Selecting the Right Omnichannel/ NBA Algorithm

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Abstract

Omnichannel marketing has risen quickly over the last decade as a strategy to unify the customer experience. It is generally accepted as a necessary and effective way of marketing and selling across industries. However, adoption has been slower within the pharma industry because of its highly regulated and complex environment. Healthcare providers, patients, and payers each play a significant role in purchasing decisions. A common solution for orchestrating an omnichannel campaign is next best action (NBA), the main objective of which is to identify the next best customer, channel, content, and cadence within the context of the campaign. Both rule-based and machine learning-based models are often leveraged to make these suggestions, but understanding which algorithms to use is challenging. This paper will identify algorithms commonly used for NBA implementation and outline criteria for selecting the best algorithm based on the business need, as there is no one-size-fits-all solution. We will focus on three machine-learning techniques: tree-based models, neural networks, and bandit algorithms. The model objectives, performance, and operational requirements will guide the criteria for selection.

Outline

Introduction

The Role of Next Best Action Algorithms in an Omnichannel Framework

Over the last decade, omnichannel marketing has risen quickly as a strategy to unify the customer experience. In simplest terms, omnichannel offers customers a seamless and coordinated experience across all promotional channels. At its core is next best action (NBA) orchestration, which determines the optimal next action to take across the four Cs: customer, channel, content, and cadence. More specifically, the application of NBA orchestration within an omnichannel framework can provide an understanding of how to engage the right *customers* with the right *message* at the right *time* through the best available *channel*. Omnichannel marketing is designed to improve the customer experience by creating a personalized journey across all touchpoints, considering the holistic view of the customer. This strategy represents a significant shift from more traditionally used multichannel marketing strategies, which rely on using multiple promotional channels in a more static and generalized manner without leveraging a fully integrated view of the customer.

Industry Trends in Marketing Strategies

Given the surge of digital engagements and intensified competition across industries, implementing an omnichannel marketing strategy is generally accepted as a necessary evolution of traditional marketing. Businesses across other industries have successfully transitioned from multichannel to omnichannel marketing, achieving improved performance and efficiency by implementing these techniques. Multiple studies have reported significant benefits, such as increased customer engagement rates and retention by switching from traditional to omnichannel marketing campaigns. It optimizes resource allocation, improves customer experience, and creates new selling opportunities. One study revealed that businesses leveraging omnichannel strategies had a 90% higher customer retention rate and a 250% higher customer engagement rate than businesses relying on traditional marketing campaigns alone.[1] However, despite proven success in other industries, the adoption of omnichannel strategies in the life sciences has been slow. Axtria's survey on Customer Engagement Planning and Execution found that many life sciences companies are still in the very early stages of implementing an omnichannel strategy.[2]

Obstacles to successfully implementing an omnichannel strategy in the life sciences include the industry's complex business model, data management maturity, infrastructure limitations, institutional rigidity, and designing a solution robust enough to handle unique business cases.[3] Selecting the appropriate algorithm for next best action orchestration is a common barrier, as no single solution can be applied in every implementation. NBA orchestration can be driven by artificial intelligence/machine learning (AI/ML) algorithms, rules-based models, or a combination of the two. The selection, design, and application of the appropriate algorithms in an NBA orchestration framework are critical to realizing the benefits of an omnichannel marketing strategy.

White Paper Objectives

This white paper outlines four criteria for selecting an algorithm for next best action orchestration in an omnichannel marketing strategy. Since there is no perfect algorithm for every NBA implementation, we balance algorithm selection across several decision criteria depending on the business need and available resources. These criteria should be considered when determining the appropriate NBA algorithm to produce a tailored approach to each business case. This paper also reviews four common algorithms for NBA implementation: business rules, tree-based models, neural networks, and multi-arm bandit algorithms. Each of these algorithms is evaluated and scored in relation to the selection criteria.

NBA Algorithm Selection Criteria

There is no "one-size-fits-all" NBA algorithm that you can implement successfully in all omnichannel marketing strategies. Each implementation of omnichannel marketing has its own unique set of business objectives, data and infrastructure limitations, and market nuances that must be considered when choosing the appropriate NBA algorithm. We focus on four key considerations when selecting the right NBA algorithm to implement: data requirements, model performance, algorithm interpretability, and operational cost. These four criteria encompass the data, technology, and business needs that often hinder successful omnichannel orchestration.

Data Requirements

The first step in learning from customer journeys and developing an omnichannel marketing strategy is collating all relevant data. The amount and type of available data varies widely from company to company and brand to brand, encompassing both data granularity and various metrics.

Capturing comprehensive sales data and other key outcome variables to drive an NBA orchestration engine is becoming increasingly difficult. In a world where biologics and specialty products are rising in importance and popularity, drilling data down to the specific physician level will require more effort.

In addition, omnichannel solutions rely on capturing a holistic view of the customer, often requiring multiple data sources to be unified into a single source. Creating datasets useful for omnichannel analysis requires dealing with numerous vendors and differences in data formats, frequencies, and lags, which introduce complexity in an algorithm design. The extent to which multiple sources can be combined will influence the accuracy and robustness of NBA suggestions.

Data availability impacts the feasibility and success of applying different NBA algorithms. Some algorithms benefit from large sets of exhaustive data, while others perform well even with missing values. A complete view of the available data sources, granularity, and how multiple sources can be integrated must be considered when selecting and designing an NBA algorithm.

Model Performance

Perhaps the most intuitive criterion when selecting an NBA algorithm is the model's overall performance. Each algorithm under consideration should be evaluated for both its ability to suggest meaningful actions during initial implementation and its long-term model stability.

The model should make suggestions that will provide the greatest impact on the desired outcome of the omnichannel strategy, such as sales or engagement metrics. An NBA algorithm's performance can be examined through retrospective studies after its implementation or by testing and training it on historical data. On occasion, both methods may be necessary. Seasoning the algorithm with historical data during the development phase significantly improves the likelihood of successful implementation in an omnichannel strategy.

When using historical data as the groundwork to train an algorithm, various benchmarks exist for assessing the model's success. Classification metrics are often the most relied upon performance statistics; they evaluate a model's ability to identify discrete output correctly. Commonly used metrics include accuracy, recall, precision, F1 scores, and area under the ROC curve, or receiver operating characteristic curve (AUC-ROC). The most important classification metric in algorithm selection depends on the implementation objectives and the nature of the data. For example:

- Accuracy and AUC-ROC measures are best for balanced data. A model trained on imbalanced data might have high accuracy because it accurately labels the majority class while inaccurately labeling the minority class.
- Recall is used when truth detection is most important or when the positives are the minority class.
- Precision is useful when limiting the number of false positives is important.
- F1 scores are helpful when both precision and recall are important.

Selecting the appropriate performance metric to study is crucial when evaluating an algorithm's ability to succeed in an omnichannel implementation.

Overfitting can be a common problem with NBA algorithms, particularly considering some implementations' complex nature and data availability limitations. When the algorithm overfits, it will yield good performance metrics on the data used to train the model but will not generalize to other contexts and newer data, ultimately leading to poor long-term model stability. The algorithm's consistency over time is imperative for the continued success of an omnichannel strategy. Models that exhibit high performance at training and testing but degrade during production are not helpful in an NBA engine, so ensuring the trained model is not overfitting is the first step in maintaining stability.

Model performance of an NBA algorithm is an important consideration during the initial implementation but should be revisited regularly after the solution is deployed. Given the nature of product lifecycles and evolving market dynamics, even stable solutions must be retrained over time. For example, models trained on data during launch might begin to fail as the brand matures. The algorithm must continue to improve and adapt to the current business context. Assessing model performance over time is vital to a successful NBA implementation throughout a product's lifecycle.

Interpretability

Another important consideration when implementing an NBA algorithm is the interpretability of the recommendations. Successful omnichannel marketing strategies require buy-in from multiple stakeholders, both top-down and bottom-up. For those familiar with different algorithms, the model performance statistics might be enough to support the implementation of an algorithm within an omnichannel strategy. For others with less technical backgrounds, the interpretability of the algorithm might be essential for acceptance of the model and its recommendations.

Model interpretability can also provide a deeper understanding of the customer, as well as the "why" behind making different suggestions, thus supporting the overall marketing strategy. In doing so, the algorithm serves as the engine for NBA suggestions and a tool for developing deeper insights into the product and market dynamics. Simply relying on the model outputs without a business understanding may lead to sub-optimal decision-making and limit business potential by neglecting a potentially rich source of additional insights and greater understanding.

Operational Cost

The last element of selecting the best NBA algorithm is the operational cost. The use of algorithms can become increasingly complex, depending on the number of brands and channels included. Costs associated with running complex programs must be factored in when choosing algorithms. If simplicity and computational load are of concern, then the orchestration may benefit from simple business rule-based algorithms. If the technology and expertise exist to run AI/ML-based algorithms, their addition can add value without being over-demanding.

The following section scores four commonly used NBA algorithms based on the above four criteria.

Algorithm Review and Scoring

Choosing the appropriate algorithm for implementing NBA will naturally vary by brand and business need. As mentioned previously, a holistic view of the business need weighed against the fit of the algorithms to address the business objectives should drive algorithm selection.

Algorithm 1: Business Rules

About the Algorithm

Any NBA orchestration applies business rules to the decision engine. Compliance and target list checks, suggestion thresholds, and guardrails on recommendations will always be required. In fact, business rules alone can be relied on for NBA orchestration and are often the first approach taken when shifting from traditional marketing to an omnichannel strategy. Typically considered the simplest approach to NBA orchestration, there are advantages and disadvantages to applying only business rules-based methods in an omnichannel strategy.

Pros and Cons

The notable benefit of a business rule-based approach is that it is easy to create and can be adapted to fit any context. Whether the available data is thin and high-level or robust and granular, business rules can still be defined and applied. Data availability is not a significant challenge when designing a rules-based approach.

Business rules-based approaches also benefit from high interpretability and low operational costs. Since business rules are manually created, the logic and reasoning behind recommendations are evident and easy to convey to stakeholders. Applying individual rules to the available data is not costly from a time or computational perspective, so operational costs are not a concern.

However, sustaining good performance long-term is a major concern. Unlike machine learning models, it is difficult to assess the performance of a business rule approach before its implementation. The impact of business rule-based NBA must be measured through lift or engagement analysis, making quick assessments on model performance impossible. Additionally, as rules become more complex or strict, there is a high possibility of losing good customers.[4] As with impact, the stability of business rule-based algorithms is often unknown and impossible to test in the short term. As more customers, experiences, and market dynamics emerge, revisiting rules can quickly become untenable.

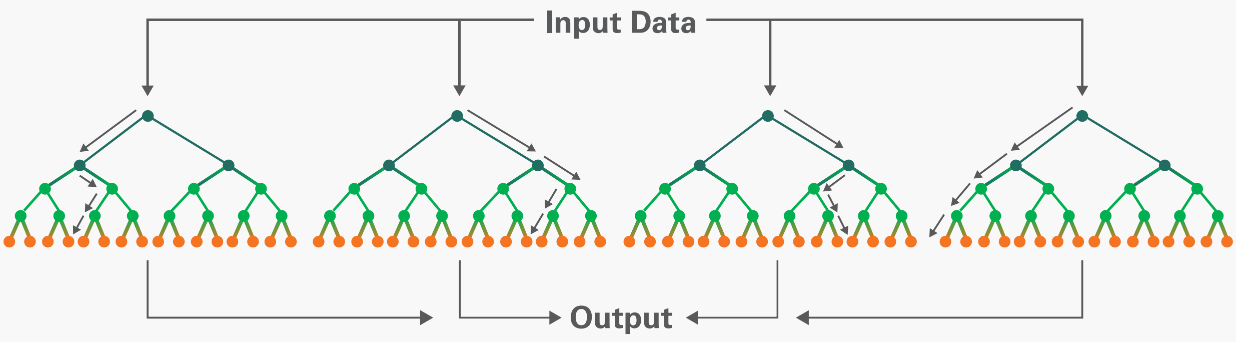
A business rule approach is often the appropriate selection when there are time constraints to building an NBA solution, when substantial data availability concerns limit the robustness of AI/ML algorithms, or when there is a desire to implement specific rules and actions.

Algorithm 2: Tree-Based Algorithms

About the Algorithm

Because of their intuitive design and high level of accuracy, tree-based algorithms are a popular supervised learning technique. A simple model called a decision tree is at the core of every tree-based algorithm. Decision trees have a flowchart-like structure containing multiple levels of true-false questions based on attributes within the training data. When new data enters the model, it moves through these layers of true-false decisions one at a time, ultimately leading to a final recommendation. Decision trees are highly explainable; however, they are prone to overfitting, which leads to poor predictive power when used individually. For this reason, decision trees are typically used in an ensemble algorithm where many trees work in tandem to predict an outcome.

Tree-Based Algorithms



Source: Axtria Inc.

Two popular ensemble tree algorithms are random forests and boosting models, such as gradient boosting.

Random forest algorithms build multiple decision trees by taking random samples from the data with replacement using a technique called bagging. The attributes included in each tree are also randomly selected. Combining these techniques allows the trees to be relatively uncorrelated with each other, allowing for a stronger final prediction.[5] Once the random forest is trained, final predictions are made based on the majority vote of all trees.

As with random forests, boosting methods aim to create a robust classifier from a series of weak decision tree classifiers. Boosting, however, trains the decision trees iteratively, where each model attempts to correct the errors of the previous model by weighting incorrect classifications higher in the next tree.[6] This process repeats until the training error is below a specified threshold or reaches a maximum number of iterations.

Pros and Cons

Tree-based algorithms have minimal limitations in terms of the size and structure of the input data. Decision trees do not require normalization (adjusting the values) or scaling (adjusting the range) of the data and are relatively unaffected by missing values and outliers. Because of this, tree-based algorithms require less data preparation than many other algorithms, leading to quicker implementation times and higher confidence in model performance. Tree-based models are also non-parametric, meaning no assumptions on data distributions are required, which makes the algorithms highly versatile.[7] Overall, data availability is not a primary concern when implementing tree-based algorithms.

Unlike a business-rule approach, model performance statistics are available when training and implementing tree-based algorithms. Monitoring performance statistics over time ensures confidence in recommendations and provides insight into the algorithm's accuracy. However, decision trees are inherently prone to overfitting, where small differences in the input data can cause drastic changes in the tree's structure.[8] Ensemble methods such as random forest and boosting, along with hyperparameter tuning, significantly lessen the effect of overfitting. Even with these methods, overfitting can still occur and impact the algorithm's decision accuracy.

As with most AI/ML algorithms, interpretability is a major concern when implementing a tree-based approach. However, several techniques, such as Shapley values or partial dependence plots, can allay those fears. Although not an immediate output of a tree-based algorithm, it is possible to produce feature importance metrics that help us understand the "why" behind NBA suggestions.

Tree-based algorithms are often the best option for implementations with data limitations and a desire to move beyond a rules-based approach. They also provide strong performance accuracy and a good foundation for supporting the adoption of an omnichannel strategy.

Algorithm 3: Neural Networks

About the Algorithm

Neural networks are another popular supervised learning technique. They process data in a way that is inspired by the human brain, operating through layers of nodes that communicate information the way neurons do. Each node can be likened to a linear regression model where there are inputs, weights, and an output. A basic neural network consists of three types of layers: input, hidden, and output. The input layer accepts data, while the hidden layers compute and pass processed data to the output layer. The weights quantify the importance of any given input variable. Once the output is generated for a single node, if it meets a certain threshold and "fires," the process moves to the next layer. The network can make increasingly complex decisions as information passes through nodes and layers.[9] Whereas decision trees are flowchart-like and deterministic, providing one output per input, neural networks are probabilistic in nature. Neural networks fit parameters to transform the input and indirectly guide the activations of subsequent neurons.

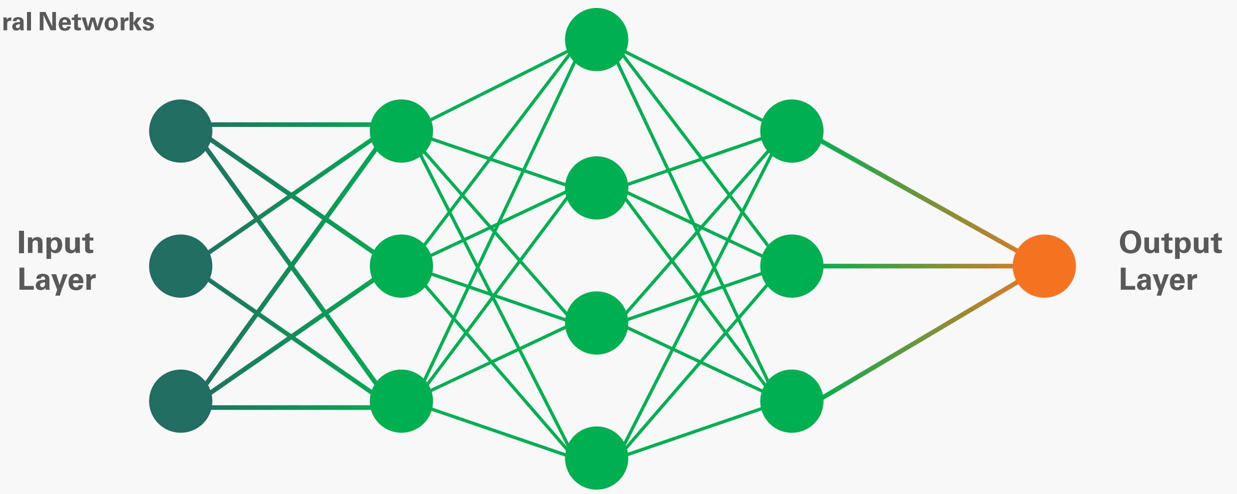
Pros and Cons

Neural networks face more limitations around the size and structure of input data than business rule- or tree-based algorithms, and they require large training datasets. Tree-based models typically outperform neural networks on small to medium-sized inputs.[10] Creating a robust neural network requires large inputs with informative features that are normalized and scaled. Neural networks perform well for brands with granular and exhaustive data sources.

When it comes to performance, neural networks are very powerful modeling algorithms capable of high accuracy. Neural networks can be more effective than tree-based models for some problems. They can model sophisticated functions and data, inferring intricate relationships between variables. However, neural networks depend heavily on training data and are sensitive to variations in the data, which leads to overfitting and generalization. Like tree-based models, neural networks may become biased toward the majority class, in which case resampling or weighting of the classes may help. Unlike tree-based algorithms, which primarily rely on high-importance variables when making predictions, neural networks utilize all variables when making a prediction. In cases where neural networks and tree-based algorithms achieve equally good performance metrics, neural networks may provide more logic recommendations and therefore be better suited for use in an omnichannel strategy.

A significant disadvantage of neural networks is that they are black box algorithms, meaning we cannot see the nature of the relationship between the independent variables and the dependent variable. The input data, and subsequent decisions about them, are spread across many thousands of neurons. Identifying the drivers and underlying reasons for the suggestions is difficult, if not impossible—making interpretability a considerable challenge.

Neural Networks



Source: Axtria Inc.

Another consideration when implementing a neural network algorithm is that training is computationally intensive and time-consuming. Neural networks can be challenging to create given the many hyperparameters, or values used to control the learning process, that require tuning.

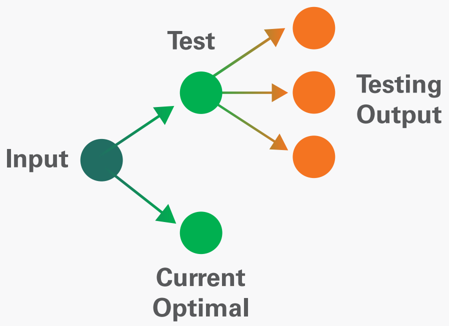
Overall, neural networks are suitable for implementations where a large training dataset is available, performance accuracy is a high priority, and complex relationships between different variables exist.

Algorithm 4: Bandit Algorithms

About the Algorithm

Multi-armed bandit (MAB) algorithms have a variety of applications, particularly in the digital marketing space. MAB algorithms help identify the optimal balance between exploring potential options and exploiting the best option in real time, based on the information available at that moment. These algorithms can identify which promotional channel (for example, banner ad or video) to display to customers to optimize a specified outcome, like clickthrough rate.[11] MAB algorithms can test pieces of marketing content to learn which one results in the highest return and then dynamically prioritize high-performing variants over lower-performing variants over time and as conditions change.

Bandit Algorithms



Source: Axtria Inc.

In practice, an additional layer composed of the environment or context surrounding the experiment is often added to an MAB algorithm. Contextual multi-armed bandits allow for additional information, such as the attributes of a user visiting a webpage, to better inform the algorithm in deciding which content to display.[11]

Pros and Cons

Bandit algorithms require smaller sample sizes and less data to implement than many other NBA algorithms because the algorithm dynamically allocates users to their optimal promotion over time. However, they require regular inflows of real-time data to optimize and improve continuously. When using limited data, bandit algorithms can perform well and potentially identify the best suggestions earlier than other methods.

Bandit algorithms are powerful and can make decisions over time, even when uncertainty exists. They perform well when testing multiple types of promotion or content simultaneously. They are also typically preferred when the opportunity cost of lost conversions or engagements is too high, such as in situations where it could mean the permanent loss of a customer.[12] However, the algorithm's performance deteriorates due to gaps or delays in the studied outcome's data capture. Additionally, bandit algorithms are not the best choice when the statistical significance of a model is a key priority. Since bandit algorithms allocate the most traffic to the best-performing variant, poor-performing variants often do not receive enough traffic to reach statistical confidence. This may lead to a lack of solid and statistically-backed insights for each element of an omnichannel program.

Bandit algorithms' reliance on real-time data means that the practicality of using them largely depends on the organization's infrastructure and ability to feed recent data into the algorithm seamlessly. These real-time data requirements often create a more resource-intensive and complex implementation. Although an operational challenge, this feature helps the bandit algorithm design to be adaptive and stable over time.

Bandit algorithms are best used in implementations where it is possible to leverage data in real time and consistently improve the recommendations. They can run complicated NBA initiatives across customers and channels, particularly when the algorithms must continually optimize themselves to capture a dynamic market landscape. Bandit algorithms are also excellent choices for quick implementations where statistical significance can be sacrificed in exchange for more conversions within a short time.

Algorithms Scored by Selection Criteria

The following table scores the algorithms based on the selection criteria previously outlined. The scoring is as follows: 1 is not preferred, 2 is neutral, and 3 is preferred. This table provides a guide that is adaptable to individual business needs. If data availability is the top priority or concern, the table can point to the best algorithms based on data requirements; likewise for other criteria.

Selection Criteria	Business Rule	Tree-Based	Neural Networks	Bandit Algorithms
Data Requirements	3	3	2	3
Model Performance	1	2	2	2
Interpretability	3	2	1	2
Operational Cost	3	2	1	1

Scoring Legend:

3	Preferred	2	Neutral	1	Not Preferred

Source: Axtria Inc.

4. Measuring Success

Business rules, tree-based algorithms, neural networks, and bandit algorithms can all be implemented to produce NBA suggestions for an omnichannel marketing strategy. However, any implementation of an NBA algorithm requires a substantial investment of time and resources, so decision-makers need to be able to justify the expenditure based on the long-term value or success of the initiative. That means the NBA algorithm's suggestions must be followed. Without those results to track, there is no way to measure how well the algorithm performs, especially in an omnichannel strategy.

Typically, the transition to omnichannel begins at the leadership level, with top-down endorsement necessary for a successful implementation. But all relevant stakeholders throughout the organization must adopt and support NBA algorithms. Once leadership endorses the effort, bottom-up adoption is often easier.[3] Furthermore, each implementation's strategic business goals and considerations must be supported by carefully selecting the appropriate algorithm. Its outputs will directly impact field sales representatives, so the recommendations must be logical and actionable. Adoption by field reps is essential, as the value of the algorithms quickly plummets if recommendations are routinely dismissed or changed in the field. Understanding the adoption of NBA suggestions is the first metric for measuring the overall success of the implementation.

Once there is buy-in and adoption, the next critical component in understanding an NBA algorithm's success is its impact on intended outcomes, such as engagement metrics or incremental sales lift. The outcome measure selected to evaluate the success of an NBA algorithm often depends on the business objectives, strategic priorities, and, ultimately, the availability of data. If sales data is available at the same level of granularity as the customer recommendations, it is possible to quantify impact through lift-based calculations. For implementations where sales and customer recommendations do not align or physician-level sales data is unavailable, engagement-based calculations can be used to understand success.

When evaluating whether an NBA algorithm implementation is successful, consider both adoption and impact on the outcomes. It is also important to note that proven adoption or impact on a particular outcome measure does not necessarily equate to success. Because implementing an NBA algorithm within an omnichannel framework is costly and complex, the measured outcome of such an implementation must be significant enough to support the investment. For example, there might be proven adoption of NBA suggestions with an associated 5% sales lift. Still, that slight increase in sales does not justify the complexity and cost of building and operationalizing the omnichannel capability. This decision point should be revisited throughout the design and implementation of an NBA engine.

Concluding Remarks

As omnichannel marketing continues to increase in popularity and demonstrates proven success across industries, the life sciences industry must adapt by incorporating strategies that provide customers with a cohesive journey throughout their interactions. Despite the challenges of orchestrating omnichannel marketing campaigns in the healthcare landscape, NBA algorithms can be adapted to most business problems. A thorough understanding of the goals and limitations unique to the company and the specific omnichannel implementation will help teams select the right NBA algorithm.

Each of the algorithms discussed in this paper has its advantages and disadvantages. Rules-based algorithms benefit from interpretability and application across individual NBA problems but lack long-term stability. Machine learning algorithms like tree-based models, neural networks, and bandit algorithms offer more robust performance but suffer from interpretability and operational costs. Organizational goals and available resources can help guide users toward an algorithm that best fits their needs. Selecting an appropriate NBA algorithm is critical to unlocking the benefits of an omnichannel marketing strategy.

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