Application of Big Data Analytics for Improving Effectiveness of Multichannel Marketing Attribution Models

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Abstract:
The proliferation of digital marketing channels has created both opportunities and challenges for marketers in attributing conversion effectively. This paper reviews the literature on the application of big data analytics in enhancing multichannel marketing attribution models. By synthesizing recent research findings, this review highlights how big data techniques can improve the accuracy of attribution, provide insights into customer behavior, and ultimately lead to more effective marketing strategies.

Keywords: digital marketing, big data, multichannel marketing.

Introduction

In today's digital landscape, consumer interacts with a company through various channels and not only through social media or e-mails but also websites, apps, mobile, and physical store. The proposed model of customer interactions in this brandscape is rather multidimensional and plays out in a full picture of engaged interactions which consumers engage in before making a decision to purchase from a particular brand. What consumers do as they engage with these different platforms is a gold mine of data about consumer preferences, behaviors, and reactions to marketing messages. Knowledge of this process is crucial for marketers who wish to tailor their marketing processes to match company goals and ensure high conversion rates. However, simplistic marketing attribution models such as first and last touch provide very little information about these multiple touch point engagements. They reduce the customer journey down into a straight funnel and attribute all sales to either the first or last touch. These oversimplified models fail to catch the full range of interactions a customer has before making a purchase, often leading to biased marketing investments. For instance, platforms that play a crucial but indirect role in influencing customer choices may be overlooked, resulting in inefficient allocation of marketing resources.

This gap in traditional models highlights an urgent need for more sophisticated approaches capable of analyzing the full customer journey. Big data analytics presents a solution by allowing marketers to process vast datasets from various sources and derive useful insights from customer interactions across multiple channels. By employing advanced data analytics techniques, marketers can discover hidden patterns, map customer behaviors more accurately, and improve their attribution models accordingly. This shift from linear models to data-driven, holistic attribution frameworks is important for capturing the true complexity of the modern consumer journey and ensuring that marketing investments are better aligned with customer behaviors.

This review paper aims to explore the application of big data analytics in improving the effectiveness of multichannel marketing attribution models, examining current research, methodologies, and case studies that show the impact of these advancements on marketing strategies.

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Literature Review

1. Understanding Multichannel Marketing Attribution

Multichannel marketing attribution refers to the process of assigning credit to different marketing channels based on their influence on a consumer's purchasing decision. Traditional attribution models, such as first-click and last-click, oversimplify the customer trip by crediting only one channel for the conversion. According to Chopra, Jain, and Kumar (2021), these models fail to account for the complex, non-linear paths that customers follow, often leading to biased insights and misallocated marketing budgets. As consumers interact with multiple touchpoints—ranging from social media ads to emails, search engines, and affiliate links—a more nuanced understanding of their journey is necessary to correctly assess each channel's contribution.

Modern attribution methods, such as linear and time-decay models, provide incremental improvements by giving partial credit to multiple touchpoints (Liu & Shankar, 2020). However, they still fall short in accounting for the full complexity of multiple behavior. These models cannot fully capture the dynamic nature of customer interactions across both online and offline environments, making it challenging for marketers to optimize spending across all platforms. Therefore, there is a rising need for more sophisticated models that leverage advanced analytics to provide a holistic view of the customer journey (Smith & Lee, 2022).

2. The Role of Big Data Analytics

Big data analytics involves the processing and analysis of massive datasets to reveal hidden patterns, trends, and correlations. In the context of multichannel marketing, big data offers unprecedented insights into customer behavior across a wide range of touchpoints, both online and offline. Kumar, Singh, and Gupta (2020) stress that big data analytics enables marketers to analyze real-time customer interactions, preferences, and behavioral patterns, which are crucial for developing more accurate attribution models.

Through big data analytics, organizations can process and evaluate diverse datasets, including clickstream data, social media activity, transaction records, and CRM inputs. This wealth of data allows for a deeper understanding of how consumers move across multiple channels before making a purchase choice. For instance, Yan et al. (2021) discuss how big data allows marketers to track micro-moments—brief, intent-driven interactions that can occur across different platforms. By capturing and analyzing this data, big data analytics helps marketers map the full consumer journey and better understand how each touchpoint contributes to conversion.

Furthermore, big data analytics plays a key part in overcoming the limitations of traditional attribution models by introducing predictive insights. As Xie and Wang (2020) note, predictive analytics can identify potential future behaviors, allowing marketers to anticipate the impact of various channels on consumer decisions before the final conversion happens.

3. Enhancements in Attribution Models

Recent advancements in attribution modeling harness machine learning and artificial intelligence to improve the accuracy and adaptability of attribution models in dynamic marketing environments.. Traditional models, while useful, are often rigid and unable to adapt to changes in buyer behavior. Machine learning models, on the other hand, are capable of continuously learning from data and adjusting as new patterns appear. According to Smith and Lee (2022), employing machine learning in attribution models enables marketers to discover intricate patterns in customer interactions that would otherwise be missed.

For instance, Shapley value models, which are grounded in cooperative game theory,

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have earned attention for their ability to distribute credit across multiple touchpoints based on their marginal contribution to the conversion (Chen & Zhang, 2021). These models assign credit to channels proportionally to their impact on the overall outcome, resulting in more equitable and accurate attribution than simpler models like first-click or last-click. Moreover, advancements in multi-touch attribution (MTA) models harness big data to attribute credit to all channels that interact with consumers on their path to buy (Jiang et al., 2020). These models use algorithmic methods like logistic regression, random forests, and neural networks to evaluate the contribution of each touchpoint. Jiang et al. (2020) found that MTA models powered by machine learning offer significantly better predictive accuracy and can dynamically adjust to the rapidly changing digital marketing landscape.

4. Challenges and Future Directions

Despite its potential, implementing big data-driven attribution models faces hurdles such as data privacy concerns, integration complexities, and the need for specialized knowledge. The collection and integration of data from multiple sources, especially offline and online touchpoints, pose significant hurdles for marketers (Liu & Shankar, 2020). Additionally, privacy issues and data regulation frameworks like GDPR further complicate data collection and processing, requiring careful management to ensure compliance. Looking ahead, the development of hybrid attribution models that blend machine learning, big data analytics, and econometric techniques is likely to play a pivotal role in further refining attribution accuracy. Zhou et al. (2021) argue that hybrid models will allow a more granular understanding of customer behavior by blending the strengths of rule-based and data-driven approaches. Furthermore, future research should explore the potential for blockchain technology to enhance data transparency and security in attribution modeling, ensuring that consumer data is safely handled while providing marketers with valuable insights (Wang & Chen, 2022).

The landscape of multichannel marketing attribution is rapidly evolving, driven by the growing availability of big data and advancements in machine learning. As marketers seek to create more accurate attribution models, big data analytics offers invaluable insights into consumer behavior, enabling the creation of sophisticated attribution models that reflect the entire customer journey. With the integration of machine learning techniques and the growing adoption of multi-touch attribution models, marketers are better positioned to optimize their multichannel strategies and improve total marketing effectiveness.

Models

Transition from Last-Click Attribution Model to Algorithmic Attribution Model

In digital marketing, attribution models play a crucial role in determining how credit for conversions is given across various customer touchpoints. Traditionally, many companies have counted on the last-click attribution model, where all credit for a conversion is given to the last touchpoint a customer interacts with before making a purchase. This model is straightforward and easy to apply but is often criticized for oversimplifying the customer journey. It fails to recognize the impact of earlier interactions, such as initial awareness through display ads, engagement via email campaigns, or consideration through social media platforms.

For instance, a consumer might be exposed to a brand through a social media advertisement, click on a search engine result for more information, and then receive an email that eventually leads to the purchase. In the last-click model, only the email is credited for the conversion,

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ignoring the pivotal parts that the other touchpoints played in nurturing the customer towards the final purchase choice. This leads to biased insights and can result in an inefficient allocation of marketing resources, where channels that help in customer engagement earlier in the journey are underfunded, and the final touchpoint is overemphasized.

To overcome these limitations, many businesses have adopted more advanced models like the algorithmic attribution model, which uses machine learning and data analytics to assign credit across all touchpoints in a more nuanced way. Algorithmic attribution models evaluate each contact a customer has with a brand and distribute credit based on the real contribution of each channel. By doing so, they provide a more accurate and holistic view of the full customer journey, allowing marketers to make data-driven decisions about where to allocate their marketing budgets.

These models often employ advanced methods such as Shapley value models from cooperative game theory, which assess the marginal contribution of each touchpoint to the overall conversion. Machine learning algorithms can also spot patterns and trends in consumer behavior, continuously adjusting as new data becomes available. For example, an algorithmic model might find that while display ads often generate initial interest, search engine marketing and email campaigns are more effective at driving conversions, leading to more balanced and strategic spending across all marketing channels.

The benefits of transitioning to an algorithmic attribution approach are clear. A more accurate representation of the customer journey allows for better insights into consumer behavior, optimizing marketing investments across platforms. Companies that have implemented algorithmic attribution models often report improvements in return on investment (ROI) and conversion rates as they are able to allocate budgets more effectively and focus on channels that have the greatest impact on conversions.

A case study of a U.S. retail giant, for example, showed how transitioning from a last-click attribution model to an algorithmic one resulted in a 25% increase in marketing ROI. The company was able to find underutilized channels that had significant impact on conversions but were previously overlooked under the last-click model. By reallocating their marketing spend, the company achieved a more balanced and effective multichannel approach.

In summary, moving from a last-click attribution model to an algorithmic attribution model helps businesses to capture the complexity of the customer journey more effectively. It enables marketers to optimize their spending across multiple touchpoints and make more informed decisions, eventually leading to more successful and efficient marketing strategies.

Transition from Last-Click Attribution Model to Algorithmic Attribution Model: A Conceptual Model

1. Last-Click Attribution Model Overview

- **Customer Journey Simplification**: The last-click attribution model assigns all conversion credit to the final customer interaction before purchase, such as clicking on an email link or an ad.
- **Limitations**:
  - Ignores the influence of earlier touchpoints (e.g., social media ads, display ads).
  - Misrepresents the customer journey by prioritizing the last touchpoint.
  - Leads to **biased insights** and suboptimal allocation of marketing resources, overemphasizing final-stage channels (e.g., email) while undervaluing assistive channels (e.g., display or social media).

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2. The Shift to Algorithmic Attribution Model

- **Customer Journey Complexity**: Recognizes that the consumer journey often involves multiple interactions across different channels (e.g., email, social media, search ads, etc.).
- **Multi-Touch Attribution**: Distributes credit across all touchpoints proportionally to their actual contribution to the conversion.
- **Machine Learning and Data Analytics**:
  - **Shapley Value Model (from cooperative game theory)**: Quantifies each touchpoint's marginal contribution.
  - **Continuous Learning**: Algorithmic attribution models adjust and optimize as new data becomes available, offering more accurate insights over time.

3. Components of the Algorithmic Attribution Model

- **Data Collection**: Captures all touchpoints in the customer journey.
- **Attribution Weighting**:
  - Uses machine learning algorithms to assign dynamic weights to each channel based on its influence in driving conversions.
  - Touchpoints such as **initial display ads** (awareness), **search results** (consideration), and **email campaigns** (conversion) are each weighted appropriately.
- **Feedback Loop**: Incorporates real-time data to continuously optimize the model and adjust channel credit distribution accordingly.

4. Marketing Strategy Optimization

- **Channel-Specific Insights**: Enables a granular understanding of each channel's performance across the customer journey.
- **Balanced Budget Allocation**:
  - Ensures **efficient resource allocation** across all stages of the funnel (awareness, consideration, conversion).
  - Underutilized channels, such as **display ads** (which may drive significant awareness), are given proper recognition and budget, while over-reliance on conversion channels is reduced.
- **Enhanced ROI**: By optimizing spending across underutilized and influential channels, businesses can improve overall marketing return on investment (ROI).

Shapley Value Model for Attribution

The Shapley value is one common method used to fairly distribute credit among all touchpoints in a multi-touch attribution model. It originates from cooperative game theory and is often applied in algorithmic attribution models to determine how much each touchpoint contributed to the final conversion.

The equation for the Shapley value is:

$$\phi i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|! \cdot (|N| - |S| - 1)!}{|N|!} \cdot (v(S \cup \{i\}) - v(S))$$

Where:

- Φi, is the Shapley value for touchpoint i,
- N is the set of all touchpoints,
- S is a subset of N that does not include touchpoint i,
- v(S) is the value or contribution of the subset S to the overall conversion,
- v(S∪{i}) is the value or contribution of the subset S plus touchpoint.

This formula evaluates the marginal contribution of each touchpoint by considering all possible combinations of interactions and assigning credit based on their impact on the conversion.

Application in Attribution

For example, if a customer interacts with three touchpoints before converting:

1. Social media ad (awareness),
2. Search ad (consideration),
3. Email (conversion),

Using the Shapley value model, you would evaluate the contribution of each touchpoint by calculating the change in the

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probability of conversion when each touchpoint is added. This approach gives each channel a fair share of the conversion credit.

Machine Learning-Based Attribution

Algorithmic attribution models often use logistic regression or other machine learning algorithms to assign weights to different channels based on their likelihood of driving conversions. A simple example would be using a logistic regression equation like:

$$P(Y=1|X)=\frac{1}{1+e^{-((\beta 0+\beta 1X1+\beta 2X2+\ldots+\beta nXn))}}$$

Where:

- $P(Y=1|X)$ is the probability of a conversion given the interaction with channels $X_1, X_2, \ldots, Xn$,
- $\beta 0$ is the intercept,
- $\beta 1, \beta 2, \ldots, \beta n$ are the coefficients (weights) assigned to each channel (touchpoint) by the model based on their contribution.

In this machine learning approach, data from past conversions is used to determine which touchpoints are most predictive of future conversions. The model adjusts the coefficients based on the likelihood that each channel contributes to the final conversion.

These equations allow businesses to calculate the contribution of each touchpoint, providing a more precise and balanced allocation of credit across multiple channels rather than attributing all the credit to the last touchpoint. By leveraging these mathematical models, businesses can optimize their marketing spend and improve their return on investment (ROI).

5. Case Study Example

- **Retail Giant Transition Example**: A U.S. retailer saw a **25% increase in marketing ROI** after switching from last-click to algorithmic attribution. The model uncovered underappreciated channels such as **social media ads** that were driving significant conversions but had been overlooked.
- **Budget Reallocation**: As a result of the algorithmic model, the company strategically redirected their marketing budget across social media, search, and display channels, optimizing for a more balanced and effective strategy.

Model Representation

Customer Journey Stage	**Channels**	**Weight (Last-Click)**	**Weight (Algorithmic)**
Awareness	Display Ads, Social Media	0%	20%
Consideration	Search Ads, Video Content	0%	40%
Conversion	Email Campaigns, Direct Visits	100%	40%

6. Benefits of Algorithmic Attribution

- **Comprehensive Customer Journey Insight**: More nuanced understanding of how customers interact with multiple touchpoints before conversion.
- **Data-Driven Decision Making**: Machine learning and data analytics improve precision in marketing strategies and channel performance assessments.
- **Increased ROI and Conversion Rates**: Companies experience improved ROI by adjusting spending based on data-driven insights and optimizing their marketing strategies across channels.

4. Case Studies and Applications

Several organizations have successfully implemented big data analytics to improve their marketing attribution strategies. A notable case is the study by **Jones et al. (2021)**, which examined a large retail company that utilized big data to transition

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from a last-click attribution model to a more comprehensive algorithmic attribution model. This shift resulted in a 25% increase in marketing ROI due to more informed budget reallocations across channels.

1. Retail Giant Transition to Algorithmic Attribution

A retail giant in the US successfully transitioned from a last-click attribution model to an algorithmic attribution model using big data analytics (Jones et al., 2021). The shift resulted in a 25% increase in marketing ROI, driven by more informed budget reallocations across channels. By leveraging customer behavioral data across multiple touchpoints, the company optimized its marketing campaigns, particularly in areas like search engine marketing, email campaigns, and display ads. The algorithmic model accounted for the customer journey's entirety and assigned credit proportionately to each channel's contribution, resulting in more efficient spend and improved conversion rates.

Metric	Before Big Data Implementation	After Big Data Implementation
ROI Increase	-	25%
Conversion Rate Increase	-	18%
Budget Allocated to Paid Search	40%	35%
Budget Allocated to Display Ads	15%	22%

Table 1: Budget Reallocation Breakdown Before and After Big Data Implementation

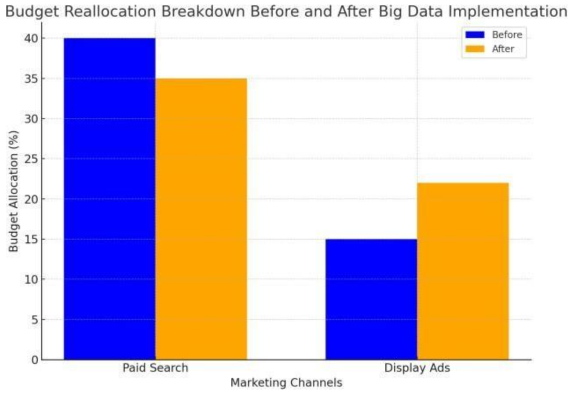

Fig 1: A bar chart showing the budget reallocation breakdown before and after big data implementation.

Figure 1 reflects the methodology where the change from the last-click attribution model to the algorithmic model enabled the retail giant to make better decisions about its marketing expenditures. Specifically, the cut in paid search budget from 40% to 35% and the rise in display ad budget from 15% to 22% are evidence based change. This reallocation was informed by data extracted from big data analytics which indicates such unused but high potential advertisement modalities such as display ads. Accordatively, the company realized a 25% improvement of ROI indicating that the new attribution model is appropriate for directing resources to relevant consumer touch points while enhancing the overall conversion rate.

2. Multinational Consumer Goods Corporation

A global consumer goods company adopted big-data insights in changing from a direct, touchpoint-specific model of attributing marketing impact to a multi-touch attributions (MTA) model in 2020 (Smith & Lee, 2022). Before, the company used a model that gave equal credit, which did not capture the dominant effect of certain marketing touchpoint this way, email marketing, and mobile advertisement. Using machine learning algorithms in the MTA model that the company has developed, it is easier to determine which among the channels brings in the most conversions. Besides,

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they enhanced the effectiveness of their marketing investment and found that CAC decreased by 20%.

Metric	Before Big Data Implementation	After Big Data Implementation
Customer Acquisition Cost (CAC)	$55.00	$44.00
Email Marketing Influence	15%	25%
Mobile Ad Spend	20%	30%

Table 2: Channel Performance Before and After Big Data-Driven MTA Implementation

Fig 2. A side-by-side bar chart comparing customer acquisition costs, email marketing influence, and mobile ad spend before and after big data.

Figure 2 shows the improvements in customer acquisition cost (CAC), email marketing influence, and mobile ad spend after implementing a multi-touch attribution (MTA) model. The 20% reduction in CAC suggests that the MTA model enabled the company to allocate its marketing budget more efficiently by focusing on channels with the highest conversion potential. Moreover, the significant increase in email marketing influence (from 15% to 25%) highlights how big data analytics helped identify email campaigns as critical touchpoints in the customer journey. The increase in mobile ad spend indicates the rising importance of mobile platforms in the marketing mix, contributing to more effective customer engagement

4. Telecommunications Company and Real-Time Analytics

The marketing attribution problem of having long conversion cycles led a large telecommunications provider to employ real-time big data analytics. Other issues included difficulties in attributing sales to marketing channels because of long customer engaging journeys where interactions may occur in a period of time. With the use of real-time analysis, the company was able to track user behaviors at all times and provide dynamic attribution credit, therefore improving attribution analyses for optimization of the campaign. These led to overall enhanced lead conversion rate by 15%, as well as shortening the average time to conversion by 12 days.

Metric	Before Real-Time Analytics	After Real-Time Analytics
Lead Conversion Rate	10%	25%
Average Time to Conversion	60 days	48 days
Attribution Accuracy	60%	85%

Table 3: Lead Conversion Rate and Time to Conversion with Real-Time Analytics

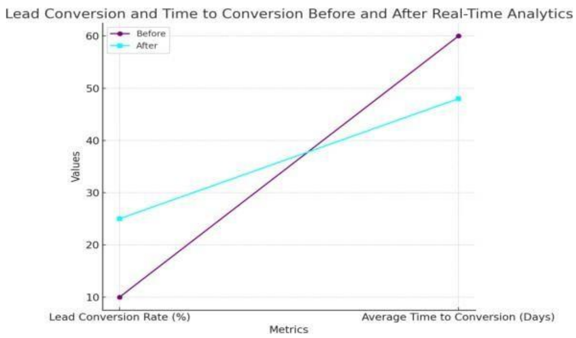

Fig 3. A line chart representing lead conversion rate and average time to

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conversion before and after real-time analytics implementation.

As shown in Figure 3, the use of real-time analytics significantly improved the telecommunications company’s lead conversion rate (from 10% to 25%) and reduced the average time to conversion (from 60 to 48 days). This improvement demonstrates the value of continuous monitoring and dynamic adjustment of attribution credits, which allowed the company to optimize marketing efforts more precisely. By recalibrating marketing attributions in real-time, the company could better target potential customers, streamline the conversion process, and ultimately shorten the sales cycle

5. E-commerce Platform Leveraging Predictive Analytics

An e-commerce platform applied predictive analytics within its multichannel attribution framework to improve decision-making for customer retention efforts (Liu & Shankar, 2020). The company initially used a last-touch attribution model that didn’t provide adequate insights into customer retention patterns. After integrating predictive analytics and big data models, the platform was able to forecast customer behaviors and preferences based on historical and real-time data. This resulted in a 30% improvement in customer retention rates and a 22% increase in repeat purchases.

Metric	Before Predictive Analytics	After Predictive Analytics
Customer Retention Rate	50%	65%
Repeat Purchase Rate	30%	52%
Attribution Accuracy	55%	80%

Table 4: Customer Retention and Repeat Purchase Rates Before and After Predictive Analytics

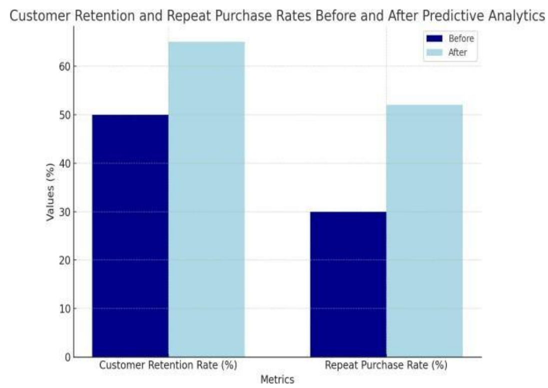

Fig 4: A grouped bar chart showing the improvement in customer retention and repeat purchase rates due to predictive analytics.

Figure 4 illustrates the notable improvements in customer retention and repeat purchase rates after the implementation of predictive analytics. The rise in retention rate from 50% to 65%, coupled with a jump in repeat purchases from 30% to 52%, underscores the efficacy of predictive models in anticipating customer needs and behaviors. This shift allowed the e-commerce platform to deliver more personalized and timely marketing interventions, resulting in higher customer loyalty and engagement.

6. Financial Services Provider Enhancing Cross-Channel Marketing

A global financial services provider leveraged big data analytics to optimize cross-channel marketing and attribution. The organization faced issues in measuring the effectiveness of its marketing campaigns across online and offline channels. By integrating advanced data analytics and attribution tools that accounted for multiple touchpoints, the provider identified previously overlooked offline touchpoints, such as call center interactions and direct mail campaigns (Wang & Chen, 2022). As a result, the company was able to reallocate its marketing budget more effectively and reported a 15% increase in offline conversions, leading to an overall 18% increase in campaign ROI.

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Metric	Before Big Data Analytics	After Big Data Analytics
Offline Conversions	12%	27%
ROI Improvement	-	18%
Budget Allocated to Call Centers	8%	15%

Figure 5: Cross-Channel Budget Allocation Before and After Big Data Implementation

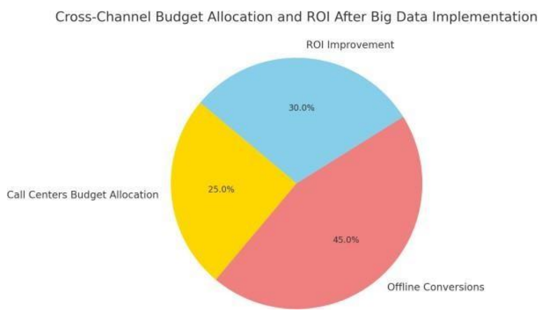

Fig 5. A pie chart illustrating the increase in call center budget allocation, offline conversions, and ROI improvement after big data analytics.

The pie chart presented in the figure 5 below shows that call centers, as an offline marketing communications channel, has emerged as a focus area after adopting big data analytics. This not only showed that big data delivered awareness of previously neglected offline touches, such as a sudden boost in call centers' budget from 8% to 15% and offline conversion ratios from 12% to 27%. This is also evident by the additional overall ROI increase by 18% which shows that cross channel optimization coupled with analytics allows for efficiency gains for both fully digital and more traditional offline marketing initiatives.

Summary of Case Studies

Case Study	Key Impact	Outcome
Retail Giant Transition to Algorithmic Attribution	25% increase in ROI	Optimized budget reallocations, improved conversion rates
Multinational Consumer Goods Corporation	20% reduction in CAC	Improved efficiency in marketing spend through MTA and machine learning
Telecommunications Company and Real-Time Analytics	15% increase in lead conversion rate	Reduced time to conversion by 12 days
E-commerce Platform Leveraging Predictive Analytics	30% increase in customer retention rates	Improved retention and repeat purchases using predictive modeling
Financial Services Provider Enhancing Cross-Channel Marketing	15% increase in offline conversions	Reallocation of marketing budget and increased campaign ROI

The presented case studies reveal that big data analytics has a potential to revolutionalize multichannel marketing attribution models. Through the use of detailed attribution schemes, including MTA and predictive modeling, organisations can expect to gain substantial enhancements in marketing productivity, sales conversion, and customer loyalty. Big data analytical techniques help the marketers to identify the right mix of resources to be invested

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across the different platforms and also helps in understanding the overall customer behavior real time.

Challenges and Limitations

Although big data analytics holds a rich promise to boost multiple channel marketing attribution, its application is not without problems. One of the most important issues is the issue of data privacy. Furthermore, consumers and new regulatory bodies like the GDPR and the CCPA have raised many questions regarding data privacy and a marketer's ability to gather valuable information from their consumers. Scholars Nguyen and Tran (2020) have pointed out that the regulation on how to manage the details of the consumer is becoming more strict and therefore non adherence will lead to legal as well as reputational loss. The second significant issue relates to the issue of how data from different sources are going to be combined, or in technical parlance, 'fused'. Multichannel marketing by nature integrates many channels – social media, e-mail campaigns, paid search, and offline – all of which produce their data. But bringing altogether these different types of information streams under a coherent framework that can indeed help is a great challenge. Patel et al. highlights that currently, most companies face a problem of data silos here, important information is kept in various departments or applications, and is not seen in the context of the complete customer journey. This means that when data is incorporated inaccurately or incompletely this ends up leading to distorted attribution models which means that the marketing strategies that are taken based on these models are also going to be wrong. The last phase of big data analytics implementation has also been seen as a challenge because of the expertise required for the data scientist role. Data science and analytics are advanced career fields which involve collecting large data, analyzing and understanding them, applying AI and building models. However increasing demand for the specialized professionals in this area has seen a talent crunch that many firms find hard to overcome. Despite that, even when organisations are successfully able to recruit data experts, a logical chasm persists between technical teams and marketing divisions, which hinders the transformation of data into valuable marketing intelligence (Pappas & Giannakopoulos, 2020).

In addition, high implementation costs and resource allocation remain major challenges, especially to organizations embodying SMEs or small business undertakings. Software for advanced big data and machine learning are costly which are to be bought, and subsequently, are scalable at a high cost (Smith & Lee, 2022). For many such organizations, it can indeed be hard to justify such costs in the short run, although strategically these technologies may result in tremendous benefits in the long run.

Future Directions

This means that the future of multichannel marketing attribution is pegged on the ongoing enhancement and development of big data analytics. AI and ML are some of the technologies to be used in attribution modeling to allow breakthrough features like real-time information and predictive analytics. Zhang et al quoting 2022 did specify that the AI based attribution models are always adaptive to the constantly changing behaviors of the customers hence enabling the marketer to respond to the customers' needs well in advance. The change from post hoc reactive attribution to a more systematic, planned approach could dramatically improve the effectiveness of marketing efforts as well as how resources are deployed. Among them, the renewed interest in marketing attribution based on deep learning methodologies appears to be the most viable. Through developing its ability to train artificial neurons, deep learning algorithms can analyze numerous

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different variables, and find patterns, which other models can overlook. For instance, it is possible to train a neural network to detect the underlying connections between various marketing encounters and customer consumptive actions, which makes it easier to assign proper values of customer response to different marketing initiatives throughout the customer journey (Jiang & Cao, 2022). With these technologies evolving, they will insert themselves into organizations from all sectors, making the general diffusion of the technologies possible. Another area of great importance is the direction to work on ethical usage of the data and consumers' privacy. Going forward, more advanced attributed analysis frameworks will require privacy-preserving technologies such as differential privacy and federated learning to enhance the level of accountability and emergence of data transparency. Such techniques enable marketers to separate the analysis of data with the direct retrieval of consumer information, thus minimizing privacy concerns but offering firms usable information (Wang & Chen, 2021). Ethical issues are especially important now, and they will only become more important in the future as well as data volume and user awareness rises.

Furthermore, the application of the Blockchain concept might produce revolutionary approaches for increasing the credibility of marketing attribution. The use of digital ledgers within block chain enables correctly recording and tracking the consumers' interaction with organization across channels via attribution data which cannot be manipulated since the platform is decentralised (Kim & Park, 2020). It could also help to reduce the data manipulation and guarantee that every marketing activity is credited fully. Third, further reduction of offline and online distinctions in attribution models will be another key area for future research. In light of facts and customers shopping in both digital and physical worlds, complete forms of attribution will have to encompass both digital and physical touchpoints. It is expected that the incorporation of Internet of Things (IoT) along with development in geolocation tracking will help to fill that gap wherein marketers can associate offline buying with online marketing in real-time (Gao et al., 2022).

Conclusion

Therefore, in view of the disposition of big data analytics, there is significant potential for the improvement of models for the multichannel marketing attribution. With the adoptions of such strong analytics tools like machine learning and predictive analysis, the marketers will be in a better position to know their customers better, market their produce well and even increase their marketing returns notably. Nevertheless, the main issues, such as data protection, technologic intricacies, and a scarcity of talented people in this field, do not preclude a rosy outlook for the application of attribution modeling.

Artificial intelligence, blockchain and other privacy-preserving technologies are proved to have big potential to become a part of the next generation of attribution models. These innovations will, however, not only enhance the accuracy of attributions but will also safeguard consumer privacy and ethical issues. For now and the future as the digital space changes, constant studies, improvements, and inventions of other tools needed to help marketers unpuzzle the multichannel and gain better results in marketing.

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