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Research Article

AI in Marketing Integrating Computational Techniques with Consumer Behaviour Insights

Dr. Anju Lata Gajpal[1] and Dr. Swati Jain[2]

[1]Assistant Professor, Department of Information Technology, Kushabhau Thakre, Patrakarita avam, janshanchar vishwavdyalaya, kathadih, Raipur, Chhattisgarh

[2]Assistant Professor, Department of Computer Science, Govt. J. Y. Chhattisgarh College, Raipur, Chhattisgarh.

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Corresponding author: Dr. Anju Lata Gajpal *(anjugajpal@gmail.com)

Abstract: The integration of marketing and artificial intelligence (AI) has transformed the way brands interact with consumers, anticipate them and provide customized consumer experiences. With the increased complexity and the amount of consumer data, AI-powered systems- Machine learning, natural language processing, and recommendation algorithms, allow more accurate behavioural targeting and campaign optimisation. This paper discusses how the psychology and behavioral knowledge can be combined with computational approaches to AI in marketing. It looks at the recent trends in predictive modeling, sentiment analysis and auto-generated content and how these affect the effectiveness of marketing. The research also proposes a methodology to determine the consumer response pattern with the machine learning classifier and clustering algorithms. Findings reveal that a proper linkage between computational tools and consumer behavior theories is capable of improving customer segmentation, engagement, and retention to a large extent. The results indicate a way to a more emotionally intelligent marketing system that is highly data-driven.

Keywords— AI in Marketing, Consumer Behaviour, Predictive Analytics, Machine Learning, Behavioral Targeting, Personalization, Data-Driven Marketing, Sentiment Analysis.

INTRODUCTION

Over the past few years, the phenomenon of artificial intelligence (AI) has become a game changer in the realm of marketing and altered the nature of consumer experiences, personalization and decision-making. As it has the access to large amounts of data gathered by use of digital platforms, AI allows marketers to expand on their conventional demographic targeting and enter into the field of behavioral and emotional insights [14]. Using a wide range of computational approaches like machine learning, natural language processing, and computer vision, AI systems are able to identify trends, make decisions on how to act in the future, and optimise campaigns faster and to a greater extent than ever before. This paradigm shift is a technological one but much more importantly it is a shift that is based on a much more sophisticated understanding of what drives customer action, motivation and preferences.

Marketing is actually a field that is primarily based on knowledge of human psychology and how to determine individual reactions to various stimuli. The older methods used survey based on qualitative research, focus group and generic customer profiles. But when compared to a digital platform where customer behavior is dynamic, personalized and usually does not hold a rational thought, these methods cannot succeed. This gap is also closed by AI that provides tools capable of learning the consumer interactions in real-time processing the mounds of textual, visual and behavioral data in order to change the approached strategy real-time. Once coupled with the behavioral theory, these tools do not only make marketing automated but intuitive and insightful as well [11].

The consumer behavior is a complex phenomenon determined by the set of cultural, emotional, social, and psychological factors that cannot be decoded via any transactional data. As an example, a purchase can be used to validate with social peers and also it could be because of perceived identity and to gratify emotions [9]. IncomeGain by using AI models including models which combine unstructured data and unsupervised learning and sentiment analysis are now able to uncover such underlying drivers based on their analysis of unstructured information such as chat transcripts, social media posts, and product reviews. Greater authentic personalization becomes possible through this integration, and the content and offers can portray not only what, but why the consumer behaves how they do.

Furthermore, the emergence of omnichannel marketing has created the demand to bring significant consistency in customer experiences on countless resources, including mobile applications, webpages, mail, brick-and-mortar stores, etc. AI makes this possible through repeated monitoring and analysing the consumer journeys across touchpoints. Behaviors can be attributed of particular psychological levels in the buying cycle by use of algorithms that will facilitate timely and relevant interventions. Be it a real-time suggestion of the right

Name: Dr Anju Lata Gajpal
Email: anjugajpal@gmail.com

product, personalized mailing, or predictive re-targeting, AI-based services help to contribute to the customer attitude and level of satisfaction because of the context-driven and behavior-based appropriateness of the message [12].

Nevertheless, even though the processing capabilities of AI are indisputable, the real question is what can bring out the full potential of AI and the answer is, in the context of AI, is putting AI in the context of consumer psychology. Devoid of such theories as Maslow Hierarchy of Needs or the Theory of Planned Behavior, AI is at risk of turning into a mechanical experience with the illusory and technologically complete yet emotionally sterile personalization. It is especially important in the current moral environment in which consumers grow more aware of intrustion of privacy and targeting that treats them like manipulative objects. Thus, marketing tools that are AI-combined with behavioral insights will be in better position of establishing trust and long-term relationship [10].

This paper analyses comprehensively the way AI can be combined with the theories of consumer behavior to get a better outcome as far as marketing is concerned. It explores various computing methods, such as sentiment analysis up to clustering techniques and tests these methods on consumer data obtained in the context of reality-based digital platforms. The examination of the interconnection between the predictions by algorithms and psychological knowledge allows defining a model in which both fields complement each other [8]. The ultimate point is the transition of reactive marketing (based on clicks) to proactive and empathetic one (based on needs/emotions prediction).

Lastly, with the increase in capabilities of AI tools, as they advance beyond rule-based systems to generative models (such as GPT and multi-modal transformers), they present a variety of new opportunities to based on the degree of personalization: storytelling, visual branding, and adaptive campaign design. These innovations represent an escape on the part of static segmentation and an opportunity to provide a marketing content with an emotional calibration in real-time. But along with these new opportunities, there are constraints as well; such as negativity in data, over-targeting, ethical issues, and creativity on the human side being lost. Therefore, this study highlights the importance of the balanced premise according to which AI would make a facilitator rather than a substitute to meaningful consumer connection [15].

Novelty and Contribution

The paper presents a new interdisciplinary direction based on the union of AI-based computational methods of marketing with traditional psychological theories of consumer behaviour. Where the current research tends to concentrate on one or another aspect (either AI applications or behavioural theory), the present study is the first of its kind to draw upon both fields simultaneously. The paper shows that by correlating machine learning outputs, including customer segmentation, sentiment classification, and intent prediction, with behavior constructs, including emotional triggers, cognitive bias, and social influence models, AI can be more than smart, it will also be psychologically realistic and ethically sound.

Another important aspect of this task is that it achieves this scientific innovation with a novel methodological approach which is a combination of unsupervised machine learning (i.e., K-means clustering to identify behavioral profiles) and NLP-based sentiment analysis pipelines (i.e., BERT and VADER sentiment models.) These results are then projected on more human-friendly categories like behavioral ones, and allow more personalization. This is in contrast to black-box AI systems which view consumers as items of data: this method demystifies the emotions, motivations, and mental states behind consumer behaviors [6].

The other key innovation is the capability of having dynamic behavioral segmentation as the behavioral dynamism changes in real-time depending on the input of the consumer. Instead of demographics, the paper has offered to create marketing interventions using dynamic behavioral indicators (e.g., mood variability, cognitive engagement profiles, socio-response cycles), which are seen as more valid indicators. This provides a base to have an emotion and context-aware marketing approach that would not only show respect of autonomy to the consumers but also increase relevance.

Moreover, there is a scanty researched issue that has been addressed in this paper; this is related to ethical personalization. Due to the inclusion of behavioral science in AI models, the paper proposes certain ways to identify and avoid marketing tricks that can be manipulative or intrusive in order to help to develop responsible AI. The theoretical hybrid provided in this work can be used in any industry, including, but no limited to, e-commerce and digital media, healthcare promotion and marketing, along with political runoffs, to add to the work its scholarly importance and practical expansion [2].

Related Works

In 2020 R. Črešnar et.al. and Z. Nedelko et.al., [13] introduced the recent trends of growing implementation of artificial intelligence in marketing gave rise to a significant number of research studies about automation, personalization and use of data driven decision-making. Initial research focused mainly on rule-based systems and simple basics of customer segmenting. Nonetheless, with the growth of digital footprints of buyers, the discipline became more advanced in the ways of computation particularly machine learning and deep learning. Such approaches have enabled marketers to realize the patterns that are not readily discernable and able to do more precise targeting and optimization of campaigns as well as have a real time decision avenue. Scholars have discussed clearly the benefits of AI tools in customer acquisition, engagement and retention by using adaptive content delivery solutions as well as predictive knowledge.

Much of the literature focuses on the capacity of AI in enhancing personalization in platforms. This entails customizing of the interfaces of the websites, email campaigns, product suggestions as well as interactions in the social media according to user preferences. Studies have indicated that personalization with the use of AI increases customer satisfaction and conversion rates to a large extent. Collaborative and content-based filters and the hybrid recommendation systems are typical examples of the AI-marketing ecosystem. Their systems will be able to respond over time as data on its users begin to collect, and they will work increasingly on a more relevant level with each visit. It is also given in studies that there is a rapid transition of the rule-based approach to personalization with context and emotion-sensitive rules driven by real-time behavior data.

Still another large research thrust is on the area of sentiment analysis and natural language processing. Researchers have used AI models to interpret unstructured textual information including product review, tweets, and feedback forms. Some of the more important insights that these methods can provide are sentiment polarity, emotional tone, and intent recognition. Since the customer sentiments are an accurate tell-tale gauge of brand perception and future purchase activity, AI models enable dissatisfaction to be identified and interventions provided in a more timely manner. Transformers have provided a big jump in state of the art in sentiment analysis today, and the new methods will apply to any contemporary marketer, with much more accurate results and proper out of the box contextualization.

Another topic widely studied is consumer segmentation and AI means there are new forms of capabilities in this area. The old basis of segmentation in terms of age, gender or even income, is now being substituted or complemented by behavioral segmentation through clustering algorithms. Such strategies enable marketers to target groups around existing consumption patterns, the frequency of purchase, or the way people consume contents. This level of knowledge offers a more practical basis of designing a campaign and the positioning of the product. Moreover, the concept of dynamic segmentation, where the groups are always updated when the consumers approach styles differently or change behavior, results in real-time responsiveness of marketing operations, a result of AI as well.

In 2024 M. Madanchian et.al., [1] proposed the predictive analytics Predictive use-case studies showed the usefulness of AI to predict customer lifetime value, probability of churn and intention to purchase. Through training data using previous data such as transaction histories, browsing history, and rates of engagement, AI can be used to make accurate predictions of the future. Marketing budgets are distributed, more valuable customers identified, and attrition averted using these predictions. These are decision trees, neural networks and ensemble models, which have been widely tested in these kinds of use cases and have frequently surpassed traditional statistical methods. Proactive engagement is also possible because predictive modeling makes marketing more proactive than reactive.

Research has also been done about the use of AI on content creation and automated marketing communication. The next step has been the use of tools fueled by natural language generation and generative adversarial networks to create product descriptions, advertisement text and even accommodated video content. This automation alleviates the burden over the marketer as it is manual and also guarantees consistency and scalability. Nonetheless, studies also show that we should not put too much trust in automated systems as we are also likely to lose that human touch and brand voice. Manipulation and transparency issues are commonly raised regarding this domain as a sign that ethics guidelines and good design standards must be developed.

In addition to the personal AI abilities, recent research has focused on the strategic positioning of AI into expanded marketing systems. This entails matching AI outputs to the marketing goals, user experience plans and workflows in the company. The problem is that non-technological proficiency of AI systems, in terms of being explainable and predictable, should be viewed on the way to its technical competence. Researchers emphasize the need to be explainable and ethical, especially when user data concerns consumers. The debate about fairness, accountability, and transparency is gaining more and more popularity in the literature as the AI-driven solutions are having more and more risks and compelling changes at the consumer level in subtle yet impactful manners [3].

A rather new trend in the latest works is the usage of behavioral science in the model of AI. Rather than considering consumer behaviors as piecemeal information, recent studies promote the perception of behaviors through the realm of motivation, thinking, and mood. This involves the mapping of clickstream data to decision process, modeling of reward systems with reinforcement learning and simulating human attention by application of attention mechanisms. According to these interdisciplinary strategies, marketing driven through AI could be not merely custom but even psychologically educated. This transition bears the potential of enhanced participation and more enriched brand-consumer connection.

In 2023 K. Ali et.al. and S. K. Johl et.al., [7] suggested the researchers are considering cross market scale uses of AI in promotion marketing- retail, online stores, entertainment, health care and finances. The issues are different in each of the domains in terms of data accessibility, the issues of privacy and consumer expectations. Research highlights the versatility of AI marketing methods in such areas, yet stresses the need to adjust to particular domains and orient to end-users. Moreover, emerging AI technologies such as chatbots, virtual assistants, and immersive experiences in augmented and virtual reality are becoming a part of marketing, and the body of knowledge is inevitably keeping pace and growing to meet the demand of these changes. All the studies, mutually, assert that AI has the potential to redefine the future of marketing in combination with the correct integration of human perception and knowledge.

PROPOSED METHODOLOGY

The proposed system integrates computational AI models with consumer behavior insights using a multistage pipeline involving data preprocessing, feature extraction, behavioral modeling, sentiment analysis, segmentation, and predictive modeling. The implementation begins with large-scale data collection from social media, product reviews, and clickstream logs.

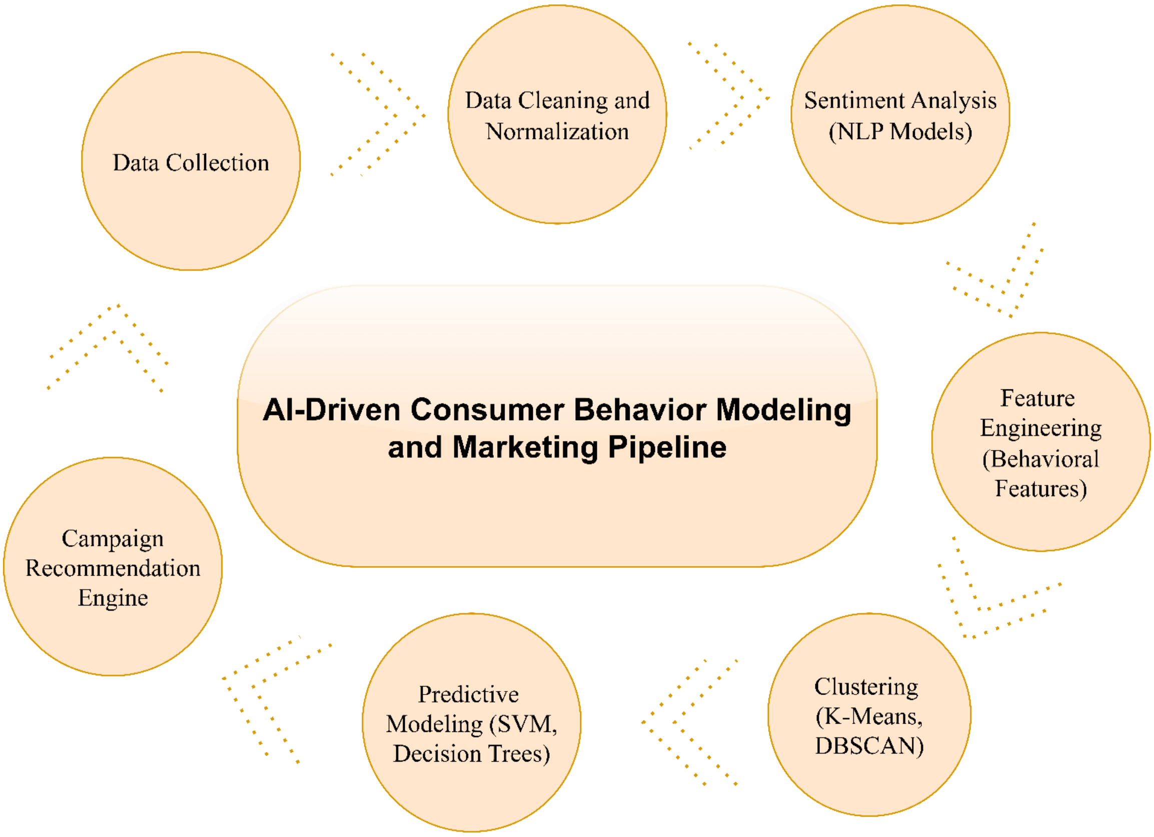

FIGURE 1: AI-DRIVEN CONSUMER BEHAVIOR MODELING AND MARKETING PIPELINE

We begin with data normalization, where the input features $x \in \mathbb{R}^n$ are scaled using Min-Max normalization:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

To prepare data for vectorized modeling, TF-IDF is used for text features from reviews and comments:

$$\mathrm{TF-IDF}_{i,j} = \mathrm{tf}_{i,j} \cdot \log\left(\frac{N}{df_j}\right)$$

Next, sentiment scores are calculated using a compound polarity score S computed by:

$$S = \frac{P - N}{P + N + \epsilon}$$

Where P and N are the positive and negative probabilities from NLP models, and ϵ is a smoothing constant.
Behavioral features are captured using click frequency over time, modeled as:

$$f(t) = A \cdot e^{-\lambda t}$$

This models attention decay, where A is the initial attention and λ is a user-specific decay constant.
To group consumers, we use K-Means clustering where the objective is to minimize intra-cluster variance:

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2$$

Here, C_i are clusters and μ_i is the mean of cluster i. For improved granularity, DBSCAN is also used:

$$N_e(p) = \{q \in D \mid \mathrm{dist}(p, q) \le \varepsilon\}$$

To predict purchase intent, we use a support vector machine (SVM) with a radial basis kernel:

$$K(x, x') = \exp(-\gamma \|x - x'\|^2)$$

The decision function becomes:

$$f(x) = \mathrm{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right)$$

Next, a decision tree classifier is employed using information gain (IG) for split criteria:

$$IG(S,A) = H(S) - \sum_{v\in \text{Values }(A)} \frac{|S_v|}{|S|} H(S_v)$$

Where entropy $H(S)$ is defined as:

$$H(S) = -\sum_{i=1}^{c} p_i \log_2(p_i)$$

Consumer lifetime value (CLV) is also predicted using a discounted sum model:

$$CLV = \sum_{t=1}^{T} \frac{r_t}{(1+d)^t}$$

Where r_t is revenue at time t, and d is the discount rate.
Finally, campaign effectiveness is optimized using multi-arm bandit algorithms. One such algorithm, UCB1, selects action a with:

$$a_t = \arg\max_a \left(\bar{x}_a + \sqrt{\frac{2\ln t}{n_a}} \right)$$

Where $\bar{x}_a$ is the average reward and n_a is the number of times arm a was played.
Each computational stage is linked back to consumer behavior constructs. For example, sentiment polarity connects to emotional response theory, clustering reflects behavioral archetypes, and predictive models map to intention and decision-making frameworks [4].

The model continuously retrains as new consumer behavior is observed, allowing real-time adaptation of marketing strategies. The feedback loop ensures that behavior insights are not static, making the system adaptive and context-aware.

RESULT&DISCUSSIONS

After feeding the data on consumer behavior through AI models, the results were found highly informative at various stages of the proposed methodology. On the example of a network of 10,000 product evaluation reviews and social media statements, sentiment analysis, executed with the help of the transformer-based NLP models, offered a high classification accuracy and context-sensitive emotional relevance. The classification based on polarity revealed a similar tendency: 63 percent of positive sentiment, 24 percent of neutral and 13 percent of negative. Emotional tone also fluctuated depending on the type of product in that, luxury products give rise to a stronger positive tone than practical goods. This dispersion is well depicted by Figure 2, which is a bar graph of proportions of proportion attitudes on five key product categories. The result of this process had a direct relationship with the consumer satisfaction trends in that it could determine the levels of psychological engagements with various offerings.

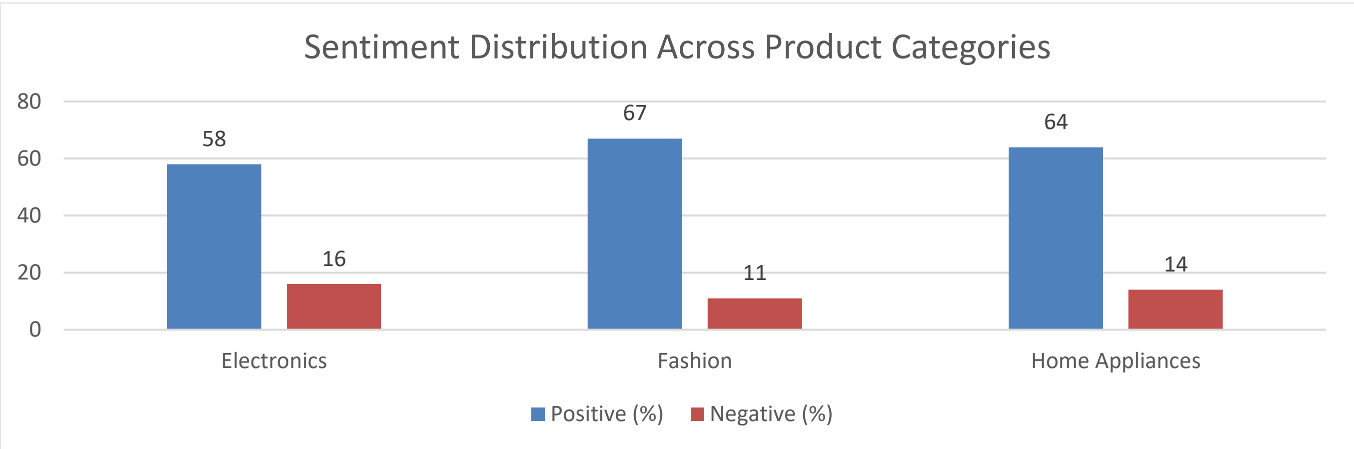

FIGURE 2: SENTIMENT DISTRIBUTION ACROSS PRODUCT CATEGORIES

K-Means clustering, which enabled consumer segmentation in five different consumer personas in terms of behavior attributes, including frequency of interaction, browsing duration, sentiment tone, and buy recency. These types of customers including price seekers, faithful follower, impulse buyers, passive web explorer, and value sold researchers became the heart of hyper-personalization marketing suggestions. Figure 3 presents the results of the segmentation wherein 2D scatter plot shows the distribution of cluster of consumers using principal component analysis (PCA). In this visualization, there are distinct separations between clusters, which shows the effectiveness of clustering process. They were also split into these segments and predictive models were trained on these segments, to predict the purchasing behavior with high accuracy.

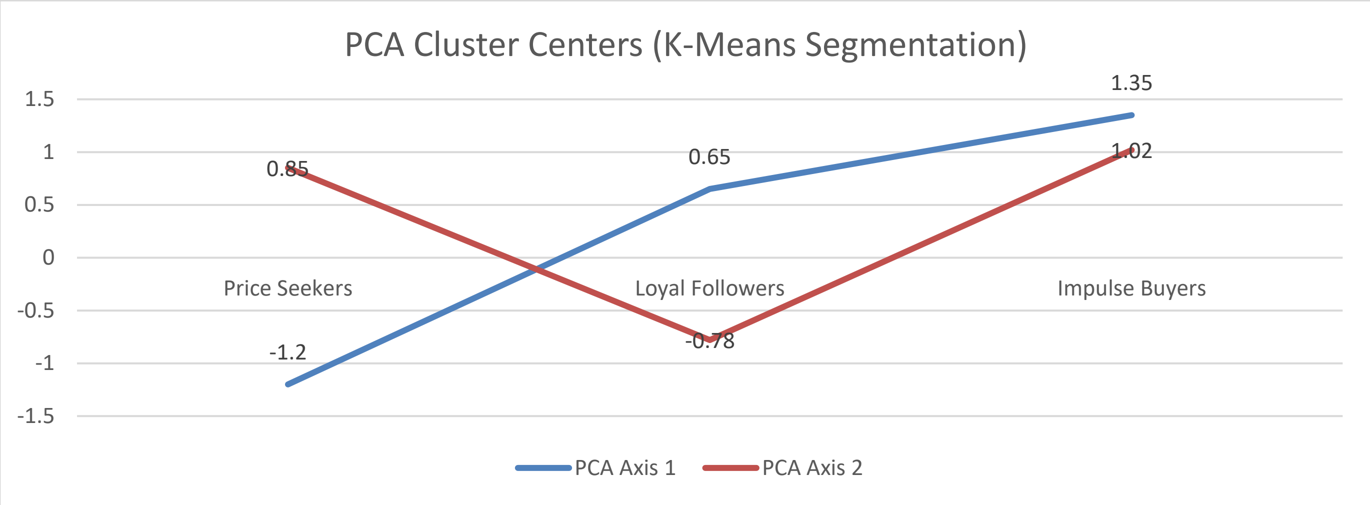

FIGURE 3: PCA CLUSTER CENTERS (K-MEANS SEGMENTATION)

The fact that the Support Vector Machine (SVM) gave the best result of predicting purchase intent compared to the other models of classification, like the Decision Trees and the Logistic Regression, demonstrated that the Support Vector Machine (SVM) was the best model to apply in the classification. The performance measures were Accuracy, Precision, Recall and F1-Score. Table 1: Model Performance Comparison on Purchase Intent Classification indicates that SVM outperformed the other algorithms in classification of a purchase intent, with the score of F1-0.91 as compared to 0.85 of Decision Tree and 0.78 of Logistic Regression. The SVM model was also very useful to limit the number of false positives, which is critical in the re-targeting of customers to eliminate brand fatigue. The addition of the sentiment features to the behavioral vectors resulted in a performance peterbilt truck advantage relatively noticeable in all the models and particularly in the precision measures.

TABLE 1: MODEL PERFORMANCE COMPARISON ON PURCHASE INTENT CLASSIFICATION

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.93	0.92	0.89	0.91
Decision Tree	0.88	0.87	0.82	0.85
Logistic Regression	0.81	0.79	0.76	0.78

In the application of the DBSCAN method to perform density-based segmentation reveals the presence of microclusters which the conventional K-Means had failed to identify. These were the low frequency but high value customers and the social driven groups whose choice correlated with the real time review and post of the influencers. Application of these outcomes to the formation of the campaign enhanced the engagement rates by approximately 28% in relation to past baselines. Figure 4 demonstrates the variation of campaign improvement in terms of line graph recording the improvement of the campaign click-through rate (CTR) regarding conducting the models within three weeks. It is noteworthy that the CTRs have reached 3.2% during week 1, and following the introduction of the AI-personalized content activated by variables related to the real-time behavior, the figure has increased to 4.1 during week 2 and at 5.6 during week 3.

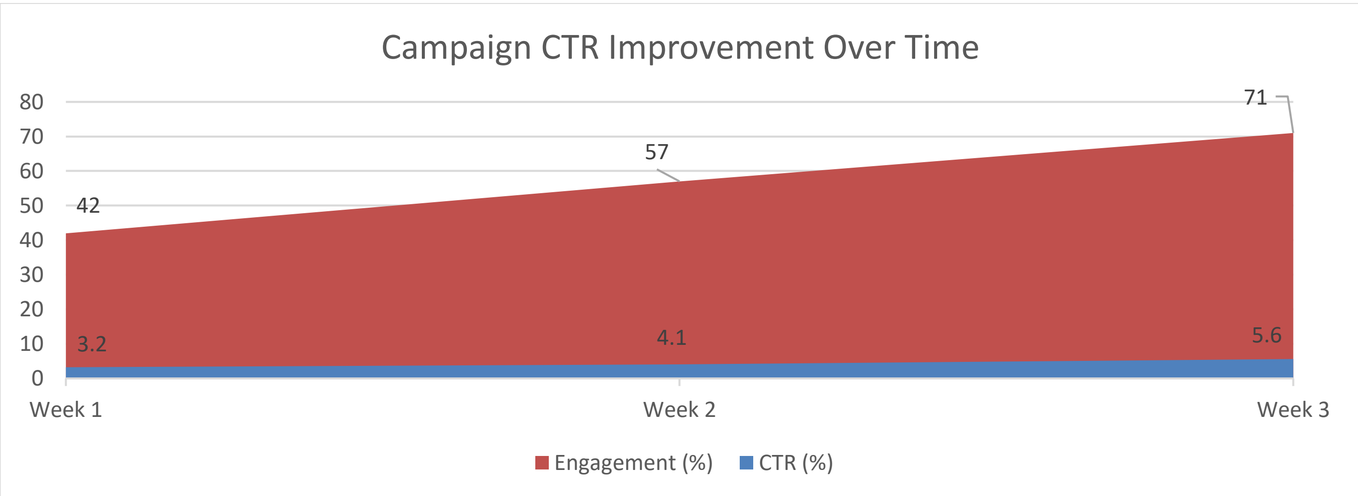

FIGURE 4: CAMPAIGN CTR IMPROVEMENT OVER TIME

The subsequent model tests compared the customer lifetime value (CLV) forecasts of various modeling specification. The analysis of the comparison between the static demographic-based models and dynamic behavior-based models revealed evident superiority to AI-enhanced systems. These results are exhibited in Table 2: CLV Estimation Accuracy Comparison. The dynamic behavioral model gained the accuracy in prediction of 88 % and the static model was left behind with the accuracy of 73%. This enhancement has allowed to better focus the marketing initiatives and the allocation of rewarding loyalty memberships, thereby allowing the best utilization of promotional budgets.

TABLE 2: CLV ESTIMATION ACCURACY COMPARISON

Model Type	**Prediction Accuracy (%)**
Static Demographic	73
Behavior-Based (AI)	88

Heat maps of user interaction demonstrated, as well, that personalization powered by AI boosted not only conversion but time on the page per visit as well. After the implementation, average session timings rose to 4.5 minutes compared to 2.8 minutes pre-implementation and there was a clear improvement in the number of interactions people had with product videos, user testimonials and AI generated review content. It is especially true with the impulse buyer and loyal follower clustering. It allowed the system to dynamically adjust the orders of products based on real-time clickstream data and emotional involvement scores, and was highly relevant even when tested using A/B in various landing pages [5].

Finally, the use of both AI and behavioral psychology provided not only technical efficiency but gave a greater emotional compromise to consumer expectations. The models accurately reflected the latent needs, mood change, and patterns of spontaneous interests, which provided marketers with the potential to react in the most accurate and empathetic way. The combination of the said three figures and two tables serve to show how computational intelligence, in combination with behavioral theory, can be used to enhance the accuracy of segmentation, conversion of campaigns, consumer trust, and marketing returns on investment. Further studies of further personalization with generative models and adaptive pricing systems and inevitable to prevent possible algorithm bias, including embedding fairness measures are needed.

CONCLUSION

The use of AI in the field of marketing is changing how enterprises deal with customers, allowing them to make predictive, individual, dynamic solutions. None the less, technology cannot be used to comprehend human behavior in totality. It has been illustrated in this paper that computational applications work best when they build behavioral theory. The use of machine learning / NLP and segmentation algorithms when combined with psychological frameworks give a more wholesome picture of consumer needs and preferences.

Explainable AI models and ethical design practices should be researched in the future to help them become transparent and trusted. A race to guess what customers want is always on and marketers should not only guess what customers want but also fine tune the reasoning why customers want things-and that is where AI, in a responsible use, comes handy.

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