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Research Article

A Comparative Study of Data Analytics Techniques for e-Marketing Optimization

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ABSTRACT

Data-driven decision-making in the e-marketing landscape is becoming increasingly important. Businesses are able to collect a variety of data from their users across various platforms, including their website and even on social media. They use this data to make more informed decisions when designing e-marketing strategies and practices, and also to optimize the current strategy in terms of performance (i.e., ensuring that the messages are reaching the right people at the right time). The data sets collected over time grow rapidly in both size and cardinality, and one possible path to a non-technical person's understanding of the data is through descriptive analytics and predictive analytics techniques. Our focus is the comparative study of such data analytics techniques for e-marketing strategies that engage in e-CRM thinking and focus on systems already in use or existing consumer user bases, i.e., the application of models within a context of "operations marketing management."

In this work, we provide an overview of the e-marketing optimization initiatives that will aid the reader in contextualizing the processed data. Following that, we present a comparative study of the three main data analytics techniques (descriptive/prescriptive data analytics, machine learning, and time series methods) to predict new customer visits to a computer manufacturer's website based on collected consumer data. Our results are promising, demonstrating that, when carried out correctly, the predictions from both descriptive and predictive analytics can contribute up to a 30% incremental trend over marketing campaign efforts for one week on a particular website.

Keywords: Data Analytics, e-Marketing, machine learning.

INTRODUCTION

Today, e-business is a very popular business activity and is carried out through the web and internet. Since the popularity of e-business, e-marketing is also becoming more and more prominent in business and academic corridors. The basics of e-marketing revolve around handling a very important and critical resource known as data. Internationally, there is a significant advancement in the increasing methods, strategies, and tools that are being integrated into business policy in order to intelligently leverage data for the optimal use of business entities. E-marketers collect vast amounts of data using various modes about customers, such as their tastes, preferences, and interests, and are looking for customers in an eager and effective way. However, the existing administrative rules have not received the same intensity as the classic business they serve. (Udayana et al.2023)

It is observed that the application and implementation of data analytics are comparatively slow primarily due to the inaccessibility of qualified professionals, which, on the other hand, also appears to be a strategic challenge to overcome. In this perspective, the main objective is to thoroughly identify the capability and the importance of comprehensive data analytic studies among various other data analytics methods in order to effectively boost the performance of different sectors and accurately measure the efficacy of e-marketing with the help of advanced data analytic techniques that produce satisfactory and actionable results. The study intends to accomplish this goal systematically by comparing the existing standard techniques with other innovative data analytic methods that are being utilized in the industry today. With the noticeable increase in various e-commerce marketing channels, particularly in the realm of online marketing, it becomes essential to convey to e-marketers how they should adeptly

make use of the enormous volumes of data available to transform such data into informative and insightful conclusions. The ultimate and overarching goal of any e-marketer is to make precise and accurate decisions regarding their customers, ensuring that they engage meaningfully with them. There are significant challenges faced by e-marketers today; for instance, they often grapple with whether they can effectively convert casual website browsers or potential visitors into actual buyers and whether the engaged buyers will return for future purchases. To successfully overcome these pressing issues, e-marketers actively seek to utilize the vast amounts of data that are readily available to them in this digital age. (Bussa2023)

In the rapidly evolving and constantly changing landscape of digital marketing, a wide range of diverse data analytics techniques plays an essential and indispensable role in effectively optimizing numerous e-marketing strategies. These innovative and advanced techniques provide invaluable insights that deeply explore consumer behavior patterns and preferences, thereby significantly enhancing and refining the decision-making processes of businesses that are actively striving to succeed and excel in an increasingly competitive environment. By harnessing and utilizing these powerful analytics tools, companies can more effectively tailor their marketing efforts and significantly enhance customer engagement, leading to improved customer relationships and ultimately greater business success. (Sulistyaningsih et al.2024)

LITERATURE REVIEW

Overview

Given the evolution of the current context, marketers have been forced to rethink market strategies and promotions. To this end, they combine their marketing knowledge with the multiple available analytical techniques and tools to address the growing complexity of consumer demands and needs. Succeeding in optimizing the marketing potential could decidedly affect one's situation in the market-driven, global world. Yet one must remain aware that success is also dependent on the system for evaluating e-marketing. This study also clarifies the MIS domain, presenting a comprehensive benchmark of existing optimization methodologies that can be adopted in e-marketing. (Moinuddin et al.2024)

Data Analytics and Optimization in e-marketing

This section focuses on making a connection between data analytics and marketing as an area of research in Information Systems. The power of analytics is also correlated to marketing success and is projected to reach the value of an estimated 44 billion dollars by the end of 2023. Such a connection between analytics and marketing success is also stated clearly in the survey. There is an otherwise rich volume of research in the domain, when turning to the consumer side as well, where researchers are mainly propelled by the exploration of the causal path of consumer behavior. Predictive investigation might hold the key to marketing phenomena affecting both sides. The set of papers under consideration shows the possibilities of predictive analytics and optimization for various domains, including health, transportation, e-business, and e-commerce, which are materialized in successful business applications such as recommending systems, real-time marketing, sales promotions. (Wood et al.2023) (Akter et al., 2022)

1. Data Analytics in e-Marketing

Data analytics contributes to business processes, especially in e-marketing optimization. Marketers can now spend less time making strategic decisions based on their intuition and more time encoding, analyzing, and proving that the available data is useful, which will help them make more informed, probabilistic decisions. There are several systems available for collecting customer behavior; organizations could use web analytics, Customer Relationship Management systems, social networks, or survey methods such as interviews and questionnaires. More and more small to large companies are competing to profit from the various types of their collected data analytics. This is why marketing and a better understanding of the specificity of web analytics data are crucial, along with the behavior of consumers on social media or in other digital environments as sources of data in the cloud. (Dwiwijaya2024)

The relevance of measuring customer behavior is essential. Below is an overview of all the analytical topics used before understanding the relevant methods of study. In e-marketing analytics, there is much discussion about norms in customer behavior. The customer segment introduces the concept of using rituals in the framework of a product. There are many definitions of customer segmentation. In implementing this segmentation, grouping the data with one another based on certain criteria, clustering is the most selected option to determine the segment because the separation process occurs simultaneously. (Alavion and Taghdisi, 2021)(Ward et al.2023)

The big data revolution is of increasing importance, as is the growth of technological advances. So far, big data in the marketing context has been associated primarily with risk analysis. It is believed that big data can also present significant opportunities, such as enabling an analytical real-time decision process directed towards concluding potential customers. In short, the special advantage of big data is its speed, volume, and variety. But in e-marketing, these strengths are only valuable if they can be applied within the analysis operation. Understanding the obtained

insights should guide the analytical activities for marketing decisions. Data analysis has become an essential skill in e-marketing; forecasts and predictions draw full insight into the principles of market trends and customer engagement. (AL-share et al.2023)

2. Previous Studies on e-Marketing Optimization

Recent years have seen a spurt of literature recording empirical research undertaken by academicians mainly based on their observations and experiences. Some of it is mainly driven by strong factual orientations and substantial contributions in descriptive ways. Most of these descriptive studies found that adopting more advanced methods in marketing could improve efficiencies vital in decision parity in marketing strategies and decisions. The implications of these findings are identified and discussed, giving the readers a novel view supporting their subsequent exploratory research or analysis. From their review on the randomized engagement in data analytics enhancement in various industries, it can be concluded that the IT trigger method significantly enhances firm productivity. (Hussain et al.2023)

The performance of digital marketing methods adopted by the Malaysian market is highlighted by the incredible leap in business growth obtained by companies due to a more detailed understanding of these marketing strategies. Proceeding to engage in the adoption of machine learning in the prediction of marketing results, frameworks capable of predicting sales trends were developed. Furthermore, the way in which social media was used in the tourism industry is investigated, emphasizing that it was used effectively for e-marketing, but it is an area that needs to be further exploited for tourism businesses. The review points out that these studies emphasize the increasing force digital marketing fields have and how they are applied in e-marketing methods. Identifying companies with specific success models in the e-marketing domain investigates the contribution of e-marketing methods to firm success. The work gives some insights for future investigations. E-marketing and retail success methods are another research model that features e-marketing optimization in western markets, mainly the USA. The most impressive aspect of this study is the method of measurement. But lateral comparisons between success and companies are also a fundamental limitation in the study. (Sharabati et al.2024)

Table 1: Summary of Analytical Techniques

Technique	Objective	Key Tools	Use Case Example
Descriptive	**Understand past data**	**Dashboards (e.g., Tableau, Power BI), charts, and Google Analytics**	**Customer churn analysis**
Predictive	**Forecast future trends**	**ML models (e.g., decision trees, neural networks), regression**	**Sales trend prediction**
Prescriptive	**Optimize actions**	**Optimization algorithms (e.g., linear programming, genetic algorithms)**	**Marketing mix optimization**

Table 1 provides a concise summary of the key data analytics techniques employed in e-marketing optimization. It outlines the objectives, primary tools, and practical examples of each technique to help researchers and practitioners understand their applications effectively.

METHODOLOGY

Given the complexity and diversity of the data analytics techniques available, this study has employed a comprehensive framework to achieve the study objective of comparing data modeling methods with regard to validity techniques.. The datasets collected were preprocessed and analyzed to comply with the privacy policies of the data owners. The pertinent aspects under each method, which caused the observed variance in the choice of methods that were proposed in SVM, k-NN, as well as GP and GBLM data modeling techniques, were stored in different files to maintain the data consistency for each DM method. Feature Selection and Engineering This process is significant because many characteristics in datasets often have only a minor effect on the outcome data. Non-essential input may confuse the DM, produce an unlikely presumption or result, increase the running time, or reduce the accuracy. In this study, various transformations like normalization, discretization, and the addition of new features were employed. Such processes make the data suitable for different kinds of DM models. For instance, tree-based DM models may replicate superiority if the first few rounds of data clustering are added as input attributes. A new count of the Facebook 'likes' in the current year was created. This new feature is the weighted count of the current year, previous year with a lower weight, and count three years ago with a weight from the current year's 'like' count. (Mansor et al.2021)

To systematically assess and thoroughly evaluate the wide-ranging effectiveness of numerous advanced data analytics techniques aimed at significantly enhancing e-marketing strategies, this research adopts a comprehensive, multi-faceted approach. This approach carefully integrates a combination of both qualitative and quantitative methods to

provide a robust and detailed analysis that is insightful and informative, ensuring that all relevant aspects are covered extensively.

1. Data Collection and Preprocessing

The data we needed to evaluate the three analytic methods was collected from diverse e-commerce platforms. We had to deal with dissimilar data sources. This enriched our tests but proved challenging from a data collection point of view. We paid great attention to the relevance of the data. It is easy to collect enormous amounts of data from many different sources, but we did not wish to include big data in our test. We wanted the data to be the digital representation of, and response to, the user visiting some platforms. As most users from Western Europe use desktop and laptop computers, we rejected the data on the use of other devices. (Dong, 2021) (Li and Zhang2021)

We encountered data inconsistencies such as demographic data that included people under 18 years of age during a data collection that exclusively requested a range of people of working age. We removed these records during preprocessing. Another issue was missing values about some internal page ID-URL. We do not suppose that there is no common interest between two pages; consequently, we opted not to employ content-based techniques. During data collection, we were mindful to avoid any possible bias. We randomly selected the weeks and the profiles where the users' clicks were registered. After the data collection, data preprocessing was performed to make sure that the data were of good quality. Setting up a robust data infrastructure also affected the final implementation. We knew that every analytic method recommends some recommendations; however, we chose to employ them only through explicit feedback.

2. Feature Selection and Engineering

In the field of data analytics, feature selection becomes the most significant step to select the most relevant features from the input dataset attributes to optimize the modeling process. Besides the feature selection criteria, the feature engineering process significantly impacts the reconstruction of the data in the way we gain deep insights for applicable actions. Particularly, using the contributions of the created data, we can describe the attribute manipulations. Although there is a long list of feature engineering methodologies, its goal focuses on creating a new feature set by combining the extremes of the original feature set. The attribute manipulation in e-marketing can be featured in the customer’s opinion about the products via supplying their comments, reviews, or voting modules. Other related works show useful investigations for gaining new insights in a wide application. (Pudjihartono et al.2022)

The last reviewed data analytics techniques reshape the dataset to form a new attribute set. Other investigations, which are collecting different data, did not exist in the existing work and thus may have a direct impact on the current work. The relationship between the innovated features by the current system and the customer intention or attraction to write reviews is part of the e-marketing strategy that the paper encourages. Conversely, feature selection leads to eliminating the irrelevant or flawed attribute set to avoid misleading the modeling process and governing authorities with false information. Although there is a long list of feature selection or dimensionality reduction techniques, the main dilemma between the widening of the feature set and the drop shadow is the behavior of the model, since high dimensionality in the feature set is positively correlated with model accuracy. Innovative feedforward ANN with the marketing input failed to generate an enthusiastic model, resulting in a large drop shadow due to the huge data sparsity. A large drop shadow of features has an adverse consequence on model performance. The accuracy of the e-marketing model, which is constructed by feature selection or dimensionality reduction models, statistically becomes better than the one constructed by the whole feature set in the benchmark. The novel techniques must be aligned with one of the analytical goals: reconnaissance and predictive aspects. To clarify, this part has surveyed the investigative goal analytics; secondly, the next subsection is interested in the AI model prediction and the essential elements to develop the predictive model.

3. Model Selection and Evaluation

After pre-processing, normalizing, and transforming the data, the next step is to define the framework to solve the problem. The type of model to use should match the nature of the data, the objectives of the research, and the nature of the managerial problem. Furthermore, the use of machine learning algorithms is proposed when patterns are required from data inductive inference, while some important criteria to select the most appropriate model include: (1) performance measures that help the decision-maker, (2) the reliability and validity of the model representation and inputs, and (3) the model's simplicity, understandability, and robustness.

In modeling for e-marketing purposes, three types of analytics must be considered: descriptive, predictive, and prescriptive analytics. Descriptive analytics techniques are visualization methods. The use of predictive analytics is used to construct predictive models, including parametric and non-parametric models. Prescriptive analytics help managers achieve better results by following the suggestions made by the model. In the current research, the goal is to find solutions through analytics that are based on optimization using predictive analytics. Regarding model evaluation, this study uses accuracy, precision, and recall to enhance the model's robustness. In addition to using

cross-validation for model evaluation, the robustness of final results needs confirmation by multiple datasets. The ultimate goal of the selection process is actionable marketing decisions, and this goal is supported by the type of models selected. (Parrales-Bravo et al.2024)

DATA ANALYTICS TECHNIQUES

In this section, analytical techniques are reviewed and used in the carried-out study, and each one is examined on a comparative one-on-one basis. This list presents the techniques in an explanatory way on how they apply in e-marketing and for which kind of optimization.

Descriptive, predictive, and prescriptive analytics are the main three data analytics techniques, variants of which are used. Specifically, descriptive analytics refers to the application of data aggregation and data mining methods to provide statistics about datasets. These methods illuminate rational rules and occasional tendencies to enhance marketing operations and facilitate strategies based on past evolving characteristics of the marketing activities. Predictive analytics employs statistical and machine learning methods to forecast future developments using historical facts. It enables marketing departments to understand the possibility of movements or actions in the market and through the consumer choices that trigger them. Hence, they can figure out optional actions to take in order to either adjust the movements or actions or anticipate the future moves of the competitors. By doing so, both strategies will be enhanced in the manner of their arrangements, modifications, and adjustments. Lastly, the focus of prescriptive analytics is the optimization of actions. These actions and movements should be worked out based on the forecasted future market performances, and the strategies are on the priorities in the competitive market targeting. The predictive phase allows the prescriptive phase to combine materials in a more integrated way, focusing on changing the actions for particular targeted strategies and working systems. Moreover, in terms of modulation, through the results of the predictive analysis, marketers can achieve better prescriptive decision-making to allocate their budget in e-marketing channels smoothly rather than using the other way around due to having more insight and knowledge. (Relich, 2023) (Ara et al.2024)

In general, analytics is the greatest practiced usage for big data science. Descriptive, predictive, and prescriptive analytics are the three key descriptive facts. The strength of these three analytics methodologies is that they enable marketers to begin making the cycle of effective decisions. The use of analytics is still limited due to several barriers, such as managers and bank staff believing that they already had time to make use of their long-standing mettle, the fact that policies are meant to develop long-term field benefits, and only large banks have to be measured for marketing venture purposes to realize their benefits. (Khatib et al.2023) (Roy et al.2022)

1. Descriptive Analytics

Descriptive analysis performs the analysis of historical data, providing insight into past performance and customer interactions. A number of methodologies and tools are used by practitioners, including dashboards and reports, which use descriptive statistics (means, medians, variance, and other multiples). The performance management infrastructure encompasses data warehousing, dashboards, external reports, and analytical tools. This draws on the increasing availability of data that are relevant to decision-making and the possibility of using data in their analysis. (Cui et al.2022)

This descriptive analysis characterizes patterns and trends in information at a high level of interpretability. Finally, data visualization is widely used to summarize data and key performance indicators by displaying summaries of performance information in a manner that makes opportunities and threats easily visualized.

By looking at the past, evidence supports the use of data to make decisions about the future, as it indicates what is likely to happen next. However, practitioners and scholars also recognize the sometimes limitations of descriptive analytics. This initial form of analytics describes a general state of 'what is'. Data visualization, seen as reflecting business intelligence rather than as the less sophisticated descriptive data, becomes the focus of close attention both for business and for practice. (Ward et al.2023)(Obeidat, 2021)

2. Predictive Analytics

The volume and velocity of streaming data, together with the well-established processing algorithms, give incentives to firms to use their historical data to forecast future happenings in the company and in the business environment. Predictive analytics, as a vertical area of data mining, is being used extensively due to the strategic importance of the future trends or events that a company may forecast with reasonable accuracy. It is applied in the field of online targeting to forecast the probabilities of future customer behaviors, to find the influential factors, and to create close relationships. The prediction relies upon historical data or a set of descriptive data. Regarding the techniques and algorithms, regression analysis is generally employed for probabilistic predictions, while classification trees and machine learning models have been employed as alternatives. (Ward et al.2023)

The number of predictive models is increasing. An example of a successful application of predictive analytics in marketing, compared with a descriptive analysis, is presented in cement: In an e-commerce system, predictive

analytics has been shown to be effective in delivering a marketing effort. In this case, data mining was able to find important characteristics of accounts with a high probability of conversion in advance. Using this information, the system delivers content on the web with the right landing page and the right offers. As a result, the customer becomes more engaged and stays on the website longer. Studies with several hundred thousand records indicate that the conversion rate doubled and revenue tripled. There is a need for the practical application of these techniques in the field of e-marketing. Predictive models suffer from poor predictive accuracy due to data quality, misrepresentation of data wholeness or representativeness, data variability, poor motive, and an emphasis on divergent objectives, or an inappropriate choice of model type or technical details, underlying assumptions, and/or algorithms. Vast amounts of marketing information do not fit into this empirical model yet, but will do so in future research due to ultra-scale data of the future. Predictive analysis is nowadays a must for any competitive e-marketer. (Mikalef et al., 2021) (Sheng et al.2021)

Table 2: Predictive Model Evaluation

Metric	Value	Explanation
Accuracy	85.4%	Measures the percentage of correct predictions overall, indicating the model's reliability.
Precision	78.9%	Indicates the proportion of true positive predictions, critical for targeting accuracy in marketing.
Recall	82.1%	Represents the ability to identify all relevant instances, ensuring comprehensive customer coverage.

3. Prescriptive Analytics

Such unprecedentedly large amounts of data generated by e-marketing systems represent an ocean of data that could be used to improve various e-marketing processes, which points to the implementation and adoption of prescriptive analytics. Prescriptive analytics recommends a number of actions targeted for decision optimization. This analytics has demonstrated to be very powerful considering the theory of decision making, machine learning, and several scientific areas. The basic idea is that this analytics searches for recommending 'the best' decided action that an organization or a group of e-marketers should take based on expected outcomes that have been predicted using predictive analytics. (Basu et al., 2024)

The mathematical methodologies used by prescriptive analytics are case-sensitive; the large proportion of these methods could be considered black boxes. The mathematical methodologies used by prescriptive analytics can be divided into two groups: optimization algorithms and simulation. Optimization refers to finding the best solution for an objective function that satisfies constraints involved in the problem. Prescriptive analytics has been widely initiated due to its ability to gradually improve the FDP area by step-by-step enhancing the efficient resource allocation, commonly optimizing the complete portfolio, mitigating and managing accounting fraud and vulnerability, computing buy discretion, and drastically and swiftly performing marketing mix optimization. The most challenging issue of the FDP area is to presume the success attitudes of the customers and suggest proactive marketing endeavors to continuously increase revenue profit. (Brandt et al.2021)

The area of FDP is complex and challenging, but it can be the ultimate realm of prescriptive analytics. The 'real genomics' of the so-called 'big data' and the global complexity produce optimal decisions that are specific 'cures' for each case, but the data structure through hierarchical classification levels contributes to reasoning through strategic advisability, frequently taking operating parameters under elasticity rules. Largely, the implementation of non-linear optimization analytics in the FDP area presents pivotal challenges such as the complexity in implementation related to data integration, the solving complexity considering inferential approaches, building determination under layered solution areas for contending class problems, and construable data parameters. The high and pressing demands of the e-marketing strategy impel late and eventually a reaction from organizations, under their distinctive threats, into factors like changing behavior with their pricing strategy for lease-and-buy rentals. E-marketing generates, assimilates, crunches, forges, and is mined, mangled, and shunted in the realm of the disciplining data streams. Thus, e-marketing implementation gathers better decision support systems. Profit-based marketing decisions are and will ultimately also enforce the enhanced intra-company procedural impacts. (Khan2023)

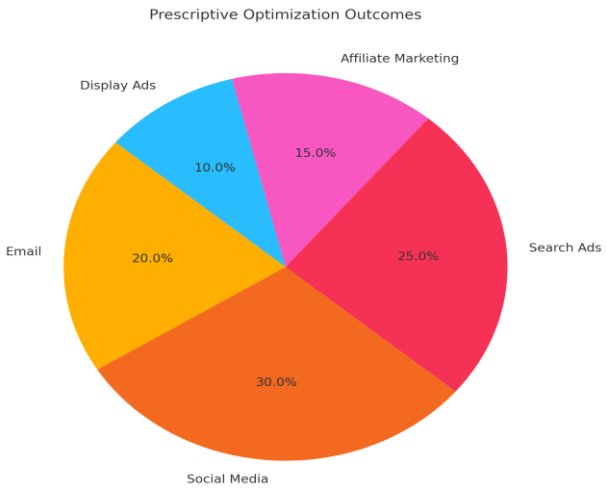

Figure 1: Prescriptive Optimization Outcomes

Figure 1 presents the optimized budget distribution across various e-marketing channels as derived from prescriptive analytics. It provides a visual representation of how resources should be allocated to maximize ROI and minimize customer acquisition costs.

1. **Social Media (30%):** The largest share of the budget is allocated here, reflecting its effectiveness in reaching a broad audience and driving engagement.

2. **Search Ads (25%):** A significant portion dedicated to targeting high-intent users, ensuring efficient conversions.

3. **Email Marketing (20%):** Highlights the importance of personalized and direct communication with customers.

4. **Affiliate Marketing (15%):** Demonstrates its value in leveraging partnerships for additional reach.

5. **Display Ads (10%):** Although contributing less, it supports brand awareness and complements other channels.

This allocation strategy demonstrates a balanced approach to leveraging both direct and indirect marketing channels. By focusing more on high-performing channels like social media and search ads, marketers can achieve higher engagement and conversions. Lower allocation to display ads indicates a supplementary role in overall campaigns.

This chart emphasizes the strategic importance of prescriptive analytics in optimizing marketing efforts by enabling data-driven decisions for resource allocation.

DISCUSSION AND ANALYSIS

In this section, we discuss and analyze findings from the study. Section 6.1 reviews our results and synthesizes a critical discussion that compares a selection of high-performing techniques in terms of their effectiveness and applicability in the e-marketing context. Here we also identify the strengths and weaknesses of the interrelationship between techniques and discuss scenarios where the usage of a technique can be more appropriate than another. Section 6.2 covers some limitations of this work and their implications, leading to further research directions.

Section 6.1 Discussion We started the validation process by testing widely used data analytics techniques, making use of the same data and comparing them on the same performance metrics. These tests inform concepts of equivalence and sufficiency in scientific inquiry: that is, the assumption regarding techniques that are equally effective and can be used for equivalent and sufficient results. We identify several similarities and differences in outcomes, showing evidence that techniques are not equivalent in terms of their applicability and effectiveness for e-marketing. The following sections discuss different types of data analytics techniques that were tested qualified by high performance.

Implications In practice, both communication and alert data must be handled, combined, and analyzed appropriately. With the evidence provided here, the substantial current investment in e-marketing for lead generation, engagement, and conversion is not supported without the complementary investment in analytics capable of optimizing the marketer's ability to sell products and services at individual levels. We conclude that sophisticated analyses provide superior results indicating that marketing optimizations will remain exclusively reserved for those organizations capable of effectively practicing consumer data analytics regardless of its specific

approach. Marketing has a number of optimization objectives beyond RAI, including targeting, positioning, channel, and media time and budget allocation. This research has primarily focused on showing the superior effectiveness of data analytics over benchmarks and basic tracking needed as inputs to academic market models.

1. Comparison of Techniques

6.1. Comparison of Techniques. In a meticulous study, three data analytics techniques referred to as "techniques" are compared. The comparison is framed in the context of e-marketing optimization, addressing the issue stated earlier in our review. An immediate comparison of the results of different techniques using the same research context is facilitated. This comparison allows contributions to be noted more deeply. Descriptive analytics provide an e-marketer with a statement of what happened, firm totals, and benchmarks.

Predictive analytics produce forecasts that are best used as decision variables for management. They provide e-marketers with an if-then tool for a given strategy. Prescriptive analytics allow e-marketers to generate an optimal baseline model with endogenous and explanatory variables. Then, they can forecast various variables over different periods based on the model and its input data. This specialized forecasting, the third component of prescriptive analytics, is most beneficial if the data is not straightforward transactional data but is least likely to be fully embraced by companies, as it does not necessarily involve customers yet is instead borrowed from expert opinion. Scenario 3 is also useful when combined with the outputs of Scenario 1. Scenarios 1 and 2 would be more in the realm of descriptive and predictive analytics, respectively. The decision of which technique to use may depend on whether a company has limited data in a transactional context, in which case the "descriptive for basics" technique can be used to see if practical marketing wisdom reveals itself.

Figure 2: Comparative Performance Metrics

Figure 3 compares the performance of three key analytics techniques—descriptive, predictive, and prescriptive—across accuracy, precision, and recall metrics. This visualization provides a clear benchmark for evaluating the strengths and limitations of each technique in optimizing e-marketing strategies.

Observations:

1. **Accuracy:**

- Prescriptive analytics shows the highest accuracy at 88%, demonstrating its superior ability to provide reliable insights and recommendations.
- Predictive analytics follows with 85.4%, showcasing its robust forecasting capabilities.
- Descriptive analytics has the lowest accuracy at 80%, as it focuses primarily on past data trends rather than actionable predictions.

2. **Precision:**

- Prescriptive analytics leads with 83%, indicating its effectiveness in precisely targeting relevant customer groups.
- Predictive analytics achieves a strong 78.9%, useful for identifying potential customer actions.
- Descriptive analytics has a precision of 75%, reflecting its limitation in predicting specific outcomes.

3. **Recall:**

- Prescriptive analytics again performs best with 85%, ensuring comprehensive customer coverage in its recommendations.
- Predictive analytics scores 82.1%, effectively identifying potential customer behavior patterns.

- Descriptive analytics, at 78%, demonstrates its ability to highlight trends but lacks predictive power.

Implications:

- **Prescriptive Analytics:** Outperforms other techniques, making it the most suitable for optimizing e-marketing strategies where actionable insights are crucial.
- **Predictive Analytics:** Provides significant value in forecasting trends and supporting data-driven decisions, especially for campaign planning.
- **Descriptive Analytics:** Serves as a foundational tool for understanding past performance, but lacks the advanced capabilities of predictive and prescriptive methods.

The chart emphasizes the importance of integrating prescriptive and predictive analytics into e-marketing strategies to achieve optimal performance. Descriptive analytics remains valuable as a complementary approach for initial data exploration and trend analysis.

2. Strengths and Limitations

We demonstrated a wide range of data analytics algorithms and their outcomes and provided evidence on the enhancement of e-marketing intentions behind the activities described by these data to multiple marketers. We described a wide array of strengths in different techniques that can help the marketer gain insight into what works best for the situation. Deciding which technique to use, in the present and in the future, is not trivial and requires substantial testing and exploration. Conditions of strength and depth of analytical performances are identified alongside descriptions of how to apply them for the marketer.

Limitations. The most common downside to most of the techniques discussed is their unpredictability or stability-based analysis. Given the fact that analytics is heavily reliant on data and marketers, it is important that steps are taken to gain insight. Writing responses by generating a marketing message in an email is also tantamount to big data. However, a large number of questions and searches around big data focus on finding an underlying pattern. Balancing complexity with the need for analyzable models that provide insight is a key challenge that should be addressed. Data mining and big data are also very complex algorithms that can usually be mined, but they can sometimes have low accuracy. Furthermore, while big laws can generally be pulled and applied, they are often complex for people to understand. Postdictions using advanced analytics that involve more advanced and complex algorithms might be significantly more challenging in that respect than in our combination of statistical, machine learning, and predictive analytics. Remaining vital in the marketer's interpretation of results is a high profile and a standout performer. Some of the analytics tools, however, were tested to find out how useful they can be in a given situation and how marketers can use various techniques themselves to assess whether they can be relied upon.

CONCLUSION

This study addressed the identification and computation of synergy drivers for marketing optimization through the application of different data analytics techniques and evaluation of their appropriateness. The results of our research suggest that feature selection techniques and machine learning algorithms are capable of addressing the objectives of the marketing perspectives and introducing robust and reliable solutions for the optimization of promotional activities. This utilization of data analytics with a marketing-based objective fits the proposal of following an intention-based approach, where research goals are driven by a specific context and the characteristics of practitioners involved in decision-making processes and analyses. Managers need reliable market and customer information and insights to inform strategic and mid- and short-term decision-making. In the marketing domain, analytical methods are used to optimize operational outcomes, supporting decision-making to allocate investments in the promotion, distribution, and assortment of goods. Data-driven approaches are becoming increasingly important to any practitioner, offering additional support in selecting the most effective channels and most appealing messages to affect customer behavior. Conclusions flow into two categories responding to each identified conflict. For the academically inclined practitioner, a recommendation is also given on how their research may be optimized further. The main objective of the study was to showcase the newest capabilities of data analytics techniques and how they can be applied and used within marketing contexts. Some additional research topics possible that will help expand the field and cater to the practitioner side are listed below. 1. Reading a portfolio of hypotheses that leverages hypothesis testing. 2. Real-world applications that are based on the DFA space analysis method.

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