (MEV). The measure of explained variation is calculated using the following formula:

$$R^2_{mev} = R^2_{mer} / (R^2_{mer} + \pi/6(1 - R^2_{mer})),$$

and also used Harel's concordance index. The predictive power of a survival model is said to be high if the quality metrics are close to 1.

Ethical review

According to the data of ethical expertise and the extract from the protocol of local ethical committee of FSBEI HE "Stavropol State Medical University" of the Ministry of Healthcare of the Russian Federation № 117 from 20.03.2023 a decision to adopt a positive ethical opinion on the approval of this scientific article was made.

RESULTS

After collecting all necessary information based on retrospective analysis since 2013, screening out incomplete and poor-quality information, the total database was 39 variables (factors) for 1472 observations (implants). The selection of potential risk factors was based on the experience of surgical specialists and the analysed literature on the topic. In 52 cases, implant rejection was observed up to 6 months after surgery. Table 1 compares the results of two groups; the group of implants for which no rejection event occurred ($n=1420$) and the group of implants for which this event occurred ($n=52$). Medians (Me) and first and third quartiles ($Q_1; Q_2$) are shown for continuous features, frequency incidence and relative frequency in %, p -value for frequency features was calculated with the χ^2 likelihood-adjusted criterion, and for continuous features with the Wald-Wolfowitz test. Osteoporosis was identified as local based on CBCT data, with bone density D4 (HU 400–600) and D5 (below HU 400) being osteoporotic. This study also correlated the form of periodontitis (gingivitis as inflammation of the periodontal gingival complex and periodontitis as involvement of the entire complex) and the extent of the process (local or generalised). Since three postoperative management options were used; placing an end cap (mostly low risk), placing a shaper (medium risk), and placing a temporary crown (high risk), each option was investigated separately for potential risk factors.

Table 1. Results of a comparison of two groups of implants that rejected and for which no rejection event occurred

Risk factors for implant rejection before 6 months	Group of implants without rejection (n=1420)	Group of implants with rejection occurred in 6 months (n=52)	p-level
	Me (Q ₁ ; Q ₃) or frequency (%)		
Age at the time of implantation, years	50.9 (44.1; 57.8)	53.2 (44.5; 59.9)	=0.075
Patient gender (female/male)	862/558	29/23	=0.478
Oral hygiene (Silnes-Loe index)	4 (4; 5)	5 (4; 5)	=0.076
Bone width, in mm	6.0 (5.0; 7.2)	5.0 (4.05; 7.0)	=0.036*
Bone height, in mm	11.1 (10.0; 13.6)	12.0 (10.0; 15.3)	=0.024*
Height of keratinised gingiva in mm	2 (2; 3)	2 (2; 2)	=0.112
Presence of diabetes mellitus	6 (0.4%)	0 (0%)	=0.996
The presence of osteoporosis	596 (42.0%)	17 (32.7%)	=0.177
Bruxism	218 (15.4%)	7 (13.5%)	=0.706
Generalised gingivitis	95 (6.7%)	1 (1.9%)	=0.113
Generalised periodontitis	416 (29.3%)	18 (34.6%)	=0.416
Localised gingivitis	291 (20.5%)	7 (13.5%)	=0.535
Localised periodontitis	65 (4.6%)	5 (9.6%)	=0.062
Gingiva biotype — high festooned, thin	311 (21.9%)	16 (30.8%)	=0.146
Gingiva biotype — low festooned, thick	56 (3.9%)	6 (11.5%)	=0.025*
Gingival biotype — medium festooned, moderately thick	1053 (74.2%)	30 (57.7%)	=0.012*
Alveolar ridge — stage I atrophy, width 6.0 mm or more	525 (37%)	17 (32.7%)	=0.520
Alveolar ridge — grade II atrophy, width 4.0 to 6.0 mm	718 (50.6%)	21 (40.4%)	=0.149
Alveolar ridge — grade III atrophy, width 3.0 to 4.0 mm	152 (10.7%)	12 (23.1%)	=0.013*
Alveolar ridge — stage IV atrophy, width 3.0 mm	12 (0.8%)	1 (1.9%)	=0.478
Alveolar ridge — V stage atrophy no AH	13 (0.9%)	1 (1.9%)	=0.517
Radiological bone density D1	53 (3.7%)	6 (11.5%)	=0.020*
Radiological bone density D2	468 (33%)	22 (42.3%)	=0.168
Radiological bone density D3	597 (42%)	17 (32.8%)	=0.174
Radiological bone density D4	277 (19.5%)	6 (11.5%)	=0.129
Radiological bone density D5	25 (1.8%)	1 (1.9%)	=0.932
Missing adjacent medial tooth	435 (30.6%)	18 (34.5%)	=0.546
Healthy adjacent medial tooth	216 (15.2%)	6 (11.5%)	=0.452
Crown on adjacent medial tooth	231 (16.3%)	8 (15.4%)	=0.862
Immediate placement after tooth extraction	80 (5.6%)	7 (13.5%)	=0.041*
Early setting (4 to 8 weeks) after tooth extraction	46 (3.2%)	1 (1.9%)	=0.569
Delayed placement (12 to 16 weeks) after tooth extraction	251 (17.7%)	17 (32.7%)	=0.011*
Use of local anaesthesia with sedation	57 (4%)	10 (19.2%)	<0.001***
Temporary crown	6 (0.4%)	0 (0%)	=0.524
Installing a plug	1159 (8%)	43 (82.7%)	=0.844
Installing the shaper	142 (10%)	9 (17.3%)	=0.116
Immediate loading with a prosthodontic structure (within 48 hours)	28 (2%)	5 (9.6%)	=0.006**
Traditional prosthodontic loading (3 to 6 months)	1045 (73.6%)	4 (7.7%)	<0.001***
Previous oral implant treatment: Biological complications from 1 to 5 years	71 (5%)	7 (13.5%)	=0.023*

*, **, *** — statistical significance of differences in coefficients from zero at $p < 0.05$, $p < 0.01$ and $p < 0.001$, respectively.

As can be seen from the comparison results in the groups, statistically significant differences at $p < 0.05$ are observed for the following factors: presence of a biological complication from 1 to 5 years of previous oral implant treatment, loading options (immediate and traditional), use of local anaesthesia with sedation, bone width and height, gingival biotype, stage III alveolar ridge atrophy, radiological bone density D1, immediate and delayed placement of implants after tooth extraction. At the $p < 0.1$ level, differences in the following

factors were significant: age at implantation, presence of localised periodontitis and oral hygiene score (Silnes-Loe hygiene index). Univariate Cox models were also built with the selected factors, potential candidates for predictors of implant rejection risk, the results of which are summarised in Table 2. The table shows the coefficient for a given trait, the risk ratio (HR) calculated on its basis by potentiation, the standard error of the coefficient, and the corresponding p -value of the error of rejection of the null hypothesis that

Table 2. Results of estimated predictors of implant rejection risk derived from univariate Cox models

Acknowledgement	Factor	Risk attitude, HR	Stand. error	p -level
Age at the time of implantation, years	0.026	1.026	0.015	0.078
Patient gender (female/male)	0.178	1.194	0.281	0.527
Oral hygiene (Silnes-Loe index)	0.400	1.492	0.238	0.092
Bone width, in mm	-0.235	0.790	0.089	0.008**
Bone height, in mm	0.087	1.091	0.032	0.007**
Height of keratinised gingiva in mm	-0.508	0.602	0.347	0.143
The presence of osteoporosis	0.500	1.649	0.296	0.091
Bruxism	-0.634	0.530	0.407	0.119
Generalised periodontitis	0.923	2.517	1.027	0.369
Localised gingivitis	2.123	8.354	1.071	0.047*
Localised periodontitis	1.947	7.009	1.096	0.076
Gingiva biotype — high festooned, thin gingiva biotype	1.267	3.549	0.447	0.005**
Gingiva biotype — low festooned, thick gingiva biotype	-0.577	0.561	0.309	0.062
Gingival biotype — medium festooned, moderately thick gingival biotype	0.577	1.781	0.309	0.063
Alveolar ridge — Stage I atrophy, width 6.0 mm or more	-0.175	0.839	1.029	0.865
Alveolar ridge — atrophy stage II, width 4.0 to 6.0 mm	-0.356	0.701	1.024	0.728
Alveolar ridge — atrophy stage III, width 3.0 to 4.0 mm	0.366	1.443	0.178	0.045*
Radiological bone density D1	-0.060	0.942	1.081	0.956
Radiological bone density D2	-0.856	0.425	0.461	0.063
Radiological bone density D3	-1.349	0.259	0.475	0.005**
Radiological bone density D4	-1.619	0.198	0.578	0.005**
Missing adjacent medial tooth	-0.549	0.578	0.350	0.117
Healthy adjacent medial tooth	0.522	1.686	0.306	0.088
Crown on adjacent medial tooth	-0.946	0.388	0.483	0.050*
Immediate placement after tooth extraction	1.029	2.700	0.421	0.010*
Delayed placement (12 to 16 weeks) after tooth extraction	0.788	2.201	0.301	0.011*
Use of local anaesthesia with sedation	1.5063	4.5099	0.3519	<0.001***
Installing a plug	-0.492	0.612	0.386	0.202
Installing the shaper	-0.725	0.484	0.733	0.323
Immediate loading with a prosthodontic structure (within 48 hours)	20.66	94200000	0.67	<0.001***
Traditional prosthodontic loading (3 to 6 months)	17.08	26280000	0.67	<0.001***
Previous oral implant treatment: Biological complications from 1 to 5 years	1.2765	3.5842	0.4113	0.002**

*, **, *** — statistical significance of differences in coefficients from zero at $p < 0.05$, $p < 0.01$ and $p < 0.001$, respectively.

the coefficient estimate is equal to zero. It should be noted that univariate models were not constructed for the factors diabetes mellitus, presence of generalised gingivitis, presence of IV and V stages of alveolar ridge atrophy, radiological bone density D5, fact of early implant placement (4 to 8 weeks) after dental extraction and presence of a temporary crown after implantation, due to the absence or very rare occurrence (1 time) of this factor in one group.

As shown in Table 2, there is an isolated statistically significant effect, at $p < 0.05$, of increasing the likelihood of implant rejection up to 6 months postoperatively:

- the presence of a biological complication from 1 to 5 years after previous oral implant treatment,
- traditional prosthodontic loading (3 to 6 months),
- immediate loading with a prosthodontic structure (within 48 hours),
- the use of local anaesthesia with sedation,
- Immediate placement of an implant after a tooth extraction,
- Delayed placement of an implant (12 to 16 weeks) after a tooth extraction,
- Stage III atrophy, when the width of the alveolar ridge is between 3.0 and 4.0 mm,
- high festooned, thin gum biotype,
- the presence of localised gingivitis,
- high bone height.

The presence of a healthy adjacent medial tooth, the presence of osteoporosis, the patient's age, and oral hygiene have a quasi-significant positive effect (at $p < 0.1$) on increasing the risk of implant loss. Bone width, presence of a crown on the neighboring medial tooth, radiological bone density D3 and D4, low festooned, thick gingival biotype have a significant isolated effect (at $p < 0.05$) on the reduction of the risk of implant rejection (at $p < 0.1$).

Based on the identification of significant factors influencing the risk of implant loss up to 6 months after

implant treatment, a multivariate Bayesian hierarchical Cox model (Gsslasso Cox) was constructed, insignificant features ($p > 0.05$) were discarded when constructing the model. The results are summarised in Table 3, which shows the coefficient at feature, risk ratio HR, confidence interval (CI) at 95% confidence level for the risk ratio, and p -value. The estimation quality of the resulting model is high: $CIH=0.899$, $R^2_{mer}=0.91$, $R^2_{mev}=0.94$.

DISCUSSION

The simulations showed that male gender averaged 2.4-fold ($HR=2.39$; $CI=(1.35-4.24)$) increased the risk of implant loss up to 6 months after implant placement. Similar results were obtained by other researchers: in Hasegawa T. et al. (2022) [14] the risk ratio is even higher $HR=6.22$; in Compton S.M. et al. (2017) [15] considered female gender as a risk predictor, which in contrast almost halved the risk of implant rejection ($HR=0.5$; $CI=(0.48-0.53)$). Increasing age by one year increased the risk ratio by a factor of 1.034 ($HR=1.034$; $CI=(1.0081.041)$). Neves J. et al. (2018) [16] has also shown that patient age over 40 years increases the risk ($OR=2.63$) and Takamoli J. et al. (2021) [17] shows that patient age over 55 years at the time of implant placement, is a predictor of even higher risk of implant loss ($OR=4.05$; $CI=(2.15-12.25)$).

Notably, in the multivariate model, periodontal inflammatory disease (PID) was not significantly associated with implant loss up to 6 months postoperatively. Similar results were obtained by Derks J. et al. (2015) [18]. A number of studies have shown that PID affects the outcome of implant loss, but only in the late period, Vercruyssen M. et al. (2010) [19], 50 months after implant placement, Levin L. et al. (2011) [20]. In another study by Compton S.M. et al. (2017) [15] showed that generalised periodontitis is a predictor of high risk of implant loss ($HR=2.53$; $CI=(2.37-2.71)$), but this study only studied patients over the age of 60.

Table 3. Results of an assessment of predictors of implant loss risk based on a multifactorial Bayesian hierarchical Cox model (Gsslasso Cox)

Acknowledgement	Factor	Risk attitude, HR	CI for HR (95%)	p -level
Gender/masculine	0.870	2.388	1.345–4.240	0.0029**
Age at the time of implantation, years	0.034	1.034	1.008–1.041	0.0111*
Oral hygiene (Silnes-Loe index)	0.891	2.439	1.205–4.701	0.0511
The presence of osteoporosis	1.707	5.512	3.684–8.248	<0.001***
Bone width, in mm	-0.195	0.823	0.716–0.946	0.0061**
Type of anaesthesia (local)	-0.756	0.469	0.234–0.944	0.0339*
Localised periodontitis	0.705	2.024	1.452–2.821	0.0391*
Low festooned, thick gum biotype	-0.723	0.485	0.358–0.658	0.0104*
CIH (Harel index) = 0.899	$R^2_{mer}=0.91$		$R^2_{mev}=0.94$	

*, **, *** — statistical significance of differences in coefficients from zero at $p < 0.05$, $p < 0.01$ and $p < 0.001$, respectively.

The oral hygiene index (Silnes-Loe) is a statistically significant factor that more than doubles the risk ($HR=2.44$, $CI=(1.21-4.70)$). These findings are in agreement with those of Takamoli J. et al. (2021) [17], who reported that an oral plaque score of more than 20% increased the odds ratio for implant rejection by a factor of 20 ($OR=20.21$; $CI=(5.2-50.98)$), as well as those of Romandini M. et al. (2021) [21], who reported the presence of plaque ($OR=3.49$; $CI=(1.13-10.75)$). In the univariate modelling phase, we showed that bruxism has no effect on the risk of early implant rejection; the same results were obtained in the Manor Y. et al. study (2009) [22].

This study showed that the presence of osteoporosis significantly increased the risk of implant repair ($HR=5.51$; $CI=(3.68-8.25)$). In contrast, Carr A.B. et al. (2019) [23] did not associate this factor with the risk of implant loss in the first year. However, Boboeva O. et al. (2021) [24] showed that osteoporosis was associated with risk ($HR=6.63$) only in older patients. Indirectly, our findings are supported by the fact that in the univariate models we assessed, radiological bone density classes D3 and D4 significantly reduced the risk of implant rejection. Similar results were obtained by Malm M.O. et al. (2021) [25] — also in a univariate analysis only, pronounced bone resorption significantly increases the risk of implant loss ($OR=9.07$; $CI=(3.57, 23.01)$). Alsaadi et al. (2008) [26] reached the same conclusions — bone density D2 increases the risk compared to class D4.

A factor of greater bone width than the population average is a predictor of reduced risk of early implant rejection ($HR=0.823$; $CI=(0.716-0.946)$). In the univariate analysis, greater bone height was also found to be a significant predictor of increased risk. An analysis of the sources showed that the vast majority of them did not look at the jaw width and height of the patient, but at the associated features, such as implant length and diameter. For example, Krisam J. et al. (2019) [27] showed that implant length >10 mm is a statistically significant factor ($p=0.01$) increasing the risk, while Hasegawa T. et al. (2022) [14] found that narrow implants (≤ 3.3 mm) increase the risk of rejection up to 10 years ($HR=3.86$).

Having a low festooned, thick gingiva biotype reduced the risk of implant loss by almost half ($HR=0.485$; $CI=(0.358-0.658)$). The soft tissue thickness factor of the gingiva is often investigated as a possible predictor of the risk of adverse events after implantation. For example, a meta-analysis conducted by Suárez-López del Amo F. et al. (2016) [28], based on 8 studies, showed that there was statistically less ($p < 0.0001$) marginal bone loss around the implant for patient groups with thick periodontal tissue.

It is noteworthy that local anaesthesia at implantation was a favourable factor for the outcome compared to local anaesthesia with sedation ($HR=1.506$). In the univariate model, the fact of local anaesthesia with sedation increased the risk of implant loss by more than 1.5 times ($HR=0.469$; $CI=(0.234-0.944)$). There is currently no protocol for choosing between local anaesthesia and sedation anaesthesia, and the choice may be forced if the clinic does not have a license for sedation

anaesthesia or no anaesthesiologist on staff. Otherwise, the physician will generally advise the patient to choose anaesthesia with sedation if the surgery is to be extended in time and in terms of the procedures to be performed (e.g., the placement of several implants at once). The use of local anaesthesia with sedation may thus correlate with the timing of the surgical procedure, and the extension of time is generally more important in complicated cases, which may affect the prognosis for the success of the implant treatment. The result is controversial and requires a separate additional study, which the authors plan to perform on an extended data set.

CONCLUSION

This study shows the feasibility of developing separate models for dental implant rejection in the early postoperative period (up to 6 months), as risk predictors different from those in the longer term are identified in this period. An adequate model (in terms of quality metrics) can serve as a risk stratification prior to surgical intervention and thus form the basis for a decision support system that is personal to each patient. The study identified the most significant risk factors for implant loss, such as male gender, advanced age, high oral hygiene index (SilnesLow), the presence of osteoporosis, and the presence of localised periodontitis. Factors that significantly reduced the risk of implant reparation were also identified: large bone width, low festoon, thick gingival biotype, use of local anaesthesia during implantation. The conclusions drawn regarding the risk reduction with local anaesthesia versus sedation are debatable and require a separate additional study, which the authors plan to perform on an extended data set.

ADDITIONAL INFORMATION

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