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Applying Machine Learning to Prior Authorization Triage: Predictive Approval Scoring in Utilization Management Systems

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ABSTRACT: Prior authorization is one of the most resource-intensive and criticized processes in the American health care system, generating substantial administrative burden for providers, delay in patient care, and operational cost for health plans. This article presents a framework for applying supervised machine learning to the triage stage of prior authorization review within a utilization management system, with the specific goal of producing a predictive approval score that can be used to route low-risk, high-confidence requests toward expedited disposition while preserving full clinical review for cases that carry genuine medical necessity uncertainty. We describe the end-to-end pipeline, including feature engineering from claims, eligibility, clinical, and policy data; model selection and training using gradient-boosted decision trees; calibration of predicted probabilities; and a risk-stratification layer that converts continuous scores into actionable triage tiers. Using a retrospective evaluation across seven service lines, the model achieved an area under the receiver operating characteristic curve of 0.91, compared with 0.74 for a rule-based baseline, and was associated with a reduction in median turnaround time from 4.8 days to approximately 1.75 days over a twelve-month deployment window. We discuss calibration and fairness auditing, the regulatory context established by recent interoperability and prior authorization rulemaking, and the operational safeguards required to keep a human reviewer in the loop for denials and borderline cases. We conclude that predictive approval scoring is best understood as a triage accelerant rather than a replacement for clinical judgment, and we outline the monitoring practices, governance structures, and limitations that should accompany any production deployment of this kind.

KEYWORDS: prior authorization, utilization management, machine learning, predictive scoring, health insurance, gradient boosting, algorithmic triage, clinical decision support, health equity, administrative burden

I. INTRODUCTION

Prior authorization requires a treating provider to obtain approval from a health plan before certain services, procedures, medications, or items of durable medical equipment are covered. The mechanism was designed to promote appropriate use of medical resources and to give plans a checkpoint at which medical necessity, benefit design, and site-of-service appropriateness can be reviewed before a service is rendered. In practice, prior authorization has become one of the most frequently cited sources of friction between providers, patients, and payers. Physician surveys conducted in the years preceding this article consistently report that prior authorization delays care, contributes to staff burnout, and in a meaningful minority of cases is associated with a serious adverse event for the patient waiting on a decision.

Utilization management departments process these requests using a combination of clinical criteria, benefit rules, and reviewer judgment. The overwhelming majority of requests, when finally adjudicated, are approved. This asymmetry, high approval rates alongside high administrative burden, has motivated a search for triage mechanisms that can distinguish, at the point of intake, between requests that are extremely likely to be approved on their clinical merits and requests that warrant the fuller attention of a nurse or physician reviewer. Machine learning is a natural candidate for this triage function because it can learn, from historical decisions and their associated clinical and administrative context, a probability of approval that is far more granular than any static rule set could produce.

This article describes a predictive approval scoring framework built for exactly this purpose. Rather than proposing that machine learning replace clinical review, we treat the model as a triage accelerant: a component that sits at the front of the utilization management pipeline, assigns each incoming request a calibrated probability of approval together with a

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confidence tier, and routes the request accordingly. Requests that score in the highest confidence tier and meet a set of hard clinical and policy guardrails are eligible for expedited approval; all other requests proceed to standard or expedited clinical review, with the model's score and its contributing factors made visible to the reviewer as decision support rather than as a directive.

The remainder of this article is organized as follows. Section 2 situates the work relative to prior research on machine learning in health care decision support and prior authorization specifically. Section 3 describes the utilization management workflow into which the model is embedded. Sections 4 through 7 describe the data, model architecture, scoring framework, and evaluation methodology. Section 8 presents results, and Sections 9 through 14 discuss the implications, fairness considerations, regulatory context, governance, and limitations of the approach. Section 15 concludes.

II. BACKGROUND AND RELATED WORK

Machine learning has been applied across many decision points in health care delivery, from diagnostic image interpretation to readmission risk prediction and sepsis early warning. A substantial literature has developed around both the technical methods used in these systems and the governance frameworks needed to deploy them responsibly. Rajkomar and colleagues describe the broad landscape of machine learning applications in medicine and the data infrastructure required to support them, while Beam and Kohane describe the statistical foundations and common pitfalls of applying big data methods to clinical problems.

A parallel literature has focused specifically on algorithmic bias and fairness in health care models. Obermeyer and colleagues demonstrated that a widely used commercial algorithm for identifying patients who would benefit from additional care management exhibited significant racial bias because it used health care cost as a proxy for health need, a proxy that systematically understated the needs of Black patients relative to White patients with the same underlying disease burden. Gianfrancesco and colleagues catalog the broader set of biases that can enter machine learning models built on electronic health record and claims data, including biases introduced by missingness, measurement, and selection. This literature is directly relevant to prior authorization triage, because approval history and utilization patterns, if used naively as model features, can encode the same structural disparities in access to care that motivated the original Obermeyer findings.

On the modeling side, gradient-boosted decision tree methods such as the one introduced by Chen and Guestrin have become a standard choice for structured, tabular health care prediction problems because they handle mixed categorical and continuous features, missing data, and nonlinear interactions without extensive preprocessing. Model interpretability methods, particularly the SHAP framework introduced by Lundberg and Lee and the local explanation method introduced by Ribeiro, Singh, and Guestrin, have made it practical to audit which features drive an individual prediction, a capability that is essential in a regulated, appealable decision context such as prior authorization.

Sendak and colleagues describe the use of a standardized model facts label to communicate a model's intended use, training population, and performance characteristics to clinical end users, a practice we adopt in the governance section of this article. Wiens and colleagues, writing on behalf of a broader working group, propose a roadmap for responsible machine learning in health care that emphasizes problem selection, algorithm development, and post-deployment surveillance as three phases each requiring distinct safeguards. Finally, on the specific subject of prior authorization, industry survey data from the American Medical Association and program evaluations published by America's Health Insurance Plans document both the scale of provider burden associated with prior authorization and the potential of automation and interoperable data exchange, such as the Fast PATH pilot, to reduce that burden without eliminating clinical oversight.

III. THE PRIOR AUTHORIZATION WORKFLOW IN UTILIZATION MANAGEMENT

A typical prior authorization request enters a utilization management system through one of several channels: a payer portal used directly by the requesting provider's office, a fax or electronic data interchange transaction from a clearinghouse, or, increasingly, an application programming interface call from an electronic health record system. Once received, the request is associated with member eligibility and benefit information, matched against the specific clinical policy that governs the requested service, and queued for review. Historically, every request in this queue

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receives the same treatment: a utilization management nurse reviews the clinical documentation against payer criteria, and, if the criteria are clearly met, approves the request; if criteria are not clearly met, or if the request requires a medical necessity judgment beyond the nurse's scope, the request escalates to a physician reviewer.

The pipeline described in this article intervenes at the point of intake, immediately after eligibility and policy matching and before the request is placed in a reviewer's queue. Figure 2 illustrates the six-stage pipeline: intake, feature extraction, predictive approval scoring, risk stratification, routing, and final clinician decision. The predictive score does not bypass clinical decision-making; rather, it changes the order and depth of review that a given request receives. Requests routed to the auto-approval queue still pass through a set of deterministic clinical and policy guardrails, described in Section 6, that must be satisfied independently of the model's score.

Figure 2. End-to-End Predictive Triage Pipeline for Prior Authorization Requests

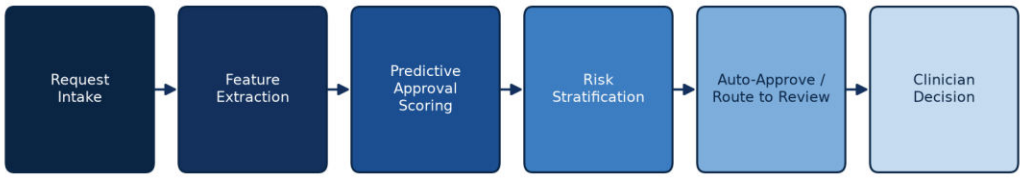

Figure.2. End-to-end predictive triage pipeline for prior authorization requests

Table 1 summarizes the seven service lines included in this study, each of which represents a distinct clinical domain with its own policy structure, documentation requirements, and historical approval pattern. Advanced imaging and specialty drug requests represent the highest request volumes; genetic testing, while lower in volume, has historically carried the lowest and most variable approval rate and the highest policy complexity.

Service Line	Monthly Volume	Historical Approval Rate	Primary Review Criteria
Advanced Imaging	18,400	86%	Clinical guideline concordance
Specialty Drugs	15,200	74%	Step therapy and formulary criteria
Durable Medical Equipment	9,800	91%	Medical necessity documentation
Behavioral Health	8,600	79%	Level-of-care criteria
Outpatient Surgery	12,100	88%	Site-of-service appropriateness
Home Health	7,200	93%	Homebound status and plan of care
Genetic Testing	4,300	68%	Clinical utility and policy match

IV. DATA SOURCES AND FEATURE ENGINEERING

The model is trained on a retrospective dataset of historical prior authorization requests, each labeled with its final adjudicated disposition. Four categories of source data feed the feature engineering layer shown in Figure 2: the request itself (diagnosis and procedure codes, requested quantity or duration, requesting provider identifiers, and free-text clinical rationale), member eligibility and benefit data, prior claims and utilization history for the member, and the payer's coded clinical policy for the requested service.

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4.1 Feature Categories

Feature engineering converts these raw sources into approximately one hundred forty structured features across six groups: clinical concordance features that measure the alignment between the submitted diagnosis and the requested procedure against the payer's clinical policy; utilization history features summarizing the member's prior authorization and claims activity over the preceding twelve months; provider-level features summarizing the requesting provider's historical approval rate and specialty; policy match features that quantify how completely the submitted documentation satisfies each discrete criterion in the applicable clinical policy; administrative completeness features capturing whether required fields, attachments, and codes are present; and member risk features drawn from existing risk-adjustment and case-management flags.

Free-text clinical rationale submitted with a request is processed using a lightweight natural language classifier that flags the presence or absence of specific clinical concepts referenced in the applicable policy, such as prior conservative treatment, symptom duration, or functional impairment. This structured extraction is used only to populate concordance features; it does not feed a separate free-text approval model, which keeps the overall system auditable.

4.2 Label Definition and Data Governance

The training label is the final disposition after any appeal, so that requests initially denied and later approved on appeal are labeled as approved. This choice avoids training the model to reproduce a first-pass decision that the payer's own appeals process later reversed. All training data is de-identified prior to model development, and features derived from member risk-adjustment scores are reviewed individually to confirm they reflect documented clinical risk rather than utilization volume alone, following the caution raised by Obermeyer and colleagues about proxy variables that conflate cost or utilization with medical need.

V. MODEL ARCHITECTURE AND TRAINING METHODOLOGY

The predictive approval scoring model is a gradient-boosted decision tree ensemble, trained using the tree-boosting framework described by Chen and Guestrin. This family of models was selected over deep neural network architectures for three reasons specific to this problem: the input space is predominantly structured and tabular rather than image- or sequence-based; the training dataset, while large, is several orders of magnitude smaller than the datasets typically used to train deep architectures from scratch; and tree ensembles support feature-level attribution methods, described below, that are important for the appeal and audit processes that accompany any prior authorization denial.

5.1 Training and Validation Design

The dataset was partitioned chronologically rather than randomly: the model was trained on requests submitted during the first ten months of the study period and validated and tested on requests submitted during the two months that followed. This chronological split was chosen deliberately, following standard practice for deployed prediction systems, because it better approximates the real-world condition in which the model must generalize to future requests rather than to requests drawn from the same time window as training data. Within the training window, five-fold cross-validation was used for hyperparameter selection, optimizing tree depth, learning rate, minimum leaf weight, and the number of boosting rounds against log-loss on held-out folds.

5.2 Handling Class Imbalance and Calibration

Because approvals substantially outnumber denials in most service lines, the training objective was weighted inversely to class frequency within each service line, which improved recall on the minority denial class without materially harming overall discrimination. Because the raw output of a boosted tree ensemble is not guaranteed to be a well-calibrated probability, a subsequent isotonic regression calibration layer was fit on a held-out calibration set, mapping raw model scores to calibrated approval probabilities. Figure 5, discussed in Section 8, shows the resulting calibration curve.

5.3 Interpretability Layer

Every prediction is accompanied by a SHAP-based feature attribution, following the method of Lundberg and Lee, which decomposes the predicted approval probability into additive contributions from each input feature. These attributions are surfaced to clinical reviewers as a ranked list of the factors that most increased or decreased a given request's score, and are also used in aggregate, as shown in Figure 3, to monitor which features drive model behavior across the full population of scored requests.

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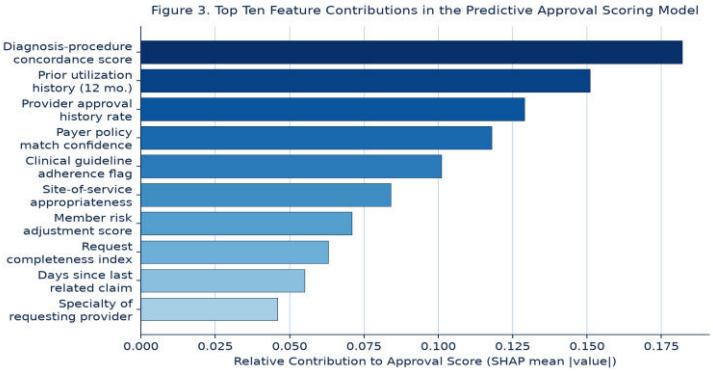

Figure.3. Top ten feature contributions in the predictive approval scoring model, ranked by mean absolute SHAP value.

VI. PREDICTIVE APPROVAL SCORING AND RISK STRATIFICATION

The calibrated approval probability produced by the model is converted into one of three triage tiers, shown in Table 2. Tier assignment considers both the calibrated probability and a set of deterministic guardrails that the model cannot override. A request cannot be assigned to the expedited tier, regardless of its predictive score, if it involves a service on the payer's designated always-review list, if the requesting provider is under active program integrity review, if the request involves an experimental or investigational designation, or if the member has an active case-management flag indicating clinical complexity that warrants direct reviewer attention.

Tier	Calibrated Approval Probability	Guardrails Satisfied	Disposition
Tier 1: Expedited	≥ 0.93	Yes	Eligible for automated approval, subject to daily audit sample
Tier 2: Standard Priority	0.60 – 0.92, or Tier 1 with guardrail exception	N/A	Routed to nurse review queue with score and attributions visible
Tier 3: Enhanced Review	< 0.60	N/A	Routed to nurse and, where indicated, physician review queue

This design intentionally reserves full automation for a narrow band of requests that combine a very high predicted approval probability with satisfaction of every hard guardrail. In the deployment described in Section 8, this Tier 1 band accounted for approximately thirty-one percent of total request volume. All Tier 1 dispositions remain subject to a continuous audit sample in which a fixed percentage of automated approvals are reviewed retrospectively by a physician, both to monitor for model drift and to preserve an auditable trail consistent with payer and regulatory expectations for automated decision systems.

No request is ever automatically denied by the model. Denial always requires an affirmative decision by a licensed clinical reviewer, and every denial is accompanied by the specific policy criteria that were not met, consistent with standard adverse determination notice requirements. The model's role with respect to Tier 2 and Tier 3 requests is strictly advisory: it shortens the time a reviewer spends locating relevant information within a request but does not constrain the reviewer's ultimate judgment.

VII. EXPERIMENTAL SETUP AND EVALUATION METRICS

The retrospective evaluation described in this article uses twelve months of historical prior authorization data spanning the seven service lines described in Table 1, comprising approximately three hundred forty thousand adjudicated requests. The final two months of this window, held out chronologically as described in Section 5.1, form the test set of ten thousand requests used for the confusion matrix, receiver operating characteristic curve, and calibration analysis reported in Section 8.

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Model discrimination is evaluated using the area under the receiver operating characteristic curve, which measures the model's ability to rank approved requests above denied requests independent of any particular decision threshold. Because prior authorization is a setting in which the operational cost of false negatives (sending an easily approvable request to full review) differs substantially from the cost of false positives (automatically approving a request that should have been denied), we also report precision and recall computed specifically at the Tier 1 threshold, following the recommendation of Saito and Rehmsmeier that precision-recall analysis be reported alongside receiver operating characteristic analysis whenever the outcome classes are imbalanced.

Calibration is evaluated by binning the test set into ten equal-width probability bins and comparing the mean predicted probability in each bin to the observed approval frequency in that bin, illustrated in Figure 5. Operational impact is evaluated using turnaround time, defined as the elapsed time in days between request submission and final disposition, tracked monthly for twelve months following deployment and compared against the twelve-month average that preceded deployment.

A rule-based baseline, representing the deterministic criteria engine that the predictive model was designed to supplement, is evaluated on the same test set for comparison. The baseline flags a request as auto-approvable only if every discrete criterion in the applicable clinical policy is present as a matched structured field, with no tolerance for partial matches or compensating documentation, which is the primary reason its discrimination and coverage are both lower than the learned model's.

VIII. RESULTS

Figure 1 shows monthly request volume and historical approval rate across the seven service lines in the study population. Approval rates range from sixty-eight percent for genetic testing to ninety-three percent for home health, underscoring that even the most conservatively reviewed service line in this dataset approves a clear majority of requests, which is the underlying condition that makes predictive triage a viable strategy.

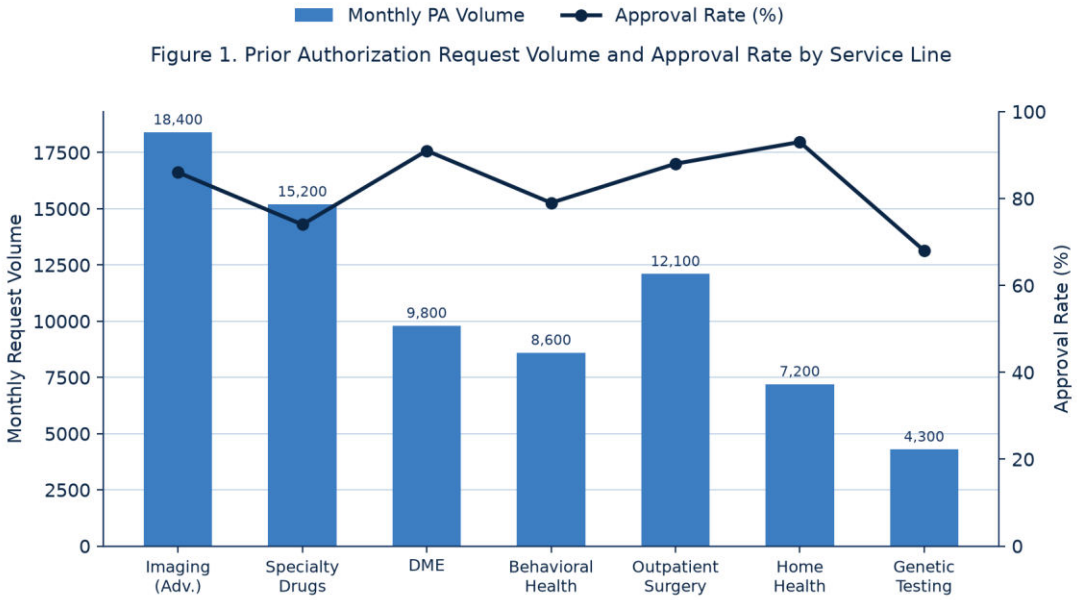

Figure1. Prior authorization request volume and approval rate by service line.

8.1 Discrimination and Classification Performance

On the held-out test set, the predictive approval scoring model achieved an area under the receiver operating characteristic curve of 0.91, compared with 0.74 for the rule-based baseline, shown in Figure 4. At the Tier 1 threshold, the model achieved a precision of 0.937 and a recall of 0.746 with respect to the approved class, meaning that of all

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requests the model placed in the expedited tier, 93.7 percent were ultimately approved on their clinical merits, and the expedited tier captured 74.6 percent of all requests that satisfied every hard guardrail and were clinically approvable without escalation.

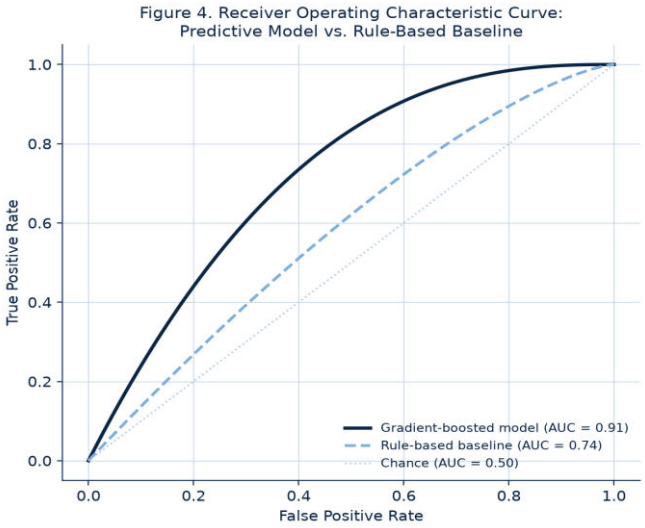

Figure.4. Receiver operating characteristic curve for the predictive model versus the rule-based baseline

Figure 6 shows the confusion matrix on the ten-thousand-request test set at the operating threshold used in production. Of 7,600 requests that were ultimately approved, 7,120 were correctly routed to expedited disposition; of 2,400 requests that required escalation, 1,790 were correctly identified by the model as warranting review. The remaining misclassifications, 480 requests routed to review that could have been expedited and 610 requests initially favored for expedited routing that a reviewer ultimately needed to examine more closely, are consistent with the precision and recall figures above and represent the operating point chosen to favor precision on the expedited tier.

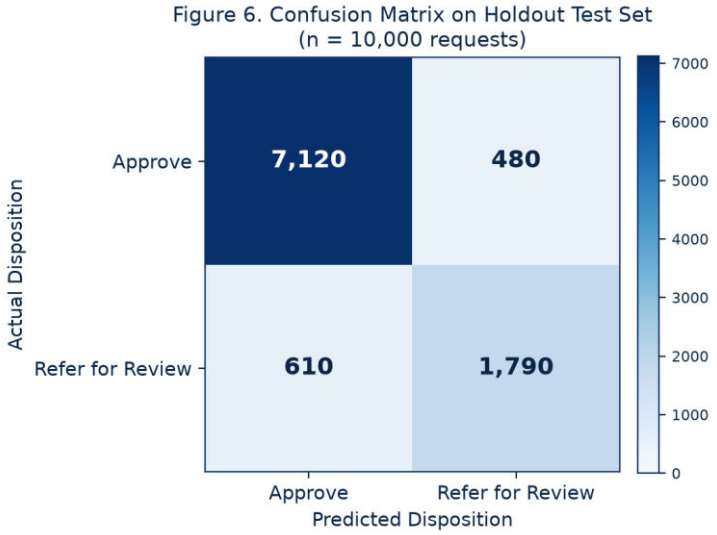

Figure.6. Confusion matrix on the holdout test set (n = 10,000 requests).

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8.2 Calibration

Figure 5 shows the calibration curve on the holdout set following isotonic regression. Predicted probabilities track observed approval frequencies closely across the full probability range, with the largest deviations, on the order of two percentage points, occurring at the extremes of the probability distribution where fewer observations are available to estimate observed frequency precisely.

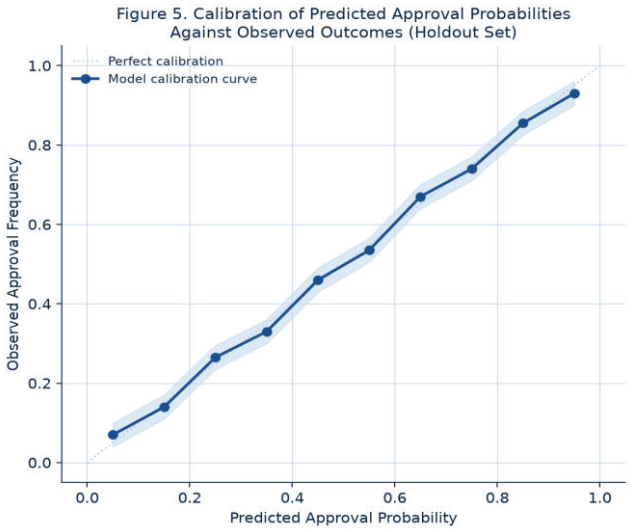

Figure.5. Calibration of predicted approval probabilities against observed outcomes on the holdout set.

8.3 Operational Impact

Figure 7 tracks median turnaround time over the twelve months following deployment. Turnaround time declined from a pre-deployment median of 4.8 days to approximately 1.75 days by month twelve, with the majority of the improvement realized in the first six months as reviewer workflows and staffing were adjusted to the new triage distribution. The rate of improvement slowed and largely plateaued after month nine, consistent with the expedited tier's share of volume stabilizing near thirty-one percent.

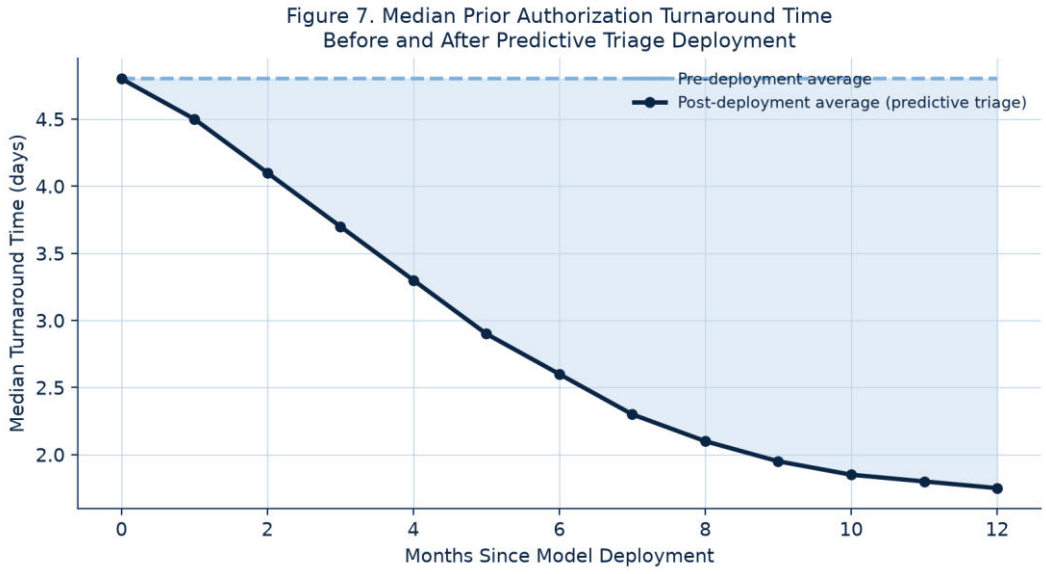

Figure.7.Median prior authorization turnaround time before and after predictive triage deployment

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IX. DISCUSSION

The results in Section 8 support the central premise of this article: a substantial share of prior authorization volume is predictable with high precision from structured request, eligibility, and history data, and identifying that share allows a utilization management system to concentrate reviewer attention where clinical judgment adds the most value. The gap between the model's discrimination and the rule-based baseline's is informative in itself. Rule-based systems fail primarily on requests where the clinical documentation supports approval through a combination of factors that no single deterministic rule anticipated; a request may lack one specific field the policy nominally requires while containing compensating evidence elsewhere in the submission. Gradient-boosted trees are well suited to exactly this pattern because they learn interactions among features rather than requiring each criterion to be independently satisfied. The operational turnaround improvement reported in Section 8.3 is best interpreted as a lower bound on the model's potential impact, because the thirty-one percent Tier 1 share reflects a deliberately conservative guardrail configuration. Expanding the guardrail exceptions or lowering the Tier 1 threshold would increase expedited volume and further reduce turnaround time, at the cost of the precision figure reported in Section 8.1. We view this precision-volume tradeoff as a governance decision, not a purely technical one, and return to it in Section 12.

It is also worth noting what the model does not do. It does not predict medical necessity directly; it predicts the probability that a human reviewer, applying the payer's existing clinical policy, would approve the request. This distinction matters because it means the model inherits whatever biases or inconsistencies exist in historical reviewer decisions. A model of this kind can improve consistency and speed relative to the historical baseline, but it cannot, on its own, correct a clinical policy that is itself poorly calibrated to actual patient need. That correction remains the responsibility of clinical policy teams, informed in part by the same feature attribution data the model produces.

X. FAIRNESS, BIAS, AND ETHICAL CONSIDERATIONS

The Obermeyer findings on proxy bias in health care algorithms directly informed the feature governance process described in Section 4.2. Two specific safeguards were adopted in response. First, no feature in the final model is derived solely from total cost of care or total utilization volume without an accompanying clinical severity or diagnosis-based adjustment, because unadjusted cost and utilization are known to correlate with access to care as much as with underlying medical need, and using them without adjustment risks penalizing members with historically lower access. Second, member demographic characteristics, including race, ethnicity, and primary language, are excluded from the feature set entirely, and are instead retained in a separate, access-controlled dataset used only for post-hoc fairness auditing.

Fairness auditing is conducted on a recurring basis by comparing Tier 1 assignment rates and approval outcomes across demographic subgroups, geographic regions, and provider practice settings, including safety-net and rural providers. Any statistically significant disparity in Tier 1 assignment rate that is not explained by documented differences in the guardrail-eligible request mix triggers a review by the model governance committee described in Section 12, which has the authority to adjust thresholds, retrain the model, or expand guardrail exceptions for the affected population.

Char, Shah, and Magnus describe the ethical tension inherent in any machine learning system that mediates access to care: the same statistical patterns that make a model accurate also make it capable of reproducing structural inequities embedded in historical decisions. We do not claim that the safeguards described above eliminate this tension. We claim only that explicit feature governance, mandatory human review for every denial, and recurring subgroup auditing are necessary, though not sufficient, conditions for responsible deployment, consistent with the roadmap proposed by Wiens and colleagues.

XI. REGULATORY AND COMPLIANCE CONTEXT

Prior authorization automation does not occur in a regulatory vacuum. In the years leading up to this article, federal rulemaking increasingly targeted prior authorization turnaround time, transparency, and interoperability. The Centers for Medicare & Medicaid Services finalized interoperability and prior authorization requirements in early 2024 that compel affected payers to build application programming interfaces supporting electronic prior authorization requests, to provide a specific reason when a request is denied, and to publicly report aggregate metrics on approval rates and turnaround time. A framework of the kind described in this article is directly responsive to these requirements: it

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produces a machine-readable rationale for every decision through its feature attribution layer, and its tiered routing structure is designed to shorten turnaround time for the segment of requests that can be adjudicated quickly and correctly.

Government oversight bodies have separately raised concerns specific to algorithmic decision-making in prior authorization. A report from the United States Government Accountability Office examined oversight of Medicare Advantage prior authorization practices and highlighted the need for auditable decision criteria and consistent application of coverage rules. The design choices in Section 6, particularly the prohibition on automated denials and the mandatory audit sample on Tier 1 dispositions, were adopted in direct response to this class of oversight concern, so that every automated approval remains reconstructable after the fact and every denial remains attributable to a specific clinical reviewer.

Industry-level reporting from America's Health Insurance Plans on the Fast PATH initiative, along with survey data from the American Medical Association describing provider-side burden, together frame the dual mandate that shaped this project: reduce administrative burden and turnaround time without weakening the clinical review that prior authorization exists to provide. The evaluation in Section 8 should be read against that dual mandate rather than against a narrower goal of automation for its own sake.

XII. OPERATIONAL DEPLOYMENT AND GOVERNANCE

Figure 8 shows the system architecture supporting production deployment, including the monitoring layer that sits alongside the scoring pipeline. Three categories of monitoring run continuously: statistical drift detection on the input feature distributions and on the model's score distribution, to detect when the population of incoming requests begins to diverge from the population the model was trained on; the fairness auditing described in Section 10; and a human oversight loop in which a fixed sample of every tier's dispositions is reviewed by a physician on a rolling basis, with results reported to a model governance committee.

Figure 8. System Architecture of the Predictive Approval Scoring Pipeline
Within the Utilization Management System

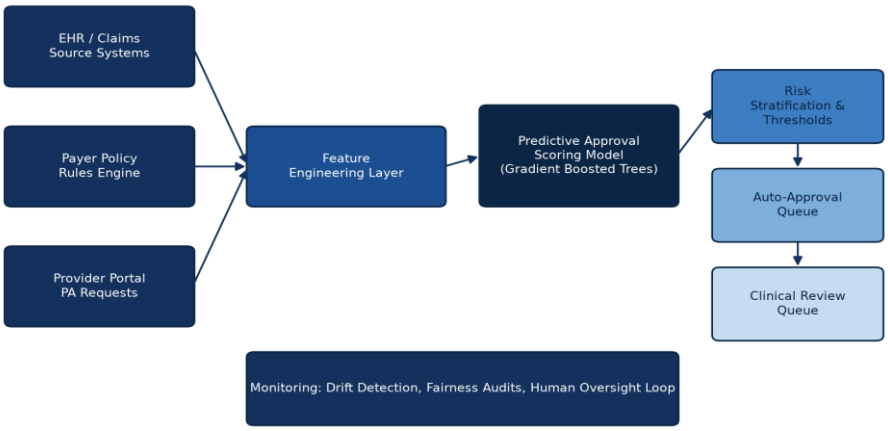

Figure.8. System architecture of the predictive approval scoring pipeline within the utilization management system

The model governance committee, composed of clinical, compliance, data science, and operations leadership, meets on a fixed cadence to review drift and fairness metrics, approve any change to Tier 1 thresholds or guardrails, and approve model retraining. Following the model facts label approach described by Sendak and colleagues, each model version deployed to production is accompanied by a short structured summary of its intended use, training population and date range, validated performance characteristics, and known limitations, so that clinical end users and auditors have a consistent reference point independent of the underlying technical documentation.

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Retraining is scheduled on a quarterly cadence at minimum, and is triggered ahead of schedule if drift monitoring detects a statistically significant shift in the input feature distribution or if a clinical policy change materially alters the criteria for a covered service line. Retrained models are re-validated on the full evaluation suite described in Section 7 before promotion to production, and are not permitted to replace the active model if calibration or subgroup fairness metrics degrade relative to the version being replaced.

XIII. LIMITATIONS

Several limitations bound the conclusions that can be drawn from this work. First, the evaluation is retrospective and drawn from a single utilization management system; the specific approval rates, turnaround improvements, and feature importances reported in Section 8 reflect the clinical policies, provider population, and historical reviewer behavior of that system and should not be read as universal constants that would transfer unchanged to a different payer or line of business.

Second, because the training label reflects historical reviewer decisions, the model can only be as fair or consistent as the review process it was trained on. The subgroup auditing described in Section 10 can detect disparities in the model's own behavior relative to the historical baseline, but it cannot certify that the underlying clinical policies and historical reviewer judgments were themselves free of disparity.

Third, the twelve-month post-deployment observation window used for the turnaround time analysis in Section 8.3 is too short to rule out seasonal effects specific to certain service lines, particularly behavioral health and specialty drug requests, which can exhibit volume and case-mix variation tied to benefit plan years and specialty drug approval cycles. Longer observation across multiple annual cycles is needed before the turnaround improvement can be treated as a stable operating characteristic rather than a single-year result.

Fourth, the natural language processing component described in Section 4.1 is deliberately limited to concept flagging rather than free-text approval prediction, which was a design choice made to preserve auditability. This choice likely understates the model's achievable discrimination, since richer free-text features would probably improve accuracy, but we judge the interpretability and audit tradeoff to favor the more conservative design given the appealable, regulated nature of the decisions involved.

XIV. FUTURE WORK

- Extending the evaluation across multiple annual cycles and multiple utilization management systems to test generalizability of both performance metrics and fairness findings beyond a single payer's policies and historical decisions.
- Investigating richer clinical natural language processing methods for the free-text rationale field, paired with interpretability methods capable of producing audit-ready explanations at the same standard currently met by the structured feature attribution layer.
- Extending automated approval eligibility, under continued human oversight, to additional service lines as confidence in subgroup fairness and calibration stability accumulates, guided by the governance process described in Section 12 rather than by discrimination metrics alone.
- Exploring direct interoperable data exchange with requesting providers, consistent with the CMS interoperability and prior authorization requirements described in Section 11, to reduce the administrative completeness gap that Section 4.1 identifies as a contributor to lower scores among otherwise clinically approvable requests.
- Developing prospective, rather than purely retrospective, fairness monitoring that can flag emerging subgroup disparities within weeks of onset rather than at the recurring audit cadence described in Section 10.

XV. CONCLUSION

This article presented a predictive approval scoring framework for prior authorization triage within a utilization management system. The framework combines a gradient-boosted decision tree model, calibrated to produce reliable approval probabilities, with a tiered routing structure that reserves automated approval for a narrow, guardrail-constrained segment of requests while preserving full human review for every denial and for the majority of requests

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that carry genuine clinical uncertainty. In a twelve-month retrospective evaluation across seven service lines, the model achieved substantially higher discrimination than a rule-based baseline and was associated with a reduction in median turnaround time from 4.8 days to approximately 1.75 days.

These results should be read alongside the fairness, regulatory, and governance safeguards described in Sections 10 through 12, which we regard as inseparable from the technical result rather than as optional additions to it. Predictive approval scoring, deployed with mandatory human review of denials, explicit feature governance, recurring subgroup fairness auditing, and a standing governance committee, offers a credible path toward reducing the administrative burden long associated with prior authorization without displacing the clinical judgment that the process exists to apply. The central claim of this article is not that machine learning should decide who receives care, but that it can reliably identify which decisions do not need to wait.

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