ANALYSIS REPORT

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Executive Summary

This report offers a thorough analysis of World Vision Australia's Bounceback Campaign, emphasising the use of data-driven strategies to increase donations, enhance donor engagement, and optimise communication channels. According to the descriptive analysis, offline campaign phases perform better than online ones, particularly in terms of average donations and donor engagement. Predictive models are used to maximise journey gaps, forecast stream allocation, and personalise donation requests. Online channels were less effective, despite being more affordable, when it came to stream selection. In contrast, offline methods produced greater engagement. Journey optimisation made personalised timing apparent and Dollar Ask analysis used machine learning models to calculate $41.86 as the ideal donation base amount. For long-term engagement, suggestions include improving digital experiences, making use of dynamic communication intervals, and encouraging real-time donation suggestions. These observations provide achievable strategies for raising donor loyalty and maximizing contributions across both online and offline streams.

Introduction

World Vision Australia's Bounceback Campaign combined offline and online communication strategies in an effort to maximise donations and engage supporters. This report focuses on using data-driven insights to improve donation patterns, streamline communication strategies, and analyse donor behaviour. The report looks at the efficacy of different campaign phases, from scalable online channels to personalised offline interactions, using both descriptive and predictive analyses. The best donation requests and communication intervals were suggested by machine learning tools, and donation amounts were predicted by predictive models like polynomial regression and clustering. This diverse approach provides guidance for future donor engagement initiatives and improves campaign results.

Assumptions

- Fiscal Year (US-based): The campaigns follow the US fiscal year format, as indicated by the 'FY' abbreviations in the Activity_Name attribute, despite the organization being based in Australia.
- Persona-Based Segmentation Accuracy: The segmentation into personas such as 'Helix Persona' and 'Primary Segment' is assumed to be accurate and representative of the supporters' behavior and engagement potential.
- Missing Data: The presence of missing or unknown values in attributes like 'Helix_Comm' and 'Helix_Persona' does not significantly affect the validity of the analysis or its conclusions about supporter behavior.
- Address Accuracy: The addresses provided in the dataset are assumed to be accurate and up-to-date for all supporters.

Descriptive Data Analysis

This descriptive analysis focuses on understanding these aspects to improve donor engagement, streamline communication strategies, and increase overall donations. The analysis highlights key findings and explains how the calculated KPIs can help inform better decision-making.

1. **Journey Optimization:** Journey Optimization examines donor behaviour throughout various phases, such as Offline Main, eDM1, eDM2, and Online Main. Each phase reflects a distinct communication strategy aimed at engaging donors at different touchpoints.

The Offline Main phase stands out with an engagement rate of 61.91% and an average donation of $51.03, showcasing the effectiveness of direct mail and phone calls in building emotional connections and yielding higher donations. In contrast, the Online Main phase, while more scalable and cost-effective, has lower engagement at 24.98% and an average donation of $27.50. Although cheaper, online methods lack the personal touch of offline channels but are still valuable for reaching a larger audience. Email marketing phases, eDM1 and eDM2, show low engagement rates of 0.75% and 1.43%, with a slight improvement in follow-up emails, but the overall impact remains limited. The Offline Main phase also has a high completion rate, while both eDM1 and eDM2 suffer from significant drop-offs, highlighting the need for email strategy optimization.

KPI Calculation for Journey Optimization: Engagement rates were calculated by dividing the number of donors who interacted with each phase by the total number of donors targeted in that phase. Average donation amounts were calculated by taking the mean donation values for each phase. Drop-off rates were calculated by assessing the number of donors who stopped engaging after each phase.

2. **Stream Selection:** Stream Selection compares the effectiveness of different communication channels—Offline vs. Online—in driving donor actions.

The Offline Main channel proves highly effective, achieving an engagement rate of 77.29% and a conversion rate of 68.05%, compared to the Online Main channel, which has an engagement rate of 50.12% and a conversion rate of 41.81%. These findings suggest that offline methods, such as direct mail and phone calls, are more successful in driving donor actions. Segment-based analysis shows that high-value donors, like Corporates & Major Donors, engage consistently across both channels, while the General Population shows a clear preference for offline communication. Offline campaigns also lead to higher average donations, around $50 per supporter, significantly outpacing the smaller contributions typically seen in online campaigns. Prioritizing offline channels may therefore enhance both donor engagement and donation totals.

KPI Calculation for Stream Selection: Engagement and conversion rates were calculated by dividing the number of donors engaged and converted by the total donors contacted for each channel. Average donation amounts were derived by calculating the mean donation across all donors in each stream.

3. Dollar Ask Calculation: The Dollar Ask analysis provides insights into donation patterns, average donation sizes, and how different donor segments respond to specific donation requests.

The Major Supporters segment stands out with an average donation of $229.1, demonstrating that personalized approaches for high-value donors significantly impact overall donations. Targeting this group with refined strategies could further maximize their contributions. In contrast, segments like the General Population and VIPs show lower average donation amounts, highlighting the need for more focused strategies to boost engagement and donation sizes. Only 2.53% of donors are high-value contributors, while 16.65% fall into the low-value category, indicating a need to refine dollar ask strategies to unlock higher potential donations. To address this, WVA is leveraging predictive models like Gradient Boosting Regressor to forecast optimal donation amounts, enabling tailored donation requests that can increase overall contributions.

KPI Calculation for Dollar Ask: Average donation amounts were calculated by taking the mean of all donations within each segment. The high-value and low-value donor percentages were calculated based on donation thresholds. Predictive models were trained using past donation data to identify patterns in donor behaviour and suggest optimal donation asks.

Predictive Modelling

1. **Journey Optimisation:** The goal of this analysis was to optimize the communication journey for supporters of the campaign. We aimed to determine the best gaps between communications to maximize engagement and response rates, while considering constraints such as the total length of each campaign (30-45 days). Additionally, we explored the optimization of communication timing based on supporter segments. EDA on the response rate is shown in Appendix. Figure 3.1 shows the average response rate over time for each stream.

Gap Optimization: We used polynomial regression to fit models for predicting response rates based on the gaps between communications. This allowed us to estimate the optimal gap for each phase transition. Constrained Optimization: Given the campaign constraints (total journey length of 30 days), the model adjusted the gaps dynamically to fit within this limit. As an example, we have taken Figure 3.2 which shows the optimised gap between offline main and offline edm1.

We adjusted the model to distribute the total journey within 30 days.

Offline Journey:
Offline Main to Offline eDM1: Optimized to 10 days.
Offline eDM1 to Offline eDM2: Optimized to 1 day.
Offline eDM2 to Offline SMS: Optimized to 19 days.

Online Journey:
Online Main to Online eDM2: Optimized to 15 days.
Online eDM2 to Online eDM3: Optimized to 15 days.

2. Stream Allocation: The goal of this analysis is to predict and allocate supporters to either an online or offline stream based on multiple factors, including the campaign, outcome card received, helix community, helix persona, primary segment, contact phases, and supporter responses. The responses column was derived from the Total Paid column, where any payment by the supporter indicates a response. We performed necessary data preprocessing steps. We handled missing values by allocating mode for missing streams, categorical variables were replaced with unknown. Missing total paid values were removed. We encoded the categorical variables, scaled the attributes and split them into 70-30%.

Different predictive models were applied. The table is given in appendix. Table 3.1 shows the performance metrics for each model – Decision tree classifier, Naïve Bayes Classifier, Random Forest Classifier, Logistic Regression, Multi-Layer Perceptron (MLP). The decision tree classifier and MLP classifier were the top performers, with accuracies above 85% and Kappa values above 0.685.

In addition to the predictive models, clustering was applied to segment supporters into online or offline streams.

Clustering Model: K-means clustering was applied to allocate supporters to streams.

- *Davies-Bouldin Index: 1.3646*

The Davies-Bouldin Index (1.36) suggests that the clusters are reasonably well-formed, though there may still be some overlap between the clusters.

3.Dollar handle Base amount optimisation: The goal of this project was to predict and optimize the base amount to get the best donations using machine learning models.

We first did Predictive Modelling by building and evaluating different regression models to predict donation amounts which did not have the best performance metrics, so we moved on doing further steps like sensitivity analysis which shows how varying the base amount impacted donation predictions and Bayesian optimisation which calculated the best base amount considering all the features.

We then did data preprocessing steps for the selected features - Dollar handle amount, Primary segment, Helix community, Helix persona. We changed them using dummy variables, scaled it and spilt them into 70-30%.

Table 3.2 shows the predictive regression models we used and the performance metrics. Random Forest Regressor is the most suitable model for predicting the base amount of dollar handle given the dataset. It provides a good balance between minimizing errors (low RMSE) and capturing the underlying patterns (high R^2 and correlation). The sensitivity analysis was performed by varying the base amount feature between $10 and $200, while keeping all other features constant. The predicted donation was recorded at each step.

Key Observations:

Sharp Decline at Low Values: There is a steep drop in predicted donations when the base amount is decreased below $25. The donation predictions sharply decrease from around $350 to approximately $150.

Stabilization Beyond $25: Once base amount reaches $25, the predicted donations stabilize and remain consistent around $150, even as the base amount is increased up to $200.

Bayesian optimization was performed to find the optimal base amount that maximizes the model's predicted donations. The upper limit for the base amount was constrained to $50 to focus on the range where sensitivity analysis showed most influence.

The Bayesian optimization resulted in an optimal base amount of ***$41.86***.

Interpretation

The descriptive and predictive analyses have provided several key insights into World Vision Australia's Bounceback campaigns.

The **descriptive analysis** highlighted the stark differences in engagement and donation patterns across various communication channels. Offline channels, particularly the **Offline Main** phase, consistently outperformed online channels in both engagement (61.91%) and donation amounts, averaging $51.03 per donation. This suggests that the emotional connection fostered by offline methods, such as direct mail and phone calls, plays a crucial role in driving higher-value donations. Conversely, online channels, while cost-effective, resulted in smaller and less frequent donations, indicating the need for optimization in digital outreach strategies.

Predictive analysis further deepened these insights, showing that personalized, data-driven approaches could significantly enhance campaign effectiveness. For **journey optimization**, polynomial regression models revealed that tailoring communication gaps based on supporter segments could maximize engagement rates. The optimal gap for offline communications was identified as 10 days between the initial and follow-up phases, with further customization required for specific supporter groups. This ensures that communications are timely and impactful, preventing donor fatigue while maintaining engagement.

In terms of **stream allocation**, the Decision Tree model proved highly effective in predicting whether supporters would engage more through offline or online channels, with an accuracy of 85.22%. Offline streams were more effective for high-value donors, while online channels offered a cost-effective way to engage broader audiences. This segmentation enables more efficient allocation of resources, ensuring that high-value donors are targeted with personalized offline communications, while online channels are reserved for low-cost outreach.

Finally, the **dollar handle optimization** analysis, informed by sensitivity analysis and Bayesian optimization, identified an optimal base donation amount of $41.86. This insight is crucial for enhancing donation asks, particularly for high-value donors, while ensuring that lower-value segments are not discouraged from contributing. By leveraging machine learning models to tailor donation requests, the campaign can maximize overall contributions while fostering long-term donor loyalty.

Recommendations

1) Enhance Digital Experience to Boost Small Donations

The engagement and conversion rates in online channels are lower than offline, partly due to a lack of emotional connection. To address this, improve digital tactics such as email personalization and user experience, making them more suitable for frequent small donations. Segment donors by donation amount and tailor online marketing efforts accordingly. Optimize the donation page by increasing loading speeds and reducing unnecessary forms, ultimately enhancing the user experience.

2) Dynamic Communication Intervals Based on Donor Behavior

Use polynomial regression model results to develop dynamic communication interval strategies for different segments, shortening communication intervals for markets with high response rates, and increasing personalised content and emotional connections for markets with low response rates.

3) Integrated Online and Offline Approach for Major Donors and Corporates

For both corporates and large donors, offline and online engagement rates are essentially equal. Use cost-effective online channels for initial engagement, followed by personalised offline maintenance. Distribute project presentations and event invitations via email and social media and arrange offline briefings and exclusive engagement opportunities when donors are identified. In addition, plan co-branded events with large companies to enhance corporate social impact.

4) Event-Driven Engagement and Digital Follow-Up for the General Public

Engage the public through a large campaign, followed by targeted screening and personalised follow-up via email and SMS. Reach out to non-donor participants who show interest (e.g., frequent visitors to the donation page) to provide additional project details. Send personalised thank you emails to first-time donors and direct them to other giving opportunities, including recurring giving options.

5) Real-Time Donation Recommendation System

Develop a real-time recommendation system using machine learning models (e.g. Random Forest Regression, Bayesian Optimization) to suggest optimal donation amounts based on a donor's historical behaviour. Integrate this system into the donation page to provide personalised, real-time recommendations that explain the impact of each amount. Options such as ‘Support Base Amount,’ ‘Suggested Donation Amount,’ and ‘Higher Donation Amount,’ each with an impact statement (e.g., ‘$25 provides one child with clean drinking water for one year’, $100 pays for a family's health care"). The introduction of the ‘projects of interest’ option, which allows donors to choose their favourite projects, enhances engagement.

6) Promote Regular Donation Scheme

Add a regular donation button with a ‘Monthly Donation’ option on the donation page. Provide long-term donors with incentives such as exclusive reports, event invitations, and small gifts to foster a sense of belonging. Establish a ‘Loyal Donor Programme’ to reward donors who contribute continuously for over a year with an exclusive badge or appreciation letter. Additionally, send semi-annual ‘Upgrade Your Donation’ emails to encourage existing donors to increase their contribution.

Appendices

Figure 3.1

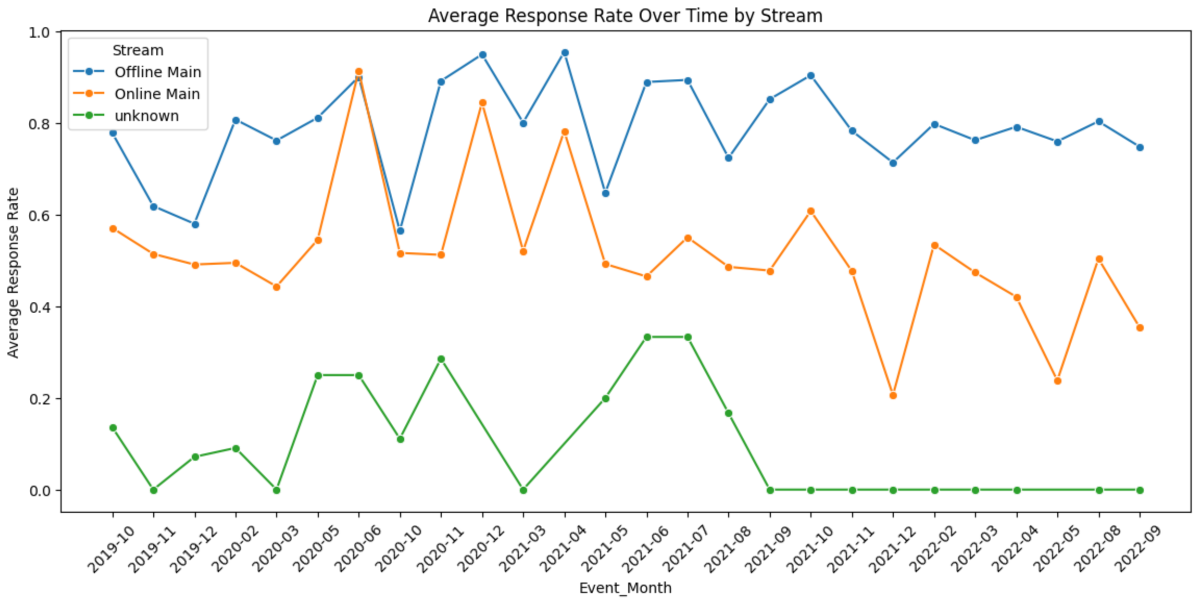

Figure 3.2

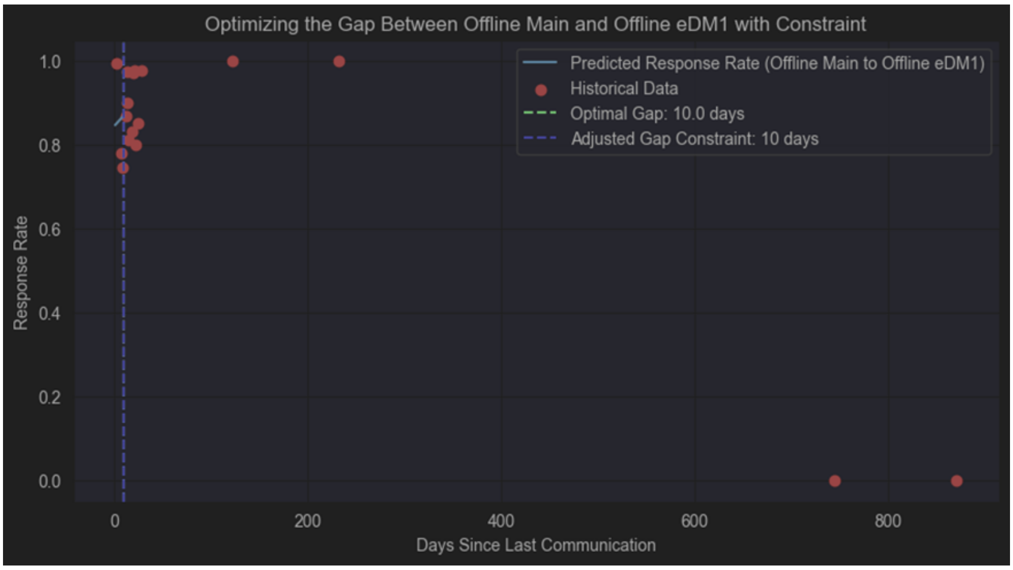

Table 3.1

Classifier	Accuracy	Precision	Recall	F1 Score	Error Rate	Kappa Score
Decision Tree Classifier	85.22%	86.36%	85.22%	85.44%	14.78%	0.6903
Naïve Bayes Classifier	82.14%	83.46%	82.13%	82.41%	17.86%	0.6267
Random Forest Classifier	81.02%	80.97%	81.02%	80.99%	18.98%	0.5853
Logistic Regression	83.76%	74.32%	83.27%	78.54%	16.24%	0.6555
Multi-Layer Perceptron (MLP)	84.95%	-	-	-	-	0.6852

Table 3.2

Model	RMSE	R^2	Correlation
Random Forest Regressor	49.721	0.3645	0.618
Linear Regression	58.220	0.1288	0.363
Decision Tree Regressor	58.511	0.1199	0.501
Gradient Boosting	49.820	0.3619	0.610
Multilayer Perceptron	0.843*	0.31	0.572

Note: The RMSE of MLP is after scaling, which is why it appears smaller than other models