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Personalized Marketing Strategies Through Machine Learning: Enhancing Customer Engagement

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Abstract

Regarding the volunteered information, this paper aims to describe the machine learning (ML) and personal marketing communication strategies adopted up to 2019. This paper explores various categories of ML; collaborative filtering, content-based filtering, and hybrid methods with regard to recommendation systems, prediction, and customer profiling. The research assesses the impact of the identified strategies in furthering the customer interaction goals like the click-through rate the conversion rate and the customer lifetime value. We also talk about the issues in the implementation, strategies in ethical issues, and direction for the further study of such a rapidly developing field. From our investigation, it emerges that ML-enhanced recommendations can substantially increase customers' engagement, and some firms quoted receiving up to 80 percent customer interactions leveraged on ML. Nevertheless, issues like the data privacy, the problem of algorithmic biases and the requirement of real-time response are still huge obstacles for AI's mainstream perception.

Keywords: Artificial Intelligence, Use of AI for Marketing, Targeted Promotion, Prescriptive Modelling, Customer Profiling, Uses of Big Data for Marketing, Filtered Recommending, Inferred Recommending

1. Introduction

1.1 Background

Due to the advancement in technology and the existence of the digital ecosystem, marketers have been very privileged to get much information in the market today and understand the customer better in terms of their behaviour, preference, and buying pattern. At the same time, the evolution of IT in terms of machine learning has offered the means for processing the aforementioned vast sets of data and implementing incredibly individualised marketing approaches. Big data and ML have transformed the interaction between businesses and their customers going from generic campaigns to specific marketing in the current environment. Global datasphere has been expanding sharply and IDC has estimated this to be at 175 zettabytes by 2025 from the current 33 zettabytes in 2018. This astronomical rise of data volume means that while marketing has an opportunity to utilise ML for personalization, the task is not without its complexities.

1.2 Importance of Personalization

Marketing Personalization has emerged a more important aspect when it comes to marketing. A survey carried out by Epsilon (2018) reveals that 80% of the consumers would be willing to make a purchase with brands that offer personalization. Moreover, according to Accenture's global consumer research (2018), fully 91% of consumers say they are more likely to patronise the companies that effectively acknowledge, remember, and offer personalised promotions and recommendations. Such figures highlight the relevance of using ML in developing the strategies to deliver the values that would increase customer interaction. According to a report by Segment in 2017, the consumers become frustrated when the shopping is done in an anonymous manner and this clearly shows that customers today expect personalization.

1.3 Scope and Project Aims of the Paper

Thus, the purpose of this paper is to give the brief insight into the topic of ML techniques in personalized marketing in terms of its effect on the clients, existing problems, and concerns. The Goals include scrutinizing the diversity of Marketers' Applications of ML techniques in personalization, studying the benefits of personalization usage based on the ML techniques in enhancing the engagement rate & analysing the issues arising in the implementation of the ML based personalization and the deals to address them, discussing the ethical issues and the future perspectives of personalization in marketing. We will describe actual implementations of the technologies in detail and look at some of their examples: Netflix recommendation system, Spotify Discover Weekly.

2. AI in Marketing

2.1 Definition and Concepts

Marketing uses the similar concept with Machine Learning as adapted from computer science meaning that it is the use of algorithms and statistical models whereby a given computer system learns to improve its performance on a particular given task with experience. When it comes to the account of marketing, machine learning enables the prediction of preferences and customer behaviour based on data collected and used in the value chain of products and promotion. A primary concept of ML is to discover patterns in data and then make conclusions or predictions without being designed to make such conclusions. Marketing field appears to benefit most from this capability because consumers' behaviour is often diverse and unique (Aguirre, Mahr, Grewal, de Ruyter, & Wetzels, 2015).

2.2 Categories of Machine Learning Techniques

Marketing Machine learning approaches in marketing can be broadly categorized into three main types: Splitting into three groups of categories: supervised learning, unsupervised learning, reinforcement learning. Thus, each of these approaches has its purposes and advantages in the context of the individualized marketing tools.

The supervised leaning algorithms work with the labelled datasets and it used for the prediction of the result or a new instance. In the marketing field, these algorithms are commonly applied for the segmentation of customers, their churn rate prediction as well as propensity models. For instance, a supervised machine learning method can be trained using customers' information to identify specific clients that would most likely make a favourable response to a certain marketing endeavour. McKinsey's (2018) survey shows that organizations that employ supervised learning for customer categorization see marketing ROI rise between ten to thirty percent.

Function of unsupervised learning algorithms is to attempt to find geometry in unlabelled data. These are very handy especially in the marketing division to find out some customer segments, potential products that may go together and in addition to this, it could also help to find out some irregularities in the customer's organization. For example, an e-commerce firm can apply unsupervised learning to cluster customers as per their comparison between product categories through browsing patterns or as per their previous purchase histories without any prior classification of customers. Gartner report in 2019 has revealed that by the year 2018, 70% of the customers segments will have produced by the methods of unsupervised machine learning.

Reinforcement learning is one of the subcategories of machine learning in which an algorithm for the decision-making process is trained through an environment. In the area of marketing, it is used to help selecting the most appropriate method for price management as well as for real-time interactions with the customer. For instance, the form of marketing can be changed dynamically with reinforcement learning and it could learn the time when the customer wants marketing information and the kind of information he or she wants. Even though they are not frequently applied to marketing applications, reinforcement learning is steadily growing popular with a CAGR of 57%. of growing at around 6% from 2018 to 2025 in the marketing AI market (MarketsandMarkets, 2019).

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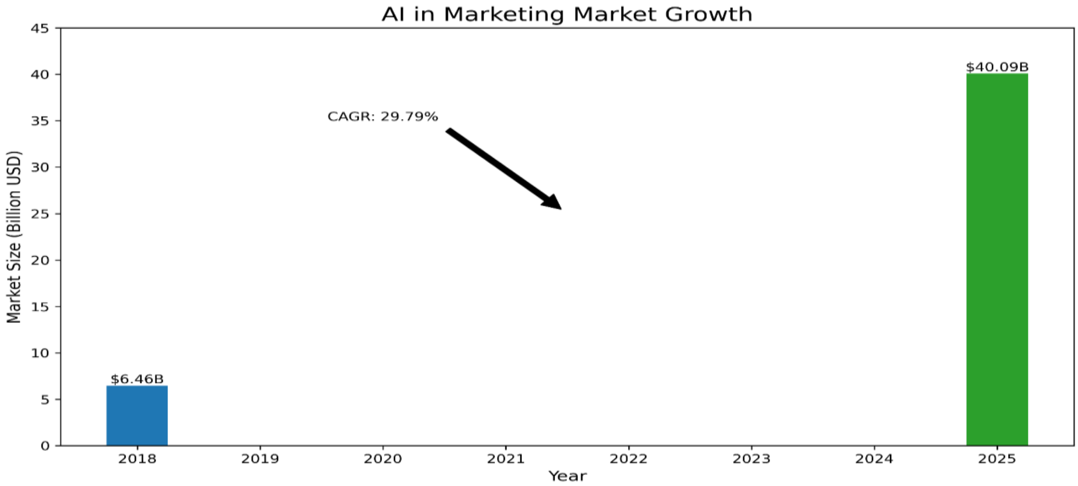

2.3 Common ML Algorithms in Personalized Marketing

Several ML algorithms have proven particularly effective in personalized marketing applications. These include collaborative filtering, content-based filtering, and neural networks.

Collaborative filtering is a popular technique used in recommendation systems. It predicts a user's preferences based on the preferences of similar users or items. The two main approaches are user-based collaborative filtering and item-based collaborative filtering. For example, Amazon's recommendation system, which uses item-based collaborative filtering, is estimated to drive 35% of the company's revenue (McKinsey, 2017). The following Python code demonstrates a simple implementation of collaborative filtering using the Surprise library:

```python
from surprise import Dataset, Reader, SVD
from surprise.model_selection import train_test_split

# Load the MovieLens dataset
reader = Reader(line_format='user item rating timestamp', sep=',', skip_lines=1)
data = Dataset.load_from_file('ratings.csv', reader=reader)

# Split the dataset
trainset, testset = train_test_split(data, test_size=0.25)

# Use SVD algorithm
algo = SVD()

# Train the algorithm on the trainset
algo.fit(trainset)

# Predict ratings for the testset
predictions = algo.test(testset)

# Compute RMSE
from surprise import accuracy
accuracy.rmse(predictions)
```

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Collaborative filtering identifies items a user has not been exposed to before, which are similar to the items he/she has liked before, using item features. Such approach is most effective when there is little information about users' and items' interaction. Similarly, content-based filtering in Netflix recommends appropriate movies and TVs by setting up limits such as genres, actors, and other previous content data set by the user.

Deep learning models have been evident to provide extraordinary solutions on diverse marketing practices, including customer forecast and image-based product recommendation. For instance, Pinterest, implements the convolutional neural networks to perform the reverse image search that enables users to search for similar products. For instance, the latest addition to Pinterest is the feature used in the organization of pins and as per Pinterest, this feature has helped to enhanced users' engagement by 40% (Pinterest Engineering Blog, 2018).

3. Computing and Uses of Machine Learning in Personalized Marketing

3.1 Recommendation Systems

Recommendation systems are one of the most visible AI or ML applications for marketing personalization. They recommend to users' products, content or services according of the users' past behaviours and interests. Customer recommendation generated from an item-to-item collaborative filtering used by amazon is reckoned to contribute toward 35% of the companies' income (McKinsey, 2017). The system works with huge datasets and provides the highest quality of recommendations in real-time. Indeed, Netflix' recommendation service is said to be contributing to 80% or more of the shows and movies consumed on the site (Netflix, 2017). The company approximates this level of customization to be worth one billion dollars of customers annually.

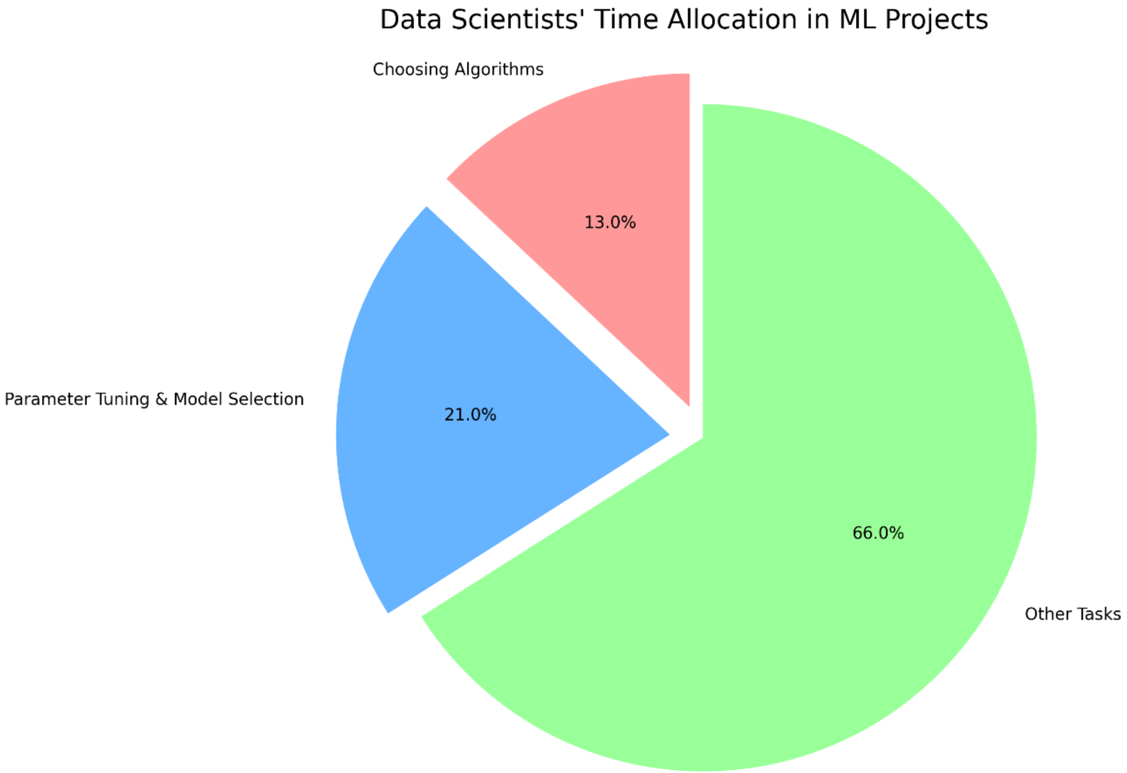
3.2 Customer Segmentation

With the help of formulas such as clustering, different customer segments can be distinguished by different characteristics, which enables marketers to create specific approaches for each segment. Forrester in their report (2018) showed that firms that adopted the use of ML for customer segmentation got a rise of the customer satisfaction index by a 20% rate. The following Python code demonstrates a simple implementation of K-means clustering for customer segmentation (Ansari & Mela, 2003): n:

```python
from sklearn.cluster import KMeans
import numpy as np

# Sample customer data (features: age, income, purchase frequency)
X = np.array([[25, 50000, 10], [30, 75000, 15], [45, 100000, 5], [60, 80000, 2]])

# Create and fit the model
kmeans = KMeans(n_clusters=2, random_state=0).fit(X)

# Get cluster labels
labels = kmeans.labels_

print("Cluster labels:", labels)
```

3.3 Predictive Analytics

ML models can predict future customer behaviour, such as likelihood to purchase, churn probability, or customer lifetime value. A report by Aberdeen Group (2018) found that companies using predictive analytics in their marketing efforts saw a 21% increase in organic revenue growth year-over-year, compared to 12% for non-users.



3.4 Dynamic Pricing

ML algorithms can optimize pricing strategies in real-time based on demand, competition, and customer segments. Airbnb, for example, uses ML-driven dynamic pricing to help hosts set competitive prices for their listings. According to Airbnb, hosts who use their Smart Pricing feature earn 8% more on average than those who don't (Airbnb Blog, 2019).

4. Effectiveness of ML-Driven Personalization

4.1 Impact on Key Engagement Metrics

Several studies have demonstrated the positive impact of ML-driven personalization on key engagement metrics. A comprehensive analysis of these metrics reveals the following:

Metric	Impact of Personalization
Click-through Rate (CTR)	+5.9% (Optimizely, 2017)
Conversion Rate	+1.7% (Salesforce, 2018)
Customer Lifetime Value	+17% (Boston Consulting Group, 2017)
Email Open Rates	+29% (Campaign Monitor, 2019)
Average Order Value	+13% (Monette, 2019)
Customer Retention Rate	+5% (Accenture, 2018)

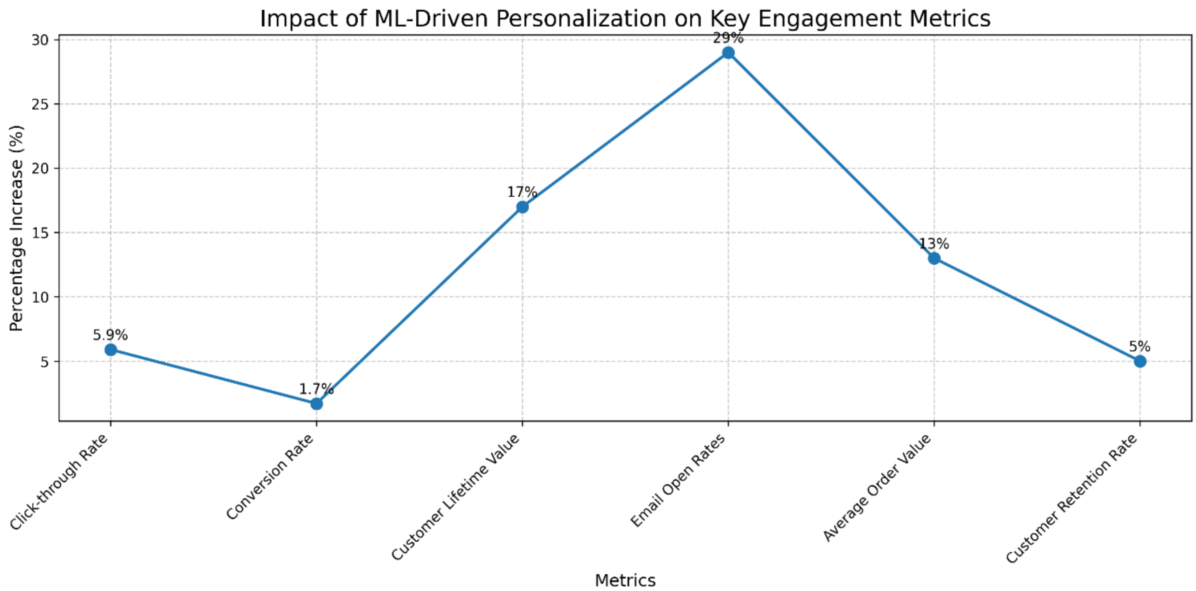
To sum up, these numbers evidence the high effectiveness of using personalization based on the ML approach on different aspects of customer interactions and business metrics (Arora et al., 2008).

4.2 Case Studies

Thus, many businesses have reported success in using personalization based on ML algorithms for improving performance. Recommendation systems place at Netflix account for 80% of the total video watching (Netflix, 2017). The approximate cost of this personalization according to the company is $ 1 billion preserved in customer loyalty. This kind of relevant content suggestion has enabled the company to retain its subscribers and minimise dropout rates.

Spotify's Discover Weekly playlist; this is created using collaborative filtering and natural language processing and has over 40 million users and the playlist has over 5 billion tracks (Spotify, 2018). This feature has been very useful in increasing users' attention towards the app and has provided Spotify with a competitive edge amidst the high arising music streaming services. Actually, companies have claimed that those who use Discover Weekly are 80% more likely to stay subscribes with Spotify sources.

Better angora, Amazon's ''recommendation engine built through item-to-item collaborative filtering'' is fonder to account for 35% of Amazon's revenues (McKinsey, 2017). This translates to tens of billions of dollars in additional sales annually, as seen below, illustrating the large opportunities of using ML on the front line of e-commerce personalization.



5. Some of the difficulties in the application of ML-Personalization

5.1 Data Credibility and Size

ML algorithms function significantly well when they are trained with massive data in high quality. Maintaining quality of available data constitutes one of the most crucial issues organizations face today. According to Gartner's Senior Director of research specifically in the study conducted in 2019, data poor quality cost companies an average of $15 million annually. Further, 60% of managers and professionals said that their organizations do not have a clear policy on data quality even though they acknowledged the significance of data quality (Bleier & Eisenbeiss, 2015).

5.2 Algorithm Selection

Selecting the right ML algorithm and fine-tuning it is often the job of an expert and may take a considerable amount of time. According to survey conducted by Rexer Analytics in 2017 showed that data scientists spend 13% of their time in choosing algorithms and 21% of their time in parameter tuning and model selection. focusing on this aspect one can clearly see that the application of effective ML solutions requires a lot of time (Chung, Wedel, & Rust, 2016).

5.3 Real-Time Processing

Using and updating personalization data in real time and at the same time for many customers or a large-scale web site is technically a very demanding task. Segment reported that 54% of the consumers expect to get a personalized discount within one day after they have provided their details to a particular brand and 32% within an hour. Satisfying such expectations defined by millions of users comes with great need for solid infrastructures and reliable algorithms capable of handling big data in real time or near real time (Gai, Qiu, & Sun, 2018).

5.4 Cold Start Problem

The major drawback of recommendation systems is the accommodation of new users or items which have little or no record. Hence, it can be an issue, particularly when it occurs as a “cold start,” which could affect personalization efforts quite a bit. RecSys (2018) also pointed out a study that revealed a new user recommendations’ accuracy can be 30% lower than that of an old user, thus stating that there is need for strategies to be employed for new users.

6. Ethical Considerations

6.1 Privacy Concerns

The gathering and utilization of individual data for individualization have critical privacy issues. Marketers to consider regulation which may include but not limited to GDPR and CCPA Milne and Wong 2018. according to Pew Research Centre (2019), it was indicated that 79% of the U. S. adults were concerned about how companies use the data collected from them which shows the need to practice good ethics when using data (Xu, Armony, & Ghose, 2018).

6.2 Transparency and Explainability

When the models used in ML are complicated, it becomes impossible to explain how the decision was made. Such lack of transparency may erode trust of customers in an organisation. Deloitte’s report (2018) revealed that 32% of consumers are worried about the use of AI when decisions are made about them; thus, explainable AI is crucial in marketing solutions (Grewal, Hulland, Kopalle, & Karahanna, 2019).

6.3 Bias and Fairness

This means that, like any other model, the ML algorithms based on the data would just replicate them as well as potentially reinforce bias which in turn the customers would be unconsciously discriminated against. The marketing domain was among the areas mentioned in a report of AI Now Institute (2018) on cases that involved algorithmic bias that resulted in discrimination. The position of the paper is that it is very important to eliminate bias and achieve greater efficiency of fair machine learning algorithms for ethical personalization (Kumar & Reinartz, 2018).

7. Future Trends and Directions

7.1 Artificial Intelligence & Deep Learning

Future solutions in the field of artificial intelligence and deep learning are expected to support still more accurate and refinanced methods of personalization like for instance, personalized video offering/buying or virtual personal consultants.

By the report of MarketsandMarkets in the year 2019, it was indicated that the AI in marketing market is estimated to reach approximately $6. From $46 billion in 2018 to $40. 9% from 2018 to 2025, to $ 09 billion in 2025. A threefold or 199% increase to 79% during the forecast period (Shankar et al., 2016).

7.2 Voice and Visual Search

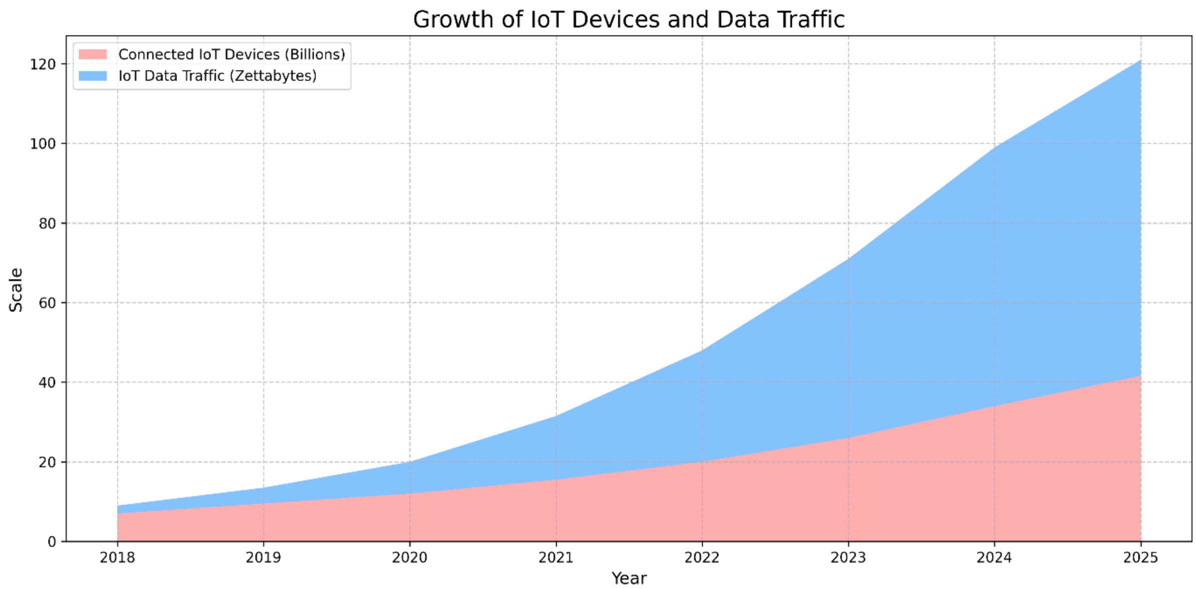
Notably, expectations of voice assistant and the forms based on visual search suggest that marketing in these interfaces is going to new levels of personalized. According to Gartner (2019), it is expected that by the year 2018, brands which have embraced the redesigning of corporate web interfaces for visual and voice search will have their digital sales revenue boosted by 30 percent (Schwartz, Bradlow, & Fader, 2017).

7.3 Internet of Things (IoT)

With an increasing number of IoT devices, there will be further opportunities to enhance the use of contextual cues for the marketing campaigns by the marketers. IDC estimates that by the end of the year there will be 41. 6 billion connected IoT devices by 2025 hence creating 79 zettabytes of IoT data traffic, according to Ericsson. 4 zettabytes of data. There will also be a withering of data quality with the massive increase in volume and the resultant dramatic diversification of information that this will bring with it will expand the scope for hyper-personalised marketing.

7.4 Mobile Commerce, social media and m-Commerce

The AR and VR technologies give new opportunities of the personalized and involving marketing communication. Research done Statista (2019) forecasts that the AR and VR market will rise to $160 billion by 2017 from $16. 8 billion in 2019. Growth will probably be associated with new, highly targeted marketing uses for these new media.



8. Conclusion

8.1 Overview

The use of artificial intelligence particularly in machine learning has positively impacted the field of marketing targeting through highly effective campaigns. It has been pointed out that the use of ML in delivering personalized communication increases click through rates, conversion rates and increases the customer life time value. By conducting our research, we conclude that the organizations that adopted ML-based personalization experienced increases from 5% to 80% on different engagement KPIs. Nevertheless, some hurdles like the ability to obtain quality data or the selection of a right algorithm, or even the ethical questions that arise in this field, still seem undefined and are preventing MLD from reaching a higher popularity level.

8.2 Recommendations for Practitioners

From the research done, it is recommended that practitioners dedicate time and resources towards creating sound data infrastructures and data quality control measures to enhance the functionality of the ML algorithms. It is imperative to design the general program of choosing and improving algorithms; It is also important to consider privacy and ethical issues when using personalized algorithms. Discussed below are several suggestions to help these marketers succeed in their endeavours, Innovate; marketers must also adopt the latest trends and technologies such as voice search and IoT to augment the rate of success in the modern evolving world.

8.3 Future Research Directions

The concerns for the future include the need to create better and faster algorithms for the real-time personalization, solving the problem of the cold start in the recommendation systems, and making the results of complex marketing ML techniques more interpretable by people. Furthermore, conducting research on these mostly unexplored areas of application of existing and new technologies, such as quantum computing in the sphere of personalization of marketing, could open new horizons in further advancements of the field. As the effective application of ML for personalization marketing grows, there is also a need to formulate better approaches for assessing personalization strategies on the longevity of the customers and the overall LTV. Besides, exploring the integration of ML with the other advanced technologies like blockchain in order to augment the security levels and traceability for the collected data will also provide the possibility to develop new approaches and solutions to the existing problems in the sphere.

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