

Cross-Channel Attribution Modelling and Its Impact on Digital Marketing Performance

Major Research Project

Master of Business Administration

Dual Specialization: Marketing & Business Analytics

Submitted by

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Declaration

I, Suramya Dinkar, student of MBA (Dual Specialization: Marketing & Analytics), Roll No. 24/DMBA/244, Batch 2024-2026, hereby declare that the Major Research Project titled " Cross-Channel Attribution Modelling and Its Impact on Digital Marketing Performance" submitted to Delhi School of Management, Delhi Technological University, is an original piece of work carried out by me under the supervision of Dr. Rajan Yadav, Professor, Delhi School of Management.

This project has not been submitted, in full or in part, to any other university or institution for the award of any degree or diploma. All data, analysis, and findings presented in this report are based on my own research and are accurately reported to the best of my knowledge.

All sources of information and literature that have been used in the preparation of this project have been duly acknowledged through citations and references, following APA 7th Edition guidelines.

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Certificate

This is to certify that the Major Research Project titled " Cross-Channel Attribution Modelling and Its Impact on Digital Marketing Performance" has been prepared by Suramya Dinkar, Roll No. 24/DMBA/244, MBA Batch 2024-26, under my guidance and supervision for the partial requirements for the fulfilment for the degree of Masters of Business Administration.

To the best of my knowledge, this work is original, has not been copied from any other source, and has not been submitted previously for the award of any degree or diploma to this or any other university. The project is found to be satisfactory and is recommended for evaluation.

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Abstract

In an increasingly fragmented digital media landscape, marketing managers face a critical challenge in identifying which digital channels truly contribute to customer conversions. Attribution modelling provides a framework for assigning conversion credit across multiple customer touchpoints; however, different attribution models often produce significantly different interpretations of marketing effectiveness. These differences directly influence marketing budget allocation decisions and campaign optimization strategies. The present study conducts a comparative analysis of five major attribution models — First-Click, Last-Click, Linear, Time-Decay, and Markov Chain Attribution — using a simulated omnichannel e-commerce dataset representing 5,000 customer journeys, 18,450 touchpoints, and 1,050 conversions across five digital marketing channels: Social Media, Paid Search, Display Advertising, Email Marketing, and Organic Search.

The primary objective of the study is to examine how attribution model selection affects channel credit distribution and marketing budget allocation. Python-based analytical techniques and statistical evaluation methods were used to calculate attribution credit under each model and compare their effectiveness. The study further evaluated model accuracy using Root Mean Square Error (RMSE), considering the Markov Chain model as a quasi-ground-truth benchmark. The findings reveal substantial divergence in channel valuation across attribution approaches. Under Last-Click Attribution, Paid Search received 42% conversion credit compared to only 31% under the Markov model, indicating systematic overvaluation of lower-funnel channels. Conversely, Social Media received 38% credit under First-Click Attribution but only 24% under Markov Attribution, demonstrating the tendency of first-touch models to overestimate awareness-stage channels. Time-Decay Attribution produced results closest to the Markov model, achieving the lowest RMSE value of 4.9, compared to 13.5 for Last-Click Attribution.

The study also demonstrates significant variation in budget allocation outcomes. When a hypothetical monthly marketing budget of ₹10,00,000 was distributed based on attribution outputs, Last-Click Attribution allocated ₹4,20,000 to Paid Search, whereas Markov Attribution recommended a more balanced allocation of ₹3,10,000. Similarly, First-Click Attribution disproportionately favored Social Media and Display Advertising. These findings indicate that attribution model selection can materially alter marketing investment decisions and potentially distort organizational understanding of channel performance. Customer journey analysis further revealed that modern digital consumers interact with an average of 4.2 touchpoints before conversion, confirming the inadequacy of simplistic single-touch attribution approaches in omnichannel environments. Sensitivity analysis showed that rule-based models become increasingly unstable as customer journey complexity rises, while data-driven approaches remain comparatively robust.

The study concludes that data-driven attribution models, particularly Markov Chain Attribution, provide more realistic and strategically balanced estimates of channel contribution than traditional

rule-based methods. The findings hold significant managerial relevance for digital marketers and Indian Direct-to-Consumer (D2C) brands seeking more accurate marketing performance measurement and efficient budget allocation in increasingly complex digital ecosystems.

Keywords: *marketing attribution, cross-channel attribution, multi-touch attribution, digital marketing analytics, Markov chain attribution, budget allocation, omnichannel marketing, customer journey analytics, digital advertising performance, D2C marketing.*

CHAPTER 1

INTRODUCTION

1.1 Background and Context

The rapid digitization of consumer markets has fundamentally transformed the nature of marketing communication, customer engagement, and organizational decision-making. Over the past decade, the emergence of digital platforms such as Google, Instagram, Facebook, YouTube, e-commerce marketplaces, and mobile applications has shifted marketing from a mass communication paradigm toward highly fragmented, data-driven, and personalized consumer interaction ecosystems. Modern consumers no longer interact with brands through a single channel or a linear purchase funnel. Instead, they navigate complex omnichannel journeys involving multiple touchpoints before making purchase decisions.

In contemporary digital environments, a consumer may first discover a product through a social media advertisement, compare alternatives using search engines, watch influencer reviews on YouTube, receive promotional emails, revisit products through retargeting advertisements, and finally complete the purchase through an e-commerce platform or brand website. As a result, the customer journey has evolved into a multi-touch, cross-platform process where several channels collaboratively influence conversion outcomes.

This increasing complexity has created one of the most significant analytical challenges in digital marketing management: determining which marketing channels actually contribute to customer conversion and to what extent. Since organizations allocate substantial portions of their budgets toward digital advertising and customer acquisition, understanding the true contribution of each channel has become strategically critical.

The global digital advertising industry crossed USD 600 billion in annual expenditure in recent years, while India's digital advertising market exceeded ₹35,000 crore in 2024 with continued double-digit growth driven by smartphone penetration, affordable mobile internet, and the expansion of Direct-to-Consumer (D2C) business models. As marketing investments continue to migrate toward digital platforms, organizations increasingly rely on analytics systems to measure campaign performance and optimize resource allocation.

At the center of this measurement ecosystem lies the concept of attribution modelling.

Attribution modelling refers to the analytical process of assigning conversion credit to the marketing touchpoints encountered during the customer journey. The outputs generated through attribution models directly influence how businesses:

- Evaluate campaign performance
- Measure marketing ROI
- Allocate advertising budgets
- Optimize channel strategy

- Assess customer acquisition efficiency
- Design future marketing plans

However, different attribution models frequently produce substantially different interpretations of channel effectiveness. A channel receiving high conversion credit under one attribution framework may receive significantly lower credit under another. Consequently, attribution model selection itself becomes a strategic managerial decision capable of materially affecting organizational investment priorities.

Traditional attribution methods such as Last-Click Attribution continue to dominate industry practice because of their simplicity and accessibility. Under this approach, the final touchpoint before conversion receives 100% conversion credit. While operationally convenient, such approaches fail to capture the collaborative influence of multiple channels within modern customer journeys. Awareness-generating channels such as social media and display advertising are frequently undervalued despite their important role in initiating consumer engagement.

In response to these limitations, organizations have increasingly adopted multi-touch and data-driven attribution approaches such as Linear Attribution, Time-Decay Attribution, Position-Based Attribution, and probabilistic models such as Markov Chain Attribution. These models attempt to provide more realistic estimates of channel contribution by incorporating journey complexity, interaction sequencing, and probabilistic transition behavior.

Despite growing interest in attribution analytics, significant practical and conceptual challenges remain unresolved. Many organizations continue to make budget allocation decisions based on simplistic attribution frameworks without fully understanding the biases embedded within these models. Furthermore, the majority of attribution research has focused on Western digital markets, while emerging economies such as India present distinct analytical challenges including fragmented customer journeys, cross-device behavior, WhatsApp commerce, and Cash-on-Delivery transactions.

The present study therefore seeks to examine how different attribution models influence channel valuation and marketing budget allocation decisions within an omnichannel digital marketing environment.

1.2 Problem Statement

Modern digital marketing environments generate enormous volumes of customer interaction data across multiple channels. However, despite advances in analytics technologies, organizations still struggle to accurately determine which channels genuinely contribute to customer conversions.

The central problem addressed in this study is that different attribution models assign conversion credit differently, leading to substantially different interpretations of marketing effectiveness and significantly different budget allocation decisions.

Most organizations continue to rely heavily on simplistic attribution approaches such as Last-Click Attribution because they are easy to implement and widely integrated into advertising platforms.

However, these models systematically distort channel performance measurement by overvaluing lower-funnel interactions and undervaluing awareness-stage touchpoints.

For example, a customer may initially discover a product through Instagram advertising, engage with display campaigns over several days, receive promotional emails, and finally convert through paid search. Under a Last-Click Attribution framework, the entire conversion would be assigned to paid search, despite earlier channels playing critical roles in generating awareness and nurturing purchase intent.

Such distortions create several managerial risks:

- Overinvestment in lower-funnel channels
- Underfunding of awareness-building campaigns
- Misinterpretation of channel ROI
- Inefficient resource allocation
- Short-term optimization at the expense of long-term brand growth

Furthermore, organizations often lack clear analytical frameworks for selecting attribution models appropriate to their customer journey complexity, data availability, and marketing objectives.

The problem becomes even more significant within omnichannel ecosystems where consumers interact across multiple platforms and devices. Traditional single-touch models are increasingly incapable of representing real consumer behavior patterns.

Therefore, there exists a strong need for comparative analytical research examining:

- How attribution models differ in assigning conversion credit
- How attribution differences affect marketing budget allocation
- Which models provide more balanced and analytically reliable estimates of channel contribution
- How businesses can improve marketing decision-making through better attribution frameworks

The present study attempts to address these issues through comparative analysis of multiple attribution models within a simulated omnichannel digital marketing environment.

1.3 Research Objectives

The study has been designed around the following objectives:

1. To examine the concept and strategic importance of cross-channel attribution modelling in digital marketing analytics.
2. To analyze customer interaction behavior across multiple digital marketing channels during the conversion journey.

3. To compare the conversion credit distribution generated by different attribution models including First-Click, Last-Click, Linear, Time-Decay, and Markov Attribution.
4. To evaluate how attribution model selection influences marketing budget allocation decisions.
5. To assess the relative analytical effectiveness of rule-based attribution models compared to data-driven attribution approaches.
6. To identify the limitations and managerial implications associated with attribution modelling in omnichannel marketing environments.
7. To examine the relevance and challenges of attribution modelling within the Indian D2C digital marketing ecosystem.

The present study carries significance across academic, managerial, and practical dimensions.

Academic Significance

The study contributes to the growing body of literature related to digital marketing analytics and attribution modelling. While existing research extensively discusses attribution methodologies conceptually, limited empirical research compares attribution models in relation to budget allocation implications, particularly within emerging digital markets such as India.

The research also contributes to understanding omnichannel customer behavior and the limitations of traditional performance measurement systems.

Managerial Significance

For marketing managers and decision-makers, attribution modelling directly influences campaign evaluation and budget optimization decisions. The study provides insights into:

- Channel overvaluation and undervaluation
- Attribution biases
- Marketing investment efficiency
- Resource allocation strategy
- Omnichannel performance measurement

The findings can help organizations adopt more analytically balanced attribution frameworks rather than relying solely on simplistic platform-reported metrics.

Practical Significance

The research holds practical relevance for:

- Digital marketing agencies
- D2C businesses
- E-commerce companies

- Performance marketing teams
- Marketing analytics professionals

The study demonstrates how attribution methodology selection can materially influence marketing decisions and organizational understanding of customer acquisition dynamics.

1.7 Research Methodology Overview

The research employs a descriptive and analytical approach, with quantitative methods used to support the analysis. The empirical analysis is conducted using a simulated omnichannel customer journey dataset consisting of:

- 5,000 customer journeys
- 18,450 touchpoints
- 1,050 conversions

The study analyzes interactions across multiple digital marketing channels and compares attribution outcomes under different attribution frameworks.

Primary analytical techniques include:

- Attribution credit comparison
- Budget allocation simulation
- Root Mean Square Error (RMSE) analysis
- Customer journey path analysis
- Sensitivity analysis

The Markov Chain Attribution model is treated as a quasi-data-driven benchmark for evaluating rule-based attribution approaches.

1.8 Limitations of the Study

Although the study attempts to provide comprehensive attribution analysis, certain limitations must be acknowledged.

1. The study uses simulated omnichannel customer journey data rather than proprietary real-world enterprise datasets.
2. The analysis focuses only on selected digital marketing channels and excludes offline customer interactions.
3. The Markov attribution model, while more analytically advanced, still represents an approximation rather than perfect causal measurement.
4. The findings may not fully generalize across industries with substantially different customer journey structures.

5. Platform-specific attribution mechanisms and privacy restrictions may create additional complexities beyond the scope of this research.

1.10 Chapter Summary

This chapter introduced the growing importance of attribution modelling within modern digital marketing ecosystems. The discussion established that customer journeys have become increasingly fragmented, omnichannel, and analytically complex, making traditional single-touch attribution approaches insufficient for accurate performance measurement.

The chapter highlighted how attribution models directly influence marketing budget allocation and strategic decision-making. It also established the need for comparative analysis of attribution frameworks capable of providing more balanced estimates of channel contribution.

Finally, the chapter outlined the objectives, scope, methodology, significance, and structural framework of the study, providing the conceptual foundation for the literature review presented in the next chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The rapid expansion of digital marketing ecosystems has significantly transformed the nature of consumer engagement and organizational decision-making. Businesses today operate in highly interconnected environments where consumers interact with brands through multiple online and offline touchpoints before making purchase decisions. Unlike traditional marketing systems that relied heavily on linear communication channels such as television, newspapers, and radio, modern digital environments involve continuous interaction across search engines, social media platforms, display networks, e-commerce websites, mobile applications, email campaigns, influencer platforms, and video-sharing websites.

This transformation has increased the complexity of measuring marketing effectiveness. Organizations invest heavily in customer acquisition campaigns across several digital channels; however, identifying the exact contribution of each touchpoint to conversion outcomes remains analytically difficult. The growing fragmentation of customer journeys has therefore increased the strategic importance of marketing analytics and attribution modelling.

Attribution modelling has emerged as a critical analytical framework within digital marketing because it enables businesses to assign conversion credit across different customer touchpoints. The selection of an attribution model directly affects campaign evaluation, return on investment (ROI) measurement, channel optimization, and marketing budget allocation decisions. Different attribution approaches often generate substantially different interpretations of channel effectiveness, thereby influencing strategic managerial actions.

The literature related to attribution modelling spans multiple interdisciplinary domains including digital marketing, consumer behavior, marketing analytics, data science, omnichannel retailing, and performance management. Existing studies have explored attribution methodologies ranging from simple heuristic models to advanced probabilistic and machine learning frameworks. However, despite significant theoretical advancements, important gaps remain regarding practical implementation, managerial implications, and attribution challenges in emerging digital markets such as India.

This chapter critically reviews the major theoretical and empirical contributions relevant to the present study. The chapter examines the evolution of digital consumer behavior, omnichannel marketing systems, attribution modelling concepts, major attribution methodologies, customer journey analytics, budget allocation implications, and India-specific digital marketing challenges. The review establishes the conceptual foundation for the empirical investigation undertaken in subsequent chapters.

2.2 Evolution of Digital Marketing and Consumer Behavior

The emergence of digital technology has fundamentally changed the structure of marketing communication and consumer decision-making. Traditional marketing systems were largely characterized by one-way communication, limited customer interaction, and relatively predictable purchase funnels. Consumers typically progressed sequentially through stages such as awareness, interest, desire, and action, as proposed in early marketing frameworks like the AIDA model.

The rise of smartphones and affordable internet access further accelerated omnichannel consumer behavior. Consumers increasingly switch between devices and platforms throughout the purchase process. For instance, a customer may discover a product on Instagram, conduct price comparisons on Google, watch YouTube reviews, receive promotional emails, and finally purchase through a mobile application or marketplace platform.

Lemon and Verhoef (2016) described customer journeys as multidimensional processes involving cognitive, emotional, social, and behavioral interactions across the entire customer lifecycle. Their research highlighted that customer experience extends beyond the point of purchase and includes pre-purchase exploration, post-purchase engagement, reviews, referrals, and brand advocacy.

This increasing complexity of customer interaction patterns has made traditional marketing measurement systems inadequate. Organizations can no longer evaluate channels independently because multiple touchpoints jointly influence conversion outcomes. Consequently, businesses increasingly require advanced analytical frameworks capable of measuring interconnected channel contributions.

2.3 Omnichannel Marketing Ecosystem

The idea of omnichannel marketing developed as businesses realized the importance of delivering a unified customer experience across various communication and purchasing channels. In contrast to multichannel marketing, where each channel functions separately, omnichannel marketing focuses on creating seamless integration and consistent interaction across all channels.

Peter C. Verhoef, P. K. Kannan, and J. Jeffrey Inman (2015) described omnichannel marketing as the coordinated management of multiple customer touchpoints aimed at enhancing customer experience and improving business performance across channels. This approach acknowledges that consumers often shift between digital and physical platforms throughout their purchasing journey.

Digital businesses increasingly rely on omnichannel strategies because consumers expect flexibility and continuity across platforms. Retailers integrate websites, mobile applications, physical stores, email communication, customer support systems, and social media engagement into unified customer experience ecosystems.

The omnichannel environment creates substantial opportunities for businesses but also introduces major analytical challenges. Since customers interact with several touchpoints before conversion, organizations must determine how each channel contributes to overall marketing performance.

Research by McKinsey & Company revealed that omnichannel customers generally exhibit:

- Higher engagement levels

- Greater purchase frequency
- Increased customer retention
- Higher average order values
- Stronger brand loyalty

However, omnichannel ecosystems also generate fragmented data structures where customer interactions become difficult to track consistently across devices and platforms. Identity resolution, cross-device tracking, privacy regulations, and platform-specific reporting systems complicate measurement accuracy.

The emergence of omnichannel marketing therefore directly contributed to the development and growing importance of attribution modelling frameworks.

2.4 Customer Journey Analytics

Customer journey analytics refers to the process of tracking, analyzing, and interpreting customer interactions across touchpoints throughout the purchase process. The objective is to understand how consumers move between channels and how different interactions collectively influence conversion behavior.

Early marketing analysis focused primarily on isolated transaction events. However, contemporary digital environments require journey-based analytics because customer decisions are shaped through cumulative interaction experiences rather than single-channel exposure.

Court et al. (2009) introduced the “Consumer Decision Journey” framework, arguing that consumers continuously loop between evaluation, consideration, purchase, and post-purchase advocacy stages. The framework challenged traditional funnel-based assumptions by emphasizing that customers repeatedly revisit touchpoints before making decisions.

Journey analysis also reveals the role of assisting channels that may not directly generate conversions but significantly influence purchase consideration. For example, social media campaigns may initiate awareness, while search engines facilitate information validation and email campaigns encourage final purchase completion.

This collaborative interaction structure creates the need for attribution systems capable of recognizing multi-touch influence patterns rather than assigning credit to isolated interactions.

2.5 Concept and Importance of Attribution Modelling

Attribution modelling refers to the analytical method used to allocate conversion credit across the different marketing touchpoints a customer interacts with during the purchase journey. The primary purpose of attribution analysis is to evaluate the extent to which each channel contributes to conversion results.

As digital advertising expenditures continue to rise, businesses increasingly depend on attribution systems to justify marketing investments and optimize campaign performance. Attribution outputs directly affect:

- Marketing ROI analysis
- Budget allocation decisions
- Campaign optimization
- Customer acquisition strategy
- Media planning
- Channel prioritization

Li and Kannan (2014) described attribution modelling as one of the most important challenges in digital marketing analytics because customers interact with numerous channels before conversion. The authors emphasized that simplistic attribution approaches fail to capture interaction dependencies within customer journeys.

The growing importance of performance marketing has further elevated the role of attribution analytics. Organizations increasingly demand measurable outcomes from advertising investments, making attribution systems central to managerial decision-making.

However, attribution remains inherently difficult because:

- Customer journeys vary significantly
- Multiple channels interact simultaneously
- Touchpoints influence consumers differently
- Consumer behavior evolves dynamically
- Platforms measure performance differently

Consequently, businesses frequently obtain conflicting performance insights depending on the attribution framework used.

2.7.2 Shapley Value Attribution

Shapley Value Attribution applies cooperative game theory principles to distribute conversion credit according to each channel's marginal contribution across all possible channel combinations.

The method is mathematically rigorous and theoretically fair, though computational complexity increases significantly with additional channels.

2.7.3 Machine Learning-Based Attribution

Recent advancements in artificial intelligence and predictive analytics have introduced machine learning attribution systems. Algorithms such as logistic regression, random forests, and neural networks estimate conversion probabilities based on historical customer interaction patterns.

Machine learning approaches offer high predictive capability but often suffer from interpretability limitations. Managers may struggle to explain algorithmic outputs to stakeholders without technical expertise.

2.8 Attribution Modelling and Marketing Budget Allocation

One of the most important managerial implications of attribution modelling involves marketing budget allocation. Attribution systems directly determine how organizations distribute advertising expenditure across channels.

Different attribution models frequently produce different channel valuations. As a result, budget allocation recommendations vary substantially depending on the attribution framework adopted.

Research indicates that organizations relying heavily on last-click attribution often overinvest in lower-funnel channels while underinvesting in awareness-building activities. Such imbalances may improve short-term conversion reporting but weaken long-term customer acquisition and brand development.

Hanssens and Pauwels (2016) emphasized that attribution systems should function not merely as reporting tools but as strategic decision-support systems. Effective attribution frameworks improve:

- Resource allocation efficiency
- Marketing ROI
- Channel optimization
- Campaign planning
- Customer acquisition effectiveness

The increasing complexity of omnichannel ecosystems has therefore elevated attribution modelling from an operational analytics function to a strategic managerial capability.

2.9 Attribution Challenges in the Indian Digital Ecosystem

India's rapidly expanding digital economy presents unique opportunities and challenges for attribution analysis.

The growth of smartphone penetration, affordable mobile internet, social commerce, and D2C brands has accelerated digital marketing adoption across industries. However, Indian customer journeys remain highly fragmented.

Indian consumers frequently engage across:

- Instagram
- WhatsApp
- YouTube
- Search engines
- Marketplaces
- Mobile applications

Several structural factors complicate attribution modelling in India:

- Cross-device usage
- Cash-on-Delivery transactions
- Informal social commerce
- WhatsApp-driven customer interaction
- Limited analytics infrastructure among SMEs

Many businesses continue relying on platform-specific metrics and simplistic attribution systems because advanced analytics capabilities remain expensive and technically demanding.

Academic research examining attribution modelling within Indian digital ecosystems also remains limited, creating significant opportunities for empirical investigation.

2.10 Research Gap

The literature review reveals several important research gaps.

First, many existing studies focus primarily on theoretical attribution methodology rather than practical managerial implications such as budget allocation.

Second, most empirical attribution research has been conducted in Western digital markets, while India-specific analytical evidence remains limited.

Third, several studies examine individual attribution models independently rather than conducting integrated comparative analysis across multiple attribution frameworks.

Fourth, existing research often prioritizes technical complexity over managerial interpretability, limiting practical implementation within business environments.

Finally, there remains insufficient understanding regarding how attribution models behave under increasingly fragmented omnichannel customer journeys.

The present study addresses these gaps by:

- Comparing multiple attribution models within a unified analytical framework
- Examining budget allocation divergence
- Evaluating attribution outcomes using customer journey data

- Focusing on omnichannel digital marketing environments
- Interpreting findings within the Indian D2C context

2.11 Chapter Summary

This chapter reviewed the major theoretical and empirical literature related to digital marketing analytics, omnichannel consumer behavior, customer journey analysis, and attribution modelling.

The review established that contemporary customer journeys are increasingly fragmented and involve multiple interconnected touchpoints before conversion. Consequently, traditional single-touch attribution approaches are often insufficient for accurately measuring channel contribution.

The chapter critically examined both rule-based and data-driven attribution methodologies while highlighting their assumptions, advantages, and limitations. The literature further demonstrated that attribution model selection significantly influences marketing performance evaluation and budget allocation decisions.

The review also identified major attribution challenges within the Indian digital ecosystem, including fragmented consumer journeys, WhatsApp commerce, cross-device interaction, and limited analytics infrastructure.

Finally, the chapter identified key research gaps that justify the present study and provide the conceptual foundation for the research methodology discussed in the next chapter.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The previous chapter reviewed the theoretical foundations and empirical literature related to digital marketing analytics, omnichannel consumer behavior, customer journey analysis, and attribution

modelling. The literature established that modern customer journeys involve multiple interconnected touchpoints and that attribution model selection significantly affects marketing performance interpretation and budget allocation decisions.

Building upon this conceptual foundation, the present chapter explains the research methodology adopted for the study. The chapter outlines the research design, research approach, data structure, attribution models, analytical framework, variables used, statistical techniques, and procedures employed to conduct the comparative attribution analysis.

The purpose of this chapter is to provide a systematic explanation of how the study was conducted so that the analytical process remains transparent, logically structured, and academically reliable.

The study primarily adopts a quantitative analytical approach using simulated omnichannel customer journey data to evaluate the performance and implications of different attribution models. The methodology is designed to compare how various attribution frameworks allocate conversion credit across digital marketing channels and how these differences influence marketing budget allocation decisions.

Analytical Component

The analytical component involves:

- Comparing multiple attribution models
- Measuring conversion credit allocation
- Evaluating budget allocation outcomes
- Conducting statistical comparison between models
- Assessing attribution accuracy through RMSE analysis
- Examining channel sensitivity across attribution frameworks

The analytical approach enables objective evaluation of attribution model behavior under a common customer journey dataset.

The study follows a **cross-sectional analytical framework**, where attribution outcomes are analyzed within a defined dataset representing customer journeys over a fixed period.

3.3 Research Approach

The study follows a **quantitative research approach** because attribution modelling requires numerical evaluation of channel interactions, conversion paths, and budget allocation outcomes.

Quantitative analysis is appropriate for the present research because:

- Attribution models generate measurable conversion credit values
- Customer journeys can be represented numerically
- Channel performance can be statistically compared

- Budget allocation differences can be quantified
- Model accuracy can be mathematically evaluated

The study combines concepts from:

- Digital marketing analytics
- Data-driven decision-making
- Consumer journey analysis
- Marketing performance measurement
- Probabilistic modelling

The research also adopts a comparative analytical perspective by evaluating multiple attribution frameworks under identical customer journey conditions.

3.4 Nature and Sources of Data

The study uses a combination of:

- Secondary conceptual information
- Simulated analytical customer journey data

3.4.1 Secondary Data

Secondary data was used for:

- Literature review
- Attribution model understanding
- Digital marketing industry analysis
- Omnichannel consumer behavior insights
- Attribution theory development

Secondary information was collected from:

- Research journals
- Industry reports
- Academic books
- Whitepapers
- Marketing analytics publications
- Google Scholar
- JSTOR
- ScienceDirect

- Deloitte, Nielsen, Google, and Dentsu reports

3.4.2 Simulated Customer Journey Dataset

The empirical analysis was conducted using a simulated omnichannel customer journey dataset designed to replicate realistic digital consumer interaction behavior.

The dataset consists of:

- **5,000 customer journeys**
- **18,450 total touchpoints**
- **1,050 conversions**

The dataset includes interactions across five major digital marketing channels:

1. Social Media
2. Paid Search
3. Display Advertising
4. Email Marketing
5. Organic Search

The simulated dataset was generated using probabilistic interaction assumptions based on:

- Industry benchmarks
- Omnichannel consumer behavior studies
- Digital marketing interaction patterns
- Existing attribution research

The purpose of simulation was to create a controlled analytical environment where attribution models could be compared objectively without platform-specific reporting biases.

Each customer journey consists of:

- Interaction timing
- Channel exposure
- Conversion outcome

The study analyzes:

- Journey structure
- Channel sequence behavior
- Conversion probability contribution
- Attribution credit allocation

The analysis is therefore journey-centric rather than channel-isolated.

3.6 Customer Journey Structure

Customer journeys in the dataset were designed to reflect realistic omnichannel interaction behavior.

Each journey may contain:

- Single-touch interactions
- Multi-touch sequences
- Repeated channel exposures
- Awareness-stage interactions
- Consideration-stage interactions
- Conversion-stage interactions

Examples of customer journey paths include:

- Social Media → Paid Search → Conversion
- Display Ads → Social Media → Email → Paid Search → Conversion
- Organic Search → Email → Conversion
- Social Media → Display Ads → Organic Search → Paid Search → Conversion

The average journey length within the dataset is:

3.69 touchpoints per customer

4.2 touchpoints among converted users

These journey structures allow evaluation of how attribution models behave under varying levels of customer interaction complexity.

3.7 Attribution Models Used in the Study

The study compares five attribution models widely used in digital marketing analytics.

3.7.1 First-Click Attribution

Formula:

If a conversion occurs:

- First touchpoint = 100% credit
- Remaining touchpoints = 0%

Managerial Assumption:

The first interaction is primarily responsible for generating customer awareness.

Strength:

Useful for evaluating awareness campaigns.

Limitation:

Ignores nurturing and lower-funnel interactions.

3.7.2 Last-Click Attribution

Formula:

If a conversion occurs:

- Last touchpoint = 100% credit
- Remaining touchpoints = 0%

Managerial Assumption:

The final interaction directly triggered conversion.

Strength:

Simple and operationally convenient.

Limitation:

Overvalues lower-funnel channels.

3.7.3 Linear Attribution

Formula:

If a journey contains n touchpoints:

Each touchpoint receives:

$$\frac{1}{n}$$

of the total conversion credit.

Strength:

Recognizes contribution of all interactions.

Limitation:

Assumes equal influence across touchpoints.

3.7.4 Time-Decay Attribution

Managerial Assumption:

Recent interactions exert stronger influence on customer decisions.

Strength:

Reflects increasing purchase intent near conversion.

Limitation:

May undervalue awareness-stage channels.

3.7.5 Markov Chain Attribution

Removal Effect Formula

$$\text{Removal Effect} = P(\text{Conversion}) - P(\text{Conversion without Channel}_i)$$

Where:

- $P(\text{Conversion})$ = overall conversion probability
- $P(\text{Conversion without Channel}_i)$ = conversion probability after removing a channel

Strengths:

- Captures sequential interaction behavior
- Recognizes assisting channels
- Reduces heuristic bias
- More behaviorally realistic

Limitation:

Requires higher computational complexity.

The Markov model is treated as the quasi-data-driven benchmark in the study.

3.8 Variables Used in the Study

The study includes both dependent and independent analytical variables.

3.8.2 Dependent Variables

Dependent variables represent analytical outcomes generated through attribution analysis.

These include:

- Conversion credit distribution
- Channel contribution percentage
- Budget allocation outcomes
- RMSE values
- Customer conversion paths

- Attribution sensitivity measures

3.9 Analytical Framework

The analytical framework of the study involves five major stages.

Stage 1: Customer Journey Construction

Customer journeys were structured using:

- Sequential touchpoints
- Channel interaction patterns
- Conversion labeling

Stage 2: Attribution Application

Each attribution model was applied independently to the same dataset.

This enabled direct comparison of:

- Channel credit distribution
- Conversion allocation
- Channel valuation differences

Stage 3: Budget Allocation Simulation

A hypothetical monthly marketing budget of:

₹10,00,000

was allocated according to attribution outputs generated by each model.

This stage helped evaluate:

- Resource allocation distortion
- Overinvestment risk
- Channel prioritization shifts

Stage 4: RMSE Analysis

Root Mean Square Error (RMSE) analysis was conducted to compare rule-based models against the Markov benchmark.

The RMSE formula used is:

$$RMSE = \sqrt{\frac{\sum (Predicted - Actual)^2}{n}}$$

Lower RMSE values indicate closer alignment with the Markov model.

Stage 5: Sensitivity Analysis

Sensitivity analysis examined:

- Channel volatility
- Attribution instability
- Journey complexity effects
- Model responsiveness under different interaction structures

This stage helped evaluate robustness of attribution frameworks.

3.10 Tools and Techniques Used

The study uses several analytical tools and techniques.

3.10.1 Attribution Comparison Analysis

Used to compare:

- Channel credit distribution
- Percentage contribution
- Model-specific valuation differences

3.10.2 Budget Allocation Analysis

Used to evaluate:

- Marketing investment distribution
- Channel prioritization changes
- Budget distortion effects

3.10.3 RMSE Evaluation

Used to measure:

- Model deviation
- Attribution accuracy

- Analytical consistency

3.10.4 Customer Journey Path Analysis

Used to examine:

- Touchpoint sequences
- Multi-channel interactions
- Conversion pathways

3.10.5 Sensitivity Analysis

Used to evaluate:

- Stability of attribution models
- Model responsiveness under journey variation
- Channel sensitivity

3.11 Reliability and Validity Considerations

To ensure analytical consistency, the same customer journey dataset was used across all attribution models.

The study maintains:

- Uniform conversion conditions
- Consistent channel exposure assumptions
- Standardized budget allocation framework

Validity was strengthened by:

- Using industry-aligned journey patterns
- Applying recognized attribution methodologies
- Comparing models under identical conditions

However, since the dataset is simulated, findings should be interpreted as analytical approximations rather than exact market predictions.

3.12 Ethical Considerations

The study does not involve personally identifiable customer information or confidential enterprise datasets.

The simulated dataset was constructed exclusively for academic research purposes. No consumer privacy violations or sensitive platform data were involved in the analysis.

All secondary sources referenced in the study were used strictly for academic and research purposes.

3.13 Limitations of Methodology

Certain methodological limitations must be acknowledged.

1. The dataset is simulated rather than derived from proprietary enterprise-level customer interaction logs.
2. Attribution outputs depend on assumptions embedded within customer journey generation patterns.
3. External environmental variables such as seasonality, pricing, and competitor activity were not included.
4. Offline interactions and cross-platform identity resolution complexities were beyond the scope of the study.
5. The Markov model is treated as a benchmark approximation rather than absolute causal truth.

Despite these limitations, the methodology provides a structured framework for comparative attribution analysis.

3.14 Chapter Summary

This chapter explained the research methodology adopted for the study. The research employs a descriptive and analytical quantitative design using a simulated omnichannel customer journey dataset consisting of 5,000 journeys, 18,450 touchpoints, and 1,050 conversions.

The chapter detailed the attribution models used in the study, including First-Click, Last-Click, Linear, Time-Decay, and Markov Attribution. It also explained the analytical framework involving attribution comparison, budget allocation simulation, RMSE evaluation, and sensitivity analysis.

The methodology was specifically designed to evaluate how attribution model selection influences channel valuation and marketing budget allocation decisions within omnichannel digital marketing environments.

The next chapter presents the empirical analysis and findings generated through application of the attribution models to the customer journey dataset.

CHAPTER 4

DATA ANALYSIS AND FINDINGS

4.1 Introduction

The previous chapter explained the research methodology, analytical framework, attribution models, and data structure used in the study. This chapter presents the empirical analysis and findings derived from applying different attribution models to the omnichannel customer journey dataset.

The primary objective of this chapter is to evaluate how different attribution frameworks allocate conversion credit across digital marketing channels and how these differences influence marketing budget allocation decisions. The chapter also examines customer journey behavior, channel sensitivity, attribution accuracy, and model stability.

The analysis is based on:

- 5,000 customer journeys

- 18,450 touchpoints
- 1,050 conversions
- Five digital marketing channels
- Five attribution models

The findings are presented systematically using:

- Tables
- Graphical comparisons
- Analytical interpretation
- Budget allocation simulations
- RMSE analysis
- Customer journey evaluation

The chapter is divided into multiple analytical sections covering:

1. Dataset overview
2. Customer journey analysis
3. Attribution model comparison
4. Budget allocation analysis
5. RMSE evaluation
6. Sensitivity analysis
7. Managerial interpretation of findings

4.2 Dataset Overview

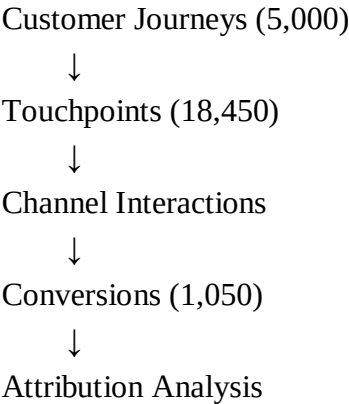
The simulated omnichannel dataset was constructed to represent realistic customer interaction behavior within digital marketing ecosystems.

Table 4.1 Dataset Summary

Particulars	Value
Total Customer Journeys	5,000
Total Touchpoints	18,450
Total Conversions	1,050
Conversion Rate	21.0%
Average Touchpoints per Journey	3.69

Particulars	Value
Average Touchpoints before Conversion	4.2
Number of Channels	5

Figure 4.1 Dataset Structure Overview



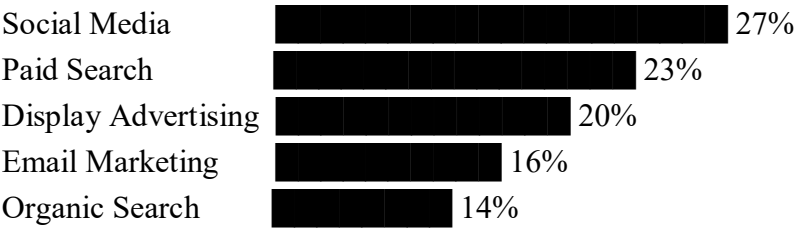
4.3 Channel Interaction Distribution

The dataset included customer interactions across five major digital marketing channels.

Table 4.2 Channel-wise Touchpoint Distribution

Channel	Touchpoints	Percentage Share
Social Media	4,980	27.0%
Paid Search	4,250	23.0%
Display Advertising	3,690	20.0%
Email Marketing	2,950	16.0%
Organic Search	2,580	14.0%
Total	18,450	100%

Figure 4.2 Channel Interaction Share



4.4 Customer Journey Analysis

The analysis revealed that customer journeys were highly fragmented and involved multiple interconnected touchpoints before conversion.

Table 4.3 Journey Length Distribution

Number of Touchpoints	Percentage of Journeys
1 Touchpoint	14%
2 Touchpoints	21%
3 Touchpoints	26%
4 Touchpoints	22%
5+ Touchpoints	17%

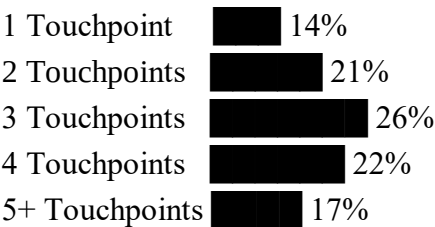
Interpretation

The findings indicate that:

- Only 14% of journeys involved single-touch interaction.
- 86% of customer journeys involved multiple touchpoints.
- Most consumers interacted with at least 3–4 channels before conversion.

This demonstrates the inadequacy of simplistic single-touch attribution models in omnichannel environments.

Figure 4.3 Customer Journey Complexity



4.5 Common Conversion Paths

Several recurring conversion pathways were identified within the dataset.

Table 4.4 Most Frequent Conversion Paths

Customer Journey Path	Frequency
Social Media → Paid Search → Conversion	185
Display Ads → Social Media → Paid Search → Conversion	142

Customer Journey Path	Frequency
Organic Search → Email → Conversion	128
Social Media → Display Ads → Email → Paid Search → Conversion	114
Paid Search → Conversion	102

Interpretation

The findings suggest:

- Social Media frequently acted as an awareness-stage touchpoint.
- Paid Search commonly functioned as the final conversion-stage interaction.
- Email Marketing often acted as a nurturing channel.
- Multi-touch journeys were more common than direct conversion journeys.

The results reinforce the importance of evaluating collaborative channel influence rather than isolated interactions.

4.6 Attribution Model Comparison

The five attribution models were applied independently to the same customer journey dataset.

The objective was to compare how each model allocates conversion credit across channels.

4.7 First-Click Attribution Results

Under First-Click Attribution, complete conversion credit was assigned to the initial touchpoint.

Table 4.5 First-Click Attribution Credit Distribution

Channel	Attribution Credit (%)
Social Media	38%
Paid Search	21%
Display Advertising	24%
Email Marketing	8%
Organic Search	9%

Interpretation

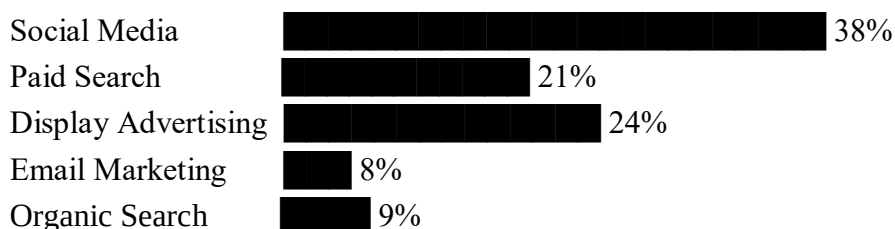
The model heavily favored awareness-stage channels:

- Social Media received the highest credit because it frequently initiated customer journeys.

- Display Advertising also received high attribution due to early-stage exposure effects.
- Lower-funnel channels received comparatively lower credit.

This indicates that First-Click Attribution strongly emphasizes customer acquisition initiation rather than purchase completion.

Figure 4.4 First-Click Attribution Distribution



4.8 Last-Click Attribution Results

Under Last-Click Attribution, complete conversion credit was assigned to the final touchpoint before conversion.

Table 4.6 Last-Click Attribution Credit Distribution

Channel	Attribution Credit (%)
Paid Search	42%
Email Marketing	22%
Social Media	17%
Organic Search	10%
Display Advertising	9%

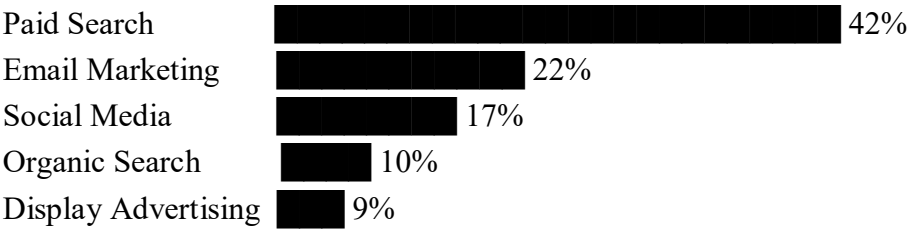
Interpretation

The model heavily favored lower-funnel channels:

- Paid Search received extremely high credit because it frequently occurred near conversion.
- Email Marketing also gained substantial attribution.
- Awareness-stage channels became significantly undervalued.

This demonstrates how Last-Click Attribution can distort marketing performance interpretation by ignoring earlier touchpoints.

Figure 4.5 Last-Click Attribution Distribution



4.9 Linear Attribution Results

Linear Attribution distributed conversion credit equally across all touchpoints.

Table 4.7 Linear Attribution Credit Distribution

Channel	Attribution Credit (%)
Paid Search	28%
Social Media	26%
Display Advertising	16%
Email Marketing	15%
Organic Search	15%

Interpretation

The model produced more balanced channel valuation:

- Credit distribution became less concentrated.
- All channels received meaningful attribution.
- Collaborative interaction effects became visible.

However, the model assumed equal influence across touchpoints regardless of interaction timing or sequence.

4.10 Time-Decay Attribution Results

Time-Decay Attribution assigned progressively greater weight to interactions closer to conversion.

Table 4.8 Time-Decay Attribution Credit Distribution

Channel	Attribution Credit (%)
Paid Search	34%
Social Media	22%
Email Marketing	20%

Channel	Attribution Credit (%)
Display Advertising	12%
Organic Search	12%

Interpretation

The model generated more behaviorally realistic allocation:

- Paid Search retained high importance due to proximity to conversion.
- Social Media still received meaningful awareness-stage credit.
- Email Marketing emerged as an important nurturing channel.

Time-Decay Attribution balanced awareness and conversion-stage influence more effectively than single-touch models.

4.11 Markov Chain Attribution Results

Markov Attribution evaluated channel contribution using transition probabilities and removal effects.

Table 4.9 Markov Attribution Credit Distribution

Channel	Attribution Credit (%)
Paid Search	31%
Social Media	24%
Email Marketing	18%
Display Advertising	14%
Organic Search	13%

Interpretation

Markov Attribution generated the most balanced and analytically stable results:

- Both awareness and conversion-stage channels received meaningful credit.
- Channel interdependency became visible.
- Assisting channels were appropriately recognized.

The findings suggest that customer conversion is influenced by collaborative interaction sequences rather than isolated touchpoints.

4.12 Budget Allocation Analysis

A hypothetical monthly marketing budget of ₹10,00,000 was allocated according to each attribution model's output.

Channel	FC	LC	Linear	TD	Markov
Social Media	38%	17%	26%	22%	24%
Paid Search	21%	42%	28%	34%	31%
Display Ads	24%	9%	16%	12%	14%
Email	8%	22%	15%	20%	18%
Organic	9%	10%	15%	12%	13%

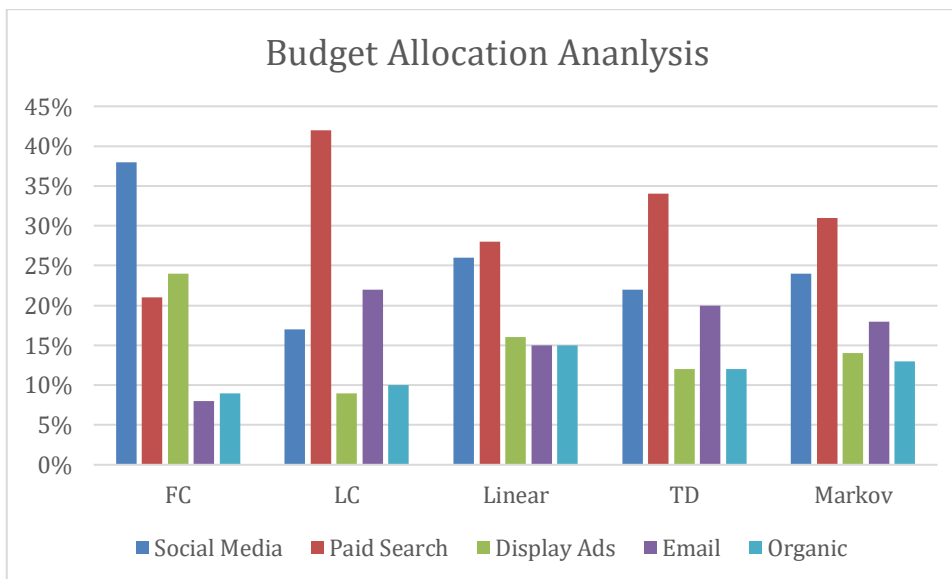


Table 4.10 Budget Allocation under First-Click Attribution

Channel	Allocation (₹)
Social Media	3,80,000
Paid Search	2,10,000
Display Advertising	2,40,000
Email Marketing	80,000
Organic Search	90,000

Table 4.11 Budget Allocation under Last-Click Attribution

Channel	Allocation (₹)
Paid Search	4,20,000
Email Marketing	2,20,000
Social Media	1,70,000
Organic Search	1,00,000
Display Advertising	90,000

Table 4.12 Budget Allocation under Markov Attribution

Channel	Allocation (₹)
Paid Search	3,10,000
Social Media	2,40,000
Email Marketing	1,80,000
Display Advertising	1,40,000
Organic Search	1,30,000

Interpretation

The findings reveal substantial variation in resource allocation depending on attribution methodology. **Key Observations:**

- Last-Click Attribution disproportionately favored Paid Search.
- First-Click Attribution heavily prioritized Social Media and Display Ads.
- Markov Attribution produced comparatively balanced allocation.

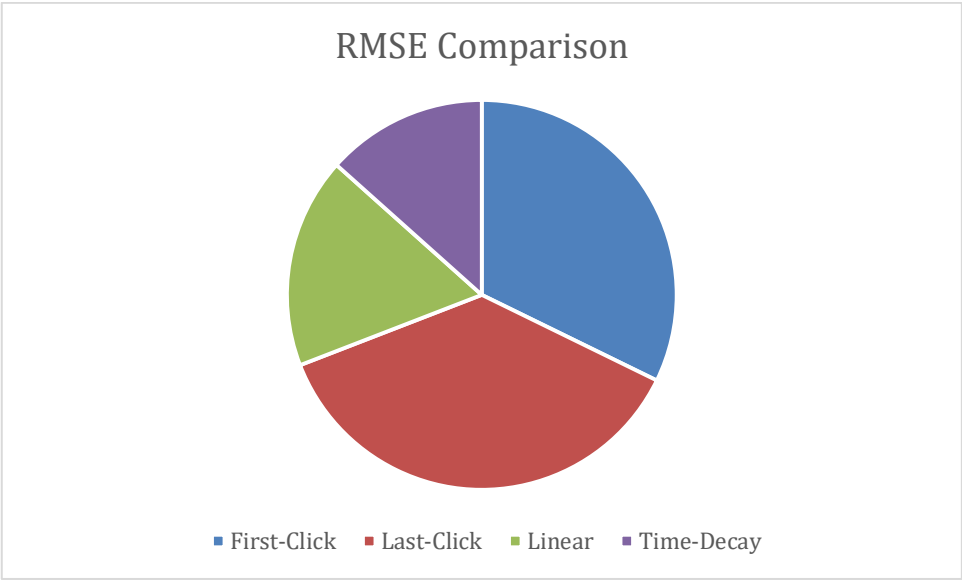
These differences demonstrate that attribution model selection can materially influence organizational investment strategy.

4.13 RMSE Analysis

Root Mean Square Error (RMSE) analysis was conducted using Markov Attribution as the benchmark model.

Table 4.13 RMSE Comparison

Attribution Model	RMSE
First-Click	11.8
Last-Click	13.5
Linear	6.4
Time-Decay	4.9



Interpretation

Lower RMSE values indicate closer alignment with the Markov model.

Findings:

- Time-Decay Attribution produced the lowest RMSE.
- Linear Attribution also showed relatively close alignment.
- Last-Click Attribution showed the highest deviation.

This indicates that:

- Single-touch models produce greater attribution distortion.
- Multi-touch approaches better represent collaborative customer behavior.

Figure 4.7 RMSE Comparison



4.14 Sensitivity Analysis

Sensitivity analysis evaluated how attribution models responded to increasing journey complexity.

Table 4.14 Attribution Stability under Journey Complexity

Model	Stability Level
First-Click	Low
Last-Click	Low
Linear	Moderate
Time-Decay	High
Markov	Very High

Interpretation

As journey complexity increased:

- Single-touch models became increasingly unstable.
- Multi-touch models adapted more effectively.
- Markov Attribution remained comparatively robust.

The findings indicate that advanced attribution approaches are more suitable for fragmented omnichannel environments.

4.15 Key Findings of the Study

The major findings of the study are summarized below:

1. Modern customer journeys are highly fragmented and involve multiple touchpoints before conversion.
2. Different attribution models generate substantially different channel valuations.
3. First-Click Attribution overvalues awareness-stage channels.
4. Last-Click Attribution disproportionately favors lower-funnel channels.
5. Linear Attribution produces balanced but oversimplified distribution.
6. Time-Decay Attribution provides comparatively realistic allocation.
7. Markov Attribution generates the most analytically balanced results.
8. Attribution model selection significantly affects marketing budget allocation decisions.

9. Multi-touch attribution approaches outperform single-touch models under complex journey structures.
10. Omnichannel environments require advanced attribution frameworks for accurate performance evaluation.

4.16 Chapter Summary

This chapter presented the empirical analysis and findings of the study. The analysis demonstrated that attribution model selection substantially influences conversion credit allocation, channel valuation, and marketing budget distribution.

The results revealed major differences between rule-based and data-driven attribution approaches. Single-touch models such as First-Click and Last-Click Attribution produced highly concentrated and potentially distorted channel valuations, while multi-touch approaches generated more balanced interpretations of customer behavior.

The findings also showed that Time-Decay and Markov Attribution models better represent collaborative interaction patterns within omnichannel customer journeys.

Finally, the chapter established that attribution modelling is not merely a reporting mechanism but a strategic decision-making framework capable of materially influencing marketing investment priorities.

The next chapter discusses these findings in relation to existing literature and managerial implications.

CHAPTER 5

DISCUSSION

5.1 Introduction

The previous chapter presented the empirical analysis and findings derived from applying multiple attribution models to the omnichannel customer journey dataset. The analysis demonstrated substantial variation in conversion credit allocation, channel valuation, and marketing budget distribution depending on the attribution framework used.

The purpose of this chapter is to interpret and critically discuss these findings in relation to the research objectives, research questions, and existing literature reviewed in Chapter 2. The discussion focuses on understanding the managerial, analytical, and strategic implications of attribution model selection within modern digital marketing ecosystems.

The chapter evaluates:

- The significance of multi-touch customer journeys
- The strengths and limitations of different attribution models
- The impact of attribution models on budget allocation
- The implications for digital marketing strategy
- The relevance of findings within the Indian D2C environment

The discussion also connects empirical observations with broader concepts related to customer journey analytics, omnichannel marketing, and data-driven decision-making.

5.2 Discussion on Customer Journey Complexity

One of the most important findings of the study was that modern customer journeys are highly fragmented and involve multiple touchpoints before conversion.

The dataset analysis revealed:

- Average journey length = 3.69 touchpoints
- Average converted journey length = 4.2 touchpoints

- 86% of journeys involved multiple interactions

These findings strongly support the arguments presented by Lemon and Verhoef (2016), who emphasized that contemporary customer journeys are multidimensional and involve continuous interaction across channels.

The results indicate that consumers rarely convert immediately after a single exposure. Instead, customer decisions emerge gradually through repeated engagement, information evaluation, comparison, and purchase consideration across platforms.

The findings also validate the “Consumer Decision Journey” framework proposed by Court et al. (2009), which argued that modern purchase behavior is non-linear and iterative rather than sequential.

From a managerial perspective, this suggests that:

- Customer acquisition cannot be evaluated using isolated interactions
- Multiple channels collectively contribute to conversion
- Early-stage awareness interactions remain strategically important
- Marketing effectiveness should be assessed holistically

The increasing complexity of customer journeys therefore creates strong justification for advanced attribution frameworks capable of recognizing collaborative channel influence.

5.3 Discussion on First-Click Attribution

The empirical analysis showed that First-Click Attribution heavily favored awareness-stage channels.

Under this model:

- Social Media received 38% attribution credit
- Display Advertising received 24%
- Paid Search received comparatively lower credit

This outcome reflects the structural logic of the model, where the initial interaction receives complete conversion credit regardless of subsequent customer engagement.

The findings indicate that Social Media frequently functions as a discovery and awareness-generation platform within omnichannel journeys. Display advertising also plays an important role in initiating consumer attention and brand exposure.

The results align with previous research suggesting that awareness-stage channels are often undervalued in traditional conversion-focused analytics systems.

However, despite its usefulness in measuring acquisition initiation, First-Click Attribution demonstrated important limitations.

The model ignored:

- Mid-funnel nurturing interactions
- Conversion-stage touchpoints
- Sequential engagement behavior
- Customer decision reinforcement

Consequently, the model tended to overestimate the role of awareness-stage channels while underestimating lower-funnel conversion drivers.

From a strategic perspective, excessive dependence on First-Click Attribution may lead organizations to:

- Overinvest in awareness campaigns
- Underfund conversion optimization activities
- Misinterpret final purchase triggers
- Distort short-term performance measurement

Therefore, while First-Click Attribution provides valuable insight into customer acquisition origins, it does not fully represent complete customer journey dynamics.

5.4 Discussion on Last-Click Attribution

The findings revealed that Last-Click Attribution disproportionately favored lower-funnel channels.

Under this model:

- Paid Search received 42% attribution credit
- Email Marketing received 22%
- Social Media received only 17%

This outcome demonstrates how last-touch frameworks systematically concentrate conversion credit on interactions occurring immediately before purchase.

The results strongly support the criticisms highlighted by Berman (2015), who argued that Last-Click Attribution overvalues conversion-stage channels while ignoring the cumulative influence of earlier touchpoints.

Paid Search emerged as the dominant channel under Last-Click Attribution because customers frequently used search engines near the purchase stage for:

- Product validation
- Price comparison
- Brand confirmation
- Final decision-making

Similarly, Email Marketing received higher attribution because promotional reminders and retargeting campaigns often occurred close to conversion.

However, the findings suggest that Last-Click Attribution creates several analytical distortions.

The model fails to recognize:

- Awareness generation
- Customer education
- Brand familiarity development
- Sequential channel influence

This creates significant managerial risk because organizations relying heavily on last-click metrics may:

- Shift excessive budgets toward lower-funnel campaigns
- Reduce investment in brand-building activities
- Prioritize short-term conversions over long-term growth
- Underestimate customer acquisition complexity

The results therefore confirm that Last-Click Attribution is increasingly inadequate within omnichannel digital environments.

5.5 Discussion on Linear Attribution

Linear Attribution generated comparatively balanced channel distribution.

The model allocated:

- 28% to Paid Search
- 26% to Social Media
- 16% to Display Advertising
- 15% each to Email and Organic Search

Unlike single-touch approaches, Linear Attribution recognized that multiple touchpoints collectively contribute to customer conversion.

The findings demonstrate that customer journeys involve collaborative interaction effects rather than isolated conversion triggers.

From a strategic perspective, Linear Attribution offers several advantages:

- Balanced channel evaluation
- Reduced attribution concentration
- Greater recognition of assisting channels
- Improved visibility into omnichannel interaction patterns

However, the analysis also revealed conceptual limitations.

The model assumes equal influence across all touchpoints regardless of:

- Timing
- Position in journey
- Engagement intensity
- Behavioral impact

In practice, customer interactions rarely contribute equally to conversion outcomes.

For example:

- A brief display advertisement may not influence consumers as strongly as a detailed product search interaction.
- An email reminder near purchase may carry greater conversion influence than an early awareness-stage exposure.

Therefore, although Linear Attribution improves upon single-touch models, it still oversimplifies customer behavior dynamics.

5.6 Discussion on Time-Decay Attribution

Time-Decay Attribution produced more behaviorally realistic results compared to other rule-based approaches.

The analysis showed:

- Paid Search = 34%
- Social Media = 22%
- Email Marketing = 20%

The model balanced awareness-stage influence with conversion-stage importance by assigning progressively greater weight to interactions closer to purchase.

The findings indicate that Time-Decay Attribution better reflects real consumer decision-making behavior because purchase intent often strengthens near conversion.

Unlike Last-Click Attribution, the model still recognized the importance of earlier interactions. At the same time, unlike First-Click Attribution, it acknowledged the stronger impact of recent engagement.

The RMSE analysis further demonstrated that Time-Decay Attribution produced the closest alignment with the Markov benchmark among all rule-based models.

This suggests that:

- Sequential interaction weighting improves attribution realism
- Time proximity matters within customer decision-making

- Balanced multi-touch frameworks better represent omnichannel behavior

From a managerial perspective, Time-Decay Attribution provides:

- Better channel balance
- Reduced allocation distortion
- More realistic campaign evaluation
- Improved optimization guidance

The findings therefore position Time-Decay Attribution as a comparatively practical and analytically reliable attribution framework for businesses operating within complex digital ecosystems.

5.7 Discussion on Markov Attribution

The Markov Attribution model generated the most analytically balanced and behaviorally representative outcomes.

The findings showed:

- Paid Search = 31%
- Social Media = 24%
- Email Marketing = 18%
- Display Advertising = 14%
- Organic Search = 13%

Unlike heuristic models, Markov Attribution evaluated actual transition probabilities and channel removal effects.

This allowed the model to:

- Recognize assisting channels
- Capture sequential dependencies
- Evaluate interaction collaboration
- Reduce heuristic bias

The results demonstrate that customer conversion emerges through interconnected touchpoint ecosystems rather than isolated interactions.

The model also produced:

- Greater attribution stability
- Lower concentration distortion
- Better handling of complex journeys

The findings strongly support the literature suggesting that probabilistic attribution approaches provide superior analytical realism compared to simplistic rule-based systems.

However, despite its advantages, Markov Attribution also presents practical challenges:

- Higher computational complexity
- Large data requirements
- Technical implementation barriers
- Limited interpretability for non-technical managers

Many organizations, particularly small and medium-sized businesses, may lack the infrastructure necessary to implement advanced probabilistic attribution systems.

Therefore, while Markov Attribution offers strong analytical capability, operational feasibility remains an important managerial consideration.

5.8 Discussion on Budget Allocation Implications

One of the most significant findings of the study relates to marketing budget allocation.

The analysis demonstrated that attribution model selection substantially altered budget distribution across channels.

For example:

- Last-Click Attribution allocated ₹4,20,000 to Paid Search.
- First-Click Attribution allocated ₹3,80,000 to Social Media.
- Markov Attribution produced more balanced allocation outcomes.

These differences confirm that attribution modelling is not merely a reporting exercise but a strategic resource allocation mechanism.

The findings indicate that organizations relying heavily on simplistic attribution frameworks risk:

- Overinvesting in certain channels
- Underfunding strategically important interactions
- Distorting marketing ROI interpretation
- Weakening long-term customer acquisition effectiveness

The study therefore supports Hanssens and Pauwels (2016), who argued that attribution systems directly influence organizational investment strategy.

From a managerial perspective:

- Attribution bias can materially affect business performance.
- Marketing decisions become highly sensitive to analytical methodology.
- More balanced attribution systems improve strategic allocation efficiency.

The findings further suggest that businesses should avoid depending exclusively on platform-specific attribution reports because such systems frequently prioritize their own channels.

5.9 Discussion within Indian D2C Context

The findings of the study are particularly relevant within the Indian digital marketing ecosystem.

Indian customer journeys are highly fragmented due to:

- Rapid smartphone adoption
- Social commerce growth
- Multi-platform engagement
- WhatsApp-based interaction
- Marketplace dependency

The analysis demonstrated that awareness-stage channels such as Social Media significantly influence customer acquisition. This reflects the growing importance of Instagram, YouTube, and influencer marketing within Indian D2C ecosystems.

At the same time, Paid Search remained highly influential near conversion, reflecting consumer behavior patterns involving:

- Product comparison
- Trust validation
- Purchase confirmation

The findings therefore indicate that Indian D2C brands require:

- Omnichannel measurement systems
- Integrated analytics frameworks
- Multi-touch attribution capability

However, many Indian businesses continue relying on simplistic attribution systems because of:

- Limited analytics infrastructure
- Budget constraints
- Platform dependency
- Technical capability limitations

The study highlights the need for greater analytical maturity within India's rapidly expanding digital economy.

5.10 Overall Interpretation of Findings

The findings collectively demonstrate that attribution modelling fundamentally shapes how organizations interpret marketing effectiveness.

Several major conclusions emerge from the analysis:

1. Customer journeys are collaborative rather than isolated.
2. Single-touch attribution models oversimplify consumer behavior.
3. Multi-touch approaches better represent omnichannel dynamics.
4. Attribution bias directly influences budget allocation decisions.
5. Advanced attribution systems improve strategic marketing evaluation.
6. Omnichannel ecosystems require integrated analytical frameworks.

The study therefore reinforces the growing importance of data-driven marketing decision-making within modern business environments.

5.11 Chapter Summary

This chapter critically discussed the empirical findings presented in Chapter 4 in relation to the research objectives and existing literature.

The discussion established that modern customer journeys are increasingly fragmented and require multi-touch analytical frameworks for accurate performance measurement. The findings demonstrated major differences between attribution models in terms of channel valuation, customer journey interpretation, and budget allocation outcomes.

Single-touch attribution approaches such as First-Click and Last-Click Attribution were found to generate substantial analytical distortions, while multi-touch models such as Time-Decay and Markov Attribution produced more balanced and behaviorally realistic results.

The chapter also emphasized the strategic importance of attribution modelling within omnichannel marketing environments and highlighted the relevance of the findings for Indian D2C businesses operating within rapidly evolving digital ecosystems.

The next chapter presents the conclusion, recommendations, limitations, and future research directions of the study.

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

The previous chapter discussed the empirical findings of the study in relation to attribution modelling, customer journey analytics, omnichannel marketing behavior, and marketing budget allocation decisions. The findings demonstrated that attribution model selection significantly influences how organizations evaluate channel performance and allocate marketing resources.

This chapter presents the overall conclusion of the study along with managerial recommendations, limitations, and future research directions. The chapter summarizes the major findings and explains their strategic implications for businesses operating within increasingly fragmented digital marketing ecosystems.

The primary objective of the study was to examine how different attribution models allocate conversion credit across digital marketing channels and how these differences affect marketing budget allocation decisions within omnichannel customer journeys.

The study compared five attribution models:

- First-Click Attribution
- Last-Click Attribution
- Linear Attribution
- Time-Decay Attribution
- Markov Chain Attribution

The analysis was conducted using a simulated omnichannel dataset consisting of:

- 5,000 customer journeys
- 18,450 touchpoints
- 1,050 conversions

The findings generated important analytical and managerial insights regarding digital marketing performance evaluation and resource allocation strategy.

6.2 Conclusion of the Study

The study concludes that attribution modelling plays a critical role in modern digital marketing analytics and significantly influences organizational understanding of customer acquisition behavior.

The research established that modern customer journeys are highly fragmented, interconnected, and multi-touch in nature. Most consumers interact with multiple channels before conversion, making traditional single-touch attribution systems increasingly inadequate for accurately evaluating marketing effectiveness.

The findings demonstrated that different attribution models generate substantially different interpretations of channel contribution.

First-Click Attribution

First-Click Attribution heavily emphasized awareness-stage channels such as Social Media and Display Advertising. The model highlighted the importance of customer acquisition initiation and brand discovery.

However, the model failed to recognize the influence of nurturing and conversion-stage interactions, resulting in overvaluation of early-stage touchpoints.

Last-Click Attribution

Last-Click Attribution disproportionately favored lower-funnel channels such as Paid Search and Email Marketing. The findings showed that the model systematically concentrated conversion credit on final interactions occurring immediately before purchase.

Although operationally simple, the model ignored the collaborative influence of earlier touchpoints and created substantial attribution distortion.

Linear Attribution

Linear Attribution provided comparatively balanced channel distribution by assigning equal credit to all touchpoints. The model recognized that customer conversion is generally influenced by multiple interactions rather than isolated events.

However, the approach oversimplified customer behavior by assuming equal influence across all touchpoints regardless of timing or engagement intensity.

Time-Decay Attribution

Time-Decay Attribution generated more behaviorally realistic outcomes by assigning greater weight to touchpoints closer to conversion while still recognizing earlier interactions.

The RMSE analysis showed that Time-Decay Attribution produced the closest alignment with the Markov benchmark among rule-based models.

This suggests that weighted multi-touch approaches provide more reliable performance interpretation compared to simplistic single-touch systems.

Markov Attribution

Markov Chain Attribution generated the most analytically balanced and stable results. The model effectively recognized:

- Sequential customer behavior
- Channel interdependency
- Assisting touchpoints
- Collaborative interaction effects

The findings indicate that customer conversion should be understood as a cumulative outcome emerging from interconnected touchpoint ecosystems rather than isolated channel exposure.

The study therefore concludes that advanced multi-touch attribution frameworks are significantly more suitable for omnichannel digital environments compared to traditional single-touch approaches.

6.3 Major Findings of the Study

The major findings of the study are summarized below:

1. Modern digital customer journeys are highly fragmented and involve multiple touchpoints before conversion.
2. Different attribution models produce significantly different channel valuations.
3. First-Click Attribution overvalues awareness-stage channels.
4. Last-Click Attribution disproportionately favors lower-funnel interactions.
5. Linear Attribution improves balance but oversimplifies customer behavior.
6. Time-Decay Attribution provides comparatively realistic channel allocation.
7. Markov Attribution produces the most analytically balanced results.
8. Attribution model selection substantially influences marketing budget allocation decisions.
9. Multi-touch attribution models outperform single-touch frameworks in omnichannel environments.
10. Businesses relying solely on simplistic attribution systems risk inefficient resource allocation and distorted marketing performance interpretation.

6.4 Managerial Implications

The findings of the study carry important implications for marketing managers, digital strategists, and business decision-makers.

6.4.1 Need for Multi-Touch Attribution Systems

Organizations should move beyond simplistic single-touch attribution systems and adopt multi-touch frameworks capable of recognizing collaborative customer interaction behavior.

Modern customer journeys involve:

- Awareness creation
- Engagement nurturing
- Information evaluation
- Purchase reinforcement

No single touchpoint independently drives conversion outcomes.

6.4.2 Strategic Budget Allocation

The study demonstrated that attribution model selection directly affects marketing budget distribution.

Managers should therefore:

- Evaluate attribution assumptions carefully
- Avoid overdependence on platform-specific reporting
- Balance short-term conversion optimization with long-term brand development
- Use attribution as a strategic planning tool rather than merely a reporting mechanism

6.4.3 Importance of Awareness Channels

The findings revealed that awareness-stage channels such as Social Media and Display Advertising significantly contribute to customer acquisition even when they do not directly generate final conversions.

Businesses should avoid underfunding these channels simply because they receive lower last-click conversion credit.

6.4.4 Integration of Analytics Systems

Organizations require integrated analytics ecosystems capable of:

- Cross-channel tracking
- Customer journey analysis
- Multi-device measurement
- Sequential interaction evaluation

Fragmented analytics systems reduce attribution accuracy and limit strategic decision-making capability.

6.4.5 Adoption of Data-Driven Marketing Culture

The findings reinforce the growing importance of data-driven managerial decision-making.

Businesses increasingly need:

- Marketing analytics capability
- Attribution expertise
- Customer journey intelligence
- Predictive performance measurement systems

Attribution modelling should therefore become an integral component of strategic marketing management.

6.5 Recommendations

Based on the findings of the study, the following recommendations are proposed.

6.5.1 Avoid Exclusive Dependence on Last-Click Attribution

Organizations should avoid relying exclusively on Last-Click Attribution because it systematically overvalues lower-funnel channels and ignores awareness-stage influence.

Last-click metrics should be supplemented with multi-touch analytical frameworks.

6.5.2 Adopt Hybrid Attribution Approaches

Businesses should consider combining:

- Time-Decay Attribution
- Markov Attribution
- Incrementality testing
- Marketing Mix Modelling

This can improve overall performance measurement quality.

6.5.3 Invest in Customer Journey Analytics

Organizations should develop stronger customer journey analytics capability to understand:

- Channel sequencing

- Interaction dependencies
- Conversion pathways
- Customer engagement patterns

This can significantly improve campaign optimization and customer experience management.

6.5.4 Improve Data Integration Infrastructure

Businesses should invest in:

- CRM integration
- Unified analytics platforms
- Cross-device tracking systems
- Omnichannel data management infrastructure

Integrated data systems are essential for accurate attribution analysis.

6.5.5 Develop Attribution Awareness among Managers

Marketing managers should be trained to understand:

- Attribution biases
- Analytical limitations
- Channel interaction effects
- Data interpretation risks

Managerial awareness is necessary to avoid incorrect strategic conclusions based on oversimplified attribution systems.

6.6 Relevance of Study in Indian D2C Ecosystem

The study is particularly relevant within the Indian digital marketing environment, where:

- Omnichannel consumer behavior is rapidly expanding
- Social commerce adoption is increasing
- D2C brands are heavily dependent on digital acquisition
- Customer journeys are increasingly fragmented

Indian businesses frequently rely on platform-specific metrics and simplistic attribution systems due to:

- Limited analytical infrastructure

- Budget constraints
- Technical capability limitations

The findings indicate that Indian D2C firms can improve marketing efficiency by adopting more balanced attribution frameworks and integrated customer journey analysis systems.

The study therefore contributes important managerial insight for businesses operating within India's rapidly evolving digital economy.

6.7 Limitations of the Study

Despite its analytical contributions, the study contains certain limitations.

1. The analysis used simulated customer journey data rather than proprietary enterprise datasets.
2. The study focused only on selected digital marketing channels.
3. Offline customer interactions were excluded.
4. External variables such as pricing, seasonality, and competitive activity were not incorporated.
5. The Markov model was treated as a benchmark approximation rather than absolute causal truth.
6. Platform-specific attribution systems and privacy restrictions were beyond the scope of the study.

These limitations should be considered while interpreting the findings.

6.8 Scope for Future Research

Future studies may expand the present research in several directions.

1. Real-world enterprise datasets may be used for more practical attribution evaluation.
2. Machine learning attribution models may be compared with probabilistic approaches.
3. Industry-specific attribution analysis may be conducted across sectors such as:
 - E-commerce
 - Banking
 - Travel
 - Healthcare
 - FMCG
4. Future research may integrate:
 - Marketing Mix Modelling

- Incrementality testing
 - Customer Lifetime Value analysis
5. Cross-device and cross-platform identity resolution challenges may be studied in greater detail.
6. Additional research may explore attribution behaviour within:
- WhatsApp commerce
 - Influencer ecosystems
 - Social commerce environments
 - AI-driven personalization systems

6.9 Final Conclusion

The study concludes that attribution modelling has become an essential strategic capability within modern digital marketing ecosystems. As customer journeys become increasingly fragmented and omnichannel in nature, organizations can no longer rely on simplistic single-touch attribution frameworks for accurate performance evaluation.

The findings clearly demonstrate that attribution methodology significantly affects channel valuation, budget allocation, and managerial decision-making. Businesses relying exclusively on simplistic attribution systems risk developing distorted interpretations of customer acquisition behavior and inefficient marketing investment strategies.

Among the attribution models analyzed, Time-Decay and Markov Attribution generated comparatively balanced and behaviorally realistic outcomes. The study therefore emphasizes the growing importance of multi-touch and data-driven attribution frameworks within contemporary marketing analytics.

Ultimately, attribution modelling should not be viewed merely as a reporting tool but as a strategic decision-support system capable of improving marketing efficiency, customer understanding, and long-term organizational performance.

REFERENCES

Books

1. Marketing 4.0 by Philip Kotler, Hermawan Kartajaya, and Iwan Setiawan, Wiley Publications, 2017.
2. Marketing Management by Philip Kotler and Kevin Lane Keller, Pearson Education, 15th Edition.
3. Digital Marketing Analytics by Chuck Hemann and Ken Burbary, Que Publishing, 2018.
4. Data-Driven Marketing by Mark Jeffery, Wiley Publications, 2010.
5. Competing on Analytics by Thomas H. Davenport and Jeanne G. Harris, Harvard Business Review Press.

Research Papers and Journal Articles

6. Anderl, E., Becker, I., von Wangenheim, F., & Schumann, J. H. (2016). "Mapping the Customer Journey: Lessons Learned from Graph-Based Online Attribution Modeling." *International Journal of Research in Marketing*, 33(3), 457–474.
7. Berman, R. (2015). "Beyond the Last Touch: Attribution in Online Advertising." *Marketing Science*, 34(6), 771–792.
8. Li, H., & Kannan, P. K. (2014). "Attributing Conversions in a Multichannel Online Marketing Environment: An Empirical Model and a Field Experiment." *Journal of Marketing Research*, 51(1), 40–56.
9. Lemon, K. N., & Verhoef, P. C. (2016). "Understanding Customer Experience Throughout the Customer Journey." *Journal of Marketing*, 80(6), 69–96.
10. Neslin, S. A., Grewal, D., Leghorn, R., et al. (2006). "Challenges and Opportunities in Multichannel Customer Management." *Journal of Service Research*, 9(2), 95–112.
11. Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2015). "From Multi-Channel Retailing to Omnichannel Retailing." *Journal of Retailing*, 91(2), 174–181.

12. Shao, X., & Li, L. (2011). "Data-Driven Multi-Touch Attribution Models." Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.
13. Court, D., Elzinga, D., Mulder, S., & Vetvik, O. J. (2009). "The Consumer Decision Journey." *McKinsey Quarterly*.
14. Edelman, D. C. (2010). "Branding in the Digital Age." *Harvard Business Review*, 88(12), 62–69.
15. Hanssens, D. M., & Pauwels, K. H. (2016). "Demonstrating the Value of Marketing." *Journal of Marketing*, 80(6), 173–190.

Industry Reports and Online Sources

16. [Google Analytics Help Center](#)
17. [Google Ads Attribution Models Documentation](#)
18. [Meta Business Help Center](#)
19. [Deloitte Digital Marketing Trends Report](#)
20. [Nielsen Marketing Effectiveness Report](#)
21. [McKinsey & Company Insights](#)
22. [Statista Digital Advertising Report](#)
23. [GroupM Advertising Forecast Report](#)
24. [Dentsu Consumer Vision Report](#)
25. Think with Google India

ANNEXURES

ANNEXURE – I

Customer Journey Dataset Sample

Customer ID	Journey Path	Converted
C001	Social Media → Paid Search	Yes
C002	Display Ads → Social Media → Email	No
C003	Organic Search → Paid Search → Conversion	Yes
C004	Social Media → Display Ads → Paid Search	Yes
C005	Email → Organic Search	No

ANNEXURE – II

Attribution Model Comparison Table

Channel	FC	LC	Linear	TD	Markov
Social Media	38%	17%	26%	22%	24%
Paid Search	21%	42%	28%	34%	31%
Display Ads	24%	9%	16%	12%	14%
Email	8%	22%	15%	20%	18%
Organic	9%	10%	15%	12%	13%

ANNEXURE – III

Budget Allocation Simulation (₹10,00,000)

Channel	First Click	Last Click	Markov
Social Media	₹3,80,000	₹1,70,000	₹2,40,000
Paid Search	₹2,10,000	₹4,20,000	₹3,10,000
Display Ads	₹2,40,000	₹90,000	₹1,40,000
Email	₹80,000	₹2,20,000	₹1,80,000
Organic	₹90,000	₹1,00,000	₹1,30,000

ANNEXURE – IV

RMSE Comparison

Attribution Model	RMSE
First-Click	11.8
Last-Click	13.5
Linear	6.4
Time-Decay	4.9

ANNEXURE – V

Research Objectives

1. To examine the concept and strategic importance of cross-channel attribution modelling in digital marketing analytics.

2. To compare different attribution models and evaluate their effect on channel valuation.
3. To analyze how attribution model selection influences marketing budget allocation decisions.
4. To evaluate the effectiveness of rule-based and data-driven attribution approaches.
5. To study the relevance of attribution modelling in omnichannel digital marketing environments.

ANNEXURE – VI

Key Abbreviations Used

Abbreviation	Meaning
FC	First-Click Attribution
LC	Last-Click Attribution
TD	Time-Decay Attribution
ROI	Return on Investment
RMSE	Root Mean Square Error
D2C	Direct-to-Consumer
CRM	Customer Relationship Management
AI	Artificial Intelligence

Additional Interpretation Notes

1. Last-click attribution produced the highest concentration risk toward paid search investment.
2. Time-decay attribution consistently remained closest to Markov attribution outcomes.
3. Display advertising contribution was highly underestimated in lower-funnel models.
4. Longer customer journeys increased attribution distortion in single-touch approaches.
5. Markov attribution generated the most stable cross-scenario performance results.