Investigating factors influencing customer response to marketing campaigns : A retail perspective

Capstone Project Report

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By

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DECLARATION

We hereby declare that this report "**Investigating factors influencing customer response to marketing campaigns : A retail perspective"** is our own work, to the best of our knowledge and belief. It contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of any other institute, except where due acknowledgement has been made in the text.

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CERTIFICATE FROM FACULTY GUIDE

This is to certify that work entitled **Investigating factors influencing customer response to marketing campaigns : A retail perspective** is a piece of work done by Angiras and Riya under my guidance and supervision for the partial fulfilment of degree of PGDM at Delhi School of Business.

To the best of my knowledge and belief this study embodies the work of the candidate. This requirement of the rules and regulations relating to the 'Capstone Project' of the institute, is up-to the standard both in respect of content and language for being referred to the examiner.

Signature ___________________________

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Abstract

This research digs into understanding how customers react to marketing campaigns in retail market. The focus is on key factors that influence these reactions. It is important to know and predict customer behaviour in a competitive retail environment where customer preferences are constantly changing , for improving marketing campaign success and engaging customers effectively

By using a detailed dataset that includes information about customers' demographics, behaviour, and transactions, this study utilizes advanced analysis methods to uncover what drives customer responses to different marketing efforts. The aims is to create a strong machine learning model that predicts the customer's response to various marketing campaigns.

Several hypotheses have been tested that includes how demographic factors affect campaign acceptance, how past buying habits impact response rates, and the role of customer engagement metrics in determining campaign outcomes.

Predictive models will provide insights that will not only enhance our understanding of customer behaviour in retail but also offer practical benefits for retailers. Predictive models can help business tailor their marketing strategies more effectively.

By using data analytics and marketing insights, businesses can make informed decisions, adopt customer-focused approaches, and stay competitive in today's challenging retail market.

Introduction

With the increased developments and changes in the economy, technology and consumer purchase behavior have led to retailers having to adapt their businesses, the products and services that they provide and the way in which they communicate with customers. Understanding and predicting customer responses to marketing campaigns are crucial for businesses to thrive. The development of new software technology has made it possible for retailers to personalize their offerings based on the consumers purchase history. Technology has also made it possible for retailers to communicate with the customer anytime, at any place and through a medium that the customer prefers. In this study , we focus on understanding key factors that influence customer's reaction to marketing efforts in a retail setting. By developing predictive models, we aim to provide actionable insights to improve the effectiveness of marketing campaigns and increase customer engagement to provide a personalised experience. This will help companies to improve customer loyalty.

The retail industry has faced numerous challenges, including the rapid changes in technology and social media as well as changes in consumer behavior. It is now necessary to use data driven methodologies to understand customers and develop strategies accordingly. However, despite the wealth of available data, understanding the complex factors driving customer responses remains a complex task.

With this study we aim to address this challenge by utilizing advanced analytics and predictive modelling. By analysing a diverse dataset we aim to uncover the underlying factors affecting customer responses to marketing campaigns. We also aim to understand how demographic factors, past purchasing patterns, and customer engagement affect customer responses to marketing campaigns.

The findings from this study are highly relevant for retailers of all types, from traditional stores to online platforms. By gaining a deeper understanding of what resonates with their target customers and how different customer segments respond to marketing strategies, businesses can make informed decisions, adopt customer-focused approaches, and stay competitive in today's challenging retail market ultimately achieve better results

Literature Review

Marketing techniques have undergone significant transformations as businesses adapt to the rapidly evolving landscape of technology and digital communication. Sinarta and Buhalis (2017) highlight this evolution. They emphasized on how advancements in technology, software, and the rise of social media have revolutionized marketing strategies. Previously, businesses primarily pushed communications to consumers, but today, they have the capability to engage with customers in real-time across multiple platforms (Rowe, 2016). This shift signifies a move towards a more interactive and personalized marketing approach, where businesses can track customer interactions on social media, gather data on purchase history, and deliver tailored messages promptly (Rowe, 2016).

The need for agility and responsiveness in marketing campaigns is underscored by Huff (2014). He notes that many companies now recognize the importance of adapting to trends quickly. This necessitates more real-time marketing efforts to effectively address the changing needs and preferences of consumers. The ability to analyze data swiftly and utilize analytical tools for targeted messaging has become essential in staying competitive and meeting customer expectations.

Additionally, the integration of social media monitoring and analytics tools has enables businesses to gain valuable insights into consumer behaviour and sentiment (Sinarta & Buhalis, 2017). Businesses can now understand how customers behave and feel. This helps them keep track of interactions and quickly respond to customer needs and opportunities as they come up.

These studies highlight a significant shift in marketing practices, driven by advancements in technology and a customer-centric approach. The emphasis on real-time interactions, data-driven decision-making, and flexible campaign strategies reflects the dynamic nature of contemporary marketing efforts aimed at fostering meaningful customer relationships.

Research Objective

1- To determine the various factors that can influence customer response to marketing campaigns in retail setting:

   We will analyse how demographic variables such as age, income levels, educational background etc affects customer reactions to marketing campaigns and also explore the role of past purchasing behaviour in shaping customer responses to marketing campaigns.

2- To develop predictive models for campaign response based on various factors

   We will build statistical models to predict customer responses to marketing campaigns. The model will incorporate demographic variables such as past purchasing behaviour data, and customer engagement metrics into the predictive models.

Research Hypothesis

1. H1: When it comes to marketing campaigns in retail , there is a significant relationship between demographic factors and customer response to marketing campaigns:

    Demographic Segments respond differently to marketing campaigns. Certain demographic groups are more receptive to a specific marketing campaign than other.

2. H2: Past purchasing behaviour significantly influences customer response to marketing campaigns:

    We can predict customers with different purchase patterns will respond differently to marketing campaigns. Customers' historical buying preferences and channel preferences will impact their likelihood of engaging with marketing promotions.

3. H3: Customer engagement metrics have a significant impact on campaign acceptance:

    Propose Customers who exhibit higher levels of engagement, such as frequent website visitors, active social media followers etc are more likely to respond positively to marketing campaigns. This can be done by establishing a correlation between customer engagement metrics and the effectiveness of marketing messages in driving customer actions.

4. H4: Predictive models incorporating demographic, behavioural, and transactional factors will accurately forecast customer response to marketing campaigns:

    Hypothesize that integrating demographic data, past purchasing behaviour, and customer engagement metrics into predictive models will improve the models' ability to predict campaign acceptance. Predictive models can help business tailor their marketing strategies more effectively.

Research Methodology

1. **Data Preparation:**
   - preprocess the dataset to remove duplicates, correct errors to ensure data accuracy.
   - Handle missing values: Impute missing data using appropriate techniques.
   - Encode categorical variables: Convert categorical variables into numerical representations .

2. **Exploratory Data Analysis (EDA):**
   - We will examine correlations between variables to identify relationships that may influence customer responses.
   - Multicollinearity; we will ensure that the issue of multicollinearity is addressed and resolved using techniques such as Principal Component analysis and VIF.

3. **Feature Selection:**
   - We selected relevant independent variables such as demographic factors, past purchase history, and customer engagement metrics.
   - Statistical significance: We used statistical tests to determine the significance of variables in predicting campaign acceptance.

4. **Model Development:**
   - Build predictive models: Utilize machine learning algorithms to develop predictive models for forecasting customer response.
   - Incorporate demographic, behavioral, and transactional factors: Include features such as age, income, purchase frequency, website visits, social media interactions, and past campaign engagement in the models for comprehensive analysis.

5. **Interpretation and Recommendations:**

- Interpret findings: Analyse model results, feature importance rankings, to understand the factors driving customer response to marketing campaigns.
- Provide actionable recommendations: Based on model insights, propose targeted strategies for campaign planning and targeting to improve campaign effectiveness and customer engagement.

Data Collection

- Data set is designed to understand the relationship between customer response and various demographic and behavioral factors including ad campaigns.
- Categorical variables are converted into numerical representations for model compatibility.

Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntMeatP	MntFishPr	MntSweet	MntGoldPr	NumDeals	NumWebP	NumCatal	NumStore	NumWebV	AcceptedC	AcceptedC	AcceptedC	AcceptedC
58138	0	0	58	635	88	546	172	88	88	3	8	10	4	7	0	0	0	0
46344	1	1	38	11	1	6	2	1	6	2	1	1	2	5	0	0	0	0
71613	0	0	26	426	49	127	111	21	42	1	8	2	10	4	0	0	0	0
26646	1	0	26	11	4	20	10	3	5	2	2	0	4	6	0	0	0	0
58293	1	0	94	173	43	118	46	27	15	5	5	3	6	5	0	0	0	0
62513	0	1	16	520	42	98	0	42	14	2	6	4	10	6	0	0	0	0
55635	0	1	34	235	65	164	50	49	27	4	7	3	7	6	0	0	0	0
33454	1	0	32	76	10	56	3	1	23	2	4	0	4	8	0	0	0	0
30351	1	0	19	14	0	24	3	3	2	1	3	0	2	9	0	0	0	0
5648	1	1	68	28	0	6	1	1	13	1	1	0	0	20	1	0	0	0
7500	0	0	59	6	16	11	11	1	16	1	2	0	3	8	0	0	0	0
63033	0	0	82	194	61	480	225	112	30	1	3	4	8	2	0	0	0	0
59354	1	1	53	233	2	53	3	5	14	3	6	1	5	6	0	0	0	0
17323	0	0	38	3	14	17	6	1	5	1	1	0	3	8	0	0	0	0
82800	0	0	23	1006	22	115	59	68	45	1	7	6	12	3	0	0	1	1
41850	1	1	51	53	5	19	2	13	4	3	3	0	3	8	0	0	0	0
37760	0	0	20	84	5	38	150	12	28	2	4	1	6	7	0	0	0	0
76995	0	1	91	1012	80	498	0	16	176	2	11	4	9	5	0	0	0	1
33812	1	0	86	4	17	19	30	24	39	2	2	1	3	6	0	0	0	0
37040	0	0	41	86	2	73	69	38	48	1	4	2	5	8	0	0	0	0

Figure 1- Coded Data Set

Feature	Description
AcceptedCmp1	1 if costumer accepted the offer in the 1st campaign, 0 otherwise
AcceptedCmp2	1 if costumer accepted the offer in the 2nd campaign, 0 otherwise
AcceptedCmp3	1 if costumer accepted the offer in the 3rd campaign, 0 otherwise
AcceptedCmp4	1 if costumer accepted the offer in the 4th campaign, 0 otherwise
AcceptedCmp5	1 if costumer accepted the offer in the 5th campaign, 0 otherwise
Response (target)	1 if costumer accepted the offer in the last campaign, 0 otherwise
Complain	1 if costumer complained in the last 2 years
DtCustomer	date of customer's enrollment with the company
Education	customer's level of education
Marital	customer's marital status
Kidhome	number of small children in customer's household
Teenhome	number of teenagers in customer's household
Income	customer's yearly household income
MntFishProducts	amount spent on fish products in the last 2 years
MntMeatProducts	amount spent on meat products in the last 2 years
MntFruits	amount spent on fruits in the last 2 years
MntSweetProducts	amount spent on sweet products in the last 2 years
MntWines	amount spent on wines in the last 2 years
MntGoldProds	amount spent on *gold* products in the last 2 years
NumDealsPurchases	number of purchases made with discount
NumCatalogPurchases	number of purchases made using catalogue
NumStorePurchases	number of purchases made directly in stores
NumWebPurchases	number of purchases made through company's web site
NumWebVisitsMonth	number of visits to company's web site in the last month
Recency	number of days since the last purchase

Figure 2- Dictionary For Coded Data set

- Independent variables-

1- AcceptedCmp1-5
2- Complain
3- Education
4- Marital
5- Income
6- NumDealsPurchases
7- NumCatalogPurchases
8- NumStorePurchases
9- NumWebPurchases
10- NumWebVisitsMonth
11- Recency

- Dependent Variable- AcceptedCmp1-5

Data Analysis

- We First Addressed the issue of **Multicollinearity** in our data. Multicollinearity refers to a phenomenon where two or more independent variables in a regression model are highly correlated with each other
- Multicollinearity can lead to several issues in regression analysis such as Unreliable Coefficients, difficulty in interpretation, overfitting and loss of Variable Importance.
- We used **Variance Inflation Factor (VIF)** to address multicollinearity. This measures how much the variance of an estimated regression coefficient is increased due to multicollinearity. High VIF values indicate problematic multicollinearity.
- Independent variable with VIF value more than 10 were dropped(Such as AcceptedCmpOverall with VIF value 40).

							95% CI		Collinearity Statistics	
Model		Unstandardized	Standard Error	Standardized	t	p	Lower	Upper	Tolerance	VIF
H_0	(Intercept)	0.151	0.008		19.800	< .001	0.136	0.166		
H_1	(Intercept)	−0.563	0.104		−5.434	< .001	−0.766	−0.360		
	Kidhome	0.003	0.016	0.004	0.158	0.874	−0.029	0.034	0.515	1.940
	Income	1.087×10^{-6}	7.190×10^{-7}	0.063	1.512	0.131	-3.227×10^{-7}	2.497×10^{-6}	0.173	5.778
	Teenhome	−0.072	0.015	−0.109	−4.746	< .001	−0.101	−0.042	0.568	1.760
	Recency	−0.002	2.154×10^{-4}	−0.198	−11.404	< .001	−0.003	−0.002	0.988	1.012
	MntWines	-8.278×10^{-5}	3.631×10^{-5}	−0.078	−2.280	0.023	-1.540×10^{-4}	-1.157×10^{-5}	0.256	3.913
	MntFruits	2.674×10^{-4}	2.189×10^{-4}	0.030	1.221	0.222	-1.619×10^{-4}	6.967×10^{-4}	0.506	1.976
	MntMeatProducts	2.356×10^{-4}	5.068×10^{-5}	0.143	4.648	< .001	1.362×10^{-4}	3.350×10^{-4}	0.315	3.174
	MntFishProducts	-2.671×10^{-4}	1.672×10^{-4}	−0.041	−1.598	0.110	-5.950×10^{-4}	6.070×10^{-5}	0.457	2.189
	MntSweetProducts	-1.511×10^{-4}	2.122×10^{-4}	−0.017	−0.712	0.477	-5.672×10^{-4}	2.650×10^{-4}	0.504	1.985
	MntGoldProds	1.227×10^{-4}	1.499×10^{-4}	0.018	0.818	0.413	-1.713×10^{-4}	4.167×10^{-4}	0.638	1.567
	NumDealsPurchases	0.014	0.004	0.076	3.333	< .001	0.006	0.023	0.571	1.750
	NumWebPurchases	0.008	0.003	0.058	2.321	0.020	0.001	0.014	0.481	2.078
	NumCatalogPurchases	0.008	0.004	0.064	2.054	0.040	3.692×10^{-4}	0.016	0.311	3.219
	NumStorePurchases	−0.020	0.003	−0.179	−6.491	< .001	−0.026	−0.014	0.392	2.551
	NumWebVisitsMonth	0.006	0.004	0.042	1.402	0.161	−0.002	0.015	0.336	2.976
	AcceptedCmp3	0.053	0.064	0.039	0.827	0.408	−0.073	0.179	0.136	7.364
	AcceptedCmp4	−0.081	0.069	−0.059	−1.178	0.239	−0.216	0.054	0.118	8.462
	AcceptedCmp5	0.034	0.068	0.024	0.498	0.619	−0.099	0.166	0.124	8.052
	AcceptedCmp1	0.002	0.066	0.001	0.024	0.981	−0.128	0.132	0.145	6.906
	Complain	0.020	0.066	0.005	0.303	0.762	−0.109	0.149	0.989	1.011
	Age	3.476×10^{-4}	6.097×10^{-4}	0.011	0.570	0.569	-8.480×10^{-4}	0.002	0.754	1.327
	CustomerDays	3.403×10^{-4}	3.528×10^{-5}	0.192	9.643	< .001	2.711×10^{-4}	4.094×10^{-4}	0.751	1.331
	maritalDivorced	−0.013	0.039	−0.011	−0.343	0.732	−0.090	0.063	0.272	3.679
	maritalMarried	−0.108	0.035	−0.146	−3.033	0.002	−0.177	−0.038	0.129	7.776
	maritalSingle	−0.002	0.037	−0.002	−0.045	0.964	−0.074	0.070	0.167	5.974
	maritalTogether	−0.110	0.036	−0.134	−3.053	0.002	−0.181	−0.039	0.155	6.470
	education2nCycle	−0.099	0.026	−0.079	−3.789	< .001	−0.150	−0.048	0.694	1.441
	educationBasic	−0.185	0.045	−0.080	−4.155	< .001	−0.272	−0.098	0.811	1.233
	educationGraduation	−0.089	0.017	−0.124	−5.224	< .001	−0.122	−0.055	0.531	1.883
	educationMaster	−0.052	0.021	−0.054	−2.547	0.011	−0.092	−0.012	0.661	1.512
	AcceptedCmpOverall	0.211	0.058	0.400	3.654	< .001	0.098	0.324	0.025	40.057

Figure 3- VIF for each Independent Variable

- We used classification machine learning Models such as K-nearest neighbour, SVM and Decision Tree.
- In machine learning, classification is a fundamental task that involves learning a model to categorize data points into predefined classes. It's analogous to sorting items into different groups based on their characteristics. Here's a breakdown of the process:
  - Data Collection: You gather a dataset containing labeled examples. Each example has features (attributes) that describe it and a corresponding class label (e.g., spam/not spam for email classification).
  - Model Training: You train a classification algorithm using the labeled data. The algorithm learns patterns that distinguish between the classes.
  - Prediction: Once trained, the model can predict the class label of a new, unseen data point.

- Types of Classification Algorithms : There are various classification algorithms, each with its strengths and weaknesses. Here's a look at three popular ones you mentioned:

  Support Vector Machine (SVM):SVMs aim to find an optimal hyperplane (a decision boundary) that maximizes the margin between the classes in the data. This margin essentially represents the confidence in the separation between the classes. SVMs are powerful for high-dimensional data and can handle complex nonlinear relationships between features
  On performing SVM classification on the dataset we received a test accuracy of 89.1%

  In feature Importance matrix AcceptedCMP5, AcceptedCMP3, MntMeatproducts, Recency and customerDays came out to be the most important factors in determining response

Support Vector Machine Classification ▼

Support Vector Machine Classification ▼

Violation cost	Support Vectors	n(Train)	n(Validation)	n(Test)	Validation Accuracy	Test Accuracy
0.020	401	1411	353	441	0.915	0.891

Note. The trained model is saved as *pred.jaspML*.

Data Split

Confusion Matrix

		Predicted	
		0	1
Observed	0	374	8
	1	40	19

Feature Importance Metrics

	Mean dropout loss
AcceptedCmp5	0.374
AcceptedCmp3	0.346
MntMeatProducts	0.340
Recency	0.337
CustomerDays	0.330
AcceptedCmp1	0.325
maritalTogether	0.321
Teenhome	0.321
Income	0.321
MntGoldProds	0.321
NumCatalogPurchases	0.320
AcceptedCmp4	0.319
MntFruits	0.319
maritalDivorced	0.319
maritalSingle	0.318

Figure 4- SVM Classification

  - K-Nearest Neighbours (KNN): KNN is a non-parametric, lazy learning algorithm. It doesn't explicitly learn a model during training. Instead, it stores all the training data. When making a prediction, KNN identifies the k nearest neighbours in the training data based on a distance metric .The new point is then classified by a majority vote of its neighbours' classes. KNN is simple to implement, interpretable and effective for certain

types of data. On the other hand, KNN can be computationally expensive for large datasets as it needs to compare the new point to all training points.
On performing KNN classification on the dataset we received a test accuracy of 88.7%

In feature Importance matrix AcceptedCMP5, AcceptedCMP1, AcceptedCMP3, Mintwines and customerDays came out to be the most important factors in determining response.

K-Nearest Neighbors Classification

K-Nearest Neighbors Classification

Nearest neighbors	Weights	Distance	n(Train)	n(Validation)	n(Test)	Validation Accuracy	Test Accuracy
7	rectangular	Euclidean	1411	353	441	0.878	0.887

Note. The model is optimized with respect to the *validation set accuracy*.

Data Split

Confusion Matrix

		Predicted	
		0	1
Observed	0	373	8
	1	42	18

Feature Importance Metrics

	Mean dropout loss
AcceptedCmp5	0.365
AcceptedCmp1	0.356
AcceptedCmp3	0.350
MntWines	0.339
CustomerDays	0.336
AcceptedCmp4	0.335
maritalDivorced	0.334
NumWebPurchases	0.334
maritalSingle	0.333
MntMeatProducts	0.328
educationBasic	0.328
NumCatalogPurchases	0.326
Kidhome	0.325
NumDealsPurchases	0.325
maritalMarried	0.324

Figure 5- KNN Classification

- Decision Tree: Decision trees are tree-like structures where each internal node represents a feature (attribute) and each branch represents a possible value of that feature. Leaf nodes at the end of the tree represent class labels. During training, the decision tree recursively splits the data based on features that best separate the classes. This process continues until a stopping criterion is met .Decision trees are interpretable , efficient for training and prediction, and can handle both numerical and categorical features. However, they can be prone to overfitting if not carefully controlled, and the decision rules can become complex and hard to interpret for very large trees.

  On performing Decision Tree classification on the dataset we received a test accuracy of 89.1%

  In feature Importance matrix AcceptedCMP5, AcceptedCMP3, recency ,income and AcceptedCMP1 came out to be the most important factors in determining response.

Decision Tree Classification

Decision Tree Classification

Complexity penalty	Splits	n(Train)	n(Validation)	n(Test)	Validation Accuracy	Test Accuracy
0.020	50	1411	353	441	0.864	0.891

Data Split

Confusion Matrix

		Predicted	
		0	1
Observed	0	372	8
	1	40	21

Feature Importance Metrics

	Relative Importance	Mean dropout loss
AcceptedCmp5	28.677	0.429
AcceptedCmp3	16.661	0.391
Recency	12.991	0.387
Income	11.319	0.340
AcceptedCmp1	8.763	0.384
NumCatalogPurchases	6.077	0.352
MntWines	4.571	0.340
NumDealsPurchases	2.824	0.340
MntFruits	2.401	0.340
Age	1.827	0.340
MntSweetProducts	1.282	0.340
NumWebPurchases	0.875	0.340
NumStorePurchases	0.691	0.340
MntFishProducts	0.438	0.340
education2nCycle	0.346	0.340

Figure 6- Decision Tree Classification

- Using SVM Classification Model we were able to build a prediction Model for making future customer response predictions.

Prediction

Loaded Model: Classification

Method	n(Train)	n(New)
Support vector machine	1411	20

Predictions for New Data

Case	Predicted
1	1
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0
11	0
12	0
13	0
14	0
15	1
16	0
17	0
18	0
19	0
20	0

Figure 7- Prediction Model

Conclusion

- Based on the analysis of various machine learning models applied to the given dataset, Support Vector Machine (SVM) classification was the most accurate model, achieving an accuracy of 89.1%. SVM also provided valuable insights into the importance of different factors in determining customer response, making it best choice among the three for predictive modelling.

- In the context of determining customer response, SVM identified the importance of various factors such as demographic attributes (age, income, education level), past purchasing behavior (frequency of purchases, amount spent), customer engagement metrics (website visits, social media interactions) and other factors available in the dataset.

- The deeper understanding that we achieved of how different factors interact and contribute to customer behaviour now can be used to tailor marketing campaigns, optimize resource allocation, and enhance customer engagement strategies effectively.

- SVM model is well-equipped to be used as a predictive tool for making future customer response predictions. By inputting new data points into the trained SVM model, businesses can forecast customer responses ,leading to more informed decision-making and improved marketing outcomes.

Key Finding And Solutions

- We were able to design a prediction model that now can be used to gain predict and analyse customer response to different marketing campaigns.

- We now can run various simulations on this model to gain insights by varying the drivers(factors) that affect customer response to marketing campaigns

- We can now understand how by altering our marketing strategies we can ensure success in our marketing campaigns. This can be done by studying various outcomes to different marketing strategies using the machine learning prediction model.

- Different factors such as demographic attributes, past purchasing behaviour etc can be studies to understand their impact on customers. This would help marketeers make data driven decisions and designs targeted marketing campaigns

- In conclusion, By utilizing Machine learning models, marketeers can make informed decisions that are cost effective and can achieve better results.

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