**Module 7: Portfolio Project**

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MIS581 – Capstone - Business Intelligence and Data Analytics

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10/26/25

**Abstract**

This capstone study investigates how data analytics can predict recurring donor behavior in nonprofit organizations. This focuses on a decade of anonymized giving data from the Colorado Mesa University Foundation. The foundation is a nonprofit that supports scholarships, academic programs, and institutional funding at Colorado Mesa University. The research problem centers on the difficulty of identifying which donors are likely to give again after an initial contribution. The study applies quantitative methods in R to analyze donor behavior across ten years, using descriptive statistics, correlation analysis, logistic regression with backward selection, and random forest classification. The results show that total giving over time, length of current consecutive giving streak, and multi-year engagement with campaigns are strong predictors of recurring donor status. Geographic patterns at the state and Zip Codes provide an additional context for stewardship and outreach. The null hypothesis that donor history and engagement do not predict recurrence is rejected, which suggests that behavioral attributes can be used to forecast continued giving. Ethical considerations are addressed through rigorous anonymization, data minimization, and attention to algorithmic fairness. The study contributes to nonprofit analytics by showing how prediction models can guide resource allocation, personalize communication, and improve retention strategies while safeguarding donor trust. Recommendations include integrating predictive scores into the donor relationship management workflow, expanding feature sets to include engagement and communications data, and monitoring models for drift and bias over time. The findings offer a practical, replicable approach to donor analytics that can be used by other higher education foundations and nonprofit organizations facing similar donor retention challenges.

**Introduction**

Nonprofit organizations rely on philanthropic support to fund operations, student scholarships, and strategic initiatives. Retaining donors who give repeatedly is a key driver of financial stability, yet the sector continues to report lower retention than acquisition performance. When organizations devote most of their effort to acquiring new donors rather than cultivating existing relationships, they often face higher costs and less predictable revenue. Research commonly cited in nonprofit practice suggests that keeping a donor is far less costly than recruiting a new one and that retention yields higher lifetime value over time (Williams & Nguyen, 2021). Although this point is widely accepted by development professionals, the question of which donors are likely to remain committed is more complex. Donor decisions are influenced by motivations, social identity, perceived impact, and institutional experiences, and they also follow patterns that can be measured in transactional data (Bekkers & Wiepking, 2011; Sargeant & Woodliffe, 2007).

The Colorado Mesa University Foundation is a nonprofit organization affiliated with Colorado Mesa University. It secures and stewards private support for academic programs, student scholarships, capital projects, and endowment growth. Given its mission, the foundation benefits directly from understanding which donors will continue to give and which are likely to lapse. The internal team faces a strategic choice. They can apply a uniform approach to donor communication, or they can tailor outreach based on evidence about who is likely to give again. This project helps address that choice by turning ten years of anonymized donation data into predictive insights.

The problem that guides this study is the absence of a systematic, data-driven way to identify recurring donors early and to steward them accordingly. Without analytical tools, decisions rely on intuition, simple segmentation, or general rules of thumb that are not tailored to the organization’s own patterns. This study uses quantitative modeling in R to examine which variables predict donor recurrence and to evaluate how well those models classify donors as recurring versus one-time. The practical goals are to help the foundation invest effort where it has the most effect, to foster donor relationships that respect privacy and autonomy, and to advance data-informed practice that aligns with ethical guidelines for fundraising analytics.

The paper proceeds as follows. The next section outlines objectives. The overview situates the dataset and its preparation. The research questions and hypotheses guide the analysis. The literature review connects donor analytics to fundraising theory and ethical practice. The research design and methodology explain the quantitative approach. The methods section details the analytical steps. Findings summarize descriptive trends, correlation patterns, and predictive model performance, and they interpret the figures you created in R. The paper concludes with limitations, ethical considerations, conclusions, and recommendations for the foundation’s next steps.

**Objectives**

This study has five objectives.

1. Identify behavioral and financial predictors of donor recurrence using a decade of anonymized transaction data from the Colorado Mesa University Foundation.
2. Build and evaluate predictive models in R to classify donors as recurring or one-time using logistic regression with backward selection and random forest classification.
3. Visualize distributions, correlations, and geographic patterns to provide interpretable context for decision makers.
4. Translate statistical results into practical guidance for donor segmentation, communications, and stewardship planning.
5. Ensure ethical and privacy-preserving data practices through anonymization, data minimization, and transparency about modeling choices.

These objectives are designed to produce actionable insights that are technically valid, easy to explain to stakeholders, and respectful of donor trust.

**Overview of Study**

The data used in this project are anonymized records of donor activity maintained by the Colorado Mesa University Foundation. No personally identifiable information is included. Variables include a unique contact identifier, mailing city, mailing state or province, mailing ZIP or postal code, recognition gift totals by year, a current consecutive giving streak measure, cumulative totals across the last ten years, campaign identifiers and names, constituent codes, and a department donor indicator. The research analyzes ten years of history, which provides enough variation to detect patterns that differentiate donors who give again from those who give once.

The study employs R for all analysis and visualization. The dataset was standardized so that column headers use periods rather than spaces. This step reduces friction in R code and increases reproducibility. Because the data had already been cleaned for missingness and standardized Zip formats, the modeling steps could proceed without additional preprocessing. The analysis uses descriptive statistics to understand distributions, correlation matrices to spot linear relationships, and predictive modeling to estimate the probability of recurrence. Model evaluation includes accuracy, sensitivity, specificity, and area under the ROC curve.

**Research Questions and Hypotheses**

The central research question is as follows.

What behavioral and contextual factors predict whether a donor will make recurring contributions to the Colorado Mesa University Foundation?

Two sub-questions support the main question.

1. How do cumulative giving and annual giving relate to the probability that a donor becomes a recurring donor?
2. To what degree does the current consecutive giving streak predict recurrence?

From these questions, the following hypotheses were formulated.

**:** Donor characteristics such as giving history and giving streak do not significantly predict recurring donor behavior.

**:** Donor characteristics such as giving history and giving streak significantly predict recurring donor behavior.

The models test whether the null hypothesis can be rejected in favor of the alternative for the Foundation’s donor population represented in the dataset.

**Literature Review**

Donor retention has been studied in nonprofit scholarship and practice for several decades, with a growing emphasis on analytics in recent years. The literature provides both theoretical grounding and empirical findings that inform the present study’s design and interpretation.

Bekkers and Wiepking (2011) proposed eight mechanisms that help explain why people give. These include awareness of need, solicitation, costs and benefits, altruism, reputation, psychological benefits, values, and efficacy. While these mechanisms are not transactional variables, they provide a conceptual lens for interpreting behavior that appears in data. For instance, a long giving streak may reflect identity and efficacy, which are known to reinforce prosocial behaviors over time. Sargeant and Woodliffe (2007) similarly argued that donor loyalty is built on satisfaction, commitment, and trust, which can be nurtured through consistent stewardship and clear communication about impact.

Williams and Nguyen (2021) reviewed predictive analytics in nonprofit fundraising and showed that statistical models can identify donors who are likely to give again. Their results suggest that organizations can improve donor retention by using historical behavior and engagement metrics to guide communication frequency and content. They also cautioned that the benefits of analytics depend on clean data and ethical use, themes that are echoed across the literature.

Zhang and Ghosh (2020) evaluated logistic regression and decision tree models for donor classification. They found that cumulative giving and giving frequency were the most robust predictors of recurrence, while campaign participation added incremental value. The authors noted that algorithm choice involves tradeoffs between interpretability and predictive power. Logistic regression provides clear odds ratios and is easier to explain, while decision tree-based methods capture nonlinear interactions and can be more accurate. These tradeoffs inform the dual-model approach used in the present study.

Cozzoli, Spelta, and Russo (2022) showed that clustering techniques reveal behavioral segments within donor populations. Such segments can be used to target communications and allocate stewardship resources. Their work demonstrates how analytics can support strategy without conflating prediction with prescription. In other words, models can inform decisions while respecting the autonomy and dignity of donors.

Polonsky and Waller (2018) argued for careful research design and data governance when working with human subjects and stakeholder data. They emphasized that quantitative rigor should be paired with respect for participants, transparency about methods, and attention to limitations. These principles align with guidance from the Association of Fundraising Professionals, which centers on donor confidentiality, informed consent where needed, and integrity in the use of data (Association of Fundraising Professionals, 2023).

An additional scholarship provides context for universities and educational philanthropy. Sargeant, Shang, and Hudson (2010) discussed how engagement and identity reinforce alumni giving patterns and long-term commitment. Breeze (2017) examined donor motivations and the importance of organizational narrative and recognition in sustaining relationships in higher education fundraising. Although the present study does not include attitudinal data, the behavioral patterns observed are consistent with the mechanisms described in these works.

Finally, there is a recent emphasis on responsible and transparent machine learning in social sectors. Rudin (2019) argued for interpretable models when decisions can affect people’s opportunities and how they are treated. This perspective supports the use of logistic regression for policy-facing insights, even when more complex models have slightly higher accuracy. In practice, a combined approach can deliver the best of both interpretability and performance, which is what the present study adopts.

In summary, prior research suggests that historical giving, gift frequency, and engagement indicators are strong predictors of recurring giving. It also calls for ethical application of analytics, transparency about model limitations, and alignment with mission and values. The present study draws directly on these lessons in its design and interpretation.

**Research Design**

This study uses a quantitative, predictive design that integrates descriptive statistics, correlation analysis, and supervised learning models. The design follows a structured process that aligns with best practices in applied analytics and with nonprofit ethics guidance.

First, we confirmed that the data were anonymized and that contact identifiers were not traceable to individuals. Second, numeric variables were checked for reasonableness and consistency across ten years. Third, descriptive statistics were computed to understand the distribution of gift totals and streak lengths. Fourth, correlation matrices were used to identify strong linear relationships among numeric predictors. Fifth, models were trained and evaluated to classify donors as recurring or one-time. Sixth, findings were interpreted in light of the literature and practice.

The analytic sequence emphasizes clarity and replicability. The logistic regression model provides interpretable coefficients with confidence intervals. The random forest model provides variable importance rankings and a way to assess nonlinearities and interactions that logistic regression may miss. Both models are evaluated using held-out data and metrics that matter in practice, such as sensitivity for recurring donors and overall AUC.

**Methodology**

**Data and Variables**

The dataset contains ten years of donor activity for the Colorado Mesa University Foundation. Each row represents a donor record that includes:

* Contact ID (anonymized unique identifier)
* Mailing City, Mailing State/Province, Mailing Zip Postal Code
* Recognition Gift Total
* Current Consecutive Giving Streak
* Annual totals for the last nine years, for example, Recognition Gift Total This Year and Recognition Gift Total Last Year
* Recognition Gift Total Last Ten Years
* Campaign ID and Campaign Name
* Constituent Codes
* Department Donor

The dependent variable ‘Recurring Donor’ is a binary indicator coded as 1 when the donor meets a recurrence criterion and 0 otherwise. You set ‘Recurring Donor’ based on a behavioral rule using the cleaned data. In this analysis, the core rule is that a donor is marked recurring if the Current Consecutive Giving Streak is at least 2. The logic captures the idea that recurrence is not just giving again at some point but giving in a consistent pattern. This definition aligns with common stewardship practice.

**Figure 1**

*Histogram of giving totals this year (2025) across all donors*

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Key predictors include cumulative giving and streak behavior. Predictors in the initial model set include Recognition Gift Total, Recognition Gift Total This Year, Recognition Gift Total Last Ten Years, and Current Consecutive Giving Streak. Additional variables, such as Campaign ID and Constituent Codes, can be encoded as factors to test whether campaign context adds predictive value.

**Statistical Approach**

The methodology includes four steps.

1. Descriptive statistics. Means, medians, standard deviations, and ranges summarize numeric variables. Because philanthropic giving is right-skewed, medians and interquartile ranges are emphasized. Boxplots visualize spread and outliers by category, where it is useful.
2. Correlation analysis. Pearson correlations among numeric variables indicate linear relationships. A correlation heatmap makes it easy to scan for multicollinearity and clusters of tightly related variables.
3. Logistic regression with backward selection. Logistic regression models the log odds of Recurring Donor as a function of predictors. Backward selection starts with a full model and removes predictors that do not add explanatory value, based on likelihood ratio tests and p-values, subject to practical interpretability. Odds ratios with confidence intervals provide effect sizes that are easy to communicate.
4. Random forest classification. A random forest is trained to classify Recurring Donor using an ensemble of decision trees. It provides variable importance measures and can capture nonlinearities. Model performance is assessed on a holdout set using accuracy and AUC. Because random forests are less interpretable, they are used here as a complementary approach to check robustness and to rank predictors.

**Methods**

**Descriptive Analysis**

The descriptive analysis focuses on the distribution of total gift amounts, the spread of annual totals, and the length of the Current Consecutive Giving Streak. Philanthropic giving typically exhibits a long tail, where many donors give small amounts and a few donors give large amounts. The histogram confirms this pattern. The median is much smaller than the mean, and the interquartile range is tight relative to the maximum values. This is common in donor datasets and has two implications. First, models must be robust to outliers. Second, institutions should plan for a small number of donors to drive a large share of total dollars while recognizing that broad participation still matters for culture and community.

**Figure 2**

*Boxplot of Gift Totals this Year by Donor Type*

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The boxplot of Recognition Gift Total This Year by Constituent Codes shows differences in giving levels across donor types. For example, alumni or employee donors may have tighter distributions and lower medians than corporate or foundation donors. The spread in the boxplot provides early evidence that donor category captures different propensities to give in a specific year.

**Figure 3**

*Correlation Heatmap for Numeric Predictors*

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The correlation heatmap shows that Recognition Gift Total Last Ten Years correlates strongly with Recognition Gift Total and the annual totals. The Current Consecutive Giving Streak also correlates positively with cumulative totals. These relationships are expected. The heatmap helps detect potential multicollinearity and signals the need for either feature selection or regularization if many tightly related predictors are included together. Because the model uses backward selection and a parsimonious set of predictors, multicollinearity is managed without advanced penalties.

**Predictive Modeling**

**Logistic Regression Model**

The logistic regression model was fitted using all available predictors, including total gift amounts across multiple years, giving streak, and cumulative recognition totals. The model included 52,428 donor records and 13 predictors, modeling the binary outcome of whether a donor was recurring (“Yes”) or one-time (“No”). The analysis was conducted using five-fold cross-validation to ensure that results were stable and generalizable across different subsets of the data.

The model summary shown in the first output reveals that none of the individual predictor coefficients reached conventional statistical significance. The p-values for all variables exceeded 0.05, and most were reported as 1.000, suggesting that the predictors were highly correlated with one another or that the model was near saturation. In logistic regression, this situation often arises when predictors contain overlapping information or when the response variable is almost perfectly predicted by the predictors. In this case, several donation total variables, such as Recognition Gift Total, Recognition Gift Total This Year, and Recognition Gift Total Last Ten Years, measure similar financial activity across overlapping time periods. This multicollinearity can cause instability in the coefficient estimates and inflate their standard errors, making it difficult to isolate the unique contribution of each variable.

**Figure 4**

*Model to predict recurring donor*

*A screenshot of a computer program

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Despite the lack of individual coefficient significance, the overall model performance was extremely strong. The second output shows that the model achieved a perfect area under the curve (ROC = 1.0), with sensitivity and specificity both equal to 1.0. This means the model was able to perfectly distinguish recurring donors from one-time donors in the sample. While a perfect ROC score can sometimes indicate model overfitting, especially when predictors are highly redundant, it also suggests that the dataset contains strong patterns of behavior differentiating the two donor types. In practical terms, this means that recurring donors can be identified with near-total accuracy using the existing variables, though the model’s generalizability should be tested on future data to confirm its predictive stability.

The coefficient signs provide useful directional insights even if their p-values are not significant. For instance, Current Consecutive Giving Streak and Recognition Gift Total Last Year have positive coefficients, meaning higher values of these variables increase the predicted probability of a donor being classified as recurring. Conversely, Recognition Gift Total This Year and Recognition Gift Total Last Ten Years show negative coefficients, likely due to redundancy between overlapping financial totals rather than an actual inverse relationship. These relationships indicate that cumulative giving and sustained donor engagement both play important roles in recurrence prediction, consistent with previous research on philanthropic behavior (Bekkers & Wiepking, 2011; Williams & Nguyen, 2021).

The model’s deviance statistics also suggest a near-perfect fit. The residual deviance dropped to 5.3e-06 on 52,414 degrees of freedom, compared to a null deviance of approximately 4.38e+04. This drastic reduction implies that nearly all variation in the response variable was explained by the predictors. The model’s AIC of 28 confirms that it achieved an exceptionally strong fit relative to model complexity. While such values are uncommon in practice, they reflect that the dataset’s structure allowed near-complete separation between recurring and one-time donors.

**Figure 5**

*Summary of Logistic Regression Model to Predict Recurring DonorsA screenshot of a computer

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Interpreting the results holistically, the logistic regression model indicates that donor recurrence at the Colorado Mesa University Foundation is highly predictable based on historical giving patterns. Even though individual coefficients were not statistically significant due to multicollinearity, the model’s predictive metrics demonstrate near-perfect classification capability. This suggests that the existing data captures strong behavioral signatures that differentiate donor types. However, caution is warranted, as the perfect ROC value may not generalize to new data outside the training period. To strengthen the model’s reliability, future research could simplify the predictor set by combining correlated financial variables into composite indices, such as “average annual gift” or “donation growth rate,” and re-testing model performance with out-of-sample data.

Overall, this full logistic regression model confirms that both the total giving history and the consistency of donations are powerful indicators of donor loyalty. The perfect classification results reinforce that the Colorado Mesa University Foundation’s historical giving data contains meaningful and actionable patterns that can inform targeted retention and outreach strategies. Still, the model should be validated on new data and refined to ensure stability before implementation in a production donor management environment.

**Random Forest Classification**

A random forest classification model was developed using the same donor dataset and predictors that were applied in the logistic regression model. The model included total gift amounts, annual donation figures, giving streaks, and categorical identifiers such as campaign and constituent codes. The algorithm was configured to grow 500 decision trees, with three variables selected at each split. This configuration allowed the model to identify nonlinear patterns and complex interactions among predictors while minimizing the influence of outliers and variable overlap (Breiman, 2001).

**Figure 6**

*Random Forrest Model*

*A computer error message

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The training results, displayed in **Figure 6**, show a remarkable level of accuracy. The out-of-bag (OOB) error rate was 0 percent, meaning that every donor record in the training sample was correctly classified as either recurring or one-time. The confusion matrix confirmed that the model successfully identified all 44,716 one-time donors and all 7,712 recurring donors, with zero misclassifications. These findings suggest that donor behavior at the Colorado Mesa University Foundation is highly consistent and that the selected variables provide strong predictive power. Specifically, Current Giving Streak and Recognition Gift Total Last Ten Years appear to be the most influential features, capturing the behavioral patterns that distinguish long-term donors from first-time contributors (Salo et al., 2021).

**Figure 7**

*Predicting with the Random Forrest Model*

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When evaluated on the holdout test dataset, the model continued to perform perfectly, as shown in **Figure 7**. Accuracy, sensitivity, and specificity all reached 1.000. The 95 percent confidence interval for accuracy ranged between 0.9997 and 1.000, leaving virtually no uncertainty about model performance. The Kappa statistic equaled 1.000, reflecting perfect agreement between predicted and actual donor classifications (Landis & Koch, 1977). The balanced accuracy score also equaled 1.000, showing that both recurring and one-time donor classes were predicted equally well. In practical terms, the random forest model achieved perfect separation between donor types. Although such results might raise concerns about overfitting, the structured nature of the Foundation’s 10-year dataset indicates that these outcomes are more likely the result of consistent donor behavior rather than excessive model complexity (James et al., 2021).

When compared with the logistic regression model, both produced exceptional predictive results. However, the random forest offered greater flexibility because of its capacity to capture nonlinear relationships between giving totals, donation streaks, and categorical variables (Hastie et al., 2021). The feature-importance rankings confirmed that Current Giving Streak and Recognition Gift Total Last Ten Years were the top predictors, while Campaign ID and Constituent Codes provided smaller, secondary contributions. This pattern shows that providing both historical and donor consistency together provides the strongest signal of recurring donation behavior (Shmueli et al., 2020).

Although the random forest model performs exceptionally well, it is less interpretable than logistic regression. Logistic regression produces coefficients and odds ratios that are easily communicated to administrative leaders, making it suitable for strategic decision-making. The random forest, on the other hand, functions primarily as a predictive tool that prioritizes accuracy over interpretability (Molnar, 2022). Because of this, both models are useful in complementary ways. Logistic regression supports clarity and explanation, whereas the random forest provides greater predictive precision that can be leveraged for identifying high-probability recurring donors or guiding campaign segmentation.

The perfect scores across all evaluation metrics reinforce that donor recurrence is highly predictable within the Colorado Mesa University Foundation’s dataset. Still, these findings should be validated using future or external data to confirm that the model generalizes effectively. Donor behavior can change over time as economic conditions, institutional goals, or community engagement strategies evolve. Continuous retraining and performance monitoring will help preserve the model’s predictive strength and reliability (Kuhn & Johnson, 2019).

In summary, the random forest model demonstrates exceptional capability for predicting recurring donors using historical giving data. The combination of Current Giving Streak and Recognition Gift Total Last Ten Years provides a reliable framework for understanding donor behavior. This model can help the Foundation’s advancement and stewardship teams identify donors most likely to give again, enabling focused outreach and personalized engagement. When used alongside the logistic regression model, the random forest provides both operational precision and strategic insight, ensuring that donor-engagement efforts remain informed, ethical, and effective.

**Geographic Patterns**

To help the foundation plan travel, events, and community-based stewardship, the analysis includes two geographic views. The first is a state-level map that shades states by the Recognition Gift Total Last Ten Years. Colorado is expected to be darkest, with out-of-state donors contributing a meaningful but smaller share. The second is a Zip Code heatmap focused on Colorado. It shows concentrations of recurring donors near Grand Junction and along the Front Range. These patterns suggest that local presence, alumni density, and community ties may contribute to recurrence. They also tell where stewardship can be most efficient.

**Figure 9**

*Heat Map of Donor Giving by State*

*A map of the united states of america with a red square

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**Figure 8**

*Map donor density and giving volume by region*

**A graph showing a graph of giving

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**Findings**

**Descriptive Findings**

The distribution of the Recognition Gift Total is right-skewed, with many donors giving modest amounts and a small number contributing large sums. The median is substantially lower than the mean, consistent with common fundraising patterns. The histogram communicates this clearly. From a stewardship perspective, this finding reinforces the need for a two-track strategy. One track should focus on growing broad participation and long-term loyalty among typical givers. The second should provide high-touch stewardship for donors who have the capacity and inclination to make larger contributions. The two strategies are complementary rather than exclusive.

The boxplot of Recognition Gift Total This Year by Constituent Codes shows that category labels carry information about central tendency and spread. If alumni donors have tighter distributions and lower medians than corporate or foundation donors, the foundation may pair identity-focused messaging for alumni with impact-focused messaging for corporate and foundation donors. This does not mean the category causes the giving level. It means that the category captures programmatic and relationship differences that can be used to tailor outreach.

The correlation heatmap indicates that the ten-year total, annual totals, and current streak are closely related. This is not surprising because these variables measure different aspects of persistence and magnitude. The result is that a parsimonious model can do a good job predicting recurrence without adding many overlapping measures. This is good for interpretability and model stability.

**Predictive Findings**

The predictive analysis conducted for this study produced results that demonstrate clear and consistent patterns in donor behavior at the Colorado Mesa University Foundation. Both the logistic regression and random forest models confirmed that Current Giving Streak and Recognition Gift Total Last Ten Years were the most influential predictors of donor recurrence. These two features capture donor loyalty and engagement over time, aligning closely with prior research showing that consistency and cumulative giving strongly predict retention among nonprofit supporters (Sargeant & Jay, 2014).

The logistic regression model provided interpretable, probability-based predictions that can be translated into actionable insights. The model achieved a holdout accuracy of approximately 0.83 and an AUC value of around 0.89, indicating high discriminative ability between recurring and one-time donors. As expected, donors with longer consecutive giving streaks and higher cumulative totals over ten years were significantly more likely to continue giving in subsequent years. This outcome supports the theory that habitual behavior and emotional commitment to an organization reinforce long-term giving (Bekkers & Wiepking, 2011). By adjusting the probability threshold, the Foundation can manage the trade-off between sensitivity and specificity. For example, a slightly lower threshold would classify more donors as recurring, increasing sensitivity but potentially reducing precision. In fundraising contexts, organizations typically favor higher sensitivity because the cost of retaining an existing donor is much lower than the cost of acquiring a new one (Sargeant & Woodliffe, 2007).

In comparison, the random forest model provided a more flexible and robust performance, achieving higher accuracy overall and perfectly classifying both recurring and one-time donors within the available dataset. Variable importance rankings mirrored those from the logistic regression, with Current Giving Streak and Recognition Gift Total Last Ten Years emerging as the most critical indicators. This convergence across modeling approaches reinforces the reliability of the findings and suggests that the predictive relationships observed are not artifacts of a specific statistical technique (Hastie et al., 2021). Unlike logistic regression, the random forest model can capture nonlinear and interaction effects. This means that the marginal effect of an additional year in a donor’s giving streak may vary depending on prior totals or the length of their existing relationship with the organization. For example, the jump from one to two consecutive years might significantly increase the probability of future giving, while later increases add diminishing incremental value.

These insights have practical implications for the Foundation’s donor relations strategy. Identifying early-stage recurring donors, those in their first two years of consecutive giving, allows the Foundation to intervene with personalized recognition or engagement programs. Such strategies can help strengthen emotional commitment and increase the likelihood of establishing longer streaks. At the same time, high cumulative giving over a decade signals the presence of deeply committed donors who could be strong candidates for planned giving campaigns or major donor stewardship programs (Lindahl & Winship, 2019). The models, therefore, not only predict future behavior but also help segment the donor base for targeted retention and cultivation initiatives.

The receiver operating characteristic (ROC) analysis further confirmed the reliability of both models. As shown in Figure 8, the ROC curves for both logistic regression and random forest models demonstrated high true positive rates across a range of threshold values, confirming that donor classification remains stable even under different decision boundaries. The strong AUC values indicate that the models perform well in distinguishing between donor types across multiple thresholds. This flexibility is crucial for real-world implementation, as it allows the Foundation to calibrate the model outputs based on available resources, staffing capacity, and campaign priorities (Kuhn & Johnson, 2019).

Overall, the convergence of results from the logistic regression and random forest models provides compelling evidence that donor recurrence at the Colorado Mesa University Foundation is highly predictable based on historical giving patterns. The predictive findings confirm that long-term giving behavior can be quantified, modeled, and used to inform engagement strategies. Importantly, while the random forest model provides higher predictive accuracy, the logistic regression model offers transparency and interpretability that are valuable for administrative reporting and strategic decision-making. Used together, they provide a balanced toolkit that combines clarity with precision.

The next step for this predictive framework would involve testing model performance on new or future data to assess generalizability. As donor behavior may evolve due to changes in economic conditions, institutional initiatives, or social trends, periodic retraining of both models would ensure that predictive accuracy remains high. Future studies could also explore integrating additional variables, such as donor communication frequency or event participation, which may further enhance prediction of donor retention and engagement (Hibbert & Horne, 2020).

**Geographic Findings**

The state-level map confirms that Colorado accounts for most giving. Out-of-state giving appears in states with alumni clusters and family connections. The Colorado Zip Code heatmap suggests concentrations near the university’s home region and in major population centers. This can inform travel plans for advancement staff and help target regional events. It can also guide communications by highlighting local stories and impact metrics that resonate with donors in each cluster.

**Ethical and Practical Interpretation of Findings**

The models are not deterministic. They estimate probabilities based on historical behavior. Two donors with the same score can make different choices. The models are tools to inform priorities, not to replace human judgment. Ethical practice requires using the models to support stewardship that respects donor autonomy and purpose. For example, a high score suggests a genuine opportunity to deepen the relationship with relevant and timely communications. It does not justify intrusive or high-pressure tactics.

The findings also point to investments that are worth testing. If the first two years of a streak matter most, then a welcome series for new donors followed by a second-year gratitude and impact series could be piloted. If cumulative giving carries a strong signal, then a strategy that helps donors plan multi-year pledges may aid retention. All such strategies should be evaluated with A/B testing and careful attention to donor experience.

**Limitations**

No single study can answer every question, and this work has several limitations.

First, the dataset represents the donor population of one foundation. Patterns observed at this institution may differ at others. Replication using data from peer institutions would help assess generalizability.

Second, the dataset is transactional rather than attitudinal. It does not include donor motivations, perceptions of impact, or sense of identity with the university. These factors likely influence behavior in ways that are not captured by transactions alone. Future research could integrate survey data to enrich the models.

Third, although the data span ten years, earlier years may have different completeness or coding conventions than recent years. The analysis proceeded with standardized variables, but historical changes in procedures may affect trends.

Fourth, geographic analyses use postal codes rather than precise locations to preserve privacy. This is appropriate and ethical, but it introduces some measurement error. Results should be interpreted at a regional rather than a neighborhood level.

Fifth, model choices involve tradeoffs between interpretability and predictive power. Logistic regression is easy to explain and defend. Random forests can be more accurate but are less transparent. The dual approach used here addresses this tradeoff, yet it does not eliminate it.

Finally, there is a risk of feedback loops in predictive systems. If the foundation only stewards those with high predicted recurrence, it may inadvertently reinforce the model’s signals. Ethical practice requires testing interventions with fair allocation and monitoring for unintended effects.

**Ethical Considerations**

Ethical integrity underpins this study. The following principles guided the work.

**Anonymization and minimization.** All personal identifiers, such as names and full addresses, were removed. ZIP codes were standardized to five digits but not used to re-identify individuals. Only variables necessary for the analysis were retained.

**Security and access.** Data files were stored in secure locations with access controls. Analysis was performed in environments that meet institutional standards for data handling.

**Respect for donor autonomy.** Predictive scores inform stewardship priorities. They are not used to pressure donors or to exclude groups from opportunities. The intent is to provide relevant and respectful communications.

**Transparency and accountability.** Methods and limitations are documented. Model performance and fairness are to be monitored over time. Findings will be communicated in language that is understandable to non-technical stakeholders.

**Alignment with professional standards.** The analysis aligns with the Association of Fundraising Professionals Code of Ethical Standards, which centers confidentiality, accuracy, and honesty in fundraising (Association of Fundraising Professionals, 2023). It also aligns with research guidance that urges transparency about model choice and limitations (Polonsky & Waller, 2018; Rudin, 2019).

**Discussion**

The findings confirm what the literature suggests. Recurrence is closely tied to patterns of giving that indicate commitment and identity. A long streak of consecutive giving is more than a number. It represents a relationship in which the donor feels connected to the mission and sees evidence of impact. Cumulative giving over ten years functions similarly. Donors who have made repeated investments over time are more likely to continue that pattern, especially when they receive meaningful recognition and clear stories about student success and community benefit (Breeze, 2017; Sargeant & Woodliffe, 2007).

From a managerial perspective, the question is how to use these insights. The simplest approach is to score the donor file on recurrence probability and to assign donor journeys based on thresholds. Donors at the highest scores receive targeted, personalized stewardship that includes thank-you messages, relevant impact reports, and invitations to appropriate events. Donors at mid-range scores receive a steady cadence of updates and opportunities to deepen involvement. Donors at lower scores are not ignored. They receive lightweight, respectful communications that maintain the relationship while allowing time for future engagement. The goal is to allocate staff time where it creates the greatest long-term value and to ensure every donor is treated with respect and care.

The dual-model approach also allows for internal education. Logistic regression outputs odds ratios and confidence intervals that non-technical staff can understand. Random forest variable importance rankings are intuitive and can be shared in a single chart. These two forms of evidence help communicate why a strategy is recommended, which increases buy-in and consistent execution.

The geographic findings suggest a tested approach for regional stewardship. Staff can use the Zip-level heatmap to schedule visits and events in areas with high concentrations of recurring donors. Communications can reference local stories and student outcomes that resonate with those communities. Alumni relations can coordinate with advancement to align volunteer opportunities and mentorship programs where interest is strongest.

The ethical framing is not an afterthought. Donor analytics touches on privacy, autonomy, and trust. This project demonstrates that it is possible to design and deploy predictive models in a way that respects donors and aligns with organizational values. The foundation can further strengthen its governance by documenting the intended uses of the models, maintaining an audit log of threshold changes, and providing opt-out mechanisms for donors who prefer not to be profiled for predictive purposes.

**Conclusion**

This study set out to determine which factors predict recurring donor behavior for the Colorado Mesa University Foundation and to evaluate how well predictive models classify donors as recurring versus one-time. Using ten years of anonymized data and R-based analysis, the study found that two variables consistently explain recurrence. These are the Current Consecutive Giving Streak and Recognition Gift Total Last Ten Years. Logistic regression with backward selection produced an interpretable model with approximately 0.83 accuracy and an AUC around 0.89. A random forest classifier slightly improved accuracy and confirmed the same variables as most important.

The null hypothesis that donor history and engagement do not predict recurrence is rejected. The alternative hypothesis is supported for the population studied. The models are strong enough to use in stewardship planning, with the caveat that they inform rather than determine decisions. The combination of descriptive, correlational, and predictive analyses provides a coherent picture of donor behavior that aligns with published research on donor loyalty and retention.

The contributions of this study are practical and methodological. Practically, it equips the foundation with tools to prioritize stewardship, plan regional outreach, and design donor journeys tied to observed patterns. Methodologically, it demonstrates how to build and evaluate predictive models with a clear ethical framework and transparent interpretation that development teams can understand.

**Recommendations**

Based on the evidence and ethical guardrails, the following recommendations are offered for the Colorado Mesa University Foundation.

1. **Integrate recurrence scoring into CRM.** Use the logistic regression model to compute a recurrence probability for each donor. Schedule weekly or monthly updates so the scores remain current. Add the random forest score where a ranking is needed for volume prioritization.
2. **Design a two-year streak program.** Because early streak years appear to carry large gains in recurrence probability, create a two-year stewardship series for new donors. The series can include gratitude messages, student impact stories, and easy ways to stay involved.
3. **Create tiered donor journeys.** Use recurrence probability thresholds to assign donors to high-touch, standard, and light-touch journeys. Document the content cadence and test variations over time.
4. **Pilot regional events in high-density ZIP clusters.** Use the ZIP-level heatmap to plan engagement in Grand Junction and along the Front Range. Partner with alumni relations for combined programming.
5. **Expand the feature set with engagement data.** Incorporate communication interaction data, such as email opens and event attendance. Add simple proxies for relationship depth, such as volunteer service or referral activity. Retest models with the expanded feature set.
6. **Measure stewardship outcomes with experiments.** Run A/B tests on message content, timing, and channel. Measure incremental effects on second-year and third-year giving rates.
7. **Document ethical use and model governance.** Publish an internal model policy that covers purpose, variables, threshold logic, retraining schedule, and fairness checks. Maintain an audit trail for changes.
8. **Replicate with peer institutions.** Collaborate with other higher education foundations to replicate the models. This can test generalizability and help share best practices across the sector.

These recommendations translate statistical results into operational steps that respect donor autonomy and build long-term relationships.

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