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Dynamic Customer Journey Analysis in Multichannel Marketing – Literature Review, Empirical Study and Implications for Researchers and Advertisers

FernUniversität in Hagen

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List of Abbreviations

AIC	Akaike Information Criterion
AM	Affiliate Marketing
ARIMA	Autoregressive Integrated Rolling Average Model
AUC	Area Under the ROC Curve
BIC	Bayesian Information Criterion
DCJA	Dynamic Customer Journey Analysis
GA	Google Advertising
GS	Google Search Results
MAPE	Mean Absolute Percentage Error
MSE	Mean Square Error
RA	Recommendations by Acquaintance
RM	Referral Marketing
RMSE	Root Mean Square Error
ROC	Receiver Operating Characteristic
TM	Telemarketing
wMAPE	Weighted Mean Absolute Percentage Error

Preface of the Authors

Purpose

Attribution models determine the contribution of touchpoints to a purchasing event in the customer journey. Previous research has not considered the timeliness of the underlying data as a factor in attribution modeling, so trends in advertising impacts of channels over time are not captured.

Design, methodology and approach

Based on Markov chains, this research paper develops a dynamic approach to customer journey analysis that enables a more accurate determination of advertising impact. By sequentially considering new data, the dynamic customer journey analysis updates the advertising impact on a rolling basis. To evaluate the prediction accuracy of advertising impacts by dynamic customer journey analysis, different attribution methods are compared. The study uses real data from an educational service company with 45,694 customer journeys over a period of 9 years from 2012 to 2020.

Findings

The comparison of attribution methods reveals clear evidence that a rolling determination of advertising impact leads to better sales forecasts. Furthermore, the study illustrates that the period of data collection influences the determination of advertising impact and should, therefore, be considered in attribution modeling.

Originality and value

In contrast to previous models, we developed a dynamic approach for customer journey analysis and tested it within an ongoing advertising campaign. We show that advertisers should conduct the customer journey analysis on an ongoing basis to enable interactive marketing control and improve advertising media allocation by monitoring the channels' advertising impact.

Hagen, January 2023

Christian Koch, M.Sc.

Univ.-Prof. Dr. Rainer Olbrich

Overview over the Research Results

I. In contrast to previous research, this paper is the first to develop a dynamic approach to analyze customer journeys and examine its suitability for measuring advertising impact and predicting sales.

II. The time periods of data collection have an impact on the measurement of advertising impact. In this regard, the timeliness of data is more relevant to determine the advertising impact of channels than collecting data over the longest possible period.

III. The consideration of current customer journey data, combined with rolling advertising impact measurement, enables continuous improvement in the accuracy of advertising impact measurement.

IV. Rolling advertising impact measurement of channels can also contribute to more accurate prediction of future sales. However, short-term changes in transition or conversion probabilities can also lead to an increased risk of forecast errors if they prove to be outliers.

V. Advertisers should continuously analyze their customer journey as part of interactive marketing management to improve the allocation of advertising resources.

1. Introduction

Increasing complexity of customer journey

Technological advances are fundamentally changing the way consumers search for information, evaluate products and services, make purchasing decisions, and share experiences.[1] This has led to a host of new technologies, channels, and devices, resulting in more extensive, versatile, and complex customer journeys, as consumers and companies now interact across numerous touchpoints in different channels.[2] Concurrently, researchers have postulated the customer journey concept as an important source of business success.[3] Gaining a deeper understanding of which channels consumers prefer, the interconnection of these channels, and how they are related to consumers' purchase intentions has increased in importance.[4] Customer journey analysis is intended to provide insights into consumers' behavior when they interact with companies at touchpoints in various purchase phases.[5] Researchers use attribution models to determine channel performance and explain how channels interact in multitouch environments by quantifying the extent to which these marketing channels contribute to company success.[6]

When determining channel performance, it is important to consider that each contact can influence consumers' attitudes and intentions.[7] As a result, consumers constantly reevaluate their experiences, goals, and expectations as they move through journey stages.[8] Understanding the factors that influence customer journeys and their dynamics is key for firms to deliver a strong and holistic customer experience.[9] Accordingly, neglecting these temporal changes can limit firms' understanding and effectiveness of customer journey management.[10] In addition, the attribution problem is endogenous and

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1 SCHWEIDEL et al. 2022, p. 1257.

2 GREWAL/ROGGEVEEN/NORDFÄLT 2016, p. 1011; LEMON/VERHOEF 2016, p. 69; VERHOEF et al. 2015, p. 174.

3 KUEHNL/JOZIC/HOMBURG 2019, p. 565; TUENRAT/PAPAGIANNIDIS/ALAMANOS 2021.

4 BECKER/LINZMAIER/VON WANGENHEIM 2017, p. 248.

5 HALB/SEEBACHER 2021, p. 295.

6 ANDERL et al. 2016, p. 458.

7 JENKINSON 2007, pp. 178 ff.; KHANNA/YADAV/JACOB 2014, pp. 129 ff.

8 HU/TRACOGNA 2020; MCCOLL-KENNEDY et al. 2015, p. 432; NORTON/PINE 2013, pp. 13 ff.; LEMON/VERHOEF 2016, p. 78.

9 ÅKESSON/EDVARDSSON/TRONVOLL. 2014, pp. 679 ff.

10 BERMAN 2020, p. 97.

measures relative channel performances in given environments.[11] Consequently, attribution results depend on specific management decisions (e.g., which channels used, budget limits), so optimization of budget attribution should be understood as an iterative process.[12]

Limitations of studies on customer journey analysis

However, previous researchers have not considered attribution as an iterative process when evaluating the suitability of their models to determine channels' advertising impact.[13] Studies to date have determined channels' advertising impacts retrospectively using data obtained in a fixed data collection period.[14] The scope of the data examined, and the data collection period varies to a large extend, from about 4 weeks[15] to 55 weeks.[16] These differing data collection periods mean that the timeliness of data at the time of advertising impacts' determination also varies, and no studies to date have considered data timeliness a factor in attribution modeling.

Given that buying behaviors vary over time and the customer journey is becoming increasingly complex, it is unclear how neglecting data timeliness affects attribution modeling. First, each contact generates new customer journey data that can influence attribution outcomes. However, previous studies only determine their model's accuracy in static environments within fixed data collection periods. As a result, extant attribution models may not account for constant-changing consumer behavior, which limits their practical validity. Second, by neglecting data timeliness, the influence of different data collection periods on attribution results remains unclear. Therefore, it is not possible for advertisers to draw conclusions about recommending periods for data collection from previous studies.

Dynamic customer journey analysis

To address this research gap, we aim with this research paper to investigate the effectiveness of dynamic customer journey analysis for determining advertising impacts of channels – to our knowledge, a novel investigation. We

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11 LI/KANNAN 2014, p. 55.

12 ANDERL et al. 2016, p. 470.

13 e.g., ANDERL/SCHUMANN/KUNZ 2015; BECKER/LINZMAIER/VON WANGENHEIM 2017; DANAHER/DAGGER 2013; DE HAAN et al. 2016; LI/KANNAN 2014; LI et al. 2018.

14 ANDERL et al. 2016, p. 463.

15 ANDERL/SCHUMANN/KUNZ 2015.

16 DE HAAN/WIESEL/PAUWELS 2016.

examine how the accuracy of advertising impact measurement can be improved through continuous consideration of customer journey data and the influence of data collection periods on attribution results.

In addition, as part of the empirical investigation, we examine the extent to which different periods of data collection, and thus the timeliness of the data, affect attribution outcomes. To achieve our research objectives, we developed a dynamic customer journey analysis to determine channels' advertising impact on a rolling basis to capture temporal change in purchasing behavior. We are able to make a rolling determination because we continuously include new data collected on a weekly basis when determining advertising impact and exclude historical data outside a predefined data collection period. We developed and tested our dynamic customer journey analysis using data from 45,694 customer journeys of a service company, collected over a period of nine years from 2012 to 2020. In doing so, we make several research contributions.

First, we propose a novel approach for dynamic customer journey analysis. Whereas extant attribution models only focus on measuring the advertising impact in fixed environments, we evaluate attribution results at different time stamps, such that we consider new customer journey data to achieve more relevant practice-oriented results. Second, by considering several measuring points, we contribute novel insights into changes in channels' advertising impacts over time. Thus, we show how attribution models need to be adapted to enable interactive optimization of budget allocations. Third, we compare how different data collection periods affect attribution results to clarify whether data accuracy should be considered in customer journey research.

Finally, dynamic customer journey analysis can help advertisers address several explicit management problems that they commonly face. Among other things, the proposed model supports more accurate prediction of future sales in multichannel strategies, which enables managers to implement interactive marketing strategies and calibrate marketing expenditures by adjusting budget allocations in the short term. As a result, they can better target marketing activities by quickly identifying changes in advertising effectiveness so that customer touchpoints can be improved when performance is poor.

Structure of the research paper

After the introduction to the importance of customer journey analysis in the first chapter, the second chapter summarizes research of the subject area. Section 2.1. discusses the concept of the customer journey in terms of customer touchpoints. Subsequently, section 2.2. explains the meaning and specifics of customer journey analysis. Section 2.3. considers attribution models as a measurement methodology for customer journey analysis, focusing on Markov chains as an analytical attribution model.

The third chapter presents studies based on quantitative real data for analytical advertising impact measurement in the context of customer journey analysis and differentiate the present study from former investigations.

The fourth chapter covers the empirical investigation into the significance of data timeliness based on dynamic customer journey analysis. Section 4.1. outlines the scope of the investigation. Section 4.2. is used to develop the basic method for dynamic customer journey analysis based on Markov chains for advertising impact measurement. In this context, section 4.3. presents an advanced method for dynamic customer journey analysis to process current customer journey data despite increased conversion times. The following section 4.4. captures the methodology for evaluating the accuracy of advertising impact measurement of dynamic customer journey analysis. Section 4.5. summarizes the descriptive statistics, followed by the empirical analysis in Section 4.6. Section 4.7. discusses the results of the empirical analysis.

In chapter five, the research paper concludes a final review. This includes a conclusion in section 5.1. and the limitations of the findings in section 5.2. leading to an outlook for further research.

2. Basics of Customer Journey Analysis

2.1. Constitutive Features of the Customer Journey

History of the customer journey concept

The historical roots of the customer journey term are difficult to trace, as the concept emerged almost simultaneously in different fields of practice and research, such as design and service management as well as marketing.[17] The term customer journey typically describes the various phases and touchpoints that consumers pass through during their purchase cycle, and that influence their customer experience.[18] Customer journeys should emerge from coherent and strategic plans, leading to added value for customers through a sequence of events, and should allow companies to differentiate and operate profitably.[19]

Customer journey phases

Divergent phase classifications of the customer journey appear in the literature, although they are close in meaning.[20] For the sake of clarity, LEMON, and VERHOEF divide the customer journey into the pre-purchase, purchase, and post-purchase phases.[21] EDWARDS, on the other hand, describes the customer journey by a six-stage process from the perception of an offer to the exchange of information about the purchase experience.[22] WIESEL, PAUWELS, and ARTS describe the customer journey in terms of an information, evaluation and purchase phase, not including the post-purchase phase.[23] In addition, recent contributions describe customer journey as a nonlinear process.[24] This description is useful for illustrating consumers' ongoing relationships with brands that lead to repeat purchases.[25]

Customer journeys today include many more interactions and opportunities to operate across global distances and in virtual locations than they did a few

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17 FØLSTAD/KVALE 2018, p. 198.

18 LEMON/VERHOEF 2016, pp. 74 f.; KUEHNL/JOZIC/HOMBURG 2019, p. 552.

19 NORTON/PINE 2013, p. 12.

20 E.g., HAMILTON et al. 2021; KRANZBÜHLER/KLEIJNEN/VERLEGH 2019; TUENRAT et al. 2021.

21 LEMON/VERHOEF 2016, p. 76.

22 EDWARDS 2011, pp. 2 f.

23 WIESEL/PAUWELS/ARTS 2011, p. 605.

24 GREWAL/ROGGEVEEN 2020, p. 4; SIEBERT et al. 2020, pp. 49 ff.

25 LEMON/VERHOEF 2016, p. 76.

decades ago.[26] Within customer journeys, touchpoints represent points of contact or communication between organizations and consumers.[27] Technological advances and increasing offline and online touchpoints result in better informed consumers who choose freely how they interact with companies.[28] There are numerous touchpoints along the journey that enable companies to interact with their customers and based on which customers can build their experience with a brand.[29] KOTLER, PFOERTSCH, and SPONHOLZ label the company website as an example of company-owned contact points, search engine advertising as an example of paid contact points, and word-of-mouth as an example of earned contact points resulting from strong public and media relations.[30] In addition to the division into owned, paid and earned contact points, there are also numerous other approaches to categorizing contact points.[31] Figure 1 shows an exemplary customer journey consisting of three purchase phases and a sequence of three contact points:

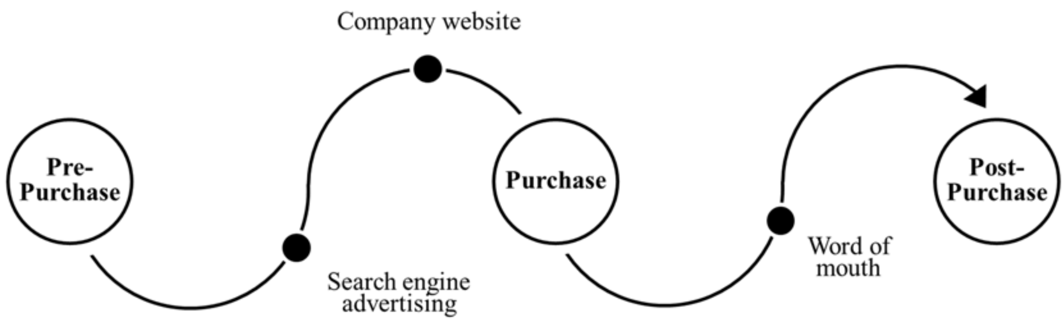

Figure 1: Exemplary Customer Journey with Three Touchpoints

Management of customer journeys

Preferred touchpoints in the phases of customer journeys vary depending on consumers and have a direct or indirect influence on the purchasing behavior.[32] One reason for this is that touchpoints vary in their ability to establish communication between customers and companies.[33] In this context, LI, and KANNAN describe that different advertising channels take on different roles

[26] NORTON/PINE 2013, p. 12.

[27] JENKINSON 2007, p. 165.

[28] FARAH/RAMADAN 2020; HERHAUSEN et al. 2019, p. 9; NORTON/PINE 2013, p. 12; EDELMAN/SINGER 2015, pp. 88 f.

[29] KUEHNL/JOZIC/HOMBURG 2019, pp. 552 f.

[30] KOTLER/PFOERTSCH/SPONHOLZ 2020, pp. 200 ff.

[31] E.g., LEMON/VERHOEF 2016, pp. 76 ff.; KLAPDOR et al. 2015, pp. 435 ff.

[32] LEMON/VERHOEF 2016, p. 80.

[33] VAN DER VEEN/VAN OSSENBRUGGEN 2015, p. 204.

when persuading consumers to make a purchase. For example, loyal customers often directly use company websites, whereas other customers first use search engines to compare options for lower prices.[34] In this context, digital touchpoints are becoming increasingly important, because of their ability to interact with customers in innovative ways, reach new customer segments, and improve access to data and customer insights.[35] Consumers' final purchase outcome is influenced by the sum of the various online and offline touchpoints, they interact with, during their customer journey.[36] Therefore, coherent and targeted management of touchpoints can influence brand perception and help to build and secure profitable business relationships.[37]

Because consumers have different channel preferences and may use multiple channels during their journey, companies feel obliged to diversify their channel portfolio and implement omnichannel strategies.[38] However, offering multiple touchpoints poses managerial risks. For example, new touchpoints mean consumers are moving between channels more frequently, which increases the complexity to manage customer experiences across all touchpoints.[39] This is more complicated as consumer decision processes and the marketing effectiveness of touchpoints change over time.[40] Neglecting this temporal change and the dynamics of customer journeys can limit the understanding and effectiveness of customer journey management.[41] To enable integrated and profitable management of consumer interactions, it is therefore necessary to know which drivers influence touchpoint selection and how this selection affects sales performance.[42]

34 LI/KANNAN 2014, p. 42.

35 LEEFLANG et. al. 2014, p. 3.

36 LEMON/VERHOEF 2016, p. 82.

37 MELERO/SESE/VERHOEF 2016, p. 27.

38 BECK/RYGL 2015, p. 174; KOZLENKOVA et al. 2015, p. 593; REBAQUE-RIVAS/GIL-RODRÍGUEZ 2019, p. 116.

39 LEMON/VERHOEF 2016, pp. 74/80.

40 VALENTINI/MONTAGUTI/NESLIN 2011, p. 72; RAMAN et al. 2012, p. 44.

41 ÅKESSON et al. 2014, pp. 679 ff.; BERMAN 2020, p. 97.

42 MELERO/SESE/VERHOEF 2016, p. 27.

2.2. Constitutive Features of the Customer Journey Analysis

Need for customer journey analysis

A better understanding of consumer activities in different purchase phases helps advertisers target their advertising messages and allow them to improve conversion predictions.[43] To enable integrated and profitable management of consumer interactions, it is, therefore, necessary to know which drivers influence touchpoint selection and how selection affects sales performance.[44]

Benefits of customer journey analysis

For this purpose, advertisers use customer journey analysis to examine which touchpoints are available to consumers, which ones consumers select, and how consumers interact with these touchpoints in various purchasing phases.[45] Customer journey analysis is useful for identifying essential touchpoints for the customer experience.[46] By examining whether touchpoints provide the best possible customer experience and evaluating process structures, this analysis can also help companies capture, understand, and improve their consumers' purchasing processes.[47]

Moreover, customer journey analysis can help companies evaluate consumers' preferences regarding purchasing processes, target advertising messages, improve conversion predictions, and develop individual marketing strategies.[48] The aim is to identify typical patterns within the customer journey and show which information needs or questions users have along the purchase decision process.[49] HACHEN sees the benefit of customer journey analysis in gaining insights into the decision-making paths and duration of customers' decision process. This is especially suitable when the analysis includes a combination of digital channels (e.g., display ads, newsletters, and social media) and offline channels (e.g., TV advertising) and considers the costs of the individual instruments.[50]

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43 ZHOU et al. 2019.

44 MELERO/SESE/VERHOEF 2016, p. 27.

45 LEMON/VERHOEF 2016, p. 79; VERHOEF/KOOGE/WALK 2016, p. 199.

46 KRANZBÜHLER/KLEIJNEN/VERLEGH. 2019, p. 308.

47 TERRAGNI/HASSANIC 2019, p. 57; TERRA/CASAIS 2021, p. 239.

48 ANDERL/SCHUMANN/KUNZ 2015, p. 185; ZHOU et al. 2019.

49 CADONAU 2018, p. 45.

50 HACHEN 2014, p. 662.

Customer journey analysis for advertising impact measurement

With all these potential benefits of customer journey analysis, its focus is on evaluating the impact of touchpoints or advertising channels.[51] In this light, it is necessary to quantify the extent to which the channels contribute to a company's success.[52] With regard to the empirical analysis, the research paper focusses on the quantification of channels' advertising impact by customer journey analysis.

In this context, HOLLAND defines the customer journey analysis as a tool for advertisers to investigate which type and number of contact points customers use up to a final target action. It also examines the extent to which the impact of media varies depending on the phase of the decision-making process, their combination, and what contribution each contact point has made regarding the target action (e.g., purchase or newsletter subscription).[53]

Information about touchpoints and their position within the customer journey should enable companies to quantify the contribution of each touchpoint, avoid overlapping campaigns, and optimize budget allocation.[54] Effects and interactions of marketing campaigns can be identified to show connections and synergies between the individual channels and contact points as well as to derive possible optimization potentials.[55]

Elements of customer journey analysis

The individual elements of a customer journey analysis are not specifically defined, so there are no generally applicable standards for the methodology in practice to date. Instead, companies such as software providers and agencies use self-developed solutions that can vary in their naming. In addition to the term customer journey analysis, designations such as customer journey tracking, cross-channel tracking, or multi-channel tracking are also used.[56]

Prerequisites for customer journey analysis

The basis of a representative customer journey analysis is extensive and largely seamless tracking of the customer across all devices and online and offline channels.[57] In this context, web tracking in particular is a widely used technique to track customers' user behavior on the internet by collecting user

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51 SCHARNA 2016, p. 35.
52 ANDERL et al. 2016, p. 458.
53 HOLLAND 2021, p. 820.
54 KANNAN/REINARTZ/VERHOEF 2016, p. 449.
55 HOLLAND 2021, p. 820.
56 HOLLAND 2021, p. 820.
57 SCHARNA 2016, p. 38.

data such as browsing history and browsing configuration.[58] There is a variety of different web tracking methods with different focuses.[59] Cookie tracking is probably the best known and most widely used tracking method.[60] Cookies are small files that store information about the user's interaction during the visit to the website with the help of exchange of strings.[61] Other methods are fingerprint tracking[62] and pixel tracking[63]. When implementing tracking features, SCHARNA points out the importance of a central system for collecting, aggregating, and presenting the data from the individual contact points, e.g., in the form of a web analysis tool with customer journey analysis functionalities. In practice, several service providers with different systems are often used for tracking at the same time, which can lead to challenges in the practical application of customer journey analysis. For example, contacts can be assigned to multiple channels simultaneously, so that contacts are counted multiple times and distort insights about cross-channel interactions.[64] Nevertheless, technological advances in terms of tracking touchpoints along the customer journey have led to a surge of academic and practical interest in attribution models.[65]

2.3. Advertising Impact Measurement of Channels in Customer Journeys using Attribution Models

2.3.1. Basics of Attribution and Attribution Models

Importance of attribution in marketing

Attribution captures and evaluates the contribution of online and offline touchpoints in the customer journey to a purchasing event.[66] Attribution is important for measuring advertising impact as part of customer journey

58 SANCHEZ-ROLA et al. 2017, p. 18; SCHELINSKI/FEUERHAKE 2019, p. 630.

59 E. g., HAMED 2013, p. 471; RÖTTGEN 2017, p. 74; WANG 2020, p. 27; LAMMENETT 2021, p. 49.

60 E. g., COFONE 2017, p. 39.

61 SIPIOR/WARD/MENDOZA 2011, p. 2; WIRTZ 2021, p. 575.

62 ECKERSLEY 2010, p. 3; VASTEL et. al. 2018, p. 729.

63 HU/Peng/Wang 2019, p. 366; LAMMENETT 2021, p. 51.

64 SCHARNA 2016, p. 38.

65 DANAHER/VAN HEERDE 2018, p. 683; KANNAN/REINARTZ/VERHOEF 2016, p. 449.

66 DANAHER/VAN HEERDE 2018, pp. 669/683; REDLER 2021, p. 434; GHOSE/TODRI-ADAMOPOULOS 2016, p. 891; KANNAN/REINARTZ/VERHOEF 2016, p. 449; SCHULTZ/DELLNITZ 2018, p. 227.

analysis. The data collected through tracking serves as the basis for attribution, whereby the customer's actions are divided up according to their relevance and assigned proportionately to the individual contact points. This makes it possible to monitor channels customer arrives at the company's website, e.g., in the form of direct entry of the website URL, organic search, recommendation websites, e-mails, or advertising banners.[67] The actual channel performance and the way channels interact in multitouch settings are revealed by attribution results.[68] These insights allow businesses to make more informed channel choices, determine conversion probabilities, implement real-time bidding tactics, and calibrate channel budgets for better budgetary allocations.[69]

Attribution models

The interest in attribution models is further enhanced when customers interact with multiple touchpoints in online environments.[70] Different methods exist for calculating the advertising impact of channels in the context of attribution.[71] In this vein, attribution models can be distinguished as heuristic or analytical models.[72]

2.3.2. Heuristic Attribution Models

Types of heuristic attribution models

Heuristic models use predefined rule sets to determine channel impacts that are applied in a standardized manner and do not consider individual factors.[73] These include simple models that attribute the contribution of an event to a single touchpoint. For example, ‘last touch’ attribution assigns the entire contribution of the purchase to the last touchpoint before an event, and ‘first touch’ attribution assigns it to the first touchpoint in the customer journey.[74] In addition, there are heuristic attribution models that use static rules to attribute the contribution of an event to multiple touchpoints in the customer

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67 KANNAN/LI 2014, p. 41.

68 ANDERL et al. 2016, p. 458.

69 ANDERL et al. 2016, pp. 458 ff.; RAMAN et al. 2012, pp. 43 ff.

70 VERHOEF/LEMON 2016, p. 82.

71 REDLER 2021, p. 434; LINDENBECK 2021, p. 629.

72 E. g., SCHULTZ/DELLNITZ 2018; ANDERL et al. 2016; NASS et al. 2020.

73 SCHULTZ/DELLNITZ 2018, p. 227; HOLLAND 2021, pp. 821 f.

74 JAYAWARDANE/HALGAMUGE/KAYANDE 2015, p. 69.

journey.[75] These include 'linear' attribution, where all channels are assigned the same contribution, and 'position-based' attribution, where for example, the first and last touchpoints are assigned a 40% contribution and the touchpoints in between are assigned 20%.[76] In addition, there are other models, such as the 'time decay' attribution, which assigns the highest contribution to those contact points that are closest in time to the target event.[77] However, user-specific models with self-defined rule sets can also be used.[78] Figure 2 shows the heuristic attribution models graphically.

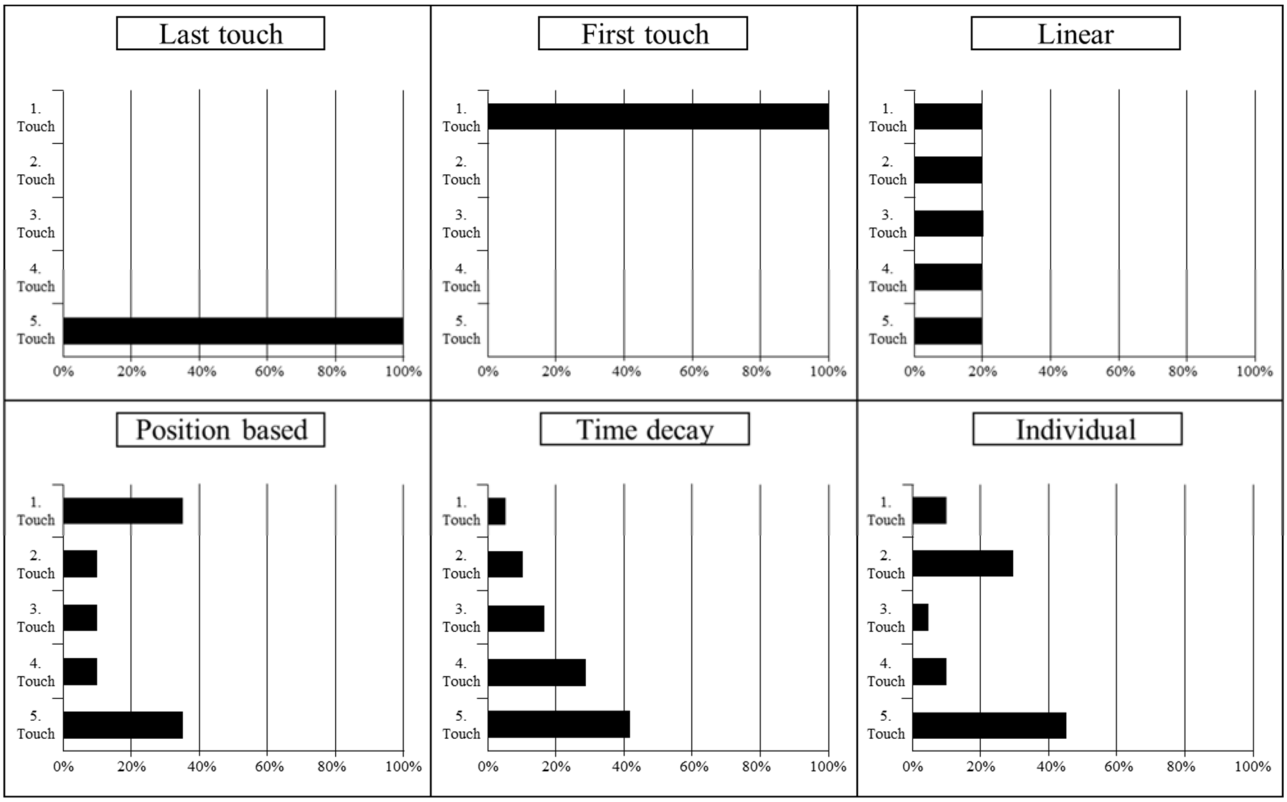

Figure 2: Heuristic Attribution Models
(Adapted from Olbrich/Schultz/Holsing 2019, p. 95; Schultz/Dellnitz 2017, pp. 231 ff.)

75 OLBRICH/HOLSING/SCHULTZ 2019, pp. 233 ff.

76 NASS et al. 2020, p. 86.

77 ZHANG et al. 2016, p. 1373; KAKALEJČÍK/BUCKO 2018, p. 50.

78 KAKALEJČÍK/BUCKO 2018, p. 50.

Limitations of heuristic attribution models

Heuristic models are considered as too simple and inaccurate in many situations because they do not comprehensively represent the reality and complexity of purchase decision processes and are always subject to certain assumptions.[79] Analytical attribution models can help.

2.3.3. Analytic Attribution Models Focussing Markov Chains

Basics of analytical attribution models

To overcome the shortcomings of heuristic attribution models, analytic models enable to capture heterogeneous user click streams, consider time effects across different marketing channels, and evaluate interaction effects between channels.[80] SCHULTZ, and DELLNITZ describe that analytical attribution models use multivariate analyses to determine the probability of an event based on the movement patterns of consumers along touchpoints. Compared to heuristic models, they are based on more sophisticated computational methods such as logistic regressions, time series analyses, or Markov chains.[81]

Success factors of attribution models

ANDERL, BECKER, VON WANGENHEIM, and SCHUMANN address criteria of successful attribution models in their study. These include criteria such as objectivity, predictive accuracy, and robustness of results. They compare different heuristic and analytical attribution models and show that Markov chains fulfill all criteria and are therefore particularly suitable to analyze online customer paths across multiple advertising channels.[82] Following the study of ANDERL, BECKER, VON WANGENHEIM, and SCHUMANN, Markov chains are selected as a suitable method for the empirical investigation of the research paper. The methodological principles are described in more detail below.

Markov chains in marketing

Markov chains have a long history in the context of marketing.[83] For example, they were tested several decades ago in the context of customer revenue modeling or to predict the likelihood of customers switching brands.[84] Markov chains represent discrete-time stochastic processes with a countable state

79 HOLLAND 2021, p. 821.
80 SCHULTZ/DELLNITZ 2018, p. 237.
81 SCHULTZ/DELLNITZ 2018, pp. 227/237.
82 ANDERL et al. 2016, pp. 463 ff.
83 E.g., HERNITER/MAGEE 1961; STYAN/SMITH 1964.
84 E.g., MORRISON/COLOMBO 1989; PFEIFER/CARRAWAY 2000.

space.[85] They describe multistage change processes based on initial distributions between states as well as transition probabilities.[86] In addition, they allow the representation of dependencies between successive observations of random variables.[87]

Markov chains in customer journey analysis

ANDERL, BECKER, VON WANGENHEIM, and SCHUMANN explain in their study the use of Markov chains for analyzing customer journeys in which several advertising channels are used before a purchase is concluded. Markov chains map individual customer journeys as Markov chains based on recorded contacts and consider the advertising channels used by consumers. In this way, the probability of occurrence of future events and the advertising impact of channels can be determined. Markov models of different orders can be distinguished. First-order Markov models assume that the current customer journey event is only influenced by the previous event. The authors additionally introduce higher-order Markov models, in which several past events influence the current customer journey event. Higher order Markov models are therefore able to account for customer journeys with multiple touch points when determining advertising effectiveness.[88]

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85 WALDMANN/HELM 2016, pp. 219 f.

86 HOMBURG 2017, p. 114.

87 ANDERL et al. 2016, p. 460.

88 ANDERL et al. 2016, pp. 461 ff.

3. Current Literature on Customer Journey Analysis and Delimitation of the Investigation

3.1. Current Literature on Customer Journey Analysis using Heuristic Models

Classification of empirical studies

Following the explanation of the basics of customer journey analysis, a list of relevant scientific contributions is provided to point out the scope of the study. Only studies based on an empirical analysis with quantitative real data is considered. In view of the different research interests in customer journey analysis, a distinction is made between two main areas of content. First, a study is considered that uses heuristic attribution models to measure advertising effectiveness. Subsequently, studies are considered in which analytical attribution models are used. The focus of the presentation of empirical studies is particularly on analytical attribution models since an analytical attribution model was also chosen as methodology for the present study using Markov chains.

Study on heuristic attribution

LINDENBECK's contribution serves as a representative study about the use of heuristic attribution models to measure advertising impact. LINDENBECK presents exemplary possibilities of advertising companies to analyze different contact points in online marketing. In this vein, the author uses heuristic models that assign advertising impact to the first (first touch), the last (last touch), or all touchpoints equally (linear). LINDENBECK uses data from a service provider. The advertising channels considered are Google advertising (search engine advertising), Google searches (organic search), affiliate network 1 and affiliate network 2 (affiliate marketing), and passive telemarketing.

The data was collected over a period of approximately 10 years and includes about 60,000 requests for informational materials as contact points and about 10,000 resulting purchases by customers. The analysis is based on frequency and probability calculations and considers, among other things, the number of sales per advertising channel and the success rate of the advertising channel path. Considering the number of advertising channels used within the customer journey, a distinction is made between one- and four-stage paths. This shows that around 96% of all sales are attributable to customer journeys that comprise a maximum of two contact points. Regarding the identification of high-revenue advertising channels, LINDENBECK concludes that the advertising channels used by the advertising company make different contributions to generation of sales. Nevertheless, the author shows that although the channels contribute differently to sales events, the three heuristic attribution models produce comparable results.

The study does not examine which of the used heuristic attribution methods leads to the most accurate measurement of advertising effectiveness. Instead, the author focuses on the implications for the use of the various advertising channels. For example, LINDENBECK shows that the isolated and combined use of the Google advertising channel leads to more than half of all sales despite increased wastage. Organic Google search is the second most important channel, followed by passive telemarketing and finally affiliate marketing networks. From these findings, the author derives implications for the advertising company about the use of the various advertising channels. For example, he recommends improving the scattering loss of search engine ads by using search terms that are only clicked on by prospects with a high probability of purchase. Regarding the identification of relevant time intervals between events, LINDENBECK states that the sale of the advertised services is accompanied by a comparatively long duration of the customer journey. In this context, he shows that the time interval between the contact points is shorter for customer journeys that result in a purchase. For this reason, advertisers are recommended to promote a rapid succession of contact points, among other things by offering concrete incentives such as time-limited price discounts.[89]

Intermediate conclusion and delimitation of the study

LINDENBECK'S study leads to practical implications that enable advertising companies to boost sales of the solutions they offer by providing and rapidly sequencing various online touchpoints. In contrast to LINDENBECK's study, this research does not aim to identify influencing factors for increasing the sales strength of advertising companies. Rather, the focus of this research paper is on developing a dynamic customer journey analysis to improve the measurement of the advertising effectiveness of channels.

With this research objective in mind, the following section presents further work on testing analytical models for measuring the contribution of advertising channels to purchase completion.

89 LINDENBECK 2021.

3.2. Current Literature on Customer Journey Analysis using Analytical Models

Studies on analytical attribution

In the following, empirical studies are presented that use analytical attribution models to determine the advertising impact of channels. In their study, DANAHER, and DAGGER compare two linear regression models in terms of their ability to assess the relative impact of multiple advertising media of a brick-and-mortar retailer of apparel and non-seasonal products. The models differ in that one of the models considers pairwise interactions of advertising channels to capture potential media synergies. In addition, the hierarchical synergy model of NAIK, and PETERS was included in the comparison, which is based on seemingly unrelated regression equations.[90] Display ads, e-mails, organic search queries, and posts on social media were considered as advertising channels in the online area. In the offline area, advertising letters, catalogs, radio spots, TV spots and newspaper ads were used. The study spanned a four-week period and included 368 TV spots, 21 newspaper ads, 16 million impressions and 15,200 paid clicks. Mean square error (MSE), Akaike information criterion (AIC), and Bayesian information criterion (BIC) are used as quality measures. The authors show that the linear regression model without considering pairwise channel interactions is best at predicting sales and profits. Accordingly, considering the media synergies of the advertising channels within the study does not lead to an improved measurement of channels' advertising impact by the linear regression model.[91]

In their paper, LI, and KANNAN compare six models based on Markov chains to determine the probabilities of website visits and sales for a hospitality franchise for attribution modeling. The channels considered were search engine ads, display ads, direct URL entry, e-mail, organic search, and referral websites. The survey period was 68 days, during which 22,369 channel uses, 815 customers and 1,128 purchases were tracked. Mean absolute percentage error (MAPE) and marginal probabilities are used as measures of quality. The authors note that accounting for carry-over and spill-over effects of advertising channels makes a significant contribution to the predictive accuracy of Markov chains. Therefore, they are considered important variables that can be

[90] NAIK/PETERS 2009.
[91] DANAHER/DAGGER 2013.

considered in attribution modeling for explaining visits and sales to the corporate website.[92]

In their study, ANDERL, SCHUMANN, and KUNZ pursue the goal of reducing the complexity of analyzing customer journey data. To this end, they use different classifications for the nine advertising channels of a German online retailer for clothing and determine which classification has the highest attribution accuracy based on forecasting sales. In doing so, they compare six logistic regression models that differ not only in the classification of the advertising channels, but also in the consideration of interaction effects. The advertising channels include affiliate marketing, search engine advertising, display ads, URL direct entry, e-mails, organic search, price comparison portals, referral websites, and retargeting. The survey period was 45 days. Within this period, 350,719 journeys were tracked, resulting in 40,297 conversions. AIC and BIC are used as measures of goodness of fit. The authors show that classifying (potential) customers based on their advertising channel and brand usage, taking interaction effects into account, leads to the best prediction results. They classify direct URL entry, search engine advertising, organic search and price comparison as customer-initiated channels and display ads, retargeting, affiliate marketing and e-mails as company-initiated channels.[93]

In another study, ANDERL, BECKER, VON WANGENHEIM, and SCHUMANN compare the advertising impact measurement of different Markov chains and heuristic attribution models. In addition, a simple logistic regression analysis and an extended logistic regression analysis are included in the comparison, which considers the order of use of the advertising channels. The sales of four companies, each from a different industry, that sell their products online are used as the data basis. These are two clothing retailers (high-priced and medium-priced), a suitcase retailer and a travel agency. In total, ten different channels were considered in the form of affiliate marketing, search engine advertising, display ads, direct URL entry, e-mails, organic search, price comparison portals, recommendation websites, retargeting and social media posts. The survey period is not specified, but the survey resulted in a total of 3,053,012 customer journeys, 44,328 conversions and 4,858,916 clicks. The ROC curve and top decile lift are used as measures of goodness of fit. The

92 LI/KANNAN 2014.

93 ANDERL/SCHUMANN/KUNZ 2015.

latter indicates the actual proportion of customer journeys that resulted in a conversion based on the conversion rate determined for the 10% of customer journeys with the highest probability of conversion. The authors show that in the model comparison, third and fourth order Markov chains and extended logistic regression analysis result in the best prediction results. Considering the robustness of the models, the authors recommend prediction with third-order Markov chains.[94]

DE HAAN, WIESEL, and PAUWELS examine the attribution accuracy of five vector autoregression models based on data of a Western European online retailer. The data set includes sales of products in the apparel, sports, consumer electronics, home and garden, and beauty and wellness categories. Each model contains data on different product categories. The online channels studied were search engine advertising, e-mails, portal marketing, price comparison portals and recommendation websites. Offline channels included television and radio advertising. The scope of the data is not disclosed. Sales generated by the online retailer are used to compare the models. The BIC and MAPE are used as quality measures. The results show that the advertising channels used by the customer have a high explanatory power about the generated sales and are therefore suitable as variables in attribution modeling. The authors identify promotional offers, 'checkouts', and days of the week as additional variables to increase predictive accuracy.[95]

In their study, BECKER, LINZMAJER, and WANGENHEIM examine various Cox regression models with respect to their ability to evaluate customer channel preferences in different industries. As in the study by ANDERL, BECKER, VON WANGENHEIM, and SCHUMANN, data from two clothing retailers (high-priced and medium-priced), a suitcase retailer and a travel agency are used. A total of ten channels were considered in the form of affiliate marketing, search engine advertising, display ads, URL direct entry, e-mails, organic search, price comparison portals, recommendation websites, retargeting and posts on social media. 3,052,911 customer journeys, 35,332 conversions, and 13,801,904 clicks were considered. The AIC, BIC, and coefficient of determination R^2 are used as measures of goodness of fit. The authors show that both the advertising channels used by consumers and the order in which the

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94 ANDERL et al. 2016.

95 DE HAAN/WIESEL/PAUWELS 2016.

channels were used are useful as purchase predictors and are suitable for attribution modeling. When considering the sequence of advertising channels, both channel-homogeneous click sequences and the combination of two different channels are accessible as purchase predictors.[96]

LI, ARAVA, DONG, YAN, and PANI present four attribution models based on deep learning techniques (long short-term memory) in their paper. They then compare them in terms of their attribution accuracy with a "last touch" model and logistic regression analysis. The Deep Learning models used are characterized by their ability to capture information from the past, such as the dependencies in the observed customer journeys, over a long period of time and to weight them according to their relevance. The model comparison is based on the number of conversions of a marketing organization using display ads, e-mails, and search engine advertising as advertising channels, where the underlying event of a conversion is not specified. The data set consists of 426,853 customer journeys recorded over a 57-day period. The area under the ROC curve (AUC) is used as a measure of goodness of fit. In the model comparison, the authors show that the models based on deep learning techniques lead to higher prediction accuracy than the last-touch model and logistic regression analysis. Furthermore, it is shown that the influence of an advertising channel on the conversion probability decreases with increasing time delay since the last contact, not considering that this effect may vary depending on the advertising channel. Nevertheless, the model that assigns a different value to the contact points depending on the time lag since the last contact achieves the highest predictive accuracy. Furthermore, it is shown that other characteristics such as age, gender and registration date of the users are suitable as predictors for estimating conversions as well.[97]

3.3. Delimitation of the Investigation

Summary of the studies

Table 1 below summarizes the research presented. Within the figure, the author(s), advertising channels, data origin, data collection period, data scope, forecasting method, and core findings of the studies are presented. Following the figure, the identified research gaps and related objectives of the research paper's empirical investigation are presented.

96 BECKER/LINZMAIER/VON WANGENHEIM 2017.

97 LI et al. 2018, pp. 2 ff.

Table 1: Summary of the Literature Review

Model type	Heuristical models	Analytical models	
Authors/ Year	Lindenbeck 2021	Danaher/Dagger 2013	Li/Kannan 2014
Method	First touch, Last touch, linear models	Linear regression models	Markov chains
Online/ Offline	Online/ Offline	Online/ Offline	Online
Channels	Online - Affiliate marketing - Organic search results - Search engine advertising Offline - Passive telemarketing	Online - Display Ads - E-Mails - Organic search results - Social media posts Offline: - Television Ads - Catalogue - Radio commercials - Promotional letters - Newspaper Ads	- Display Ads - E-Mails - Referral websites - Organic search results - Search engine advertising - URL entry
Data source	Service company	Stationary retailer for clothing and non-seasonal products	Hospitality franchise company
Data collection period	10 years	4 weeks	68 days
Data scope	- 60.000 information requests - 3.568 sales	- 368 television spots - 21 newspaper Ads - 16 million impressions - 15.200 paid search engine clicks	- 1.997 website visitors - 22.369 channel uses - 815 customers - 1.128 sales
Key results	- Advertising channels show different advertising effects. - Measured advertising impact differs little between heuristic attribution models. - Search engine advertising leads to the most signups, followed by organic search, passive telemarketing, and affiliate marketing. - Time windows between touchpoints are shorter for customer journeys that lead to a purchase.	- The linear regression model without consideration of pairwise interactions of the channels is best suited for forecasting revenues and profits. - Consideration of media synergies of the advertising channels within the study did not lead to attribution accuracy of the linear regression model.	- The consideration of carry-over and spill-over effects of the advertising channels makes a significant contribution to the advertising impact measurement of Markov chains.

Model type	Analytical models		
Authors/ Year	Anderl/Schuman/Kunz 2015	Anderl/Becker/von Wangen-heim/Schumann 2016	De Haan/Wiesel/Pauwels 2016
Method	Logit models	Markov chains	Vector autoregression mo-dels
Online/ Offline	Online	Online	Online/Offline
Channels	- Affiliate marketing - Display Ads - E-Mails - Referral websites - Organic search results - Price comparison site - Retargeting Ads - Search engine advertising - URL entry	- Affiliate marketing - Display Ads - E-Mails - Referral websites - Organic search results - Price comparison site - Search engine advertising - Retargeting Ads - Social media posts - URL entry	Online - E-Mails - Referral websites - Portal marketing - Retargeting Ads Offline: - Radio Ads - Television Ads
Data source	Online retailer for clothing	Two retailers of clothing (high-priced and medium-priced)/ retailers of suitcases/ travel agency	Online retailer for goods in the areas of clothing, sports, consumer electronics, home and garden, and beauty and wellness
Data collection period	45 days	unknown	385 days
Data scope	- 350.719 journeys - 343.556 users - 40.297 conversions	- 2.430.495 clicks - 624.503 journeys - 28.294 conversions	-
Key results	- Classifying consumers according to their advertising channel and brand usage, considering interaction effects, increases the accuracy of advertising impact measurement.	- Third and fourth order Markov chains and extended logistic regression analysis lead to the most accurate advertising impact measurement. - Considering the robustness of the models, the authors recommend using third-order Markov chains for attribution modeling.	- Advertising channels have a high explanatory power regarding the sales achieved and are suitable as variables in attribution modeling. - Other factors that influence sales forecasts are promotional offers, checkouts, and days of the week.

Model type	Analytical models	
Authors/ Year	Becker/Linzmajer/ von Wangenheim 2017	Arava/Dong/Yan/Pani 2018
Method	Cox regression models	- Deep learning model (Long short-term memory) - Last touch model - Logit models
Online/ Offline	Online	Online
Channels	- Affiliate marketing - Display Ads - E-Mails - URL entry - Referral websites - Organic search results - Price comparison site - Retargeting Ads - Social media posts - Search engine advertising	- Display Ads - E-Mails - Search engine advertising
Data source	Two retailers of clothing (high-priced and medium-priced)/ retailers of suitcases/ travel agency	Marketing organization
Data collection period	-	57 days
Data scope	- 3.052.911 Customer Journeys - 35.332 Conversions - 13.801.904 Klicks	- 426.853 Customer Journeys
Key results	- The advertising channels used by consumers and the order in which the channels were used are suitable for predicting future purchases. - When considering the sequence of advertising channels, both channel-homogeneous click sequences and the combination of different channels are suitable as variables for measuring advertising impact.	- The deep learning models used lead to higher attribution accuracy than the last-touch model and logistic regression analysis. - The influence of an advertising channel on the probability of conversion decreases with increasing time lag since the last contact. - The attribution model, which assigns a different value to contact points depending on the amount of time since the last contact, has the highest predictive accuracy. - Other attributes such as user age, gender, and registration date are suitable predictors for estimating convergence.

Delimination The studies presented compare attribution models regarding their suitability for determining advertising impact based on different quality criteria. A number of three[98] to ten channels[99] is considered. In previous studies, researchers determined a channel's advertising impact retrospectively using data obtained in fixed data collection periods[100], ranging from about 4 weeks[101] to 55 weeks.[102] The analysis with heuristic attribution models even considers a data collection period of 10 years. However, since it does not pursue the goal of evaluating the accuracy of advertising impact measurement, in contrast to the investigations of analytical attribution models, it is neglected regarding the further empirical investigation.

Different data collection periods in the studies mean that the timeliness of data at the time of advertising impacts' determination also varies. These studies determine models' accuracy in given environments within fixed data collection periods and do not consider data accuracy; therefore, the results represent only snapshots and may vary over time. Whether attribution models studied can capture constant-changing consumer behavior in determining advertising impact of channels remains unclear. Against the backdrop of changing purchasing behavior and the increasing complexity of customer journeys, the question arises to what extent ignoring data timeliness affects the determination of advertising impact. For example, if new advertising texts improve conversion rates of search engine advertising over the course of observation, the future impact of the channel will be underestimated unless this trend is considered. On the other hand, a decline in conversion rates over time, e.g., due to the lack of precision in new keywords, would lead to an overestimation of the channel's impact. Either way, changes in the channel's advertising impact that occur during the historical data collection period may bias the determination of the channel's future advertising impact.

Moreover, each consumer interaction generates new customer journey data that can influence attribution results. However, previous studies do not consider how attribution results change when new data is included, so the consistency of their results is doubtful.

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98 LI et al. 2018.

99 BECKER/LINZMAIER/VON WANGENHEIM 2017.

100 ANDERL et al. 2016.

101 ANDERL/SCHUMANN/KUNZ 2015.

102 DE HAAN/WIESEL/PAUWELS 2016.

Against this background, this study extends existing literature on multichannel online advertising by applying a novel attribution method to determine channels' advertising impact on a rolling basis to capture temporal changes in purchasing behavior. Following ANDERL, BECKER, VON WANGENHEIM, and SCHUMANN (2016), we use Markov chains as a base for dynamic customer journey analysis.

4. Empirical Study on Dynamic Customer Journey Analysis

4.1. Research Framework

We address the limitations of previous attribution models by developing a dynamic customer journey analysis to determine advertising impact of channels on a rolling basis considering new data. The empirical study is an extension of the journal article by KOCH, LINDENBECK, and OLBRICH (2023).[103] Within this extension, the methodology of dynamic customer journey analysis is explained in more detail. This should enable researchers to investigate the methodology in further studies and encourage advertisers to measure their advertising impact by using dynamic customer journey analysis.

Introduction to the research framework

The study contains data from a service company. On its website, the company provides content on its services offered and the possibility to request information material on their services. The data set primarily records the channel a consumer used before making an information request (contact). The channels investigated are paid Google advertising, organic Google search results, affiliate marketing, telemarketing, referral marketing, and recommendations by acquaintances. Referral marketing refers to partners who advertise the service company's offers on their websites and forward consumers to the service company's website. In addition, consumers specify how they became aware of the company when requesting information material. We use this value if no channel is identified by tracking. Timestamps of contacts and sales enable to determine time lags between customer journey events (conversion time).

The channels investigated are paid Google advertising, organic Google search results, affiliate marketing, telemarketing, referral marketing, and recommendations by acquaintances. Referral marketing refers here to partners who advertise the service company's offer on their websites and forward consumers to the service company's website.

Data set

The study is based on anonymized data on information requests and sales of the provider. Usable data is available for a period of nine years, from 2012 to 2020, and comprises 45,694 customer journeys and 4,753 sales.

[103] KOCH/LINDENBECK/OLBRICH 2023.

4.2. Development of the Methodology for Dynamic Customer Journey Analysis

4.2.1. Markov Chains

Basics of Markov chains

Following the study by ANDERL, BECKER, VON WANGENHEIM, and SCHUMANN (2016), we use Markov chains as base for the dynamic customer journey analysis. Markov chains can map individual customer journeys based on recorded touchpoints. Markov graphs $M = \langle \mathrm{S}, \mathrm{W} \rangle$ are defined by a set of states $S = \{s_1, \ldots, s_n\}$ and a transition matrix W. The transition probability $w_{i,j}$ corresponds to the probability that a consumer reaches a state j after a state i, also called 'conversion probability'.[104] For example, if one in ten consumers changes from state i to state j, the transition probability $w_{i,j}$ is 10%.

The maximum time lag between two states within the dataset is 12 months. All graphs contain the states 'Start' as the customer journey's starting point, 'Sale' as the sale that results from a contact, and 'Null' as the customer journey that ends after 12 months without a sale. In addition, each diagram contains touchpoints used before making the contact. Because customer journeys can include multiple touchpoints when consumers make multiple contacts, we used a higher-order Markov model that considers how often multiple contacts occur and how they influence transition probabilities. In total, the study includes nine states:

States within the study

(1) Start	Customer journeys' starting point
(2) $\mathrm{C_{GA}}$	Contacts through channel Google advertising
(3) $\mathrm{C_{GS}}$	Contacts through channel Google search results
(4) $\mathrm{C_{AM}}$	Contacts through channel affiliate marketing
(5) $\mathrm{C_{TM}}$	Contacts through channel telemarketing
(6) $\mathrm{C_{RM}}$	Contacts through channel referral marketing
(7) $\mathrm{C_{EB}}$	Contacts through channel recommendations by acquaintances
(8) Sales	Sales after contacts
(9) Null	Customer journeys without sales 12 months after contacts

Transition probabilities

To determine transition probabilities, we evaluate which transition forms exist and how often they occur. Regarding the number of cases, we consider customer journeys with up to three contacts. This corresponds to 99.04% of

104 ANDERL et al. 2016, pp. 461 ff.

the entire data set. Figure 3 shows a Markov model based on three exemplary customer journey variants. In the example, 75% of all customer journeys begin with a contact initiated through the Google advertising channel. The other 25% of customer journeys start with a contact originating from the affiliate marketing channel. Variant 1 describes customer journeys in which there was only one contact initiated via the Google advertising channel. This variant leads to a sale in 10% of cases. Variant 2 also represents customer journeys with one point of contact, but here the contact was initiated via the affiliate marketing channel. This variant leads to a transition probability from contact to sale of 5%. Variant 3 comprises a total of 2 contacts and corresponds to 7.50% (75% ×10%) of all customer journeys. Here, the transition probability after one contact via the Google advertising channel and one contact via Google search results is 25%.

The transition probabilities of the Markov chains are used in further course of the work to predict sales resulting from contacts in the customer journey. The sales determined serve as the basis for evaluating the advertising impact of the various channels, making the transition probability an important variable for determining the advertising impact of channels.

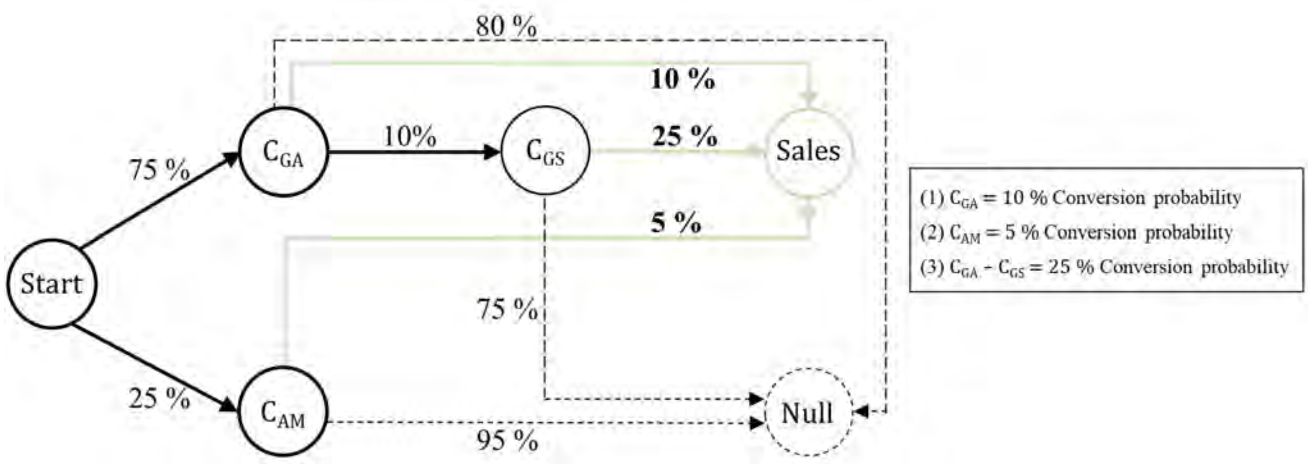

Figure 3: Exemplary Markov Graph
(Adapted from ANDERL et al. 2016, p. 462)

4.2.2. Dynamic Customer Journey Analysis

Need for dynamic customer journey analysis

Advertisers continuously generate new customer journey data that can influence attribution results. However, as explained in section 3.2.4., previous studies only determine the accuracy of attribution models based on a single historical data set, which limits the practical usability of the attribution models examined. The period in which the customer journey data examined was collected (data collection period) varies to a large extend in previous studies, so the timeliness of the data at time of advertising impact measurement also varies. However, the timeliness of the data is not considered in advertising impact measurement of the attribution models. Trends in advertising impact of channels over time are therefore not captured and can lead to advertisers using their advertising resources inappropriately. Against this background, we developed a dynamic customer journey analysis to evaluate the advertising impact of channels on a rolling basis with data that is as current as possible.

Development of dynamic customer journey analysis

Dynamic customer journey analysis differs from previously studied models by determining advertising impact continuously using data within a rolling data collection period, meaning that new customer journey data, collected and aggregated weekly, are continuously considered when determining transition probabilities. In contrast, the model does not consider historical data collected before a predefined data collection period.

Shorter data collection periods lead to a stronger influence of current customer journey interactions and bear the risk of overestimating trends in advertising impact determination. Longer periods level trends more, but new data have comparatively less influence on determining transition probabilities. As noted previously, data collection periods of earlier contributions ranges from 4 to 55 weeks; the present study tests a rolling determination with a data collection period of 6 months. The dynamic customer journey analysis, thus, determines advertising impacts of channels based on transition probabilities from information requests to sales within a rolling data collection period of the last 6 months before a point of observation.

The formula for determining transition probabilities from information requests to sales using dynamic customer journey analysis is as follows:

$$w_{C,Sales} = \frac{\sum_{t_y=1}^{6} Sales_{C_{t_y}}}{\sum_{t_y=1}^{6} C_{t_y}}$$

$\mathrm{t_y}$	month
y	time lag (months) to the point of observation
$\mathrm{C_{t_y}}$	number of contacts in t_y
$\mathrm{Sales_{C_{t_y}}}$	number of sales resulting from C_{t_y}

With each month in which new customer journey data is collected, determined transition probabilities are updated (Figure 4). If, for example, 6 months are defined as a rolling data collection period, for example all contacts per channel and the resulting sales from months 13 to 18 would be considered to determine the transition probabilities at the first point of observation (end of month 18). If, for example, 5,000 contacts were generated via Google advertising channel in months 13 to 18, resulting in 500 sales, the determined transition probability of the channel Google advertising would be 10% at the first time of observation (end of month 18). If one month later, in the period from month 14 to month 19, 6,000 contacts were generated via Google advertising, resulting in 400 sales, the transition probability would drop to 6.67% at the second point of observation (end of month 19). The methodology of the dynamic customer journey analysis is shown in Figure 4.

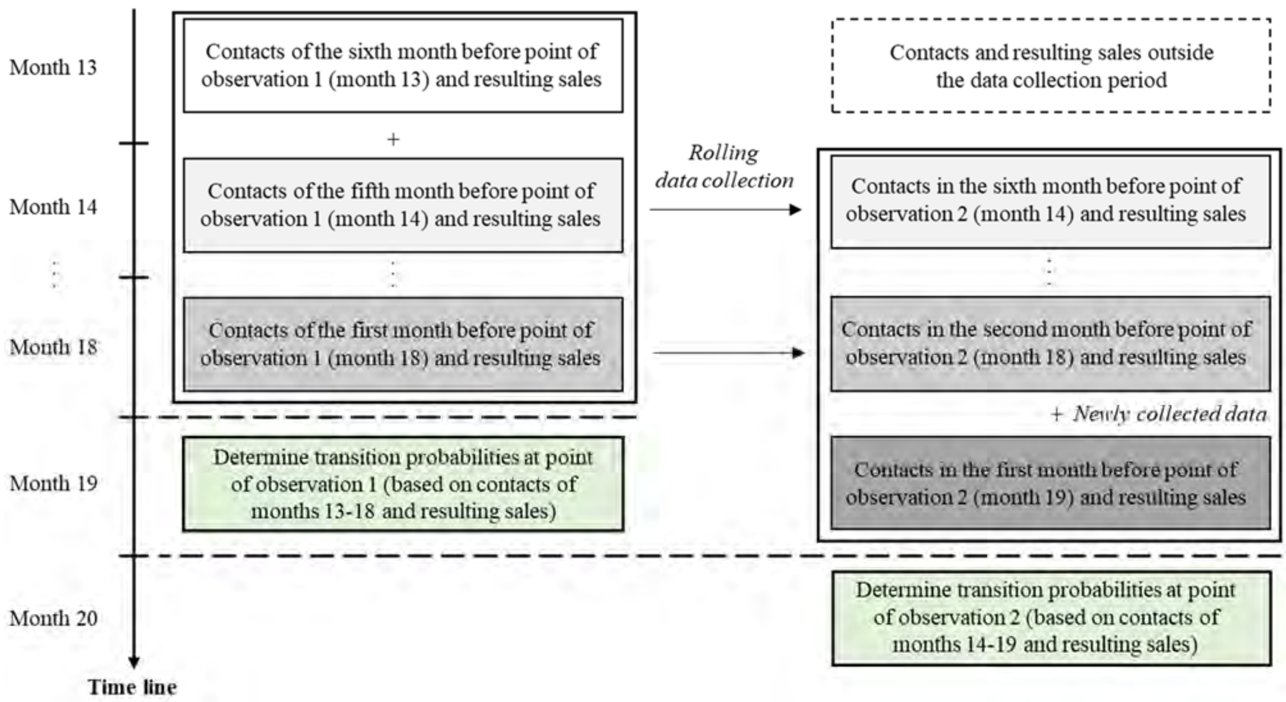

Figure 4: Method of Dynamic Customer Journey Analysis

Forecasting of future sales

To determine the accuracy of dynamic customer journey analysis for measuring advertising effectiveness, sales are forecast for a test period based on transition probabilities determined (see section 4.4.). Sales are the product of determined transition probabilities and expected number of contacts, so it is also necessary to estimate future information requests of the test period.

$$Sales = C \cdot w_{C,Sales}$$

C	number of contacts
$w_{C,Sales}$	transition probability from contacts to sales

Forecasting of information requests

We forecast information requests using a time series analysis based on an autoregressive integrated rolling average (ARIMA) model, developed by JENKINS[105] as well as BOX, JENKINS, and REINSEL[106] (2008), a proven method of forecasting time series.[107] Information requests of the last 52 weeks before the point of observation serve as the forecast's data basis. In line with dynamic customer journey analysis, we updated the forecast monthly on a rolling basis. If the ARIMA model would forecast 1.000 contacts for our test period, then our estimation of sales would be 100.00 at the end of month 18 ($w_{C,Sales}$ = 10.00%) and 6.67 at the end of month 19 ($w_{C,Sales}$ = 6.67%).

4.3. Processing Current Data in Customer Journey Analysis

Challenges in customer journey analysis

Determining transition probabilities using dynamic customer journey analysis is based on contacts and resulting sales of the last 6 months before a point of observation. Especially in the context of extensive decision-making processes, however, it is not immediately apparent whether a contact results in a sale. As mentioned previously, the possible time lag between a contact and a sale (conversion time) in the analyzed data set can be up to 12 months. As a result, it is not possible to definitively determine how many sales will result from contacts observed over the last 6 months before the point of observation. To include current data in dynamic customer journey analysis despite these time lags, it is necessary to estimate future sales that will still result from

105 JENKINS 1979.

106 BOX/JENKINS/REINSEL 2008.

107 MASTRANGELO et al. 2013.

previous contacts, considering the specific point of observation.

In the following, we therefore present the extended dynamic customer journey analysis, a methodology that enables advertisers to evaluate the advertising impact of their channels based on the most current customer journey data despite the conversion time of contacts.

Advanced method

To consider current customer journey data when determining the advertising impact, the presented methodology of dynamic customer journey analysis is extended. The individual steps of the extended dynamic customer journey analysis are summarized in the following table 2 and then explained in more detail:

Table 2: Method of Extended Dynamic Customer Journey Analysis

No.	Step
1.	Determination of observed sales (that already happened before the point of observation)
2.	Determination of future sales (that will still follow in the remaining conversion time)
2.1.	Subdivision of sales by their conversion time
2.2.	Determination of separated transition probabilities per month after contact
2.3.	Determination of future sales resulting from contacts in the data collection period
3.	Summation of observed and future sales resulting from contacts in the data collection period
4.	Determination of transition probabilities based on the dynamic customer journey analysis

Division of observed and future sales

Due to the conversion time from contacts to sales of up to 12 months, not all sales resulting from contacts of the data collection period of 6 months are available at the point of observation. To determine the advertising impact of channels using current data, it is necessary to forecast a realistic number of sales, considering the number of contacts of data collection period and their conversion time for each channel. For implementation, we must determine how many sales have already been achieved from past contacts at the point of observation (observed sales) and how many are likely to follow in the remaining conversion time (future sales).

The division of observed and future sales in shown in figure 5:

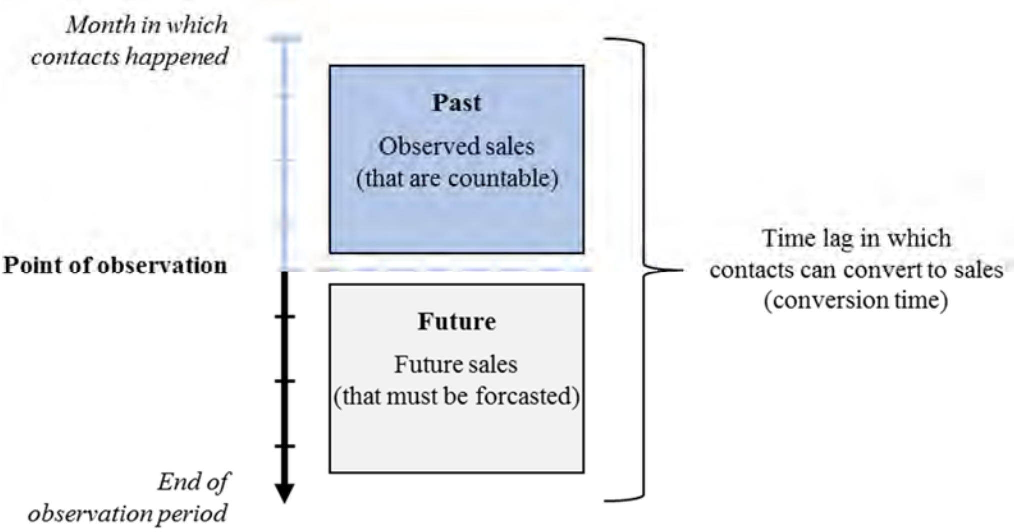

Figure 5: Separation of Previous and Future Sales
(Own Figure)

The following steps that are needed to perform the dynamic customer journey analysis must be carried out individually for each advertising channel.

Step 1: Determination of observed sales

Step 1 is to determine the number of sales that already resulted from contacts of the data collection period at the point of observation. Since the observed sales are countable at the time of observation, there is no need for forecasting or further steps to count them.

In contrast to the observed sales, the future sales that will follow in the outstanding conversion time must be estimated *(step 2)*. The number of future sales depends on the specific point of observation. Accordingly, the forecast of future sales must be broken down in such a way that a separate number of future sales can be determined for each month of the outstanding conversion time. This makes it possible to adjust the forecast of future sales depending on the outstanding conversion time. To determine a separate number of future sales per month after the contact, three sub-steps are required, as explained below.

Step 2.1: Subdivision of sales by their conversion time

The forecast of future sales per month after contacts happened is based on historical data. Therefore, we must first determine how many contacts happened per month in the past, how many sales resulted from these contacts, and how long the corresponding conversion time was. Based on conversion time, it is then possible to determine how many sales were achieved in each month after the contacts happened *(step 2.1.)*. In the following, exemplary data is used to illustrate the methodology of extended dynamic customer journey analysis. Based on 500 exemplary contacts of one month, table 3 shows a possible distribution of 50 sales that occurred within the conversion time of 12 months after the month the contacts happened:

Table 3: Exemplary Subdivision of Sales per Month After Contacts

State	Quantity
C	500
Sales in the month of contacts (0)	20
Sales 1 month after contacts (+1)	10
Sales 2 months after contacts (+2)	5
Sales 3 months after contacts (+3)	4
Sales 4 months after contacts (+4)	3
Sales 5 months after contacts (+5)	2
Sales 6 months after contacts (+6)	2
Sales 7 months after contacts (+7)	1
Sales 8 months after contacts (+8)	1
Sales 9 months after contacts (+9)	1
Sales 10 months after contact (+10)	1
Sales 11 months after contact (+11)	0
Sales 12 months after contact (+12)	0
$\sum$	**50**

To determine the advertising impact of channels, the contacts and resulting sales of the last 6 months (data collection period) before a point of observation are evaluated as part of dynamic customer journey analysis. Due to the conversion time of up to 12 months, it must be considered that not all sales of the data collection period are observable at the point of observation. For example, if the point of observation is at the end of month 18, only the number of sales in month of the contacts (0) can be determined for contacts of month 18. The period 1 month after the contacts (+1) until twelve months after contacts (+12) is still in the future at the point of observation. Sales from contacts of month 18 that are generated 1 month after the contacts (+1) until twelve months after contacts (+12) are therefore not yet observable. Accordingly, it is not possible to consider only observed sales generated within the data collection period to determine future sales. Figure 6 provides a visual representation of the availability of sales per month after the contacts happened.

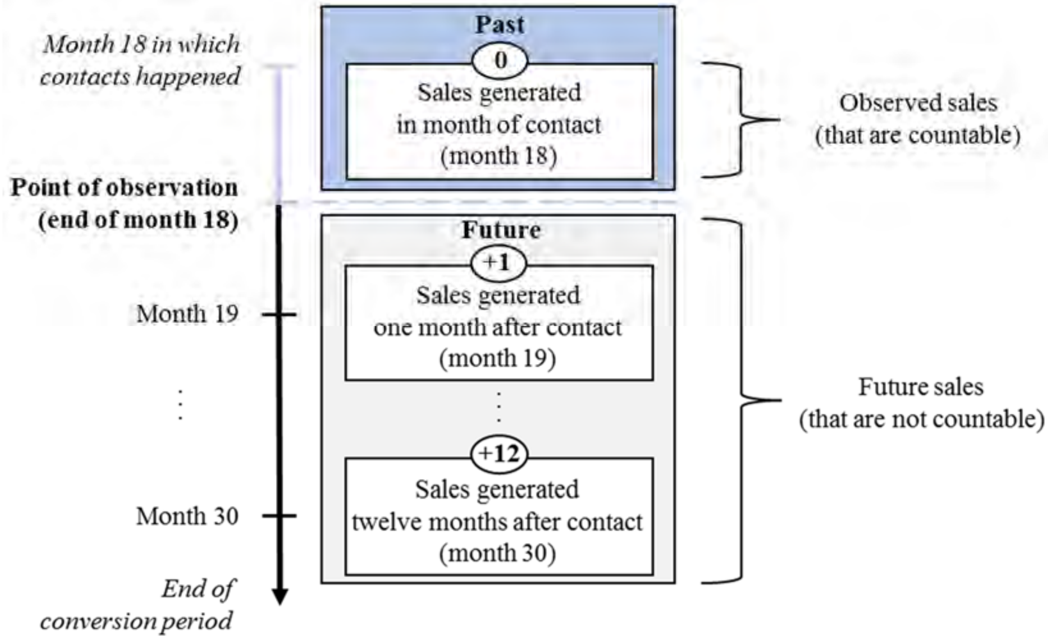

Figure 6: Exemplary Availability of Sales per Month After Contact (Own Figure)

To consider actual sales data for determining advertising impact despite this data lack in the data collection period, the most recent observable sales at the point of observation are used alternatively. At the point of observation (end of month 18) data about sales generated one month after contacts happened are recently observable for contacts of month 17. Accordingly, sales generated two months after contacts happened are recently observable for contacts of month 16. The recently observable sales per month after contacts happened are aggregated, so that in the result sales can be determined for each of the 12 months after the contacts happened.

Table 4 shows the availability of sales within an exemplary data collection period of 6 months and a point of observation at the end of month 18. To simplify the table, the months in which contacts happened are shown vertically (Y-axis) and the sales that result in the months following the contacts are shown horizontally (X-axis). The table should be interpreted in such a way that, for example, if the contact happened in month 17 and the conversion time was one month (+1), the sales result in month 18. Referring to our data example in table 4, this means that sales resulting in the month of contacts (0) can be collected based on contacts from months 13 to 18, while the most recent data for sales resulting 12 months after contact (+12) must be collected based on contacts from months 1 to 6.

Table 4: Exemplary Availability of Sales per Month After Contacts

	Conversion time of sales (in months after contacts)												
Month of contacts	**0**	**+ 1**	**+ 2**	**+ 3**	**+ 4**	**+ 5**	**+ 6**	**+ 7**	**+ 8**	**+ 9**	**+ 10**	**+ 11**	**+ 12**
Month 1													0
Month 2												0	0
Month 3											0	0	0
Month 4	Observed sales									0	0	0	0
Month 5	(that are outside the								0	0	0	0	0
Month 6	data collection period)							1	0	0	0	0	0
Month 7							1	0	0	0	1	0	
Month 8						0	0	0	0	0	0		
Month 9					1	0	0	0	1	1			
Month 10				1	0	0	1	0	0				
Month 11			1	0	1	1	0	0					
Month 12		2	0	1	1	0	0						
Month 13	4	1	0	1	0	1							
Month 14	2	2	1	0	0								Future sales
Month 15	4	1	2	1									(that are not countable
Month 16	3	2	1										at point of observation)
Month 17	3	2											
Month 18	4												
Σ	**20**	**10**	**5**	**4**	**3**	**2**	**2**	**1**	**1**	**1**	**1**	**0**	**0**

■ = Observed sales (that are within the data collection period)

Step 2.2: Determination of separated transition probabilities per month after contact

To forecast future sales resulting from contacts of the data collection period based on these observed sales, it is necessary to calculate transition probabilities for each month after the contacts happened *(step 2.2.)*. For this purpose, the sales within the defined data collection period must be aggregated for each of the 12 months after the contacts happened. For example, if a data collection period of 6 months was defined, then for each of the 12 months after the contacts happened, we aggregated how many sales were generated in the last 6 observable months prior to a point of observation. For example, in table 4, 20 sales occurred within the data collection period in the month of contacts (0). The 20 sales were generated from contacts of the months 13 to 20. The sum of the sales per month after the contacts happened is divided by the contacts made during the same period. The result is a transition probability from contacts to sales for each month in the conversion time. Table 9 below shows the determination of transition probabilities within a 6-month data collection period separated by months of the conversion time. The point of observation is at the end of month 18:

Table 5: Exemplary Determination of Transition Probabilities per Month After Contacts

Conversion time	Collection period (6 months)	C	Sales	$W_{C,Sales}$
Month of contacts (0)	Month 13 – Month 18	500	20	4.00%
1 month after contacts (+1)	Month 12 – Month 17	600	10	1.67%
2 months after contacts (+2)	Month 11 – Month 16	450	5	1.11%
3 months after contacts (+3)	Month 10 – Month 15	450	4	0.89%
4 months after contacts (+4)	Month 9 – Month 14	400	3	0.75%
5 months after contacts (+5)	Month 8 – Month 13	500	2	0.40%
6 months after contacts (+6)	Month 7 – Month 12	550	2	0.36%
7 months after contacts (+7)	Month 6 – Month 11	600	1	0.17%
8 months after contacts (+8)	Month 5 – Month 10	450	1	0.22%
9 months after contacts (+9)	Month 4 – Month 9	500	1	0.20%
10 months after contacts (+10)	Month 3 – Month 8	450	1	0.22%
11 months after contacts (+11	Month 2 – Month 7	500	0	0.00%
12 months after contacts (+12)	Month 1 – Month 6	450	0	0.00%
			∑	**10.00%**

■ = Transition probabilities from contacts to conversions per month after contact

Step 2.3: Determination of future sales resulting from contacts in the data collection period

Based on the transition probabilities determined for each month after the contacts happened, we determined the future sales from contacts of the data collection period *(step 2.3.)*. To estimate these future sales, contacts within the data collection period and the determined transition probabilities per month after contact *(cf. step 2.2.)* are multiplied. This procedure is repeated for each month in which future sales may still be made from contacts of the data collection period.

Table 6 illustrates the determination of future sales with an example. The point of observation is at the end of month 18 so that the 6-month data collection period is from month 13 to month 18. In month 13, sales resulting from the 100 contacts are observable until 5 months after contacts (20 observed sales). Accordingly, no estimate of sales is required for these observable periods. However, future sales must be estimated for the remaining months of the data collection period. So, for contacts that happened in month 13, sales still need to be forecast for the period 6 to 12 months after the contacts. For example, if the sum of the transition probabilities for the months in the open data collection period of month 13 is 0.65%, the number of future sales still resulting from the 100 contacts of month 13 are calculated as 0.65.

This procedure is repeated for each month of the data collection period, and the number of estimated future sales aggregated. The sum of forecasted future sales in this example is 34.40.

Table 6: Exemplary Determination of Future Sales for Contacts within the Data Collection Period

Coll-ection period	**C**	**$W_{C,Sales}$**										
		0	**+1**	**+2**	**+3**	**+4**	**+5**	**+6**	**…**	**+12**	**∑**	**Sales**
Month 13	100	20						0.40 %	0.25 %	0.00 %	0.65 %	**0.65**
Month 14	150	16					0.60 %	0.40 %	0.25 %	0.00 %	1.25 %	**1.88**
Month 15	200	15				1.00 %	0.60 %	0.40 %	0.25 %	0.00 %	2.25 %	**4.50**
Month 16	150	13			1.11 %	1.00 %	0.60 %	0.40 %	0.25 %	0.00 %	3.36 %	**5.04**
Month 17	150	15		1.75 %	1.11 %	1.00 %	0.60 %	0.40 %	0.25 %	0.00 %	5.11 %	**7.67**
Month 18	200	7	2.22 %	1.75 %	1.11 %	1.00 %	0.60 %	0.40 %	0.25 %	0.00 %	7.33 %	**14.66**
Point of observation (end of month 18)												
Σ	**950**											**34.40**

■ = Observed sales

■ = Forecasted transition probabilities of future sales

■ = Forecasted future sales

For each channel, the calculated future sales (see *Step 2.3*) are summed with the observed sales (see *Step 1*) for each month of the data collection period. The following table summarizes the observed and future sales from table 7:

Step 3: Summation of observed and future sales

Table 7: Exemplary Determination of Observed and Future Sales

<table>
<tr><th rowspan="2">Collection period</th><th rowspan="2">C</th><th colspan="10">Sales</th></tr>
<tr><th>0</th><th>+1</th><th>+2</th><th>+3</th><th>+4</th><th>+5</th><th>+6</th><th>…</th><th>+12</th><th>∑</th></tr>
<tr><td>Month 13</td><td>100</td><td colspan="6">20</td><td colspan="3">0.65</td><td>20.65</td></tr>
<tr><td>Month 14</td><td>150</td><td colspan="5">16</td><td colspan="4">1.88</td><td>17.88</td></tr>
<tr><td>Month 15</td><td>200</td><td colspan="4">15</td><td colspan="5">4.50</td><td>19.50</td></tr>
<tr><td>Month 16</td><td>150</td><td colspan="3">13</td><td colspan="6">5.04</td><td>18.04</td></tr>
<tr><td>Month 17</td><td>150</td><td colspan="2">15</td><td colspan="7">7.67</td><td>22.67</td></tr>
<tr><td>Month 18</td><td>200</td><td>7</td><td colspan="8">14.66</td><td>21.66</td></tr>
<tr><td colspan="12">Point of observation (end of month 18)</td></tr>
<tr><td>∑</td><td>950</td><td colspan="9"></td><td>120.40</td></tr>
</table>

■ = Observed sales

■ = Forecasted transition probabilities of future sales

■ = Sum of observed and forecasted future sales

Step 4: Determination of transition probabilities

To determine the transition probabilities in a final step, the sum of observed and estimated future sales in the data collection period is divided by the sum of contacts in the data collection period. In our example the transition probability at the point of observation (end of month 18) is calculated as:

$$w_{C,Sales} = \frac{\sum_{t_y=1}^{6} Sales_{C_{t_y}}}{\sum_{t_y=1}^{6} C_{t_y}} = \frac{120.40}{950} = 12.67\%$$

C_{t_y} number of contacts in t_y

$Sales_{C_{t_y}}$ number of sales resulting from C_{t_y}

The resulting transition probability serves as the basis for determining sales in the test period, considering the forecasted contacts of the ARIMA model.

4.4. Methodology for Comparing Accuracy of Advertising Impact

Comparison of methods

The aim of attribution modeling is to determine the advertising impact of channels as accurately as possible. To determine the performance of dynamic customer journey analysis in this context, its suitability for determining transition probabilities and resulting sales is compared with the results of other attribution methods.

To evaluate the accuracy of dynamic customer journey analysis, we collected contacts over a test period of 4 months (March 30, 2020–July 19, 2020). Furthermore, we determined how many sales resulted from these contacts within 365 days after the test period's end. The goal was to predict as accurately as possible the number of sales at the test period's end based on estimated contacts of the ARIMA model and determined transition probabilities of the dynamic customer journey analysis. We made the first forecast before the test period's start and then recalculated it monthly until the test period's end, considering observed information requests and sales.

We compared the predicted sales with results of other attribution models, which differ from dynamic customer journey analysis in determining transition probabilities. First, we evaluated the usefulness of rolling determination of advertising impact as the main feature of dynamic customer journey analysis. The other methods do not remove historical data when determining transition probabilities, regardless of how much time had passed since they were collected. Second, we analyzed the influence of the data collection period on attribution results by varying the periods of the observed models. In this way, we can measure the extent to which the period of data collection affects the determination of transition probabilities.

Method I determines transition probabilities using only contacts and sales collected in the test period to evaluate the shortest possible data collection period. Because of the short data collection period, the influence of current data on the determination of transition probabilities is the highest in the method comparison.

Method II tests the longest possible period by determining transition probabilities based on all consumer interactions in the data set. We excluded from the analysis only contacts made up to 12 months before the test period. The reason for this is that due to the conversion time of up to 12 months between contacts and sales, a final determination of transition probabilities is not possible without estimating missing values. For *Method II*, this results in a data collection period of 94 months before the start of the test phase.

To also account for information requests up to one year prior to the test period, *Method III* extends *Method II* by estimating these open data points based on contacts and sales of the entire data set (see Ch. 4.3.). The amount of considered data increases the later the point of observation is. As a result, the influence of current data on the determination of transition probabilities decreases the later the point of observation is.

Method IV (DCJA) is the dynamic customer journey analysis with a rolling data collection period of 6 months. In this case, the contacts and resulting sales from months 7 through 12 (19 through 24) are used to determine the exclusion effects in month 13 (25).

Table 8: Summary of Investigated Methods

Method	Rolling Time Window	Data Collection Period
Method I	No	Test period
Method II	No	Whole data set (without forecasting future sales)
Method III	No	Whole data set (with forecasting future sales)
Method IV (DCJA)	Yes	Rolling 6 months

Determination of forecast errors

We determine forecast errors using root mean square errors (RMSE) and weighted mean absolute percentage errors (WMAPE). The advantage of RMSE over mean squared errors is that they have the same unit as the sales forecast and are, therefore, easier to interpret. The formula for determining the RMSE is as follows:[108]

$$RMSE = \sqrt{\frac{1}{n}\sum_{i}^{n}(Y_i - \hat{Y}_i)^2}$$

n Number of channels

Y Observed sales

Ŷ Forecasted sales

An example calculation of the RMSE can be found in table 9 below:

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Table 9: Exemplary Determination of RMSE

Channel	**Y**	$\hat{Y}$	$(\mathbf{Y} - \hat{\mathbf{Y}})^2$	**RMSE**
Google advertising	40	50	100	$\sqrt{\frac{\mathbf{300}}{\mathbf{6}}} = \mathbf{7.07}$
Google search results	25	20	25	
Affiliate marketing	0	5	25	
Telemarketing	20	10	100	
Referral marketing	5	10	25	
Recommendation by acquaintances	10	5	25	
$\sum$	**100**	**95**	**300**	

The key figure wMAPE is an extension of mean absolute percentage error (MAPE). If channels generate small sales numbers, MAPE will indicate high forecast errors for these channels even if there are small absolute differences between forecast and observed values. To avoid such overestimation, WMAPE weight forecast errors of individual channels by setting these sales of the channel in relation to total sales. For this purpose, the absolute forecast errors of the individual channels are summed and divided by the sum of the observed sales of all channels. The formula for determining the wMAPE is as follows:[109]

$$wMAPE = \frac{\sum_{i=1}^{n} \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \times Y_i}{\sum_{i=1}^{n} Y_i}$$

n	Number of channels
Y	Observed sales
$\hat{Y}$	Forecasted sales

An example calculation of wMAPE can be found in table 10 below:

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Table 10: Exemplary Determination of wMAPE

Channel	Y	$\hat{Y}$	$\lvert Y - \hat{Y} \rvert$	wMAPE
Google advertising	40	50	10	$\frac{\frac{\mathbf{40}}{\mathbf{100}} \times \mathbf{100}}{\mathbf{100}} = \mathbf{40\%}$
Google search results	25	20	5	
Affiliate marketing	0	5	5	
Telemarketing	20	10	10	
Referral marketing	5	10	5	
Recommendation by acquaintances	10	5	5	
$\sum$	**100**	**95**	**40**	

The forecast errors between forecasted and observed sales are determined monthly per point of observation in the test period. The method with the lowest forecast errors has the highest accuracy for determining the advertising effectiveness of advertising channels.

4.5. Descriptive Statistics

Descriptive statistics of the data set

The overall dataset includes 45,694 customer journeys and 4,753 sales over a 115-month period (Table 11). Every month consists of 4 weeks and thus 28 days. In 88.06% of the customer journeys, there was only one contact, in 9.94%, there were two, and in 2.00%, there were three. With a share of 81.26%, a large part of the customer journeys begins with a contact via the channels Google advertising or Google search results. The distribution of the sales shows similar results. Here, customer journeys that started with these channels generated 78.27% of sales. The coefficients of variation indicate high dispersions of contacts and sales between months. Furthermore, the dispersion of contacts and sales varies greatly between the different channels. This makes it difficult to predict future events in the customer journey.

Table 11: Descriptive Statistics

Variables	n $_{(C1)}$	n $_{(C2)}$	n $_{(C3)}$	Σ n	min*	max*	mean*	sd*	var. coef.*
C_{GA}	26,023	3,029	574	29,626	64	562	264.82	101.10	38.18%
C_{GS}	6,565	772	168	7,505	14	149	66.97	30.79	45.98%
C_{AM}	2,528	117	59	2,704	1	120	23.69	19.82	83.68%
C_{TM}	1,789	166	29	1,984	0	50	17.53	11.00	62.74%
C_{RM}	1,581	197	35	1,813	2	76	16.55	11.73	70.89%
C_{RA}	1,754	259	49	2,062	2	54	18.14	8.65	47.70%
Σ C	40,240	4,540	914	45,694					
$Sales_{GA}$	1,768	618	142	2,528	7	53	22.64	9.37	41.39%
$Sales_{GS}$	930	217	45	1,192	1	31	10.73	5.49	51.20%
$Sales_{AM}$	48	13	11	72	0	5	0.63	0.97	153.13%
$Sales_{TM}$	233	47	4	284	0	16	2.57	2.61	101.67%
$Sales_{RM}$	200	53	3	256	0	15	2.25	2.40	106.51%
$Sales_{RA}$	314	91	16	421	0	13	3.70	2.73	73.82%
Σ Sales	3,493	1,039	221	4,753					

Google advertising (GA); Google search results (GS); affiliate marketing (AM); telemarketing (TM); referral marketing (RM); recommendation by acquaintances (RA); *aggregated at monthly level (based on *Σ n*)

4.6. Empirical Study

General results of the empirical study

To assess the accuracy of the methods regarding sales prediction, contacts of each channel are first estimated using the ARIMA model. Considering the sample autocorrelation and partial autocorrelation function leads to the selection of a first-order (1,0,0) autoregressive model (Mastrangelo et al. 2013). The ARIMA forecasting results at baseline (t_0), one month after baseline (t_1), two months after baseline (t_2), three months after baseline (t_3), and four months after baseline (t_4) are summarized in table 12. The results show a continuous reduction of forecast errors when considering observed contacts, which also has a positive effect on the sales forecast. Since the number of contacts can be determined immediately, in contrast to the resulting sales, discrepancies between forecast and observed values are inevitably resolved by the test period's end.

Table 12: Results of Contacts Forecast

		t_0	t_1	t_2	t_3	t_4
C_{GA}	Observed	936.00				
	Forecast	770.74	794.17	838.33	898.06	936.00
C_{GS}	Observed	205.00				
	Forecast	178.39	167.68	171.22	184.04	205.00
C_{AM}	Observed	14.00				
	Forecast	71.86	45.69	27.83	18.42	14.00
C_{TM}	Observed	20.00				
	Forecast	23.43	20.52	21.04	21.32	20.00
C_{RM}	Observed	131.00				
	Forecast	63.55	80.24	92.67	109.47	131.00
C_{RA}	Observed	27.00				
	Forecast	26.15	24.94	25.38	25.60	27.00
Σ C	RMSE Forecast	27.54	20.72	15.65	8.79	0.00
	WMAPE Forecast	24.12%	19.82%	13.97%	6.57%	0.00%

Google advertising (GA); Google search results (GS); affiliate marketing (AM); telemarketing (TM); referral marketing (RM); recommendation by acquaintances (RA)

For the sales forecast, transition probabilities of the test period are determined using methods I to IV (Appendix 1). Then, we multiplied the transition probabilities by the forecast contacts, resulting in sales estimations of the test period. For each channel and method, we determined forecast errors separately per point of observation (Table 13).

Table 13: Results of Sales Forecast

		t_0	t_1	t_2	t_3	t_4
$Sales_{GA}$	Observed	102				
	Forecast Method I	0.00	15.88	24.83	47.41	63.00
	Forecast Method II	64.42	66.37	70.05	75.05	78.70
	Forecast Method III	65.02	65.78	66.96	81.65	95.51
	Forecast Method IV (DCJA)	73.54	75.81	71.81	88.24	96.01
$Sales_{GS}$	Observed	50				
	Forecast Method I	0.00	4.93	14.27	29.13	32.00
	Forecast Method II	27.06	25.44	25.97	27.92	31.10
	Forecast Method III	27.90	26.76	26.07	38.45	44.56
	Forecast Method IV (DCJA)	41,31	34.68	33.72	42.51	44.39
$Sales_{AM}$	Observed	0				
	Forecast Method I	0.00	0.00	0.00	0.00	0.00
	Forecast Method II	2.08	1.32	0.80	0.53	0.40
	Forecast Method III	1.97	1.17	0.75	0.42	0.23
	Forecast Method IV (DCJA)	1.71	0.76	0.47	0.34	0.13
$Sales_{TM}$	Observed	3				
	Forecast Method I	0.00	0.00	0.00	1.42	1.00
	Forecast Method II	3.24	2.84	2.91	2.95	2.77
	Forecast Method III	3.42	3.36	3.24	2.03	2.57
	Forecast Method IV (DCJA)	5.72	3.89	2.85	3.28	1.58
$Sales_{RM}$	Observed	14				
	Forecast Method I	0.00	8.60	8.42	8.61	10.00
	Forecast Method II	9.56	12.07	13.94	16.46	19.70
	Forecast Method III	9.26	13.14	14.28	10.41	16.82
	Forecast Method IV (DCJA)	7.06	10.07	12.26	12.74	14.97
$Sales_{RA}$	Observed	6				
	Forecast Method I	0.00	0.00	0.00	0.00	0.00
	Forecast Method II	5.42	5.17	5.26	5.30	5.59
	Forecast Method III	5.34	5.59	5.98	6.78	6.79
	Forecast Method IV (DCJA)	1.26	2.46	3.97	6.00	6.11
Σ Sales	RMSE Method I	41.64	35.16	31.51	22.29	15.92
	WMAPE Method I	100.00%	83.19%	72.85%	50.53%	39.43%
	RMSE Method II	15.34	14.55	13.04	11.00	9.51
	WMAPE Method II	38.77%	36.82%	32.96%	30.16%	27.97%
	RMSE Method III	15.10	14.79	14.30	8.31	2.65
	WMAPE Method III	38.21%	35.57%	34.44%	21.52%	9.25%
	RMSE Method IV (DCJA)	11.62	10.69	12.32	5.62	2.45
	WMAPE Method IV (DCJA)	30.43%	28.93%	29.06%	13.22%	8.13%

Dynamic Customer Journey Analysis (DCJA); Google advertising (GA); Google search results (GS);
affiliate marketing (AM); telemarketing (TM); referral marketing (RM); recommendation by acquaintances (RA)

Due to time lags between contacts and sales, sales generated from contacts cannot be finally determined until 12 months after the test period's end. However, the results show that prediction errors of all methods improve with considering observed customer journey data over the test period. Nevertheless, considering different periods and approaches to determining advertising impact results in prediction differences of the methods.

Results of method I

In *Method I*, transition probabilities were determined solely based on contacts and sales generated during the forecast period. Despite the continuous reduction in forecast errors due to including observed data during the test period, *Method I* results in the weakest forecast accuracy at each point of observation. For example, The RMSE is 41.64 at the beginning, 31.51 after 2 months (WMAPE 72.85%), and 15.92 (WMAPE 39.43%) at the test period's end. The high prediction errors highlight the difficulty of determining representative transition probabilities based on data from short periods. Thus, the time lag of contacts and sales leads to a persistent underestimation of transition probabilities and makes it difficult to determine impact of channels within an ongoing advertising campaign.

Results of method II

For *Method II*, the transition probability was determined based on all historical data except for contacts that occurred less than one year prior to point of observation. At the beginning, *Method II* achieved the highest forecast accuracy with 3.34 estimated sales for telemarketing, 9.56 for referral marketing, and 5.42 for recommendation by acquaintances. On the other hand, we found high errors for sales in Google advertising with 64.42, Google search results with 27.06, and affiliate marketing with 2.08. The RMSE at the beginning of the test period is 15.34 (WMAPE 38.77%). Although prediction errors decrease over time, the effect is particularly due to the continuous improvement in estimating contacts. Two months after starting the test period, the RMSE is 13.04 (WMAPE 32.96%) and at the end, it is 9.51 (WMAPE 27.97%). Compared to other methods, the improvement in prediction accuracy is much smaller due to the long period of data collection and the resulting lack of adjustment of transition probabilities.

Results of method III

Method III extends *Method II* by estimating pending sales that resulted from contacts occurred less than one year prior to the test period. The RMSE of Method III at the baseline is 15.10 (WMAPE 38.21%), which is lower than the values of *Method I* and *Method II*. Moreover, considering the observed customer journey data leads to a more significant improvement in prediction accuracy. Only one month after starting the test period, the RMSE of *Method*

III is 14.79 (MAPE 35.57%), which is comparable to that of *Method II* with 14.55 (WMAPE 36.82%). However, the prediction error of *Method III* at three months, 8.31 (WMAPE 21.52%), and at four months, 2.65 (WMAPE 9.25%), is significantly lower than that of *Method II*, with 11.00 (WMAPE 30.16%) and 9.51 (WMAPE 27.97%), respectively.

Results of method IV

Method IV is the dynamic customer journey analysis. Already at the beginning of the test period, this method has the lowest RMSE with a value of 11.62 (WMAPE 30.43%). Furthermore, prediction errors decrease more over time in contrast to other methods. Nevertheless, considering the smaller data size of 6 months initially leads to comparatively high prediction errors for sales of single channels. For example, the dynamic customer journey analysis predicts 7.06 sales for referral marketing, while the observed number is 14 sales. By estimating 9.56 sales (*Method II*) and 9.26 sales (*Method III*), other methods achieve higher forecast accuracy here. Furthermore, the accuracy of estimated sales decreases sporadic despite considering the observed customer journey data. For example, 50 sales are achieved via Google search results, with 41.31 sales forecast at the beginning of the test period and 34.68 sales one month after beginning. Even though the RMSE stagnates in total between 10.69 (WMAPE 28.93%) one month after baseline and 12.32 (WMAPE 29.06%) two months after baseline, the forecast error of *Method IV* is lower than the values of other methods at each point of observation. The accuracy of *Method IV* stands out from the other methods especially after three months with a RMSE of 5.62 (WMAPE 13.22%) and after four months with 2,45 (WMAPE 8.13%). Only *Method III* shows a comparable forecast accuracy at the observation’s end with 2.65 (WMAPE 9.25%).

Summary

In total, the dynamic customer journey analysis leads to lowest forecast errors of the compared methods. At the test period’s beginning, the forecast differences of the methods are comparatively small despite different data collection periods to determining transition probabilities. However, due to the rolling determination of transition probabilities, we observe a significantly stronger reduction of forecast errors in dynamic customer journey analysis during the test period. Thus, it is better suited to detect performance changes of channels when determining their advertising impact.

4.7. Discussion and Implications of the Empirical Results

Influence of channels on purchasing behaviour

Next, we look more closely at key findings of our empirical analysis and compare them with previous studies focusing differences in channel impact, continuous attribution measurement, and data collection periods. First, our study supports findings of previous investigations' conclusions that channels influence consumers' purchasing behavior and contribute differently to generating sales.[110] For example, Google advertising leads to most sales, resulting in 102 of the 170 total sales during test period, whereas affiliate marketing is the weakest channel with 0 sales. Nevertheless, transition probability from information requests to sales of Google advertising is low at 10.90%, compared with organic Google search at 24.39%. From a scientific perspective, the results show consumers' different channel preferences.

Surprisingly, most frequently used channels are not those that have the highest conversion rate; for example, conversion rate here is highest for the least-used channels Google search results and recommendation by acquaintances, which suggest preferences for organic advertising channels. From a managerial perspective, these results show that advertisers can use customer journey analysis to identify channels' advertising impact, forecast future sales, and derive channel-specific strategies. Here, advertisers should focus on their organic discoverability and use customer recommendations to increase marketing return on investment by more frequently using promising channels. Especially with high-traffic and scalable channels like Google advertising, advertisers should optimize quality of their ads (by, e.g., using targeted keywords, creating appealing ad texts, maintaining exclusion lists to increase channel's impact). Furthermore, advertisers should critically examine channels with low sales and few consumer interactions, such as affiliate marketing in our data set, and replace them with alternative channels.

Continuous determination of advertising impact

Second, our study shows that contacts and sales generated by channels change over time, such that trends occurring during historical collection periods may bias attribution results and interpretation of channels' advertising impact. In this sense, attribution accuracy benefits from continuous consideration of new customer journey data. However, previous studies have not considered how attribution results change when new data is included and only determine their models' accuracy in given environments within fixed

[110] e.g., BECKER/LINZMAIER/VON WANGENHEIM. 2017; KLAPDOR et al. 2015.

time periods.[111] As a result, the influence of an ongoing consideration of new customer journey data on attribution accuracy could not be identified.

Advertisers should continuously determine the advertising impact of their channels to assess consumer's purchasing behavior over time more accurately. This would enable interactive marketing control by adjusting advertising campaigns at short notice. If, for example, the number of sales one month after the start of the campaign is below the expected forecast, additional ads can be placed, advertising channels can be modified or media budget can be reallocated promptly to ensure sales targets. On the other hand, dynamic Markov chains also make it possible to identify higher than expected interest from (potential) buyers at an early stage to increase entrepreneurial return, e.g., by an early expansion of product ranges or price increases.

With regard to academic contributions, our study shows that attribution researchers need to use continuous measurement of attribution rather than observing fixed periods. Using this type of measurement would make reported results less conditional on management decisions present at point of observation. For this purpose, we developed a framework to consider current customer journey events for attribution despite time lags between contacts and sales.

Influence of data collection periods on forecast accuracy

Finally, our results show that data collection periods influence forecast accuracy. Even though data collection periods of data differ in previous studies,[112] the influence of these varied data collection periods on attribution results has not been considered so far. To fill this research gap, we examined different data collection periods in a common setting. We found that a rolling survey period of 6 months resulted in better predictions than considering a short data set of a few weeks and a long data set of up to 94 months.

From a research perspective, our results indicate that channels' advertising impacts are not linear over time and can vary, so advertising impact determination may be biased by long data collection periods. In contrast, when using short data periods, researchers must consider that attribution values represent only snapshots. Advertisers should, therefore, not view customer journey

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111 e.g., ANDERL/SCHUMANN/KUNZ 2015; BECKER/LINZMAIER/VON WANGENHEIM 2017; DANAHER/DAGGER 2013; DE HAAN/WIESEL/PAUWELS 2016; LI/KANNAN 2014; LI et al. 2018.

112 e.g., ANDERL/SCHUMANN/KUNZ 2015; DE HAAN/WIESEL/PAUWELS 2016.

analysis as a one-time event, but rather as a continuous process to improve advertising allocation, by considering current developments in channels' advertising impact.

5. Conclusions

5.1. Summary

Dynamic customer journey analysis

This study presents a dynamic approach to analyzing customer journeys and examines its ability to determine advertising impact and predict sales. In contrast to previous models, our model's consideration of current customer journey data in combination with a rolling advertising impact determination leads to continuously improved forecast results.

Influence of data collection periods on advertising impact measurement

The results clearly illustrate that data collection periods influence determination of advertising impact. The comparison of different methods leads to the assumption that timeliness of data is more relevant for determining a channel's advertising impacts than collecting data over the longest possible period.

Continuous determination of advertising impact

Finally, the study shows that continuously determining the advertising impact of channels enables researchers to forecast future sales more accurately. However, it is important to note that short-term changes in transition probabilities can also lead to an increased risk of forecast errors if they prove to be outliers. Nevertheless, advertisers should conduct customer journey analysis continuously to enable interactive marketing control and improve advertising media allocation by monitoring channels' advertising impact.

5.2. Limitations of the Results and Outlook for Further Research

We acknowledge several limitations of our research, which point to worthwhile future research avenues. First, to test our dynamic customer journey analysis, we considered data from a single data set. Similar to BECKER, LINZMAJER, and VON WANGENHEIM (2017), we recommend verifying the results using data sets from different industries and product groups.[113]

Additional data collection periods

Second, for testing the dynamic customer journey analysis, we used a rolling data collection period of 6 months. Future studies should investigate addi-

[113] BECKER/LINZMAJER/VON WANGENHEIM 2017.

tional data collection periods to learn about appropriate data periods for customer journey analysis. It would also be conceivable to weight the underlying data according to their timeliness. Third, future researchers should investigate how data can be extrapolated (e.g., with time series analyses) to identify trends in advertising impacts earlier. In this context, machine learning approaches, for example used by LI, ARAVA, DONG, YAN, and PANI (2018), could provide more accurate estimates of customer journey events by detecting patterns within the data set.[114]

Removal Effects

Fourth, we evaluated accuracy of dynamic customer journey analysis comparing predicted and observed sales in a test phase of four months. Future studies should evaluate results using other key figures, such as removal effects,[115] which express advertising effectiveness of channels by determining how the probability of a purchase is reduced when a channel is removed from customer journey. In addition, future researchers should extend the period of test phase.

Including further channels

Regarding the selection of advertising channels, it should be noted that while various online channels were included in the study, consideration of other channels was not fully exploited. To account for the increasing complexity of customer journeys, additional touchpoints, such as social networks, should be explored. Complementary to Markov chains, there are other attribution models that are suitable for researchers to examine the usefulness of the rolling determination.

Deeper analysis of channels

In addition to expanding the number of advertising channels, it is also possible to analyze the channels in more depth. For example, the Google advertising channel can be considered in a more differentiated way by distinguishing between the keywords used within the ads. Corresponding findings make it possible to further clarify performance differences of individual advertising channels and to increase the closing power of companies through a more targeted design of the channels within the customer journey. Future studies should therefore consider further variables that allow deeper insights into the use of individual advertising channels.

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[114] LI et al. 2018.

[115] ANDERL et al. 2016.

The study is based on quantitative data, which does not provide any insight into why users choose certain advertising channels within the customer journey. Taking qualitative data into account would also make it possible to gain insights into the background of user behavior. For example, it could be discussed why prospects who use Google advertising are less likely to close a deal than those who use organic Google search results. Corresponding insights would enable advertisers to design advertising channels that have a lower probability of closing a deal more similarly to those with a higher probability of closing a deal.

Appendix

Results of Transition Probabilities Forecast

		$w_{C,Sales}$				
$w_{C,Sales}$	Method	t_0	t_1	t_2	t_3	t_4
$w_{C_{GA},Sales}$	Observed	10.90%				
	Method I	8.36%	8.36%	8.36%	8.36%	8.41%
	Method II	0.00%	2.00%	2.96%	5.28%	6.73%
	Method III	8.44%	8.28%	7.99%	9.09%	10.20%
	Method IV (DCJA)	9.57%	9.80%	8.85%	10.32%	10.51%
$w_{C_{GS},Sales}$	Observed	24.39%				
	Method I	15.17%	15.18%	15.11%	15.13%	15.18%
	Method II	0.00%	2.94%	8.33%	15.83%	15.61%
	Method III	15.64%	15.96%	15.23%	20.89%	21.74%
	Method IV (DCJA)	22.88%	16.46%	19.69%	23.10%	21.65%
$w_{C_{AM},Sales}$	Observed	0.00%				
	Method I	2.89%	2.84%	2.81%	2.80%	2.79%
	Method II	0.00%	0.00%	0.00%	0.00%	0.00%
	Method III	2.74%	2.56%	2.70%	2.29%	1.63%
	Method IV (DCJA)	1.62%	1.68%	1.70%	1.84%	0.95%
$w_{C_{TM},Sales}$	Observed	15.00%				
	Method I	13.83%	13.81%	13.78%	13.75%	13.97%
	Method II	0.00%	0.00%	0.00%	6.67%	5.00%
	Method III	14.31%	13.37%	11.29%	12.88%	14.26%
	Method IV (DCJA)	20.35%	27.19%	26.36%	26.10%	17.92%
$w_{C_{RM},Sales}$	Observed	10.69%				
	Method I	15.04%	15.03%	15.19%	15.23%	15.09%
	Method II	0.00%	10.71%	9.09%	7.87%	7.63%
	Method III	14.58%	16.38%	15.41%	9.51%	12.84%
	Method IV (DCJA)	8.67%	14.20%	16.01%	12.60%	16.68%
$w_{C_{RA},Sales}$	Observed	22.22%				
	Method I	20.72%	20.68%	20.66%	20.63%	20.60%
	Method II	0.00%	20.00%	16.67%	21.05%	18.52%
	Method III	20.41%	22.42%	23.55%	26.48%	25.14%
	Method IV (DCJA)	8.39%	9.92%	15.64%	23.42%	22.62%

Dynamic Customer Journey Analysis (DCJA); Google advertising (GA); Google search results (GS); affiliate marketing (AM); telemarketing (TM); referral marketing (RM); recommendation by acquaintances (RA)

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Parallel to his academic career, Rainer Olbrich worked for a German consultancy focusing on marketing, strategy, and portfolio projects from 1985 to 1989. He has worked for more than 30 years in the education sector, on various projects and as an expert for leading German companies, organizations, and public institutions. In the University of Hagen he has also served as a vice-president for research, dean, speaker of the council of deans, and vice-dean.

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