

EXPLORING UPLIFT MODELLING IN DIRECT MARKETINGCindy-Lee Mayes¹, Krishna K Govender²**Da Vinci Institute of Technology, South Africa**^{1,2}cindystowman@gmail.com¹, krishna@davinci.ac.za^{2*}**Article History**

Received on 1 November 2019

1st Revision on 12 November 20192nd Revision on 22 November 2019

Accepted on 26 November 2019

Abstract

Purpose: This research examines the importance of an uplift marketing model compared to traditional response models, used in direct marketing.

Design/Research method: A multi-method research approach was used which included a survey using an electronic questionnaire and a semi-structured interview.

Finding: The research findings reveal that the value of employing uplift models in direct marketing, is that it factors change in behaviour from the action, which traditional response models do not.

Limitation: The study was conducted in a single institution and focused only on customers with banking needs.

Implication: By employing an uplift model in direct marketing it is possible to increase marketing return-on-investment and positively impact brand loyalty and brand perception. Thus, marketers need to be cognizant of these findings and strategize accordingly.

Keywords: direct marketing, customer management, marketing model, marketing communication

How to Cite: Mayes, Cindy-Lee., and Govender, Krishna K. (2019). Exploring uplift modelling in direct marketing. *International Journal of Financial Accounting and Management*, 1(2), 1-11.

1. INTRODUCTION

According to research (Adobe and Microsoft, 2018), 94% of consumers will discontinue their relationship with a brand because of irrelevant marketing. While some traditional marketing roles have changed or become redundant, the rise in data science and the creation of new marketing channels, such as digital marketing, has resulted in the emergence of new marketing roles. An important development for marketing professionals is the need to understand the science or analytics and creative processes that will be vital in bridging the gap between data and design, which is key to the success of any marketing campaign (Lund, 2012). In light of the above, this paper reports the findings of a study conducted among a convenience sample of South African banking consumers, to explore the impact of uplift models in direct marketing, by addressing the following objectives:

- To ascertain the effect of Uplift models on marketing return-on-investment (costs and response rates).
- To evaluate the consequence of Uplift models on customer experience and brand loyalty.
- To compare the impact on customer attrition based on churn risk versus an Uplift model.

Flowing from the research objectives, the key questions and sub questions were framed around: What are the effects of uplift marketing models on direct marketing costs, response rates, customer experience and brand loyalty.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The core function of direct marketing is to generate a response and influence the behaviour of a target audience. Thus, every day people are exposed to thousands of marketing messages where companies attempt to sell numerous products or services. In South Africa, in recent years, various pieces of legislation have been passed to curb this practice, which necessitates understanding the impact of legislation on direct marketing in South Africa. Marketing in South Africa has seen some radical changes since the implementation of the Electronic Communications and Transactions Act, No. 25 of 2002, The Consumer Protection Act, No. 68 of 2008, and The National Credit Act, No. 34 of 2005, and as such, businesses had to change the way they interact with clients and how they utilise client data (Republic of South Africa, 2009).

The Protection of Personal Information Act, No. 4 of 2013 does not prohibit direct marketing, but it regulates how direct marketing is conducted with the primary focus being on protecting the consumer. Given the legislations and limited audience that one may be able to market to in the future, predictive modelling now plays a key role in the success of marketing campaigns.

Marketing Models

A predictive model is an instrument that predicts the likelihood that the individual will exhibit the predicted behaviour as determined by a score and the higher the score, the higher the likelihood (Siegel, 2016). A standard predictive model scores customers' or other organisational elements individually, per the likelihood of behaviour, for example, response or attrition. With power shifting to the customer, switching of service providers will happen at a more frequent rate, with buying of products from multiple providers demonstrating a preference for tailored products and services (EY, 2013). However, predicting customer behaviour is no longer enough, and thus conventional predictive analytics is limiting, as it predictively scores each customer for projected buying, churn or other behaviour. As an alternative, a business decision is optimised when it is based on the predicted marketing influence on the customer's future behaviour.

Since introducing statistical credit scoring in the 1950s, statistical modelling has been applied to various problems in customer management and over time, the use of predictive modelling has become progressively more sophisticated in customer targeting, when employed in demand stimulation and customer retention (Radcliffe & Surry, 2011). For many customers, the choice of which offer or contact should be made, often makes the difference between a sale and no sale (Siegel, 2011), and this leads to uplift modelling.

Uplift modelling

'Uplift modelling is a branch of machine learning which aims to predict not the class itself, but the difference between the class variable behaviour in two groups, namely treatment and control. Objects in the treatment group have been subjected to some action, while objects in the control group have not. By including the control group, it is possible to build a model which predicts the causal effect of the action for a given individual' (Jaroszewicz & Zaniewicz, 2017). An uplift model is also known as the differential response, true lift, impact, incremental impact, incremental response, net lift, net response, incremental lift, persuasion, or true response model (Larsen, 2010; Rzepakowski and Jaroszewicz, 2010; Radcliffe and Surry, 2011; Kubiak, 2012; Lund 2012; Nassif, 2013; Nasif, *et al.*, 2013; Guillen *et al.*, 2014; Kane *et al.*, 2014; Lo and Pachamanova, 2015; Gubela *et al.*, 2017).

In business, to drive decisions for greatest impact, analytical models must predict the marketing influence of each decision on customer purchasing behaviour. Uplift modelling improves conventional response, and churn models present significant risk by optimising the wrong product or service. This change is fundamental to empirically driven decision making (Siegel, 2011). Portrait Software (2006) highlight numerous benefits of using uplift modelling in the areas of demand generation and customer retention, which include inter-alia, reducing costs because of a reduction in the number of customers required to achieve a given level of business stimulation, increasing the level of business generation achieved for any given level of spend, lowering customer unhappiness by reducing the level of negatively received information, enhancing understanding inside the organisation of the efficacy of several kinds of marketing spend, removing many or all the adverse effects related with mis-targeted marketing initiatives and reducing customer churn.

There are four qualifying criteria important for evaluating the potential impact of uplift modelling (Portrait Software, 2006), namely, control groups, size of the customer base, influences and overall level of uplift. Uplift modelling needs the systematic use of randomised control groups and this is therefore only of benefit to organisations already using it. Furthermore, reasonable volumes are required to model the second-order effect and organisations with large customer bases tend to benefit disproportionately more, than those with fewer customers.

Traditional models¹ versus uplift models

Although there are several traditional marketing models, none of the traditional marketing models attempted to factor change in behaviour, because of the direct marketing campaign. For example, a response model attempts to predict the likelihood that a customer will take up an offer if contacted, whereas an uplift model attempts to estimate the increase in the likelihood that a customer may take up an offer if contacted, compared with not being contacted, thus modelling the change in behaviour, as shown in Table 1.

Table 1: Response model vs. uplift model equation.

Response Model	Uplift Model
$P(O = 1 x; T)$	$P(O = 1 x; T) - P(O = 1 x; C)$

In Table 1, the Response model predicts the probability that the outcome (O) is 1 (positive) for those customers in the treated group (T), but it does not consider the behaviour from the control group (C). An Uplift Model considers the change, such as an increase in probability when customers are treated versus not being treated.

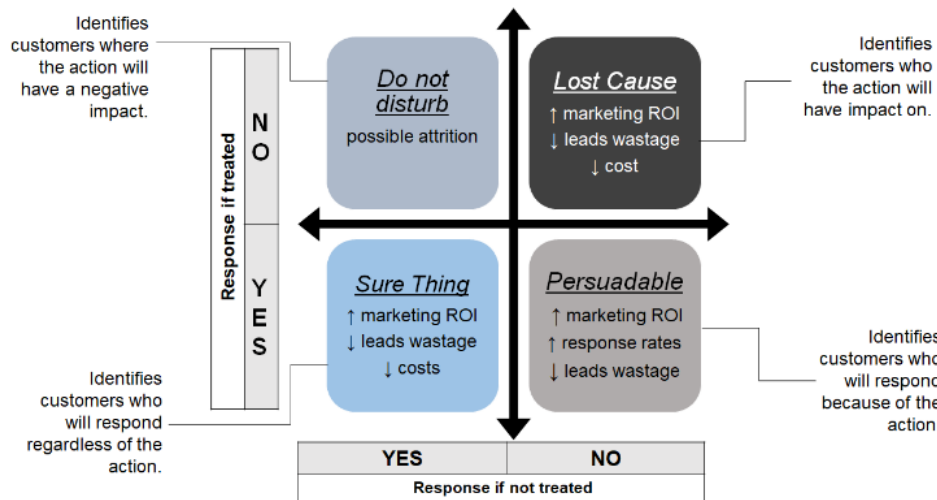
Jaroszewicz and Rzepkowski (2012) and Jaroszewicz and Jaroszewicz (2012), explain that customers can be segmented into four groups. However, traditional models such as Response models are not able to segment the customers, given that traditional models do not attempt to factor the change in behaviour, which an uplift model does. What traditional models do not consider are those customers who would have responded or purchased if there was no marketing campaign, which in turn results in wasted costs that negatively impact net profits or the return on investment

Uplift modelling in direct marketing

The usefulness of employing uplift models in direct marketing is that it factors the change in behaviour from the action, which enables marketers to strategically direct their marketing efforts. Figure 1 displays

a summary of the usefulness of employing uplift models in direct marketing. The purpose of this paper is not to engage into a discussion of various marketing models, but to merely mention some of the traditional models so as to differentiate them from Uplift marketing model.

Figure 1: The usefulness of employing an uplift model in direct marketing



Source: Adapted from Jaroszewicz & Rzepakowski (2012) and Siegel (2016)

Although current market penetration and purchase models do not attempt to link the purchase result with the marketing activity designed to stimulate the activity, they are deemed to be more sophisticated, in that they attempt to correlate the purchase result with the marketing activity. However, the problem emerges when one tries to separate the impact of the action from other factors and spontaneous purchases. Thus, to separate the impact of the action from other factors and impulsive buying, one should model the change in those probabilities caused by the action as opposed to the response probabilities themselves.

Several researchers (Guillen et al., 2014; Kane et., 2014; Lo and Pachamanova, 2015; Gubela et al., 2017), have implemented Uplift marketing modelling in various context, inter-alia, insurance, finance, patient care, online merchandise and retail domains. However, no evidence exists of research being conducted in a direct marketing context.

In light of the above, this research aims to compare uplift and traditional response models in direct marketing, by investigating the processes and impact of employing traditional response models in direct marketing versus uplift models.

3. RESEARCH METHODS

A mixed methods study was conducted, which included a survey as well as focus group interviews. The data was collected using a self-administered questionnaire transmitted via Survey Monkey. The questionnaire was distributed electronically to a convenience sample (41 participants) via an email link to the survey. In addition, personal interviews were conducted with nine (9) respondents, using an unstructured questionnaire. This approach is in line with Saunders *et al.*'s (2016) guidelines for the minimum non-probability sample size.

The population comprised economically active individuals who were in a position financially, to take up the respective products or solutions that an organisation is marketing. Therefore, participant sampling was conducted using the purposive sampling (non-probability) method.

The email request for participation included the reason for the survey and a brief overview of the research aim and objectives of the study. The questionnaire was divided into three sections, namely:

- Section 1: Demographics.
- Section 2: Questions which aimed at understanding the impact of irrelevant marketing on the buyer; for example the relationship with the brand and product take-up.
- Section 3: Questions pertaining to factors that influenced buying decisions and customer experience.

In sections 2 and 3, 5-point Likert scale questions were used. An example is provided below:

Indicate how likely are you to take up a product from a contextual or relevant marketing campaign?
For example, if you are looking at buying a house and you receive a home loan offer versus receiving a home loan offer when you are not in the market to buy a house.

1	2	3	4	5
Very likely	Likely	Neither likely nor unlikely	Unlikely	Very unlikely

Construct validity of the questionnaire was assured by conducting a pilot study among a group of five colleagues at the researcher's place of employment. Since the questions were developed from previous studies (Kubiak, 2012; Larsen, 2010), this was taken as assurance of the validity and reliability of the questionnaire.

4. RESULTS AND DISCUSSIONS

Table I reflects a summary of survey responses to the survey.

Question	Answer Choices	Response	Summary
What is your age?	18 - 22	0.00%	0
	23 - 38	88.89%	8
	39 - 54	11.11%	1
	55 or older	0.00%	0
What is your gender?	Female	55.56%	5
	Male	44.44%	4
	Prefer to self-describe	0.00%	0
What is the highest level of education you have completed?	Grade 12	0.00%	0
	Diploma	22.22%	2
	Bachelor's Degree	33.33%	3
	Honours Degree	22.22%	2
	Master's Degree	22.22%	2
	Doctorate	0.00%	0
What is your gross annual salary (before deductions)?	Other (please specify)	0.00%	0
	< R100 000	0.00%	0
	R100 000 - R299 999	0.00%	0
	R300 000 - R749 999	88.89%	8
	R749 000 - R1 499 999	11.11%	1
> R1 500 000	2.33%	0	
How likely are you to take up a product from a contextual or relevant marketing campaign? For example, if you are looking at buying a house and you receive a home loan offer versus receiving a home loan offer when you are not in the market to buy a house.	Very likely	25.00%	11
	Likely	34.09%	15
	Neither likely nor unlikely	4.55%	2
	Unlikely	25.00%	11
	Very unlikely	11.36%	5
What is the likelihood of an irrelevant marketing campaign negatively affecting your perception of a brand? For example, if you receive a marketing campaign to apply for a credit card however you have an existing one or you don't want or need a credit card.	Very likely	31.11%	14
	Likely	28.89%	13
	Neither likely nor unlikely	0.00%	0
	Unlikely	26.67%	12
	Very unlikely	13.33%	6
If you were considering exiting a relationship with a Service Provider and you are included as part of their retention campaign, how likely are you to be driven away by the marketing action?	Very likely	17.78%	8
	Likely	37.78%	17
	Neither likely nor unlikely	11.11%	5
	Unlikely	24.44%	11
	Very unlikely	8.89%	4
Have you ever taken up a product following a marketing campaign that you would have taken up without the marketing campaign? For example, you received a marketing campaign to apply for a credit card however you would have applied for the credit card without the marketing campaign.	Yes	66.67%	30
	No	33.33%	15
What influences your buying decisions?	My family or friends	13.33%	6
	Influencers or Celebrities	2.22%	1
	Client referrals or testimonials	20.00%	9
	Brand perception	40.00%	18
	Marketing campaigns from companies	11.11%	5
	Other (please specify)	13.33%	6
What from the options below is most likely to result in you exiting a relationship with a Service Provider?	Poor Service	77.78%	35
	Irrelevant Marketing or Spamming	4.44%	2
	Pricing (too expensive)	11.11%	5
	Lack of innovation	2.22%	1
	Other (please specify)	4.44%	2

Table 1: Summary of Responses

Table 2 below is a summary of the thematic analysis of the focus group study using a semi-structured interview method.

Table 2: Thematic analysis of the study based on the semi-structured interviews

INITIAL CODING		CODING	THEME AND RELATIONSHIP
Summary comments	Conceptual Code	Code number	Theme
They don't care about me.	How they feel	Code 1	Expectation or perception of Service Provider
They should know what (products) I have with them, why sell me things I don't need?	How they feel	Code 1	Expectation or perception of Service Provider
They don't know what is going on in their business.	What they think	Code 1	Expectation or perception of Service Provider
They know me; drives brand loyalty.	How they feel and behave towards a brand	Code 2	Buying is influenced by how they feel and what they need.
I want to talk to someone, I want human intervention.	What they want or need	Code 1	Expectation or perception of Service Provider
I want to feel like they care, like they understand me.	What they want or need	Code 1	Expectation or perception of Service Provider
I trust my friends or family. I don't know the company, even the client testimonials may be a lie.	How they feel	Code 2	Buying is influenced by how they feel and what they need.
I want to be able to trust my service provider.	What they want or need	Code 1	Expectation or perception of Service Provider
I want them to be there when I need them.	What they want or need	Code 1	Expectation or perception of Service Provider
I expect my banker (service provider) to be proactive.	What they want or need	Code 1	Expectation or perception of Service Provider
They don't know me.	How they feel	Code 1	Expectation or perception of Service Provider
They don't know my needs. They should be engaging with me to know what I need.	How they feel and what they want	Code 2	Buying is influenced by how they feel and what they need.
When I've made up my mind, I've made up my mind. I have disengaged. There is a reason for my decision and no marketing will make me change my mind.	Why the exit a relationship	Code 3	Breakdown in a relationship happens when there is no longer a value exchange.
When I've decided to end a relationship with a service provider, it's because value have been destroyed.	Why the exit a relationship	Code 3	Breakdown in a relationship happens when there is no longer a value exchange.
My buying is influenced by conducting my own research, because Influencers are paid to promote the product.	How they feel	Code 2	Buying is influenced by how they feel and what they need.
My buying is influenced by my needs at the time.	What they want or need	Code 2	Buying is influenced by how they feel and what they need.
I will exit a relationship when I don't find value. Its no longer relevant to what I need.	Why the exit a relationship	Code 3	Breakdown in a relationship happens when there is no longer a value exchange.
I expect my service provider to be responsive. I expect you to listen to me and understand what I need.	What they want or need	Code 1	Expectation or perception of Service Provider
When I engage with you, I engage as one person not as a group, so don't treat me like I'm part of a group.	What they want or need	Code 1	Expectation or perception of Service Provider
Solutionise for what I need. I want to feel like you are looking at me and not through me. I am a person and not a number.	What they want or need	Code 1	Expectation or perception of Service Provider
When someone goes above and beyond, when they understand my situation and helps me through it, I don't shop around. I get comfort from their service and will continue using them.	What they want or need	Code 2	Buying is influenced by how they feel and what they need.
I need to have an emotional connection for me to have an exceptional customer experience.	What they want or need	Code 2	Buying is influenced by how they feel and what they need.
If I trust you, you can have my business.	How they feel	Code 2	Buying is influenced by how they feel and what they need.
Trust means that an organisation thinks about my future and why they are conducting transactions on my behalf.	How they feel	Code 1	Expectation or perception of Service Provider
When I have a problem, they must solve it for me.	What they want or need	Code 1	Expectation or perception of Service Provider

Based on the information captured in Table 2, the researcher identified three themes, namely, expectation or perception of the service provider; buying is influenced by how they feel and what they need; and breakdown in a relationship happens when there is no longer a value exchange. Further analysis of the data presented the following overarching theme, namely, the desire for personalisation or contextual engagements, which translates to “taking time to understand who I am; I am more than just a customer number and be there for me when I need you, in both the good times and the bad.” The benefit of the above dynamic in a relationship is that it builds trust and results in a value exchange that is beneficial for both parties.

Theme 1: Expectation of the Service Provider

Personalisation was a recurring theme that emerged from the feedback from all participants. It can therefore be concluded that:

- Consumers want personalisation and they expect this from the organisations with which they conduct business.
- There is a relationship between personalisation and brand loyalty.
- Consumers also expect that the personalisation is contextual and happens as close to the trigger event or even in real-time.
- Irrelevant engagements result in a negative perception of the brand and possible customer attrition.
- Consumers expect human intervention when required; even with the increase in technology.

Theme 2: Buying is influenced by how they feel and what they need

On the basis of the data analysis, it was concluded that contextual engagements and brand perception play a crucial role in driving purchase decisions. Therefore, it is clear that:

- Engaging consumers at a time when the product or solution is not relevant, will result in wasted marketing expenditure.
- Referrals from family and friends influence consumers’ buying decisions more than marketing campaigns.
- Trust is a pre-requisite in the buying process.
- Customers will not enter a transactional relationship with an organisation if they think the organisation does not understand their needs.
- Emotional connections with organisations influence the buying decision.

Theme 3: Breakdown in a relationship happens when there is no longer a value exchange

It was also concluded that the requirement for a long-term business relationship is a continued exchange of value, manifesting itself in terms of the following:

- Consumers will exit a relationship if the cost of doing business with an organisation exceeds the value they derive from the relationship.
- Poor service remains a key reason for customer attrition.
- When there is no longer an exchange of value, no amount of marketing initiatives can reactivate a customer.
- Trust is an important human value.

Discussion

Jaroszewicz and Rzepakowski’s (2012) research demonstrates that when applying Uplift models, customers can be segmented into four groups, and this cannot be achieved through traditional models. Siegel (2016) highlights that an Uplift model predicts each prospective customer placement within the four conceptual segments, thus supporting the views of Jaroszewicz and Rzepakowski (2012).

The four conceptual segments are:

- *Do Not Disturb*: Contacting these prospects will have a negative reaction.
- *Lost Causes*: Will not take-up an offer whether contacted or not.
- *Sure Things*: Will take-up the offer whether contacted or not.
- *Persuadables*: Will have a positive reaction to the contact as they will only take up an offer as a result of the interaction.

Since product-centric engagements do not cultivate customer loyalty, it is recommended that organisations develop a clear and focused customer engagement strategy. Uplift models cultivate brand loyalty which is critical to business success, and it will predict each prospective customer placement within four conceptual segments. This allows organisations to strategically drive their engagement strategies, based on the quadrant in which the customer is segmented.

If based on the data analysis process using a traditional response model, a bank customer is identified as having a high propensity to take up a credit card, then a marketing message should be directed to him/her. However, when one overlays an uplift model, the customer could be segmented within the 'Lost Cause' quadrant, meaning that this customer will not take-up this product even if engaged with. Marketers with a product-centric approach will market the credit card given the high propensity for take up, and an Uplift model will apply a customer-centric approach by not marketing to this customer.

Radcliffe and Surry (2011), who appear to be the first to model the incremental impact that a marketing campaign will have on a customer's behaviour, found that applying an Uplift modelling approach to direct marketing can positively impact marketing return-on-investment.

Trust determines comfort level and is therefore a key enabler for business success, by becoming both a commodity and a requirement for consumers intending to conduct business with an organisation. Trust can be achieved through focused relationships with existing clients, enabled through understanding their needs and proposing solutions for those needs. An analysis of client needs is enabled through behavioural analytics and marketing strategies by employing an Uplift model.

Despite the value of Uplift modelling in direct marketing, Yue (2013) highlights four challenges in using Uplift modelling, compared with traditional propensity models, namely:

- at an individual level, one cannot determine who provided the incremental value, and thus the Uplift impact of a specific marketing campaign can only be observed at the population level.
- when compared with gross propensity models, an Uplift model is more volatile, resulting in the need for two additional inputs, namely; Uplift percent due to the market treatment vs. non-market treatment.
- it requires a better planned sampling strategy when compared with the propensity model setup and, requires both randomised treatment groups and control groups. Uplift model results often show counterintuitive results when compared with propensity models and sometimes the best customer segment in propensity models is the worst segment, identified by Uplift modelling.

Recommendations

Marketers must shift from campaigns which were historically a 'spray and pray' approach to conversations or interactions, which will provide a prospect or customer with the ability to engage with an organization. Contextual engagements result in dialogue and lead to a relationship-orientated mind-set that drives brand engagement and loyalty. It is recommended that organisations enable this

through changing the point of departure by adapting current marketing strategies from campaigns to interactions and recognising that behavioural data empowers contextual interactions, by identifying key customer moments. The usefulness of employing an Uplift model in this context is that it supports an organisation's marketing strategy and highlights opportunity segments.

It would be assumed that staff occupying customer relationship management roles are normally selected for their personality. However, it is also recommended that training in what is a constantly evolving environment, be reviewed to ensure that it addresses behavioural changes resulting from the ever-changing societal norms and pressures.

Contextual marketing in an era where consumers are more connected than ever before and where they expect brands to understand their needs, is no longer an option but a necessity, for brands to remain relevant and gain an advantage over their competitors.

5. CONCLUSION

An uplift model predicts each prospective customer placement within four conceptual segments and each segment informs the marketing strategy and action that will result. Figure 1 articulates the four segments and the type of customer it identifies; this will drive a marketer's engagement strategy.

Marketing return-on-investment increases as targeting the 'Persuadables' reduces marketing costs, given the reduction in the target market size, due to the exclusion of the remaining three segments. Response rates increase for the same reason, coupled with the probability that the customer will only take up an offer as a result of the action. Customer experience increases since targeting the 'Persuadables' drives contextual engagements and removing the 'Do Not Disturb' segment mitigates the potential negative effect, such as customer complaints and attrition.

Uplift marketing can reduce marketing costs, since an Uplift model identifies a segment called *Persuadables*, where engagement will have a positive reaction as the consumer will only take-up an offer as a result of the interaction. This reduces marketing costs as marketers do not have to spend money on targeting customers who fall in the remaining three segments depicted in Figure 1.

6. LIMITATION AND STUDY FORWARD

The study was conducted in a financial institution (bank) which offers credit cards and similar products via direct marketing. For the framework to be more generalizable, different samples representing different products should be incorporated in future studies. This study was based on a qualitative research approach and possible future research can be based on applying an Uplift model to the data set for a marketing initiative. The conclusions also highlight the potential for further in-depth research on a number of critical areas; for example, including trust-related variables in Uplift model development.

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