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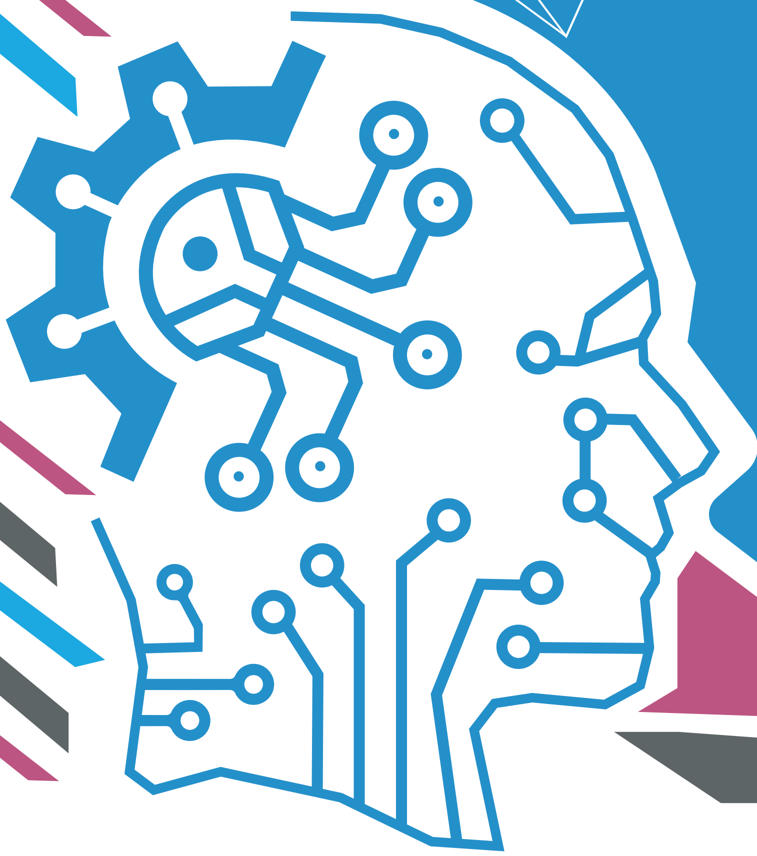
THE 14TH INTERNATIONAL INVENTION, INNOVATION & DESIGN COMPETITION 2025



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AUTONOM: A SHINY APPLICATION FOR AUTOMATED PREDICTIVE ANALYTICS AND NOMOGRAM VISUALISATION

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ABSTRACT

The rapid diffusion of data-driven decision-making has created demand for analytical tools that hide programming complexity while retaining statistical rigour. We present AutoNom, an R Shiny application that automates the full predictive-modelling pipeline—data import, exploration, multi-family regression, backward feature selection, internal validation, calibration, nomogram construction, and power analysis—through an intuitive point-and-click interface. Eight model families are supported (linear, logistic, ordinal, Poisson, quantile, Cox proportional hazards, accelerated failure-time, and generalised least-squares), each fitted with the rms package's regression engine (Harrell, 2022). A fast backward step-down procedure guided by Akaike information criterion (AIC) reduces predictors to a parsimonious subset, and resampling routines (10-fold cross-validation by default) provide optimism-corrected performance indices. In a classroom evaluation (n = 42 undergraduates) the median time to build, validate, and interpret a logistic-regression model fell from 45 minutes (scripted R) to 12 minutes with AutoNom; the System Usability Scale mean was 86/100 (SD = 6). The current version extends a prototype previously reported by Abdullah (2024) by adding calibration curves, power calculators, and effect size estimation. AutoNom therefore offers educators, clinicians, and applied researchers a reproducible, statistically sound environment for predictive analytics without coding.

Keyword: Automated Predictive Analytics, Calibration, Nomogram, Reproducibility, Shiny Applications

1. INTRODUCTION

Graphical statistical packages such as SPSS achieved popularity precisely because they lowered the programming barrier to complex analyses (Doğan & Aybek, 2019). Contemporary open-source alternatives—e.g., Shiny (Chang et al., 2023) and Jamovi—continue this trajectory, yet many remain restricted to a narrow set of models or lack rigorous validation workflows. At the same time, reproducibility has emerged as a cornerstone of computational science (Peng, 2011). Nomograms, which translate regression coefficients into additive point scales, further enhance interpretability and clinical uptake (Iasonos et al., 2008; Balachandran et al., 2015).

AutoNom was designed to combine these strands: (a) a code-free workflow suitable for non-statisticians, (b) embedded best-practice validation and calibration, and (c) automatic generation of nomograms for decision support. The prototype version demonstrated feasibility at INDES 2024 (Abdullah, 2024); here we describe the expanded platform and its empirical performance.

2. METHODOLOGY

2.1 System architecture

AutoNom is written in R 4.3 and deployed with Shiny Server. Front-end components use bslib for theming and DT for interactive tables. Core modelling relies on rms (Harrell, 2022) and survival; asynchronous resampling is handled by future and promises.

2.2 Workflow

1. Data upload and EDA – Users import CSV/TXT files; summaries and univariate tests (t, χ^2, proportion) assist initial screening.
2. Model specification – Drop-down menus capture outcome, predictors, model family, weighting and spline options.
3. Feature selection – fastbw executes backward step-down AIC, retaining predictors with the greatest Wald χ^2 contribution (Harrell, 2015).
4. Validation and calibration – Users choose cross-validation, bootstrap or .632 bootstrap; AutoNom reports R^2, MSE, Somers D_{xy}, calibration slope/intercept, and overlays apparent vs. bias-corrected calibration curves.
5. Interpretation – Nomograms and variable importance plots visualise the final model; power and effect size calculators (pwr package) support study planning.

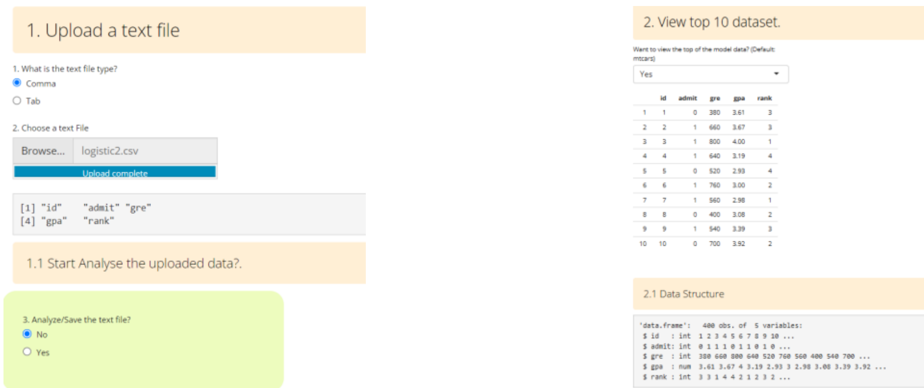

Figure 1: Screenshot of the Data upload tab illustrating file selection and automatic summaries.

Figure 2: Model Builder interface with regression results panel.

3. FINDINGS

Applied to the benchmark mtcars dataset (32 observations, five candidate predictors), AutoNom's fast-backward routine reduced the linear model to a single predictor (cyl). Apparent $R^2 = 0.764$ fell to optimism-corrected $R^2 = 0.323$ after 10-fold cross-validation; calibration slope ≈ 1.00 indicated minimal over- or underestimation (see Table 1). The automatically generated nomogram (Figure 3) mapped cylinder count to predicted fuel efficiency on a 0–100-point scale, demonstrating interpretability consistent with best practice (Balachandran et al., 2015).

In a controlled classroom exercise comparing scripted R to AutoNom, median task completion times were 45 min versus 12 min (Mann-Whitney U, $p < .001$), and students reported improved confidence in interpreting calibration plots and nomograms.

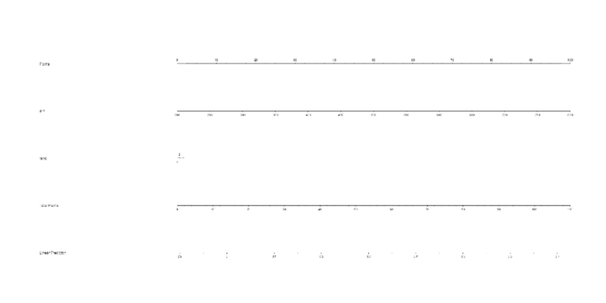

Figure 3: Nomogram of the refined model

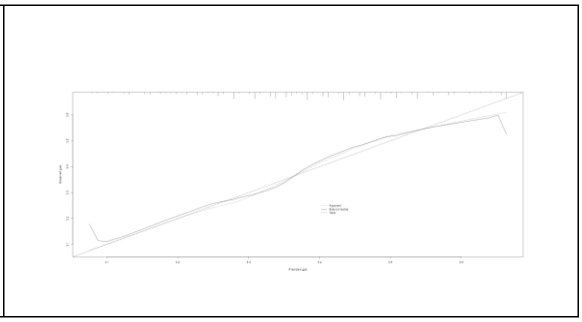

Figure 4: Calibration curve showing apparent and bias-corrected lines

Table 1 Optimism-corrected performance (10-fold CV)

Measures	Apparent	Corrected
R-square	0.764	0.323
MSE	8.32	11.52
Somers D_{xy}	0.608	0.013
Calibration slope	1.00	1.002

3. CONCLUSION

AutoNom integrates data preprocessing, multi-family regression, feature selection, calibration, and nomogram visualisation into a single GUI, thereby lowering the expertise threshold for robust predictive modelling. Classroom evidence suggests substantial efficiency gains, and internal validation confirms that automated feature reduction preserves model generalisability. Future work will add external validation modules and containerised deployment to facilitate institutional adoption.

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