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Automated Feature Engineering for Multi-Period Claim Experience in Dynamic Actuarial Risk Modeling

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Abstract: Actuarial risk modeling increasingly relies on longitudinal claim experience to capture evolving policyholder behavior and portfolio dynamics. Traditional feature engineering in this domain often depends on manual specification, which limits scalability and may overlook complex temporal interactions. This study investigates automated feature engineering techniques for multi-period claim experience within dynamic actuarial risk modeling. The objective is to evaluate whether algorithmic feature construction can improve predictive accuracy, stability, and interpretability compared with conventional manual feature sets. A synthetic but realistic claim dataset spanning multiple observation periods is used, incorporating frequency, severity, reporting delay, and payment patterns. Automated feature generation methods, including deep feature synthesis and genetic programming, are applied to create candidate predictors. These features are then integrated into several dynamic modeling frameworks, such as gradient boosting, random forests, and regularized regression. Model performance is assessed through cross-validated discrimination, calibration, and error metrics. Results indicate that automated feature engineering yields consistent gains in discriminatory power and reduces prediction error relative to baseline manual features. The most valuable engineered features capture temporal trends, volatility, and interaction effects that are not easily specified by hand. Stability analysis further shows that a subset of automated features remains robust across resampling and time-based validation. The findings suggest that automated feature engineering can enhance dynamic actuarial risk models by uncovering latent multi-period claim patterns while maintaining acceptable interpretability. Practical implications include more efficient model development, improved risk segmentation, and better support for pricing and reserving decisions. However, careful validation is required to avoid overfitting and to ensure that engineered features align with actuarial intuition. This research contributes a structured evaluation framework and highlights opportunities for integrating automated feature construction into routine actuarial practice.

Keywords: Automated Feature Engineering; Actuarial Risk Modeling; Multi-Period Claims; Dynamic Modeling; Predictive Analytics

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1. Introduction

1.1. Research Background and Motivation

The evolution of actuarial risk modeling has progressively shifted from static underwriting assessments toward dynamic frameworks that incorporate multi-period claim experience [1, 2]. Capturing temporal dependencies, interaction effects, and evolving policyholder behavior is essential for accurate risk differentiation. However, conventional manual feature engineering struggles to represent these complex longitudinal patterns, often relying on domain heuristics that fail to generalize across heterogeneous portfolios [3]. This limitation motivates the adoption of automated feature engineering, which can systematically extract and transform multi-period claim histories

into informative representations, thereby enhancing predictive performance and adaptability in dynamic actuarial risk modeling [4].

1.2. Objectives and Contributions

This research aims to evaluate automated feature engineering techniques for capturing multi-period claim experience within dynamic actuarial risk models. The primary objective is to determine whether algorithmic feature generation can outperform traditional manual specification in predicting policyholder behavior and claim frequency [5]. The study further seeks to assess the interpretability and stability of these automated features across varying economic conditions [6, 7]. Expected contributions include a robust framework for integrating automated feature engineering into actuarial practice, empirical evidence on its predictive gains, and practical guidance for actuaries adopting machine learning pipelines in dynamic risk assessment [4, 8].

2. Literature Review

2.1. Feature Engineering in Actuarial Science

Traditional actuarial feature engineering relies heavily on domain expertise to construct frequency, severity, and temporal claim indicators from raw policy and loss records [8, 9]. These manual specifications typically capture aggregate exposure measures and simple lagged structures, yet they struggle to scale across multi-period experience data and often overlook complex nonlinear interactions among rating variables [10]. Consequently, conventional approaches face persistent challenges in dimensionality, reproducibility, and the systematic discovery of higher-order temporal dependencies, motivating the need for automated alternatives.

2.2. Automated Feature Generation and Dynamic Risk Models

Automated feature generation has emerged as a powerful paradigm for alleviating the manual burden of feature construction in actuarial modeling [11, 12]. Deep feature synthesis and genetic programming approaches autonomously construct high-order, non-linear transformations from raw policyholder data, enabling the discovery of latent risk interactions that traditional actuarial specifications often overlook [13, 14]. In parallel, dynamic risk modeling frameworks emphasize the temporal evolution of claim experience, requiring features that capture multi-period dependencies, seasonality, and regime shifts [15]. The efficacy of such frameworks is therefore fundamentally contingent upon the quality and temporal richness of the underlying feature space, motivating the integration of automated generation techniques with dynamic actuarial architectures [10].

3. Materials and Methods

3.1. Data Description and Preprocessing

We constructed a synthetic multi-period claim dataset to emulate the longitudinal experience of a non-life insurance portfolio over ten consecutive annual periods. Each policyholder record comprises claim frequency, claim severity, reporting delay, and payment patterns, with covariates spanning policy attributes and temporal indicators. Preprocessing proceeded in three stages [16, 17]. First, data cleaning removed duplicate records, corrected negative monetary values, and imputed missing severity entries using median substitution within homogeneous risk cells. Second, reporting delay was modeled as a discrete random variable, and claims were allocated to their corresponding development periods to preserve the run-off triangle structure. Third, we constructed rolling time windows of varying lengths to capture multi-period claim experience, aggregating frequency and severity measures across adjacent periods [12, 18]. Continuous variables were standardized, and categorical variables were encoded via one-hot representation. The resulting dataset supports dynamic risk modeling by retaining both cross-sectional heterogeneity and temporal dependence, enabling the subsequent automated feature engineering procedures to operate on a consistent and reproducible data foundation.

3.2. Automated Feature Engineering Framework

The framework employs deep feature synthesis to systematically generate candidate features by applying mathematical and aggregation primitives across relational claim data, capturing multi-period temporal dependencies [19]. Genetic programming further evolves high-order interaction terms through symbolic regression, optimizing predictive utility against a dynamic actuarial loss function. Feature selection utilizes recursive elimination with stability selection to mitigate overfitting, retaining only features that demonstrate consistent importance across bootstrap resamples. Validation is conducted through time-series cross-validation, ensuring temporal robustness and preventing data leakage from future periods. Selected features are integrated into dynamic risk models via a sequential update mechanism, where period-specific feature vectors are incorporated into a state-space representation. This integration allows the model to adapt to evolving claim experience, with feature importance weights recalibrated at each period using a forgetting factor to emphasize recent observations. The resulting pipeline automates the transformation of raw claim histories into a compact, temporally aware feature set, enhancing predictive accuracy in dynamic actuarial contexts [20].

3.3. Experimental Design and Parameter Settings

The experimental design evaluates automated feature engineering against dynamic actuarial risk modeling. As detailed in Table 1, the framework is governed by six core configurations [21]. The table has columns Parameter, Value/Range, and Description. Rows include: Observation Window, 5 years, multi-period claim history; Feature Generation Methods, 6 algorithms, includes deep feature synthesis and genetic programming; Validation Scheme, 5-fold time-series cross-validation, preserves temporal order; Model Types, 4 algorithms, gradient boosting, random forest, regularized regression, and neural network; Hyperparameter Search, 100 iterations, random search with early stopping; Evaluation Metrics, AUC, Gini, RMSE, and Log Loss, discrimination and calibration. A five-year observation window captures longitudinal claim experience, while six feature generation algorithms, including deep feature synthesis and genetic programming, construct the candidate feature space. To preserve temporal dependencies, a 5-fold time-series cross-validation scheme is adopted. Four model types are benchmarked: gradient boosting, random forest, regularized regression, and neural networks. Hyperparameter optimization employs random search over 100 iterations with early stopping. Performance is assessed using AUC, Gini, RMSE, and Log Loss, covering both discrimination and calibration [19, 22]. This protocol ensures robust, reproducible comparison across automated and conventional pipelines.

Table 1. Experimental Parameters for Automated Feature Engineering and Dynamic Risk Modeling

Parameter	Value/Range	Description
Observation Window	5 years	Multi-period claim history
Feature Generation Methods	6 algorithms	Includes deep feature synthesis and genetic programming
Validation Scheme	5-fold time-series cross-validation	Preserves temporal order
Model Types	4 algorithms	Gradient boosting, random forest, regularized regression, and neural network
Hyperparameter Search	100 iterations	Random search with early stopping

Evaluation Metrics	AUC, Gini, RMSE, and Log Loss	Discrimination and calibration

4. Results

4.1. Comparative Model Performance

As detailed in Table 2, the comparative analysis reveals distinct performance differentials across feature engineering strategies. The baseline manual approach establishes a reference point with an AUC of 0.742 and a Gini coefficient of 0.484, alongside an RMSE of 0.312 and a Log Loss of 0.561. Automated Genetic Programming demonstrates a substantial improvement, elevating the AUC to 0.801 and the Gini to 0.602, while concurrently reducing error metrics to an RMSE of 0.278 and a Log Loss of 0.512. Automated Deep Feature Synthesis yields a competitive AUC of 0.789 and a Gini of 0.578, with an RMSE of 0.284 and a Log Loss of 0.523. The hybrid strategy, which integrates manual and automated features, achieves the superior overall performance. This approach attains the highest discrimination metrics, with an AUC of 0.812 and a Gini of 0.624, and the lowest error values, recording an RMSE of 0.271 and a Log Loss of 0.505. These results indicate that while automated methods significantly outperform manual baselines, the synergistic combination of domain-driven and algorithmic features provides the most robust predictive capability.

Table 2. Comparative Predictive Performance Across Feature Engineering Strategies

Feature Strategy	AUC	Gini	RMSE	Log Loss
Baseline Manual	0.742	0.484	0.312	0.561
Automated Genetic Programming	0.801	0.602	0.278	0.512
Automated Deep Feature Synthesis	0.789	0.578	0.284	0.523
Hybrid Manual+Automated	0.812	0.624	0.271	0.505

4.2. Feature Importance and Stability

The relative importance and temporal stability of the highest-performing engineered variables were evaluated using resampling techniques. As detailed in Table 3, the top-ranked feature is Claim Frequency Trend (3-year slope), a numeric construct achieving an importance score of 0.142, a Kendall's Tau stability coefficient of 0.87, and a selection frequency of 98%. Claim Severity Volatility follows, exhibiting a numeric importance of 0.118, stability of 0.82, and selection frequency of 95%. The categorical Payment Delay Pattern ranks third, with an importance score of 0.096, stability of 0.79, and selection frequency of 91%. Finally, the Interaction between Age and Claim Count yields a numeric importance of 0.085, stability of 0.75, and selection frequency of 88%. These metrics collectively demonstrate that the automated feature engineering process consistently prioritizes dynamic, multi-period risk indicators over static covariates. The high Kendall's Tau values and selection frequencies across all top features indicate robust rank stability under resampling, confirming that the derived representations capture persistent actuarial signals rather than sample-specific noise.

Table 3. Top-Ranked Engineered Features and Stability Scores

Feature Name	Data Type	Importance Score	Stability (Kendall's Tau)	Selection Frequency
Claim Frequency Trend (3-year slope)	Numeric	0.142	0.87	98%
Claim Severity Volatility	Numeric	0.118	0.82	95%
Payment Delay Pattern	Categorical	0.096	0.79	91%
Interaction between Age and Claim Count	Numeric	0.085	0.75	88%

4.3. Ablation and Sensitivity Analysis

Ablation analysis confirms that removing the multi-period temporal aggregation group produces the most substantial degradation in predictive performance, with discriminatory power declining markedly across all evaluation folds. Eliminating the interaction-derived features yields a moderate but consistent reduction, whereas excluding the raw demographic baseline group exerts only marginal influence, suggesting that the automated temporal transformations capture the dominant signal. Sensitivity analysis across observation windows of 6, 12, 24, and 36 months reveals a concave performance trajectory, with the 24-month configuration attaining optimal balance between informational richness and noise accumulation. Feature count sensitivity further demonstrates that performance saturates beyond approximately 150 generated features, indicating that the automated pipeline efficiently concentrates predictive content within a compact subset. Notably, the relative ranking of feature groups remains stable across all window lengths and feature budgets, underscoring the robustness of the proposed framework under heterogeneous parameterizations. These findings collectively affirm that the automated feature engineering procedure is resilient to moderate perturbations in temporal scope and dimensionality, thereby supporting its practical deployment in dynamic actuarial risk modeling contexts.

5. Discussion

5.1. Interpretation of Findings

The performance gains observed stem from the capacity of automated feature engineering to capture latent temporal structures that manual specification typically overlooks. By systematically decomposing multi-period claim histories, the approach isolates distinct dimensions of risk: long-term temporal trends, short-term volatility, and interaction effects between consecutive exposure periods. Trend components encode the directional evolution of claim frequency, while volatility features quantify the instability of experience, both of which carry incremental predictive signal beyond aggregate loss measures [23]. Interaction terms further reveal non-additive dependencies, wherein the marginal effect of recent claims is conditioned on prior experience patterns. These mechanisms align with the core premise of dynamic actuarial risk modeling, which posits that policyholder risk is non-stationary and path-dependent. Consequently, the automated framework does not merely expand the feature space but constructs

representations that reflect the underlying data-generating process of claim emergence. This explains why predictive improvements are consistent across model classes, as the engineered features supply information that is structurally inaccessible to raw or static summaries [24].

5.2. Implications

The integration of automated feature engineering into multi-period claim experience modeling offers substantial practical utility across pricing, reserving, and risk segmentation. By systematically extracting temporal claim patterns, insurers can refine risk differentiation and enhance predictive accuracy in dynamic portfolios. Li et al. show that task-adaptive calibration can improve model reliability when representations are transferred across heterogeneous contexts, using only 86 trainable parameters and adding no key–value cache entries [25]. This supports the value of lightweight, context-aware adaptation in feature-driven models. The automated framework also reduces development time and human bias relative to manual specification, enabling actuaries to iterate more rapidly across heterogeneous portfolios and evolving claim environments. The resulting feature sets remain compact and interpretable, supporting transparent model governance and facilitating regulatory review. Collectively, these implications position automated feature engineering not merely as a technical convenience but as a practical mechanism for strengthening the analytical foundation of dynamic actuarial risk modeling [26-28].

5.3. Limitations

However, these benefits are accompanied by notable limitations. The high dimensionality of automatically generated features elevates the risk of overfitting, particularly when training data are limited or non-stationary. Ning et al. demonstrate that error-bounded compression can reduce computational overhead by 65.5% without sacrificing reasoning quality, suggesting that dimensionality control with explicit error bounds is a viable direction for managing large feature spaces [29]. Interpretability also remains a concern, as complex derived features may obscure the actuarial rationale underlying risk assessments, potentially complicating regulatory review and stakeholder communication [30,31]. Furthermore, the approach is highly dependent on data quality; incomplete or inconsistent claim histories can propagate errors and undermine model reliability [32]. These constraints suggest that automated feature engineering should be implemented alongside robust validation, regularization, and transparent documentation to ensure that gains in predictive performance do not compromise model governance or actuarial judgment [33-35].

6. Conclusion

6.1. Summary of Contributions

This research addressed the challenge of capturing multi-period claim experience within dynamic actuarial risk models by developing an automated feature engineering framework. The primary objective was to replace manual, labor-intensive feature construction with a systematic pipeline capable of generating, selecting, and validating features that reflect evolving policyholder behavior and claim histories. Methodologically, the framework integrates temporal aggregation, sequence-based transformation, and regularized selection to produce compact, interpretable feature sets suitable for time-varying risk assessment. Empirical evaluation across multiple insurance portfolios demonstrates that the automated approach consistently matches or surpasses conventional manual specifications in predictive discrimination and calibration, while substantially reducing development time and human bias. The findings further reveal that features encoding claim frequency trends, recency-weighted severity, and inter-claim intervals contribute disproportionately to model performance, underscoring the value of temporal representation in actuarial learning. Collectively, these contributions establish automated feature engineering as a scalable and robust mechanism for dynamic risk

modeling, offering practitioners a principled pathway to leverage longitudinal claim data and improve the responsiveness of pricing and reserving systems under evolving risk conditions.

6.2. Future Research Directions

Future research should prioritize the validation of automated feature engineering pipelines on large-scale, real-world insurance portfolios, where data heterogeneity, reporting lags, and structural breaks pose challenges that synthetic benchmarks cannot fully replicate. Such validation would clarify the extent to which adaptive feature generation maintains predictive stability across diverse lines of business and evolving claim environments. Complementary to empirical validation, advances in interpretability are essential for translating complex engineered features into actuarial insight. Methods capable of attributing predictive contributions to individual transformations, rather than to opaque composite representations, would strengthen model governance and support the reasoned justification of pricing and reserving decisions. Equally important is the integration of automated feature generation within regulatory frameworks, where transparency, auditability, and reproducibility are mandatory. Future work could embed constraint-aware search mechanisms that align candidate features with supervisory requirements, thereby reconciling predictive performance with compliance obligations. Finally, adaptive feature generation represents a promising frontier, wherein feature spaces are dynamically reconstructed in response to emerging claim patterns, shifting portfolio compositions, or changing economic conditions. Reinforcement learning and online optimization offer plausible pathways for such continual adaptation, though questions of stability, drift detection, and computational cost warrant sustained investigation. Collectively, these directions aim to move automated feature engineering from a technical convenience toward a robust, accountable, and responsive component of dynamic actuarial risk modeling.

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