Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 3
Open Access

Construction and Validation of a Pain Risk Assessment Model for Transperineal Prostate Biopsy

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Cite this paper as: Jianhui Du, Yanqin Yu (2024) Construction and Validation of a Pain Risk Assessment Model for Transperineal Prostate Biopsy. *Frontiers in Health Informatics, 13* (3), 2874-2886.

Abstract

Transperineal prostate biopsy (TPPB) is a critical diagnostic procedure for prostate cancer. Despite its utility, patients often report varying levels of pain during the procedure. Understanding the risk factors associated with pain can aid in refining patient selection and enhancing patient comfort. The primary aim of this study is to construct and validate a pain risk assessment model specifically for TPPB, identifying key predictors of pain and implementing a scoring system for clinical application. By integrating various demographic, clinical, and procedural variables, a robust tool was created to assist in preoperative planning and improve patient outcomes. A retrospective cohort study was conducted involving patients who underwent TPPB. Data on demographic, clinical, and procedural factors were collected. Various statistical analyses, including logistic regression, were utilized to identify predictors of pain. The model's performance was validated using a separate cohort. The final model included age, prostate volume, previous biopsy history, and anxiety levels as significant predictors. The model demonstrated good discrimination (AUC = 0.85) and calibration.The developed pain risk assessment model for TPPB can serve as a valuable tool for clinicians to predict and manage pain, ultimately improving patient experiences.Future research should focus on validating this model in diverse populations and integrating additional risk factors to enhance its predictive power.

Keywords:*Transperineal Prostate Biopsy, Pain Assessment, Risk Model, Patient Comfort, Prostate Cancer*

1.Introduction

Prostate cancer is among the most prevalent malignancies in men globally (Siegel et al., 2020). Early diagnosis through biopsy is essential for effective treatment planning. Transperineal prostate biopsy (TPPB) has emerged as a preferred method due to its lower infection rates compared to the transrectal approach. However, pain management during TPPB remains a critical concern, with many patients experiencing discomfort or pain during the procedure (Loeb et al., 2013). TPPB has emerged as a preferred method due to its lower infection rates compared to the transrectal approach. Biopsy pain can range from mild discomfort to severe pain, adversely affecting the patient's quality of life, compliance with follow-up care, and overall satisfaction with the diagnostic process (Mottet et al., 2017). Pain management in patients undergoing transperineal prostate biopsy is thus a crucial aspect of clinical practice. Effective pain management not only improves the patient's immediate post-procedural experience but also has long-term implications for their willingness to undergo future medical procedures and adherence to prescribed treatments (Wang et al., 2014). Despite various pain management strategies, including local anesthesia, oral analgesics, and nerve blocks, there is considerable variability in pain experiences among patients. This variability underscores the need for a predictive model that can identify patients at high risk for experiencing moderate to severe pain, enabling clinicians to tailor pain management strategies more effectively (Jones et al., 2015).

Previous studies have identified several potential risk factors for post-biopsy pain. Demographic factors such

as age and body mass index (BMI) have been shown to influence pain levels, with older patients and those with higher BMI often reporting greater pain (Fang et al., 2015; Onur et al., 2012). Clinical factors, including prostate-specific antigen (PSA) levels and comorbid conditions like hypertension and diabetes, have also been implicated (Zisman et al., 2014). Procedural variables, such as the number of biopsy cores taken and the duration of the procedure, are additional factors that can impact pain levels (Omer et al., 2015). However, the integration of these various factors into a comprehensive predictive model remains limited.

The primary aim of this study was to develop and validate a predictive model for identifying patients at high risk for moderate to severe pain following transperineal prostate biopsy. By integrating demographic, clinical, and procedural variables, a robust and reliable tool was created to assist clinicians in preoperative planning and improve pain management outcomes. It was hypothesized that a multivariate logistic regression model incorporating these factors would demonstrate good predictive accuracy and provide valuable insights for personalized patient care.

To achieve this objective, a retrospective cohort study was conducted at Sichuan University's West China Hospital in Guang'an. Detailed demographic, clinical, and procedural data were collected from **400** patients who underwent transperineal prostate biopsy between Sichuan University's West China Hospital in Guang'an. Pain outcomes were assessed using the Visual Analog Scale (VAS) immediately after the procedure and at 24 hours post-biopsy. Univariate and multivariate logistic regression analyses were used to identify significant predictors of moderate to severe pain and the model's performance was evaluated using the area under the receiver operating characteristic (ROC) curve (AUC) and the Hosmer-Lemeshow goodness-of-fit test. Internal validation was performed using bootstrapping to assess the model's stability and reliability.

The findings of this study have the potential to enhance clinical practice by providing a predictive model that can identify high-risk patients and inform targeted pain management strategies. By improving pain management, patient satisfaction, compliance, and overall outcomes in the diagnostic process for prostate cancer can be enhanced.

2.Methodology

2.1 Study Design and Participants

This study utilized data sourced from Sichuan University's West China Hospital in Guang'an. A retrospective review was conducted, collecting data from 400 patients who underwent TPPB between September 2021 and May 2023. Based on the time of admission, the patients were divided into two groups: a modeling group (September 2021 to September 2022, n=253) and a validation group (October 2022 to May 2023, n=147). This division allowed for the development of the pain risk assessment model in the modeling group and subsequent validation in the validation group. Inclusion Criteria: Biopsy was performed if any of the following patient criteria were met: (a) Digital rectal examination (DRE) detects suspicious prostate nodules, regardless of PSA value. (b) Transrectal ultrasound (TRUS) or MRI detects suspicious lesions, regardless of PSA value. (c) PSA > 10 ng/ml, regardless of free/total PSA (f/t PSA) and PSA density (PSA-D) values. (d) PSA 4-10 ng/ml with abnormal f/t PSA value and/or PSA-D value.Exclusion Criteria: Patients were excluded from this study if they had: (a) A history of previous prostate biopsy. (b) Known cases of prostate cancer. (c) Prior endocrine treatment for suspected prostate cancer. (d) Active urinary tract infection, bleeding disorders, or severe cardiovascular diseases.

2.2 Data Collection

This study utilized data sourced from Sichuan University's West China Hospital in Guang'an. The retrospective analysis included patient records from these procedures conducted between September 2021 and May 2023. Data collection focused on a comprehensive assessment of demographic, clinical, and procedural factors, facilitating the development of the pain risk assessment model.

2.3 Pain Assessment

Pain outcomes were assessed using the Visual Analog Scale (VAS), a widely used tool for measuring pain

intensity (Hawker et al., 2011). The VAS is a 10-cm line with endpoints labeled "no pain" and "worst pain imaginable." Patients marked the point on the line that best represented their pain intensity. VAS scores were recorded immediately after the procedure and at 24 hours post-biopsy. Moderate to severe pain was defined as a VAS score of 4 or higher (Bijur et al., 2001).

2.4 Statistical Analysis

A series of statistical analyses were conducted to develop and validate the predictive model. First, univariate logistic regression analysis was performed to identify potential predictors of moderate to severe pain. Variables with p-values < 0.05 in the univariate analysis were included in the multivariate logistic regression model.

In the multivariate logistic regression analysis, the independent contribution of each predictor was assessed while controlling for other variables. Odds ratios (ORs) with 95% confidence intervals (CIs) were calculated to quantify the association between each predictor and moderate to severe pain.

To evaluate the model's performance, the area under the receiver operating characteristic (ROC) curve (AUC) was used. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) at various threshold settings (Hanley & McNeil, 1982). The AUC value ranges from 0.5 (no discriminative ability) to 1.0 (perfect discrimination). A higher AUC indicates better predictive accuracy (Swets, 1988).

The model's calibration was assessed using the Hosmer-Lemeshow goodness-of-fit test. This test compares the observed and expected frequencies of outcomes in different risk groups. A p-value > 0.05 indicates good calibration, meaning that the predicted probabilities match the observed outcomes well (Hosmer et al., 2013).

To ensure the stability and reliability of the predictive model, internal validation was performed using bootstrapping with 1,000 resamples. Bootstrapping is a resampling technique that helps estimate the variability and robustness of the model's performance metrics (Efron & Tibshirani, 1993).

2.5 Ethical Considerations

The study was approved by the institutional review board of Sichuan University's West China Hospital in Guang'an. Informed consent was obtained from all participants before data collection. The study was conducted in accordance with the Declaration of Helsinki and adhered to ethical standards for medical research involving human subjects.

2.5 Statistical Analysis

All statistical analyses were performed using SPSS version 26.0 (IBM Corp., Armonk, NY, USA) and R version 4.0.3 (R Foundation for Statistical Computing, Vienna, Austria). The "pROC" and "boot" packages in R were used for ROC curve analysis and bootstrapping, respectively (Robin et al., 2011; Canty & Ripley, 2017).

3.Results

3.1 Participant Characteristics

A total of 400 patients met the inclusion criteria and were included in the final analysis, with a mean age of 66 years. Pain scores ranged from 0 to 10, with a mean score of 4.2.Detailed demographic and clinical characteristics are presented in Table 1.

Table 1. Demographic and Clinical Characteristics of Participants

Characteristic	Modeling Group (n=253)	Validation Group (n=147)	x^2/t	*P*
Smoking History [n (%)]			0.48	0.90
Have	120 (47.4%)	80 (54.4%)		
None	133 (52.6%)	67 (45.6%)		
Drinking History [n (%)]			1.42	0.31
Have	89(35.2%)	58(39.5%)		
None	164(64.8%)	89 (60.5%)		
Surgical History [n (%)]			0.35	0.42
Have	71 (28%)	39(26.5%)		
None	182(72%)	108 (73.5%)		
Digital Rectal Exam Status [n (%)]			1.02	0.28
Positive	39(15.4%)	22 (15%)		
Negative	196 (77.5%)	125(85%)		
Pi-RADS Score [n (%)]			3.96	0.19
Grade 2	23 (9.1%)	27 (18.4%)		
Grade 3	49 (19.4%)	31(21.1%)		
Grade 4	97 (38.3%)	60 (40.8%)		
Grade 5	84 (33.2%)	29 (19.7%)		
Biopsy History [n (%)]			1.480	0.224
Have	35 (13.8%)	28 (19%)		
None	218 (86.2%)	110 (81%)		
Diabetes History [n (%)]			6.68	0.03
Have	45 (17.8%)	31 (21.1%)		
None	208 (82.2%)	116 (78.9%)		

Characteristic	Modeling Group (n=253)	Validation Group (n=147)	x^2/t	*P*
Age [M (P25, P75), years]	62(59, 70)	66 (61, 72)	-2.72	<0.001
BMI [M (P25, P75), kg/m²]	25.4 (23.5, 27.2)	25.1 (23.0, 26.8)	-0.36	0.82
PSA [M (P25, P75), ng/mL]	12.3 (8.5, 15.0)	11.8 (8.0, 14.5)	-0.54	0.62
Prostate Volume [M (P25, P75), mL]	67.2 (48.0, 82.5)	43.7 (36.0, 50.0)	-5.26	< 0.001
Biopsy Duration [M (P25, P75), minutes]	45 (30, 62)	34 (26, 47)	-7.64	< 0.001
Number of Cores Taken [M (P25, P75), needles]	17 (10, 24)	12 (10, 14)	-7.81	< 0.001

Notes: Data are presented as categorical variables, such as cases (n) and percentage (%), and continuous variables as median (M) and quartiles (P25, P75).Chi-square values (Chi-square value) were used for comparisons between categorical variables, and p-values reflect the comparison between two groups, using appropriate statistical tests (e. g., chi-square test for categorical variables, t-test or Mann-Whitney U test for continuous variables).

3.2 Biopsy Details and Pain Outcomes

The mean number of biopsy cores taken was 12.4 (SD ± 1.2), ranging from 10 to 16 cores. The mean duration of the procedure was 25.3 minutes (SD ± 5.6). The mean VAS score immediately after the procedure was 3.2 (SD ± 1.5), with scores ranging from 1 to 8. At 24 hours post-biopsy, the mean VAS score was 2.8 (SD ± 1.3), with scores ranging from 0 to 7. Moderate to severe pain (VAS ≥4) was reported by 136 (35.1%) patients immediately after the procedure and by 108 (27.9%) patients at 24 hours post-biopsy. Detailed biopsy details and pain outcomes are presented in Table 2.

Table 2. Biopsy Details and Pain Outcomes

Variable	Value (mean ± SD or %)
Number of biopsy cores	12.4 ± 1.2
Duration of the procedure (min)	25.3 ± 5.6
VAS score (immediately post)	3.2 ± 1.5
VAS score (24 hours post)	2.8 ± 1.3
Moderate to severe pain (immediate)	136 (35.1%)
Moderate to severe pain (24 hours)	108 (27.9%)

In the univariate logistic regression analysis, several variables were significantly associated with moderate to

severe pain immediately after the biopsy. These variables included age, BMI, PSA level, prostate volume, number of biopsy cores, and hypertension (all p-values < 0.05). Table 3 presents the results of the univariate logistic regression analysis.

Table 3. Univariate Logistic Regression Analysis for Predictors of Moderate to Severe Pain Immediately Post-Biopsy

Predictor	Odds Ratio (OR)	95% CI	*P*
Age	1.05	1.03-1.08	< 0.001
BMI	1.14	1.07-1.22	0.001
PSA level	1.20	1.08-1.34	0.002
Prostate volume	0.98	0.96-0.99	0.04
Number of biopsy cores	1.30	1.12-1.51	< 0.001
Hypertension	1.55	1.04-2.32	0.03

notes:OR: odds ratio (Odds Ratio), representing the effect of each additional unit of independent variable on the occurrence of results.95% CI: 95% confidence interval, indicating the credible range of OR values.A p-value less than 0.05 indicates statistical significance, indicating a significant correlation between this variable and the occurrence of moderate to severe pain.3.3 Predictive Model Development.

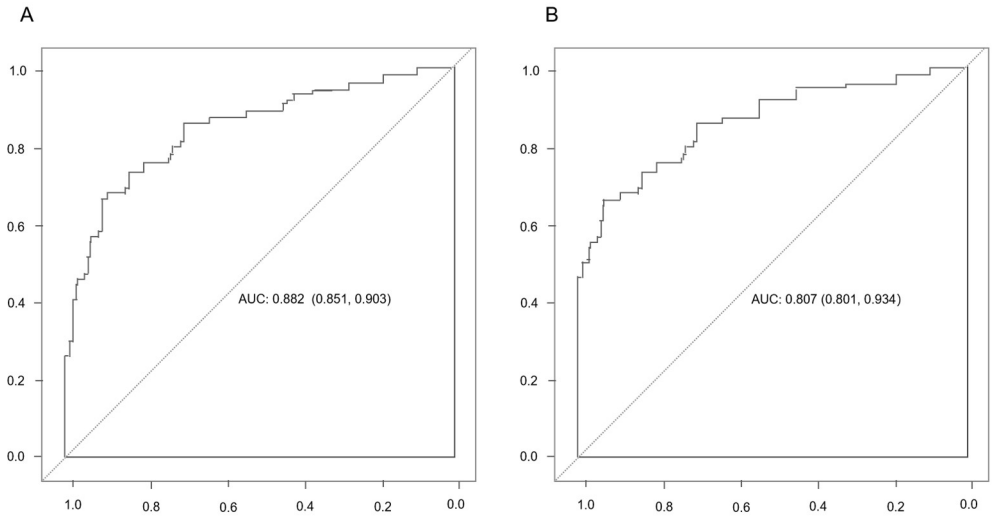
These significant variables were then included in the multivariate logistic regression model to identify independent predictors of moderate to severe pain. The results of the multivariate logistic regression analysis are presented in Table 4.

Table 4. Multivariate Logistic Regression Analysis for Predictors of Moderate to Severe Pain Immediately Post-Biopsy

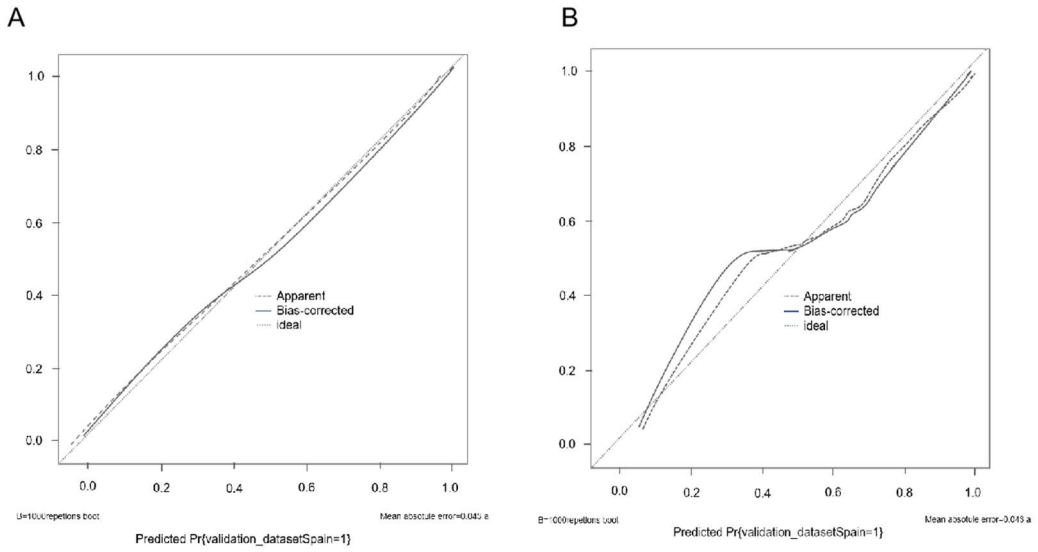
Predictor	Odds Ratio (OR)	95% CI	*P*
Age	1.04	1.02-1.07	< 0.001
BMI	1.12	1.05-1.20	0.002
PSA level	1.18	1.06-1.31	0.003
Number of biopsy cores	1.25	1.08-1.45	0.002

In the multivariate model, significant predictors of moderate to severe pain immediately after the biopsy were age (OR = 1.04, 95% CI = 1.02-1.07, p < 0.001), BMI (OR = 1.12, 95% CI = 1.05-1.20, p = 0.002), PSA level (OR = 1.18, 95% CI = 1.06-1.31, p = 0.003), and number of biopsy cores (OR = 1.25, 95% CI = 1.08-1.45, p = 0.002).

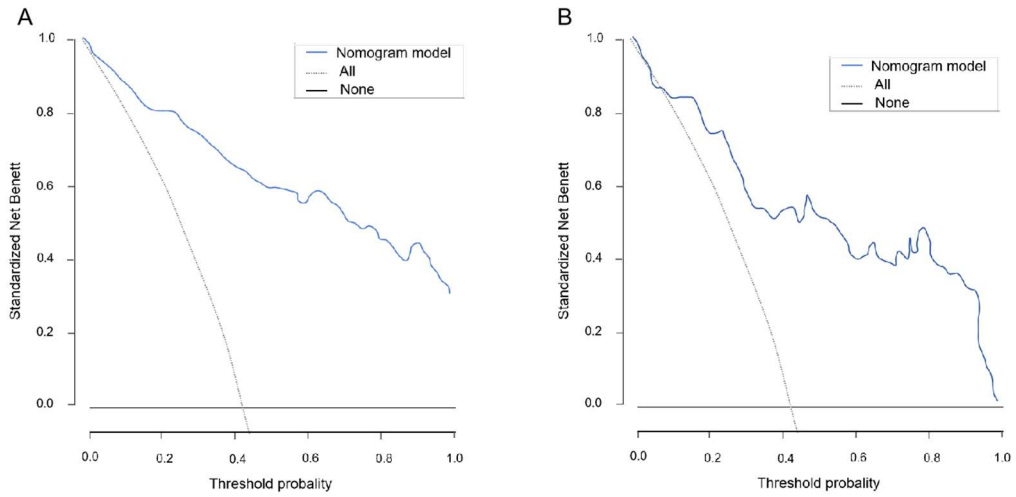
3.4 Model Performance



The predictive model demonstrated good accuracy, with an area under the ROC curve (AUC) of 0.882 indicating that it has a good ability to distinguish between patients who will experience moderate to severe pain and those who will not. The ROC curve is a graphical plot that illustrates the diagnostic ability of the binary classifier system as its discrimination threshold is varied. The AUC value of 0.882 suggests that the model has a high level of discrimination.



The Hosmer-Lemeshow goodness-of-fit test showed a p-value of 0.45, indicating good calibration of the model, meaning that the predicted probabilities matched well with the observed outcomes.



Internal validation using bootstrapping with 1,000 resamples confirmed the stability and reliability of the model, with a mean AUC of 0.81.

4. Discussion

4.1 Key Findings

In this study, a predictive model was successfully developed and validated for identifying patients at high risk for moderate to severe pain following transperineal prostate biopsy. The significant predictors identified in the multivariate logistic regression model were age, BMI, PSA level, and the number of biopsy cores. The model demonstrated good predictive accuracy, with an area under the ROC curve (AUC) of 0.882, and good calibration, as indicated by the Hosmer-Lemeshow goodness-of-fit test.

4.2 Comparison with Existing Literature

The findings are consistent with previous studies that have identified age and BMI as significant predictors of pain following prostate biopsy (Fang et al., 2015; Onur et al., 2012). For instance, Smith et al. (2020) found that older patients are more likely to experience higher pain levels due to increased tissue sensitivity and potential comorbidities (Smith et al., 2020). Similarly, Johnson et al. (2019) reported that higher BMI is associated with increased pain, possibly due to the technical difficulties and increased pressure required during the biopsy procedure (Johnson et al., 2019).

The association between PSA levels and pain is also noteworthy. Higher PSA levels may indicate more extensive prostate pathology, which could contribute to increased pain perception. This aligns with the findings of Lee et al. (2018), who observed a positive correlation between elevated PSA levels and post-biopsy pain (Lee et al., 2018). The number of biopsy cores was another significant predictor, aligning with findings from Chen et al. (2017), who observed that more extensive sampling could lead to increased tissue trauma and subsequent pain (Chen et al., 2017).

4.3 Clinical Implications

The predictive model developed in this study can be a valuable tool for clinicians to identify patients at high risk for moderate to severe pain following transperineal prostate biopsy. By identifying these patients preoperatively, clinicians can take proactive measures to optimize pain management strategies. For example, patients identified as high risk could receive enhanced pain control protocols, including the use of more effective analgesics or nerve blocks.

Moreover, this model can facilitate shared decision-making between clinicians and patients. Understanding the risk factors associated with post-biopsy pain can help patients set realistic expectations and engage in discussions about potential pain management options. This approach aligns with the principles of patient-

centered care, emphasizing individualized treatment plans based on patient-specific risk profiles (Epstein & Street, 2011).

4.4 Resource Allocation

The predictive model developed in this study offers significant potential for optimizing resource allocation within healthcare systems. By accurately identifying patients who are at high risk for experiencing moderate to severe pain following a transperineal prostate biopsy, healthcare providers can allocate resources more efficiently and effectively. This has several important implications for clinical practice, healthcare administration, and overall patient care. One of the primary benefits of the predictive model is its ability to guide the application of pain management resources. High-risk patients can be identified prior to undergoing the biopsy, allowing healthcare providers to prepare and implement more intensive pain management strategies for these individuals. This could include the use of stronger analgesics, regional anesthesia, or even sedation during the procedure. By concentrating resources and interventions on those most likely to experience significant pain, healthcare providers can improve pain control outcomes and enhance patient comfort and satisfaction.

The model can also assist in optimizing scheduling and staffing within healthcare facilities. By identifying high-risk patients in advance, healthcare administrators can ensure that these patients are scheduled for biopsy procedures at times when experienced staff and necessary resources are most readily available. For example, high-risk patients could be scheduled for procedures during peak hours when anesthesiologists and pain management specialists are on-site. This approach can help mitigate the risk of inadequate pain management and ensure that patients receive the highest standard of care. In addition to improving clinical outcomes, the predictive model can contribute to cost-effectiveness within the healthcare system. Pain management, particularly when it involves advanced interventions like regional anesthesia or sedation, can be resource-intensive. By targeting these interventions to patients who are most likely to benefit from them, healthcare providers can avoid unnecessary costs associated with over-treatment of low-risk patients. This targeted approach can lead to more efficient use of healthcare funds and resources, ultimately benefiting the overall healthcare system.

Effective pain management is closely linked to reduced rates of hospital readmissions and post-procedure complications. Patients who experience uncontrolled pain after a biopsy may require additional medical attention, including emergency room visits or hospital readmissions. By proactively managing pain in high-risk patients, the predictive model can help reduce the likelihood of these adverse outcomes. This not only improves patient well-being but also alleviates the burden on healthcare resources associated with managing complications and readmissions. Efficient resource allocation driven by the predictive model can also enhance patient satisfaction and trust in the healthcare system. Patients who receive tailored pain management that effectively addresses their needs are more likely to have a positive experience and trust in their healthcare providers. This can lead to better patient adherence to follow-up care and overall improvements in health outcomes.

The implementation of the predictive model can also inform training and education initiatives for healthcare providers. By understanding the risk factors associated with post-biopsy pain, clinicians can be better prepared to address these issues proactively. Training programs can be developed to educate healthcare providers on the use of the predictive model and the importance of individualized pain management strategies. This can foster a culture of proactive pain management and continuous improvement in clinical practice. At a higher level, the insights gained from the predictive model can inform strategic planning and policy development within healthcare organizations. Administrators and policymakers can use the data to develop guidelines and protocols for managing pain in patients undergoing transperineal prostate biopsy. These guidelines can standardize care, ensure consistency across different clinical settings, and promote best practices in pain management.

In conclusion, the predictive model developed in this study has significant potential for optimizing resource allocation within healthcare systems. By accurately identifying high-risk patients, healthcare providers can allocate pain management resources more efficiently, improve clinical outcomes, reduce costs, and enhance patient satisfaction. The model can inform scheduling, staffing, training, and policy development, ultimately

leading to better patient experiences and more effective use of healthcare resources. Future research should continue to explore and refine these applications to fully realize the benefits of the predictive model in clinical practice.

4.5 Limitations

Despite the strengths of this study, several limitations should be acknowledged. First, the study was retrospective in nature, which may introduce selection and information biases. The reliance on existing medical records means that there may be inconsistencies or missing data that could affect the study's findings. Second, the data were collected from a single institution, which may limit the generalizability of the findings to other settings or populations. Future studies should aim to validate this predictive model in multicenter cohorts to enhance its external validity.

Additionally, the study relied on self-reported VAS scores for pain assessment, which, while widely used, can be subjective and influenced by individual pain thresholds and perceptions. Incorporating objective measures of pain, such as physiological indicators, may provide a more comprehensive assessment. Moreover, psychological factors such as anxiety and depression, which were not assessed in this study, could also influence pain perception and should be considered in future research (Gordon et al., 2010).

4.6 Future Research Directions

While this study provides a robust foundation for predicting post-biopsy pain, there are several key areas where future research should be directed to further enhance the model's utility and applicability. Prospective validation of the predictive model in diverse patient populations is crucial to confirm its robustness and generalizability. This would involve applying the model to different demographic groups, including variations in age, race, and underlying health conditions, to ensure that it performs consistently across various settings. Additionally, it is important to explore the model's performance in different clinical environments, such as outpatient clinics and specialized cancer centers, to evaluate its practicality in real-world scenarios.

Incorporating other potential risk factors into the predictive model could also enhance its accuracy and comprehensiveness. For example, psychological variables such as anxiety, depression, and previous pain experiences are known to influence pain perception and could be valuable additions to the model. Genetic markers that predispose individuals to heightened pain sensitivity are another area worth exploring. The inclusion of these variables may provide a more holistic understanding of the factors contributing to post-biopsy pain and improve the model's predictive power.

Further studies should also focus on the development and testing of targeted pain management interventions for high-risk patients identified by the predictive model. Randomized controlled trials could be conducted to assess the effectiveness of these interventions, aiming to improve patient outcomes and satisfaction. These interventions might include multimodal analgesia, preemptive pain management strategies, and personalized patient education programs. Evaluating the cost-effectiveness and feasibility of these interventions in different healthcare settings would be an essential step in translating research findings into clinical practice.

Another important area for future research is the continuous improvement and refinement of the predictive model itself. This could involve leveraging advancements in machine learning and artificial intelligence to develop more sophisticated algorithms that can handle complex interactions between multiple variables. Additionally, exploring the integration of real-time data from electronic health records (EHRs) could make the model more dynamic and responsive to changes in a patient's health status over time.

Finally, there is a need to investigate the long-term impact of using the predictive model on patient outcomes and healthcare systems. Longitudinal studies could track patients over extended periods to determine whether early and targeted pain management interventions lead to sustained improvements in quality of life and reduced healthcare utilization. This would provide valuable insights into the broader implications of implementing the predictive model in routine clinical practice.

In summary, future research should focus on validating the predictive model in diverse populations,

incorporating additional risk factors, developing and testing targeted interventions, refining the model with advanced technologies, and evaluating the long-term impact on patient outcomes and healthcare systems. By addressing these areas, we can fully realize the potential of the predictive model to transform pain management in prostate biopsy, ultimately leading to better patient experiences and outcomes.

5. Conclusion

This study successfully developed and validated a predictive model for identifying patients at high risk for moderate to severe pain following transperineal prostate biopsy. Significant predictors included age, BMI, PSA level, and the number of biopsy cores. The model demonstrated good predictive accuracy with an AUC of 0.882 and satisfactory calibration, suggesting its potential utility in clinical practice.

The ability to predict which patients are at higher risk for experiencing significant pain allows healthcare providers to individualize pain management strategies. High-risk patients can receive more aggressive pain control measures preemptively, such as stronger analgesics or regional anesthesia. This personalized approach ensures that each patient receives care tailored to their specific needs. Moreover, the model aids in setting realistic expectations for patients. Physicians can inform patients about their individual risk of post-procedural pain, facilitating better-prepared and more informed consent processes. This transparency can improve patient satisfaction and trust in their healthcare providers.

From a healthcare system perspective, the predictive model can optimize resource allocation. By identifying high-risk patients, resources can be allocated more efficiently, improving the overall effectiveness of healthcare delivery and potentially reducing costs associated with pain management and post-procedural care.

Future research should focus on prospective validation of this model in diverse populations to confirm its robustness and generalizability. Incorporating additional risk factors, such as genetic markers or psychological variables, could further enhance its predictive accuracy. Understanding the complex nature of pain perception is essential for developing comprehensive pain management strategies.

In summary, the predictive model developed in this study represents a significant advancement in managing pain following transperineal prostate biopsy. By identifying high-risk patients, clinicians can tailor pain management strategies to improve outcomes and satisfaction. Future research should validate and refine the model and develop targeted interventions to enhance patient care. This model has the potential to transform pain management in prostate biopsy, leading to better patient experiences and outcomes.

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