OPTIMISING DONOR ASK STRATEGIES FOR LONG-TERM IMPACT

Part D - Report

GROUP 42

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Executive Summary

This report addresses critical challenges in World Vision Australia's (WVA) Bounceback campaign to optimise donor ask strategies for long-term financial sustainability. The aim was to develop a data-driven approach to replace WVA's current one-size-fits-all fundraising strategy, which risks donor fatigue through inappropriate ask amounts. The goal was to solve: "How might WVA segment donors and personalise ask amounts to maintain ongoing donations, minimise communication fatigue, and lower disengagement risk?"

The analysis conducted a three-phase approach. **Business understanding** revealed three critical challenges: rising ask amounts exceeding donor capacity, uniform multipliers across different campaigns despite varying responsiveness, and segmentation overlooking key donor attributes. **Exploratory Data Analysis** examined donor behaviour patterns, revealing quarterly giving trends with Q4 Christmas peaks, demographic concentration in older supporters (55+), and concerning year-over-year declining donations despite faster response times from loyal donors. **Predictive modelling** developed and validated two complementary models: Random Forest Classification model to predict donation bands (Small <$30, Medium $30-60, High $60-100) based on supporter characteristics. Multiple Linear Regression model to estimate precise donation amounts for personalised ask strategies.

Several critical findings show fundamental challenges to WVA's current approach:

- Donor Behaviour Patterns: Cumulative average paid amount emerged as the strongest predictor of future giving behaviour, contributing approximately 60% of model predictive power. This finding validates the hypothesis that donation history is more reliable than demographic or response-based segmentation.
- Seasonal Impact: Christmas and EOFY periods demonstrate significantly higher responsiveness and upgrade likelihood, with Christmas campaigns ranking among the top 15 predictors in the classification model.
- Tenure Stability: Longer tenure donors exhibit more stable giving behaviour, with high-band donors achieving 71% recall accuracy compared to 62% for medium-band donors, indicating that established donors can sustain gradual ask increases.
- Frequency vs Amount Trade-off: Analysis revealed that donation frequency is a stronger driver of total revenue than per-gift size, suggesting retention strategies should focus on sustaining giving habits rather than inflating individual asks.
- Age-Based Vulnerabilities: Donors aged 55+ contribute the most but also show visible churn risk, while younger donors contribute less but demonstrate potential for digital-first engagement strategies.

Based on the above-identified insights, comprehensive proposals were made through behaviour-based segmentation, replacing current methods with four data-driven segments based on donation history. Personalised ask strategy implements prediction-anchored amounts using weighted regression of the last three gifts, showing 61% improvement in prediction accuracy. Campaign optimisation applies seasonal multipliers reflecting natural giving patterns and realigns communication channels. Implementation is projected to achieve a 15-25% reduction in donor churn rate, potentially protecting significant portions of the identified $775k revenue at risk.

Several areas require development, including data enrichment through enhanced demographic capture and geographic indicators, advanced modelling with propensity scoring for sophisticated ask strategies, and validation requirements through controlled A/B testing. Operational challenges include technology infrastructure investments and staff training needs. Ethical considerations must ensure personalisation maintains donor privacy boundaries and avoids over-targeting tactics that could damage long-term relationships.

Business Background

World Vision Australia (WVA) is the largest international, non-governmental Christian charity in Australia, working to improve the lives of vulnerable children and their communities. A significant share of its funding comes from recurring donations, particularly through child sponsorship programs.

Therefore, to maintain long-term impact, retaining donors is essential. The Bounceback campaign supports this by strengthening connections with donors who may have reduced or paused their giving. Bounce-back focuses on re-engagement by reminding donors of the impact of their contributions and presenting clear, achievable opportunities to resume or increase support. For this campaign to succeed, WVA must strike the right balance between maintaining financial sustainability and respecting donor capacity and preferences.

The current fundraising model faces three key challenges:

1. Ask amounts are rising through multiplier-based calculations, which may exceed some donors' capacity or willingness to give, creating a risk of disengagement.
2. The same multipliers are applied across all campaign types, even though donor responsiveness differs between Christmas, Birthday, and Education.
3. Donor segmentation relies mainly on past response behaviour, overlooking attributes such as age, donation history, or giving potential, which reduces the ability to tailor requests effectively.

Consequently, WVA risks donor fatigue, disengagement, and lost revenue because its current approach uses broad, one-size-fits-all strategies for ask calculations and segmentation. A more data-driven approach is needed to personalise ask amounts, strengthen donor engagement, and sustain long-term giving.

Problem Statement

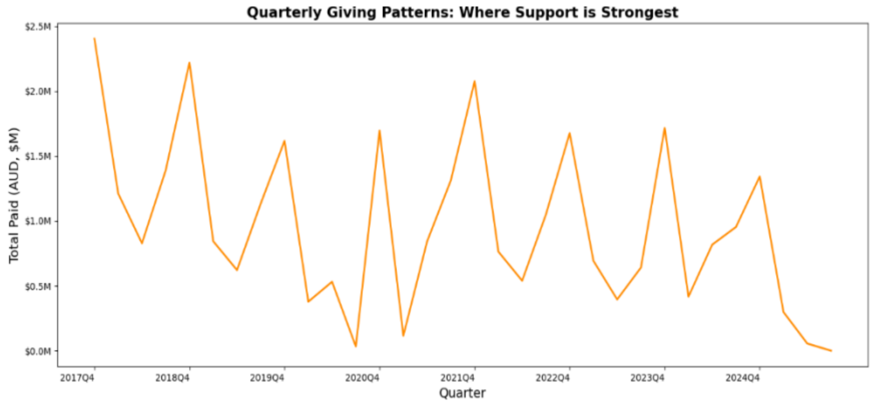
How might WVA segment its donors and personalise ask amounts in the Bounceback campaign to maintain ongoing donations, minimise communication fatigue, and lower the risk of disengagement?

Assumptions

- Dollar Handle Representation: The total paid donation amount is a reliable proxy for the donor's giving capacity.
- Post-Pandemic Data Reliability: Only post-2023 data is considered for dollar handle personalisation to avoid the influence of erratic donation behaviour during the pandemic.
- Ask Ladder Flexibility: WVA can adjust ask amounts within appeals without materially increasing operational costs.
- Communication Channels: A multi-channel approach (email, SMS, phone, social media, and direct mail) is available, with flexibility to vary message frequency by segment.
- Donor Responsiveness by Campaign Type: Responsiveness to appeals differs significantly by campaign (e.g., Christmas, Birthday, Education), and these variations can be captured and modelled.
- Segment Stability: Donor attributes such as age, income proxy (via dollar handle), and long-term giving patterns remain relatively stable over time and can be used for segmentation.
- Data Completeness: Key donor attributes (donation history, demographics, communication history) are sufficiently complete and reliable to support segmentation and modelling.
- Retention Priority: Retaining existing donors is more cost-effective than acquiring new ones, so optimisation efforts focus primarily on current supporters.
- Operational Readiness: WVA has the capacity to implement data-driven changes (e.g., personalised ask ladders, tailored communications) within existing fundraising operations.
- Ethical Boundaries: Donor personalisation will be implemented in ways that respect privacy and avoid over-targeting or pressure tactics.

Descriptive Analytics

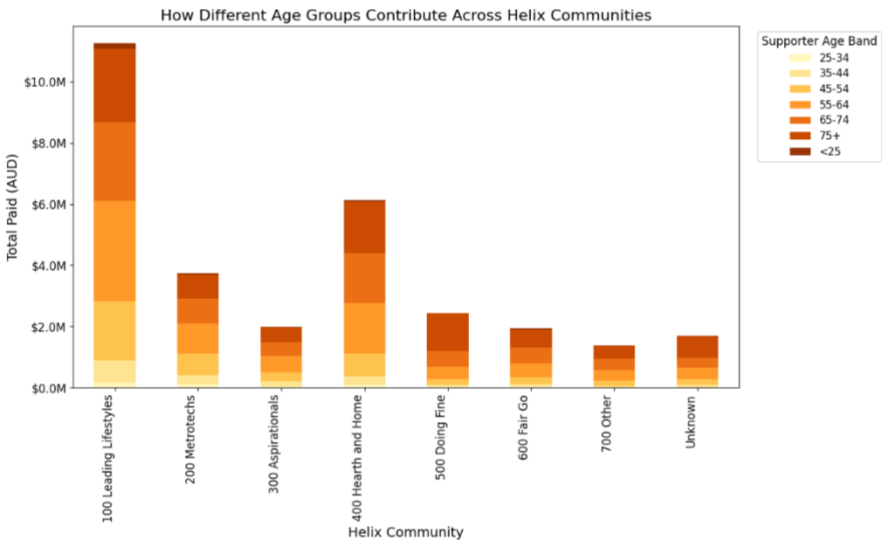
Quarterly Giving Patterns



Donations peak consistently in Q4 each year, reflecting strong seasonal giving around Christmas and end-of-year campaigns.

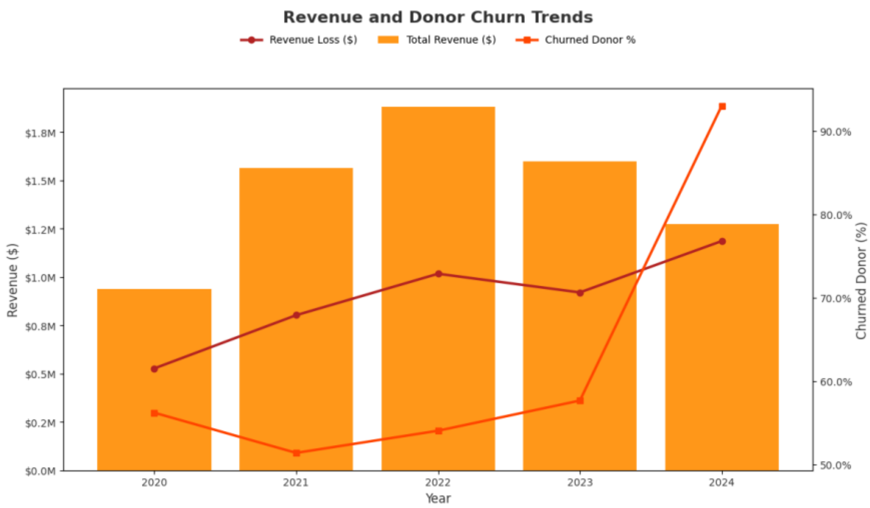
Lower giving occurs in Q1–Q3, suggesting donors are less responsive outside key cultural and emotional periods.

Contribution by Age across Helix Communities



Donations are concentrated in the "Leading Lifestyles" and "Health and Home" communities, driven mainly by older supporters (55+). Younger groups contribute less, especially in aspirational and emerging segments, reflecting lower

Donor Contribution and Churn Rate



From 2020 to 2023, year-over-year donor churn stayed high but stable, hovering around 51–58%, so roughly one in two donors lapses the following year, even as total revenue fluctuated and peaked in 2022. In line with this, the estimated next-year revenue at risk also rises (Appendix, A2).

Note: The 93% churn in 2024 is an artefact, it's comparing 2024 donors to 2025, and because 2025 data is partial, the 2024 churn rate is inflated.

Donations by Bounceback

Donations received for each bounceback			
Fiscal Year	Bounceback Type		
	Birthday	Christmas	Education
2023	50,056	55,002	37,897
2024	51,522	53,268	32,268
2025	13,096	39,549	-

Average Response Time by Bounceback

Average response time (days) by Bounceback			
Fiscal Year	Bounceback Type		
	Birthday	Christmas	Education
2023	~24	~19	~31
2024	~19	~38	~25
2025	~12	~19	-

Donations are falling year-on-year across Birthday, Christmas, and Education bouncebacks.This shows that donor engagement is **shrinking in volume**. Simply applying the same multiplier across campaigns is not effective

Donors are responding faster, with Birthday and Education campaigns showing major improvements since 2023. Despite fewer donors overall, those who remain are more loyal and engaged, forming a strong core base for personalised campaigns.

Predictive and Diagnostic Analysis

To guide future Bounce-back campaigns, diagnostic analysis and predictive modelling are conducted. The diagnostics provided hypotheses and key findings that shaped model design. Building on descriptive insights, we modelled how supporter characteristics and past behaviour can inform actions such as personalised asks and better segmentation.

Two predictive models were chosen and developed:

- Random Forest Classification predicts the next donation band (Small, Medium, High) based on supporter traits and campaign timing.
- Multiple Linear Regression estimates the likely donation amount a supporter may give in upcoming campaigns.

Model 1: Random Forest

This model predicts which donation band a supporter is likely to give next: Small (<$30), Medium ($30–60), or High ($60–100). This allows WVA to match asks to donor capacity, avoiding both unrealistic and undervalued requests.

Key Features Used in the Model:

- Cumulative average paid: the average amount a donor has contributed across campaigns. For example, if someone gave $20, $40, and $60, their average is $40. This shows their overall giving pattern and helps set a reasonable future ask.
- Upgrade flag: whether the donor has recently increased their giving.
- Seasonal flags (Christmas, EOFY): whether a donation occurred during major campaigns.
- Supporter tenure: how long the donor has been giving to WVA.

Hypothesis	Methodology	Evidence*	Conclusion
Hypothesis 1: Longer Tenure Stabilises Giving Behaviour	Tenure variables were included in the Random Forest model: • Supporter tenure: total time with WVA • Pledger tenure: time since becoming a pledger • Child sponsor tenure: duration of child sponsorship	Tenure features ranked consistently in the top 10 predictors. High-band donors (longer tenure) achieved Recall = 0.71, compared with Recall = 0.62 for Medium-band donors. Errors for High-band donors occurred mainly within adjacent bands (High vs Medium), not Small, indicating stability.	Tenure is strongly linked to stable donor behaviour. Long-tenure donors can be approached with gradual ask increases, balancing growth with loyalty.
Hypothesis 2: Seasonal Campaigns Increase Upgrade Likelihood	Two seasonal flags were added to the Random Forest model: • is_christmas: donation made during Christmas • is_eofy: donation made during EOFY These tested whether seasonal timing contributed to upgrades into higher ask bands.	is_christmas ranked among the top 15 predictors. Higher rate of Medium-to-High upgrades observed during Christmas donations. Model performance showed Balanced Accuracy = 0.692, indicating upgrade patterns were captured reliably.	Christmas campaigns are linked with increased giving and upgrades. Timing higher value asks to seasonal periods can strengthen campaign results.
Hypothesis 3: Higher Cumulative Averages Predict Upgrade Potential	The feature cumulative_avg_paid was engineered to measure a donor's average gift across their history (excluding the current donation). It was used to test whether higher averages predict movement into higher ask bands.	cumulative_avg_paid contributed ~60% of model predictive power, far exceeding other features. High-band donors achieved the strongest performance (Precision = 0.71, Recall = 0.74, F1 = 0.73). 14,335 High-band donors correctly classified, with only 1,139 misclassified into Small.	Cumulative average paid is the most reliable predictor of upgrade potential and should be the anchor for donor capacity modelling.

Table 1. Hypotheses for Random Forest Classification Model

Model 2: Regression Model

This model predicts a supporter's next donation amount so personalised ask amounts can be derived to avoid over or under asking as identified in the problem statement.

Key Features Used in this Model

- Frequency of Gifts: The number of donations a supporter has made in the past three years.
- Child Supporter Tenure: The total duration a donor has been a child sponsor.

Hypothesis	Methodology	Evidence*	Conclusion
Hypothesis 4: Donation frequency relates to giving and can guide ask setting	For each supporter, compute Donation_Count and test its association with giving at the transaction level and supporter (aggregated) level.	Per-gift: Indication of weak association, frequent donors do not give much more per transaction. Per-supporter: Presence of strong positive association, frequent donors contribute substantially more to total because they give more often.	Frequency is a reliable predictor of total contribution and should inform forecasting and ask setting. Emphasis should be on sustaining the giving habit (cadence and engagement), not on inflating each individual ask.
Hypothesis 5: Prediction Anchored Asks Improve Repeat Giving	Donation dataset filtered to include birthday campaigns only, ProductTemplateCode = 'BB' and supporters with ≥7 prior BB gifts. Prediction: next-gift anchor from last three gifts with weights 0.6/0.3/0.1. Ladders: (i) Prediction-centred 0.8×/1.0×/1.3× (rounded $50); (ii) Current WVA multipliers (dollar-handle rules). Evaluation: donors who gave to Birthday 2025 (partial year), comparing mid-ask accuracy and ladder fit.	With 717 high-frequency donors in 2025, the prediction anchored ask matched actual gifts much better. MAE 45.5 (pred) vs 117.4 (current) (≈61% lower), and 56% of gifts fell within the A–C range vs 22% today. Mid ask was within ±10% of the gift far more often (32% vs 4%) and cut severe over-asking from 61% to 25%, indicating a much more right sized ask.	Anchoring the ask to the predicted next gift closely matches donor behaviour and sharply reduces over-asking. This should raise response and expected value and lower churn versus fixed multipliers. *(2025 is partial, hence further A/B test measuring response and retention is required.)*

Table 2. Hypotheses for Multiple Regression Model

Note: The proof for all 'evidence' aspects of the hypothesis can be found in the Appendix section of the Presentation slide.

Interpretation

Key observations

- A donation behaviour-led segmentation can be adopted, where supporters are grouped by cumulative giving, frequency, and tenure rather than response status or demographics. These features predict next-gift band and amount more reliably in our models.
- Seasonality in donations can be noticed. Christmas/EOFY periods show higher responsiveness and upgrades, these windows can be used for higher-value but right-sized asks personalisation.
- Donation frequency is a stronger driver of total revenue than per-gift size. Frequent donors can be kept active through cadence and retention tactics rather than larger single asks.

- Donors aged 55+ contribute the most but also show visible churn. Retention and conservative ask escalation for this group should be prioritised
- Younger donors contribute less, but with no clear channel preference. A targeted digital-first approach is the logical strategy to engage them.

Strategic Implications

- Precision Asking: Classification assigns donors to optimal ask bands, while regression fine-tunes amounts for high-capacity supporters. This prevents over-asking loyal donors and under-asking capable ones.
- Resource Focus: Seasonality insights show Christmas and EOFY outperform other campaigns. This guides smarter prioritisation of campaign timing and resource allocation.
- Sustainable Growth: Older donors drive current revenue but face churn risk, while younger donors are under-engaged. Predictive insights support retention strategies for the former and digital-first activation for the latter.

Recommendations

Adopt donation behaviour-based segmentation

Proposed segmentations were mainly developed based on descriptive analysis of donation data. The ask amounts indicated for segments were derived from past birthday donation data, which are subject to change for other campaigns (Appendix, A1).

1. New supporters & Non responders: Most of the supports who donated for the first time have given $20, hence it has been adopted as the base ask for this segment.
2. Growth potential: Consisting of supporters who've donated 3-5 times, and as the donation median of this group revolves around $40, the base ask is set to be that amount.
3. Mid capacity: Consisting of supporters who've donated 5-6 times, and base ask was set to $70 by combining the median ($50) and average ($80) donation for this group.
4. High Capacity: All donors who have donated 7 times and more. Inclusive of any supporter who donates $100. Individualised asks are derived for all supporters in this segment based on donation prediction (Appendix, A3).

Personalise the donation asks

For high-capacity donors, personalised ranges (Ask A, B, C) can be anchored on predicted values with multipliers such as 80%, 100%, and 130%. For new supporters with only one past gift, a stepped approach is recommended. For example, Ask A = past gift × 1, Ask B = past gift × 1.25, Ask C = past gift × 1.5. In practice, predicted asks are based on a weighted regression of the last three gifts (with weights of 0.6, 0.3, and 0.1), ensuring that more recent giving behaviour has greater influence while still accounting for longer-term patterns. For mid and growth segments, ask handles should be set around group medians (e.g., $40–70). This balances incremental revenue with donor comfort.

Campaign Design Proposals

- Seasonal ask multipliers: Descriptive analysis shows a Q4 peak with Christmas as the strongest Bounceback period. Campaign-level multipliers can be set to reflect this pattern and plan messaging accordingly: Christmas = 1.15, Birthday = 1.00, Education = 0.95.

- Realign communication cost: Older donors (the highest-value cohort) respond well to the offline mode of communication. Younger donors (<45) contribute less and show no strong channel preference; hence, a digital/ online engagement approach can be employed. Reduce physical packs to younger non-engagers and redirect savings to high-capacity older segments.
- Online open ask optimisation: On online donation pages, Ask B can be optimised into an open input pre-filled with the base amount, with Ask A and Ask C displayed as the lower and upper suggestions. This provides flexibility to donors while also setting bounds.

Key Insights

By implementing the proposed solution, we expect the following.

- Reduction in donor churn rate
  Based on the research evidence, it is seen that nonprofits implementing personalised donation strategies based on giving history achieve significantly better retention outcomes compared to traditional one-size-fits-all approaches. By implementing the proposed personalised ask amount solution, a reduction in donor churn rate of 15-25% is expected (Aristidou et al., 2025; Hural, 2024; ExactAsk, 2017).
- Increase in overall revenue
  Based on the churn analysis, the 2025 revenue at risk ≈ $775kfrom 2024 donors). Implementing personalised ask ladders and behaviour-based segmentation is expected to protect a significant share of this at-risk revenue and improve year-over-year retention.

Suggestions

- Data enrichment to improve prediction: Additional features per supporter and campaign can be captured, such as ask ladders provided in prior campaigns, area code of the donors, which would lead to better prediction of donation asks.
- Propensity scoring model: With the availability of additional data, such models can be employed. For instance, donors who gave $10 last time might have a 50% chance to give $10 again, 30% to give $20, but near 0% to give $50. In contrast, donors who gave $50 might reliably give $50–$75 but drop off if asked $100+. By quantifying such patterns, a personalised ask ladder can be designed for segments.
- Controlled testing to validate impact: The recommendations are based on patterns in historical donation data. To be confident in their impact, A/B testing is suggested to compare personalised asks with standard approaches to see what really improves revenue and supporter satisfaction.

References

Aristidou, A., Dunckelman, A. & Fankuchen, S. 2025, 'How AI Can Deepen Nonprofit Relationships', Stanford Social Innovation Review (Fall). https://ssir.org/articles/entry/artificial-intelligence-donor-engagement

ExactAsk 2017., *Donor Lifetime Value and Relationship-Based Fundraising* [PDF]. https://f.hubspotusercontent40.net/hubfs/295648/Donor_Lifetime_Value_and_Relationship_Based_Fundraising_Whitepaper.pdf

Hural, S. 2024, 'The Use of AI in Fundraising: Maximizing Donations with Data-Driven Asks', Nonprofit Tech for Good, 16 May. https://www.nptechforgood.com/2024/05/16/the-use-of-ai-in-fundraising-maximizing-donations-with-data-driven-asks/

Appendix

Proposed segmentation and ask personalisation

For a birthday campaign

Segmentation	Definition	Ask A	Ask B	Ask C
High capacity	High Frequency (7-10) Measure (> $100) Personalised Ask	Predicted Ask x 0.8	Predicted Ask x 1	Predicted Ask x 1.3
Mid capacity	Measure $60.1-100 Age > 45	$55	$70	$90
Growth potential	Measure $30.1-60 Age < 45	$30	$40	$50
New Supporters/Non-responders	Measure < $30 New and unengaged supporters	$15	$20	$25

A1: Table indicating segmentation and ask values for the birthday campaign.

Yearly churn rate metrics calculation

Calculation - flags churn = gave in year Y but not in Y+1

Year	Total Revenue	Churned Donor %	Revenue loss for the next year
2020	$9,38,186.50	56.18%	$5,27,073.18
2021	$15,62,558.45	51.36%	$8,02,530.02
2022	$18,82,294.60	54.02%	$10,16,815.54
2023	$15,96,600.00	57.64%	$9,20,280.24
2024	$12,75,044.04	93.02%	$11,86,045.97

Also, please note 2024 shows 93% because it's comparing 2024 donors to 2025, and 2025 data is partial, so churn is inflated.

Prediction Calculations
The trend of churn rate increase for 2021–2023 is +3.14 percentage points per year.
Therefore, predicted churn %
2024 (pred.) = 57.64% + 3.14% ≈ 60.78%

Predicted "Revenue loss for the next year"
Revenue loss for 2025 : ≈ 1,275,044.04 × 0.6078 = $774,971.79
(≈ $774,972)

```
 Year  Next_Year  Total_Supporters  Retained_Donors  Churned_Donors  Churn_Rate_%  Retention_Rate_%                                      Note
 2017       2018             14546           6941.0          7605.0         52.28             47.72
 2018       2019             29249          11482.0         17767.0         60.74             39.26
 2019       2020             22216           6301.0         15915.0         71.64             28.36
 2020       2021             12462           5461.0          7001.0         56.18             43.82
 2021       2022             18007           8758.0          9249.0         51.36             48.64
 2022       2023             18330           8429.0          9901.0         54.02             45.98
 2023       2024             15570           6596.0          8974.0         57.64             42.36
 2024       2025             14907           1040.0         13867.0         93.02              6.98
 2025       2026              2609              NaN             NaN           NaN               NaN Next year not in file; churn not measurable yet.
PS D:\python stuff\data>
```

A2: Churn rate metrics

Example of personalised ask for a high capacity doner

Supporter_ID	Donation_Date	Total Paid	Campaign_Key	Frequency	Supporter_Tenure
154669	17-05-2024	550	1976	10	10
154669	27-03-2024	550	1957	9	10
154669	28-09-2024	400	1923	8	10
154669	14-03-2023	300	1907	7	9

Proposed Solution
Multiple regression model with weights 0.6, 0.3, 0.1 on the last 3 gifts
Supporter 154669 next-gift prediction: 605
Ask A = 605*0.8 = $500
Ask B = 605*1 = $600
Ask C = 605*1.3 = $800
**All asks rounded to the nearest 50*

Current dollar handle calculation
Last donation amount x multiplier
(round up to nearest 50)
Ask A = 550*1.25 = $700
Ask B = 550*1.5 = $850
Ask C = 550*2 = $1,100

Independent variable correlation

```
Transaction-level Pearson r(TotalPaid, Donation_Count): 0.125
Transaction-level Spearman ρ(TotalPaid, Donation_Count): 0.224

Supporter-level correlations (Pearson / Spearman):
  total_amount  vs Donation_Count: 0.378 / 0.798
  avg_gift      vs Donation_Count: 0.156 / 0.392
  last_gift     vs Donation_Count: 0.096 / 0.169
PS D:\python stuff\data> 
```

```
== Correlation between TotalPaid and Supporter_Tenure ==
Transaction-level: Pearson=0.056  Spearman=0.112   (n=788223)
Supporter-level: total_amount vs tenure: Pearson=0.068  Spearman=0.207   (n=25649)
Supporter-level: avg_gift vs tenure: Pearson=0.073  Spearman=0.134   (n=25649)
Supporter-level: last_gift vs tenure: Pearson=0.075  Spearman=0.131   (n=25649)
PS D:\python stuff\data> 
```

A3: Personalised ask calculation