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DATA-DRIVEN ATTRIBUTION MODELING IN DIGITAL MARKETING

B a c k g r o u n d . ***In the contemporary digital environment, marketing communications have evolved into multi-channel, personalized, and dynamic interactions, necessitating an increasingly precise quantification of the efficacy of each user touchpoint with a brand. Conventional rule-based marketing attribution models, which exclusively assign value to a singular touch-point of contact, no longer yield the requisite level of analytical granularity. In response to these methodological challenges, advanced economic and mathematical methodologies, notably models predicated on Markov chains and Shapley values, are progressively being deployed to facilitate a rigorously reasoned and quantitatively justifiable allocation of value across all contributing channels.***

M e t h o d s . ***The research methodology is based on a combination of general scientific and specialized methods. Specifically, it utilized theoretical modeling, comparative analysis, as well as stochastic modeling (Markov chains) and cooperative game theory (Shapley values).***

R e s u l t s . ***This research rigorously investigated marketing attribution in the digital environment, demonstrating the inherent limitations of traditional rule-based models and substantiating the superior efficacy of adaptive approaches, particularly Markov chains and Shapley values. The empirical implementation and comparative analysis of the Shapley value model confirmed its enhanced precision and capacity to objectively quantify each channel's contribution, leading to actionable insights for strategic marketing optimization. This study provides a robust framework for understanding multi-touch attribution, emphasizing the critical role of data-driven methodologies in contemporary marketing analytics.***

C o n c l u s i o n s . ***The work is relevant for marketing analysts and digital strategy teams, as it presents a comparative analysis of rule-based and algorithmic attribution models and offers practical solutions for campaign optimization. The Shapley Value model was implemented in Python and tested on real-world marketing data. The practical value lies in the ability to use the results for better budget allocation, identifying undervalued channels, and increasing return on marketing investment (ROMI).***

K e y w o r d s : ***marketing attribution, digital marketing, data-driven attribution, Shapley values, Markov chains, multichannel analytics, Python.***

Background

In the contemporary digital landscape, marketing communications have evolved to become multichannel, personalized, and dynamic, thereby intensifying the need for precise measurement of the effectiveness of each user interaction with a brand. In this context, marketing attribution emerges as a response to the growing demand for understanding the actual contribution of each channel to business outcomes. The primary objective of marketing attribution is to assist brands in discerning the significance of every touchpoint within the broader customer journey. By identifying which channels or touchpoints yield higher conversion rates, marketing teams can optimize budget allocation and communication strategies. Such insights enable marketers to clearly recognize the sequences of user actions that most frequently lead to desired behaviors and, ultimately, to conversions. Moreover, marketing attribution enhances the customer experience by facilitating a deeper understanding of the customer journey, highlighting pivotal touchpoints, and identifying areas for improvement.

As a technical process, marketing attribution entails the systematic collection, processing, and analysis of user interaction data. The data collection stage is implemented through core tracking technologies such as cookies, tracking pixels, UTM tags, and other mechanisms that enable the identification of traffic sources and user behavior on websites. These data, in turn, form the foundational basis for constructing effective attribution models.

Traditional rule-based marketing attribution models, which attribute the entirety of value to a singular touchpoint, no longer provide a sufficient level of analytical precision. In response to these limitations, attention is increasingly gravitating towards the adoption of data-driven attribution models. While the market currently furnishes a diverse array of tools enabling the application of classification algorithms, Bayesian analysis, and other techniques for marketing attribution, substantial potential remains for advancing this class of models through more sophisticated mathematical approaches. Specifically, stochastic modeling and game theory present compelling avenues for development. In particular, Markov chain models and Shapley value-based approaches enable a rational and quantitatively verifiable allocation of value across all digital marketing channels. The adoption of such models thus presents novel opportunities for developing evidence-based frameworks for marketing resource allocation and for the strategic governance of communication channels. Consequently, research into marketing attribution models retains substantial relevance. This imperative is driven, on the one hand, by the exigencies arising from the escalating complexity of the modern digital landscape, alongside heightened demands for computational precision, analytical transparency, and judicious budget management; and, on the other hand, by the imperative for businesses to access practical tools for resolving marketing attribution challenges.

The paper aims to propose an accessible, high-quality, and effective data-driven tool for addressing marketing attribution challenges within today's complex digital multichannel environment. To achieve this objective, several key tasks were undertaken: conducting a comparative analysis of current marketing attribution models in terms of their capabilities and limitations in practical digital marketing applications; outlining the strong potential of data-driven approaches – particularly stochastic and game-theoretic models – for enhancing the accuracy of channel contribution evaluation in a complex multichannel context; conceptualizing the process of attribution modeling based on Shapley values using Python libraries; and practically implementing the proposed approach using real-world marketing campaign data to develop actionable recommendations for improving digital marketing performance.

The research findings demonstrate that rational and effective marketing attribution models, along with accessible tools, can be successfully adopted by companies of various sizes and levels of IT infrastructure maturity. These tools can contribute to improved marketing campaign performance, more efficient advertising budget allocation, and better decision-making based on more accurate analytical models.

Literature review. Recent years have witnessed substantial advancements in the field of digital marketing, particularly in attribution modeling, which enables companies to more effectively assess the impact of their marketing efforts. Foundational studies, such as the systematic review (Dhar, & Singh, 2020), underscore the escalating complexity and paramount importance of attribution modeling for comprehending customer pathways to conversion, concurrently providing a comprehensive overview of extant methodologies and delineating prospective research trajectories. Similarly, a review (Yusup et al., 2024) centers on the pivotal role of artificial intelligence within digital marketing, a factor critical to the advancement of novel algorithmic attribution models.

Modern attribution approaches actively employ advanced algorithmic techniques. The authors of such a study (Lee et al., 2021) conduct a comparative analysis and interpretation of models for predicting online conversions, an integral component of assessing marketing touchpoint efficacy. Karray, Martín-Herrán, and Sigué (2022) address the management of advertising investments across marketing channels, thereby underscoring the critical importance of multichannel analytics and strategic budget allocation. Particular emphasis is placed on models capable of accounting for the intricate interactions among touchpoints. Dhar and Singh (2020) presented a comprehensive literature review on attribution modeling in marketing, offering a solid theoretical foundation and identifying key directions for future research. Furthermore, other researchers (Zhao, Mahboobi, & Bagheri, 2022) delve into game-theoretic models of marketing attribution, enabling the equitable distribution of value among various marketing channels based on their incremental contribution, notably through the application of Shapley value theory.

Understanding user behavior and optimizing advertising activities are central to effective digital marketing. A simulation-based model is proposed to forecast the dynamics of consumer behavior under digital advertising influence and to support budget allocation decisions (Dorokhova et al., 2023). Furthermore, contemporary research actively utilizes data science for modeling. Some studies (Chornous, & Fareniuk, 2021) apply data science technologies to model the marketing mix in pharmaceutical companies, demonstrating the practical application of algorithmic models for evaluating investment effectiveness. Ben Mrad and Hnich introduce an intelligent attribution modeling framework in this context (Ben Mrad, & Hnich, 2024) that leverages advanced analytics to optimize digital marketing performance. Likewise, Seth and Ramakrishnan present innovations in multi-touch attribution models tailored to the pharmaceutical sector, moving beyond traditional marketing analytics to capture the nuanced contributions of diverse channels (Seth, & Ramakrishnan, 2025).

Recent literature demonstrates a significant evolution of marketing mix modeling (MMM) and attribution analytics, moving from classical brand-management frameworks (Cain, 2014) toward data-driven, digitally oriented methodologies. Studies on digital strategy adaptation (Dumitrescu et al., 2018) and foundational reviews of attribution modeling (Gaur, & Bharti, 2020; Mathew, 2016) highlight the increasing analytical complexity of evaluating channel effectiveness. Research further explores advanced approaches for multi-channel attribution across competitors (Li et al., 2017) and the shift toward inferential and post-cookie attribution techniques (Kamena, 2021; Hosahally et al., 2025). Modern MMM has progressed from traditional regression models to AI-powered and neural-network–based architectures (Gujar et al., 2024; Mulc et al., 2025), while applications in real business environments confirm their practical suitability (Ravid, 2025; Sciarrino et al., 2025). Additional studies emphasize model comparison (Sharma, Meena, & Ibrahim, 2017), omnichannel attribution challenges (Méndez-Suárez, & Monfort, 2021), and the integration of multi-information fusion to bridge MTA and MMM (Zhou, Pei, & Li, 2024). Together, these works reflect a consolidated trend toward more granular, algorithmic, and privacy-resilient attribution models in contemporary digital marketing.

A review of contemporary literature reveals a growing trend towards applying sophisticated algorithmic models based on game theory, machine learning, and stochastic modeling (including Markov chains) for more precise marketing attribution and investment optimization in digital and multichannel marketing. These studies form the foundation for more effective strategies that consider the dynamics of consumer behavior and the complexity of interactions between marketing channels. This paper conducts a comparative analysis of modern attribution models and proposes and implements a model based on Shapley values in a Python environment, which can be beneficial for real-world businesses of various sizes and IT infrastructure maturities.

Methods

The paper employs both general scientific and specialized research methods. General scientific methods include the dialectical method, systems approach, methods of analysis and synthesis, and induction and deduction.

Within the framework of economic-mathematical modeling, stochastic modeling (Markov chains) and elements of cooperative game theory (specifically, Shapley values) are considered. The methodological toolkit of the study also encompasses methods from probability theory, rule-based modeling, data analysis and processing using the Python programming environment (pandas, numpy, matplotlib libraries), methods of comparative analysis, and results visualization. The application of these approaches ensured a comprehensive analysis of the selected problematic area and enhanced the reliability of the conclusions drawn.

The marketing attribution models examined in the study are categorized into two main groups: deterministic (rule-based models) and adaptive (algorithmic). The first group of models includes Single-Touch Attribution Models, specifically First Touch Attribution and Last Click Attribution, as well as Multi-Touch Attribution Models such as Linear Attribution, Time-Decay Attribution, Position-Based Attribution, W-Shaped Attribution, and Custom Attribution (Sun, 2023). Web analytics platforms, such as Google Analytics, traditionally use a Single-Touch Attribution approach by default for conducting attribution analysis.

Adaptive models study historical user data to identify patterns in interactions with marketing channels. Among these models, the most common is the data-driven attribution approach (Ben Mrad, & Hnich, 2024), which involves using classification algorithms, Bayesian analysis, or ensemble methods to distribute value among channels based on their actual contribution to conversion. The group of adaptive models also includes Markov chains, which are probabilistic models explored in this study. Markov chains enable the representation of user interaction sequences and the calculation of transition probabilities between touchpoints (Mehta, & Singhal, 2020). Markov chains are characterized by a defined state space, a transition matrix (describing probabilities between states), and an initial state or distribution. The constructed graph represents interaction points with existing transitions corresponding to specific probabilities. Graph construction is based on historical user interaction data. Conversion is modeled as a final state, while abandonment (null) is an alternative terminal state. To assess the significance of each channel, the "removal effect" approach is applied. This involves analyzing how the elimination of a specific node impacts the probability of achieving conversion (e.g., purchase, other primary action). Markov chains effectively account for not only the sequence of touchpoints but also their interdependencies, including the presence of cycles (loops) that occur when a user repeatedly interacts with the same channel. For more complex graphs with numerous cycles, iterative approximation methods are used to estimate conversion probability, even with an infinite number of possible paths.

The Shapley value model implemented in this study originates from game theory. The main problem addressed by the Shapley value is the fair distribution of credit in a game where players can form coalitions (Zhao, Mahboobi, & Bagheri, 2022). In the context of marketing attribution, game theory is utilized to model customer interactions with marketing channels as a cooperative game, where each marketing channel can be viewed as a player. The collective of all players/channels works together to drive conversions and assigns each touchpoint fair credit (using these Shapley values) for a conversion based on its true contribution. The calculation of Shapley values for each channel i is performed using the formula:

$$\phi_i(N, v) = \frac{1}{|N|!} \sum_{S \subseteq N \setminus \{i\}} |S|!\,(|N| - |S| - 1)! \cdot [v(S \cup \{i\}) - v(S)], \quad (1)$$

where N – the set of all channels (players); $S \subseteq N \setminus \{i\}$ – a subset of channels not including channel i; $v(S)$ – the value function (conversion rate) generated by the coalition S; $v(S \cup \{i\}) - v(S)$ – marginal contribution of channel i to coalition S; $|S|!\,(|N| - |S| - 1)!$ – weighting factors considering the number of permutations of channels before and after the inclusion of channel i.

For each channel, all coalitions to which it does not yet belong are iterated over, and its marginal contribution to each of them is evaluated. The marginal contribution is defined as the difference between the value of the coalition after the inclusion of the given channel and its initial value:

$$\text{contrib}_i(S) = v(S \cup \{i\}) - v(S). \quad (2)$$

The contribution can be weighted using a combinatorial coefficient that accounts for the number of possible orders in which the channel can enter the coalition:

$$\text{weight}_i(S) = \frac{|S|! \cdot (|N| - |S| - 1)!}{|N|!}. \quad (3)$$

Thus, the Shapley model provides an objective and mathematically justified assessment of each channel's contribution to conversion based on its marginal effect across all possible channel coalitions.

Results

Model Comparison. The analysis of rule-based attribution models has revealed their advantages but also highlighted significant limitations, primarily in their ability to accurately capture the complex nature of consumer behavior. Table 1 presents a comparative overview of the main traditional marketing attribution models.

Table 1

Comparative Table of Main Rule-Based Marketing Attribution Models

Attribution model	Value Distribution	Optimal Use Case
First Touch	All value is assigned to the first touchpoint	Measuring the effectiveness of initial brand awareness
Last Touch	All value is assigned to the last touchpoint	Determining the final influence on decision-making
Linear	Value is evenly distributed across all touchpoints	When all touchpoints are considered equally important in the conversion process
Time-decay	More value is given to recent interactions, less to earlier ones	For longer sales cycles or when recent interactions have a stronger impact on conversion
Position-based	Value is distributed among different touchpoints (depending on the model or platform)	When both the first and last interactions are important
Custom	Value is assigned according to what is most important for the business	Best suited for companies with specific goals or unique customer journeys

Source: compiled by the authors.

Against the backdrop of the limitations of traditional models, adaptive approaches are gaining increasing importance. These approaches account for temporal dynamics, the sequence of touchpoints, and their statistical significance in driving conversion.

Markov chains effectively model the interrelationships between marketing channels, considering the sequence of actions, repeated interactions (cycles), and context in higher-order models. They are particularly useful for analyzing complex and long conversion paths where traditional attribution models are insufficient. The application of the "removal effect" metric allows for the identification of channels with a critical impact on conversion, while robustness to noise and flexibility ensure the model's scalability. Nevertheless, the model has several limitations: it is based on correlations rather than causal relationships, which may lead to erroneous attribution of results to channels. Additionally, the classical "memoryless" approach does not always accurately reflect user behavior in complex scenarios. Model implementation requires a significant volume of data, access to complete user paths (including non-converting ones), and the use of specialized computational tools. Despite these challenges, Markov chains remain a powerful tool for evaluating channel effectiveness, provided a critical approach is taken to modeling and interpreting results.

The Shapley value model is widely used in the analytical systems of major advertising platforms to quantitatively assess the contribution of marketing channels to conversions by analyzing all possible channel coalitions. Due to the exponential growth in the number of combinations, its practical implementation requires substantial computational resources. To enable scalability for large datasets, approximation techniques and SHAP (SHapley Additive exPlanations) tools are commonly employed. The key advantages of the model include a fair and proportional allocation of channel influence that accounts for channel interactions, enhancing both interpretability and predictive accuracy compared to traditional approaches. At the same time, the model is constrained by high computational complexity, sensitivity to data variation, the need for large volumes of detailed data, and the inability to account for the sequence of interactions. These limitations highlight the need for further development of extended versions and efficient algorithmic solutions.

Table 2 presents a comparative analysis of the main characteristics of Markov chain-based and Shapley value-based attribution models.

Table 2

Comparative Analysis of Markov Chain-Based and Shapley Value-Based Attribution Models

Comparison feature	Markov chain-Based Model	Shapley value-Based Model
Model Type	Probabilistic, sequential	Game-theoretic, cooperative
Analysis of Channel Order Context	Takes the transition order into account	Order is not critical
Dependence on Temporal Structure	High	Minimal
Consideration of Channel Interactions	Limited, based on transitions	Comprehensive, considers all coalitions
Robustness to Sample Size Variation	High with large samples	Depends on computational resources
Computational Complexity	Moderate	High (exponential growth)
Flexibility to Adapt to Complex Scenarios	Limited by the first-order model	High due to the coalition-based approach
Interpretability of Results	High, but requires an explanation of the transition probability matrix	High, especially with SHAP visualizations
Dependence on Specification of Payoff Function (Business Goals)	Does not require an explicit definition	Requires a characteristic function
Relevance in Modern Tools	Common in web analytics	Integrated in modern ML platforms

Source: compiled by the authors.

The comparative analysis indicates that the Markov chain model is effective for accounting for the order of actions and is less resource-intensive, whereas the Shapley value model provides a more precise evaluation of each channel's contribution but requires substantial computational resources. Therefore, the choice between the two depends on the complexity of user paths, analytical objectives, and available resources. Both models have practical applications; however, in scenarios involving complex funnels and a high demand for attribution accuracy, the Shapley value model should be preferred. The following conceptual steps are proposed for its implementation in Python.

Conceptualization. The first stage involves performing preliminary data analysis. Using the Python libraries pandas, numpy, and matplotlib, the dataset is loaded and its structure is initially explored (including general data overview and exploratory data analysis – EDA), missing values and anomalies are identified, key variables are determined, and preliminary visualizations of interactions between variables are created (libraries matplotlib, seaborn, and plotly.express).

Next, data preparation for modeling is conducted. This stage includes aggregating data to the user level by constructing ordered sequences of channels (user journeys), which enables the representation of individual interaction paths with the campaign. For each user, a set of channels interacted with is formed, along with a record of whether a conversion occurred. A coalition table is created containing unique channel combinations and the corresponding number of conversions, providing a basis for subsequent calculations.

The following step is building the attribution model based on Shapley values. The methodology involves generating the full set of possible channel coalitions, calculating the marginal contribution of each channel across all possible combinations, and normalizing the results to obtain relative influence shares. The resulting values are visualized using Python's graphical tools to enhance interpretability and facilitate comparison of individual channel contributions.

To improve the robustness of the analysis, it is advisable to additionally implement rule-based marketing attribution models, such as Linear Attribution and Last Touch Attribution. This allows for the comparison of the adaptive approach results with traditional methods, identification of key discrepancies in channel contribution assessments, and evaluation of model quality through benchmarking against baseline methods. To implement the previous three steps, in addition to the aforementioned Python libraries (such as NumPy and pandas), the study also employed Seaborn and Plotly Express libraries for data visualization, as well as the built-in Python modules itertools.combinations for working with iterators and collections.defaultdict for enhanced data structures.

The next stage involves a comparative analysis of the obtained results, during which the effectiveness of channels across different attribution models is evaluated. This analysis enables the identification of key channels that demonstrate consistent influence across various approaches, as well as the detection of channels whose contribution significantly increases only within the context of multichannel interactions.

The final stage consists of formulating conclusions and practical recommendations for optimizing marketing budgets, enhancing channel effectiveness, and designing multichannel campaigns based on attribution results. These insights empower companies to make informed and rational strategic decisions grounded in data.

Experiment. To develop the Shapley value–based attribution model, a real dataset from a digital advertising campaign was utilized, comprising 10,037 records of user interactions with various marketing channels throughout January 2018. The campaign promoted a digital product offering online educational services. The key variables selected for modeling include user_id (a unique identifier distinguishing individual users within the dataset), marketing_channel (indicating the channel through which the marketing message was delivered: Email, Facebook, Instagram, Push, House Ads), date_served (the date the marketing message was shown, necessary for determining the order of touchpoints in the user journey), and converted (a binary variable: True if the user completed a conversion such as a purchase or subscription following the interaction, False otherwise. This is the primary target variable for attribution modeling as it defines interaction success. These variables contain a minimal amount of missing data (up to 0.2%) and allow tracking of individual user paths to conversion. Other subscription-related variables were excluded due to their irrelevance to the attribution analysis. Missing values in critical variables were handled by row deletion without compromising data quality. Exploratory data analysis focused on deriving insights, verifying data distributions, and preparing for modeling, with particular attention to the conversion rate, frequency of channel usage, and channel combinations leading to conversions. The analysis revealed a moderate class imbalance, with successful conversions (converted = True) constituting approximately 60% of observations and unsuccessful ones (converted = False) about 40%, which is favorable for model training without additional adjustment. Regarding channel usage, House Ads emerged as the most engaged channel with over 250 impressions, followed by Instagram and Facebook (~105 impressions each), indicating an uneven distribution of marketing efforts. The relationship between impression frequency and number of conversions showed a direct linear correlation: House Ads led both in impressions and conversions, whereas Instagram and Facebook exhibited high conversion rates despite fewer impressions. Email and Push had limited impressions and correspondingly fewer successful interactions. These findings confirm that an increase in interaction volume directly correlates with a rise in the absolute number of conversions (Fig. 1).

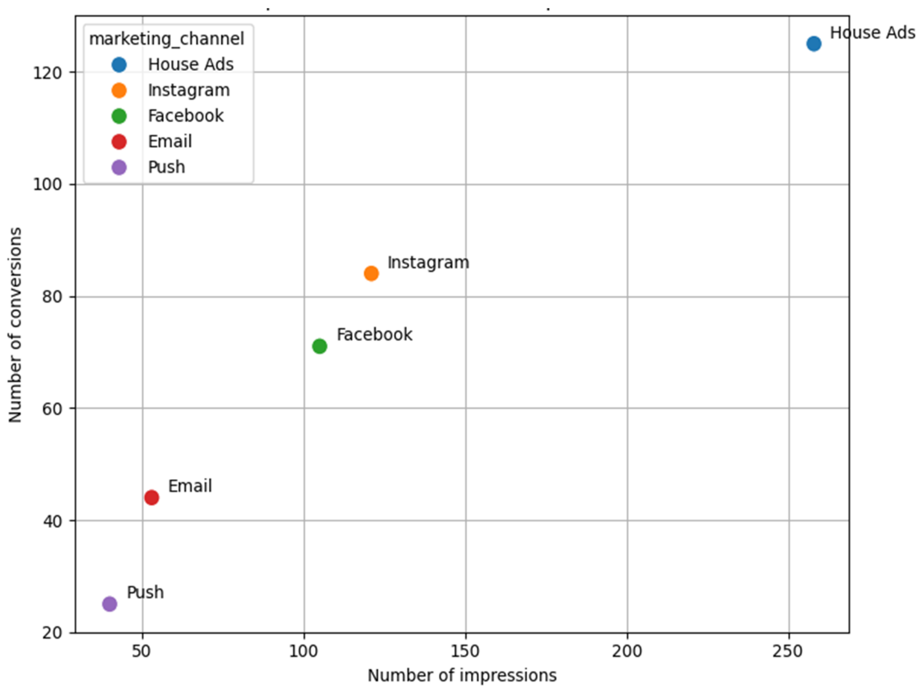

Fig. 1. Relationship Between the Number of Impressions and Conversions

Source: Compiled by the authors using Python environment

Continuing the analysis of channel effectiveness, the next stage focused on examining the interrelationships among marketing channels that appear together within a single user's journey. Frequency of impressions and conversion rates – even when combined with conversion share metrics – do not fully capture the multichannel nature of digital campaigns. It is therefore essential to identify which channels most frequently co-occur in user interactions. A channel co-occurrence matrix constructed in the Python environment (see Fig. 2) revealed that House Ads is the most integrated channel, frequently appearing alongside Instagram (70 cases), Facebook (43), and Push (20), emphasizing its central role in the campaign. Instagram also frequently co-occurs with Facebook (29), forming a stable interaction cluster. In contrast, Email and Push are less commonly found in combinations, typically appearing in isolated or supplementary scenarios.

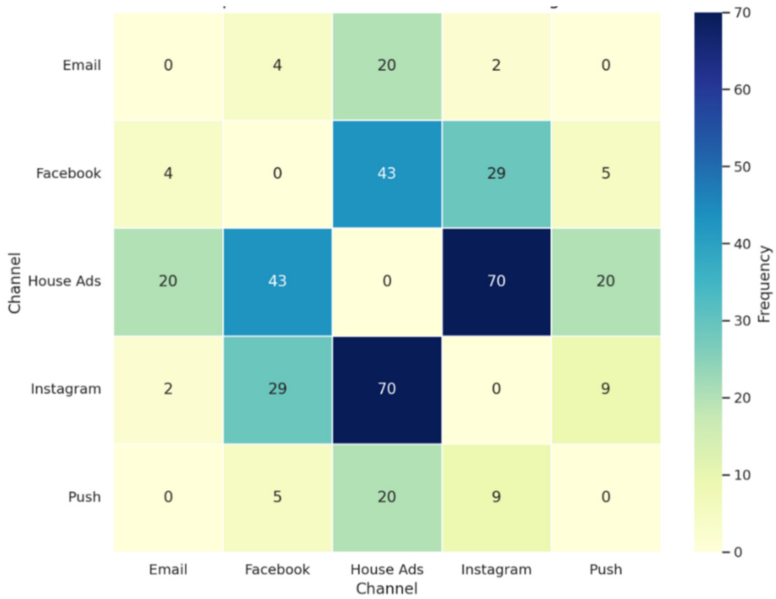

Fig. 2. Heatmap of Channel Co-Occurrence Frequency per User

Source: Compiled by the authors using Python environment

The data indicate a moderate class imbalance, with approximately 60% of interactions resulting in conversions. House Ads clearly dominate in both the number of impressions and conversions, followed by Instagram and Facebook in intermediate positions. Although Email demonstrated a lower reach, it exhibited a high conversion rate when applied in a targeted manner. The analysis of channel combinations confirms the central role of House Ads and the strong interconnection between Instagram and Facebook, which constitutes an important business insight for evaluating the results of attribution models.

In the next stage of the study, a Shapley value–based marketing attribution model was constructed to determine the marginal contribution of each marketing channel to conversions, taking into account all possible combinations of its occurrence in user paths. Before calculating the Shapley values, the data were aggregated at the user level: for each user_id, the unique marketing_channel values that appeared in the sequence of impressions were concatenated. The uniqueness function ensured that each channel in a user journey was considered only once, but preserved the order of appearance. The result was a string such as 'Email, Push, Facebook', representing the user's journey. Each user was also assigned a binary label indicating whether their path ended in a conversion.

The following step involved grouping users by unique channel combinations, reflecting all observed channel coalitions in actual journeys. For each such coalition, the number of conversions completed by users who followed that specific path was calculated. As a result, an aggregated coalition combination was constructed, with each entry representing a specific channel combination along with the corresponding number of successful conversions (Fig. 3).

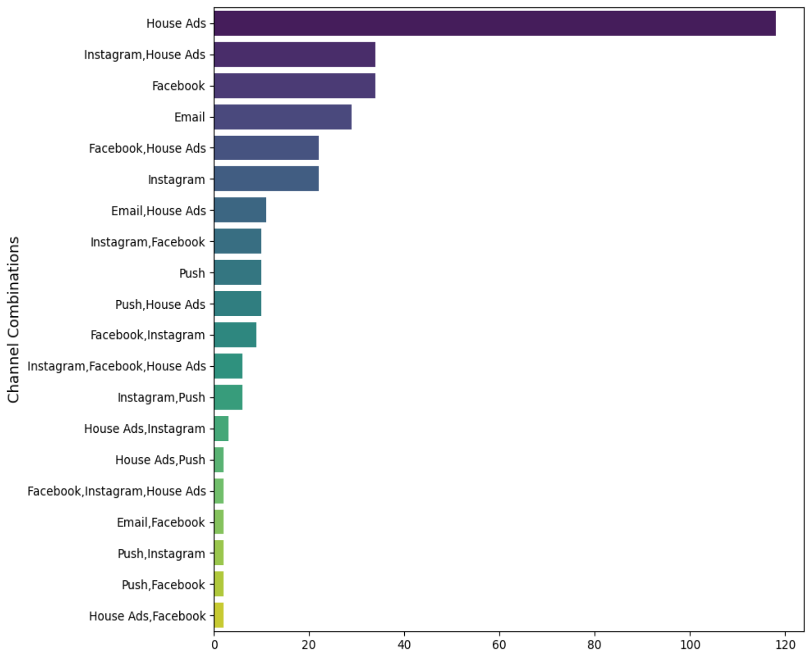

Fig. 3. Main Channel Combinations by Conversions

Source: Compiled by the authors using Python environment

To proceed with the calculation of Shapley values, a complete set of potential channel coalitions that could theoretically arise within user interactions was generated. This involved creating all possible non-empty subsets from the available list of channels, including individual channels, pairs, triplets, and so forth. These subsets are treated as coalitions, with each possessing a potential "value", i.e., the number of conversions associated with that specific channel combination (Cooper, 2022). For this stage, a function was implemented that, given a list of channels, generates all possible combinations (subsets) of length from 1 to n, where n is the number of unique channels in the dataset. These combinations represent all configurations in which the channels may jointly appear. An auxiliary function converts each subset into a sorted string format (e.g., 'Email, Facebook'), ensuring consistent storage of values in subsequent dictionaries. This process produced the analytical space of all possible coalitions, forming the foundation for computing the marginal contribution of each channel.

The next stage involved defining the value function *v(S)*, which calculates the overall "value" or effectiveness of a given coalition – its conversion strength. For each coalition (e.g., ['Email', 'Facebook']), the function searches for all its subsets (such as ['Email'], ['Facebook'], and ['Email, Facebook']) and sums their corresponding values from the conversion_dict.

$$v(S) = \sum_{T \subseteq S} \text{conversion}(T), \tag{4}$$

where S denotes a coalition of channels, and T refers to a subset of S that is present in the conversion dictionary.

For example: *v(['Email', 'Push']) = conversion('Email') + conversion('Push') + conversion('Email, Push').*

Next, the Shapley values for each channel i were calculated using the classical formula (1).

The calculation was implemented as a separate function that received as input an aggregated Data Frame containing channel combinations and the corresponding number of conversions for each. From this Data Frame, a dictionary was created where the keys were strings representing the channel combinations (e.g., "Email, Push"), and the values represented the number of conversions attributed to each coalition. This structure enabled efficient access to the necessary values during computation. Subsequently, all channels that appeared in solo combinations – i.e., in user paths where only one channel was encountered – were identified. The next step involved calculating the coalition value function, as previously defined, for all possible subsets of channels. For example, if a coalition consisted of three channels, its value was computed as the sum of conversions for all single, pairwise, and triple combinations present in the dataset. For each channel, all coalitions in which it was not initially present were iterated over, and its marginal contribution to each was evaluated (using formulas (2) – (3)).

As a result, each channel received a Shapley value, interpreted as its average marginal contribution to achieving a conversion, taking into account all possible coalitions and interaction sequences. The highest Shapley value was observed for the House Ads channel, with a contribution of 137.33, indicating its critical role in the user's path to the target action. This result confirms not only its high frequency of use but also its significance in combinations with other channels – House Ads consistently delivers the highest incremental value to the coalitions it is part of. Facebook ranked second in terms of influence, with a Shapley value of 51.83, reflecting the channel's stable effect both in solo and multi-channel pathways. Email and Instagram demonstrated similar levels of influence – 36.33 and 31.50, respectively – indicating moderate yet systematic involvement in conversion chains. The lowest contribution was observed for Push (15.00), which correlates with its less frequent usage and limited marginal effect in the context of interactions with other channels.

To evaluate the results, normalization of the values was performed by converting the absolute contributions of the channels into relative shares (Table 3). This process involved dividing each channel's contribution by the total sum of contributions, thus determining its share of the overall conversion impact. House Ads accounts for 50% of the total influence. While functionally effective, this also indicates a potential dependence of the overall conversion strategy on this internal channel. Such a concentration poses a risk of overreliance but simultaneously presents an opportunity to scale this successful pattern to external or emerging channels. Facebook, with a share of 19.06%, may serve as a connecting touchpoint between user interactions across different channels. This signals the potential for further investment in Facebook as a channel with growth capacity through enhanced engagement. Email and Instagram exhibit relatively similar performance – 13.36% and 11.58%, respectively – demonstrating consistent, though moderate, contributions to conversion. Push notifications represent only 5.51% of the total. Despite the low share, this communication channel holds potential for targeted impact, particularly in reactivating dormant users or executing time-sensitive promotional campaigns.

Table 3

Normalized percentage contributions of channels to conversion according to three attribution models, %

Marketing Channel	Attribution Model		
	Shapley Values Attribution	Linear Attribution	Last Touch Attribution
House Ads	50.49	47.86	60.23
Facebook	19.06	18.08	14.62
Email	13.36	10.62	8.48
Instagram	11.58	16.81	10.82
Push	5.51	6.63	5.85

Source: compiled by the authors.

To evaluate the effectiveness of the developed model and validate the accuracy of the calculated contributions, its results were compared with classical rule-based attribution models, which constituted the next step of the study. Specifically, the logic of the Linear Attribution model was implemented, in which the contribution to conversion is evenly distributed among all channels present in the user's journey. This model does not account for the order of influence but only for the presence of a channel. Each channel involved in the path to conversion receives an equal share of the attribution. After normalizing the contribution of each channel, the highest percentage contribution, similar to the Shapley Values model, was assigned to the House Ads channel (47.86%). Facebook ranked second (18.08%), followed by Instagram (16.81%), while Email accounted for 10.62%. The smallest share was assigned to Push notifications (6.63%). Additionally, a Touchpoints table (Table 4) was created to determine the specific stage in the user journey at which each channel had the greatest impact. For instance, in the sequence Email → Facebook → House Ads, Email corresponds to Touchpoint 1, Facebook to Touchpoint 2, and House Ads to Touchpoint 3. The maximum number of touchpoints in the dataset is three.

Table 4

Distribution of Channel Contribution by Touchpoints (Linear Attribution)

Channel	Touchpoint 1 (%)	Touchpoint 2 (%)	Touchpoint 3 (%)	Total (%)
House Ads	44.07	61.44	100.0	47.86
Facebook	18.68	16.49	0.0	18.08
Instagram	17.90	13.03	0.0	16.81
Email	13.18	0.00	0.0	10.62
Push	6.17	09.04	0.0	6.63

Source: compiled by the authors.

The analytical results indicate that the House Ads channel demonstrates dominance across all stages of the user journey, including the final touchpoint. Facebook and Instagram primarily appear at the initial and intermediate stages (1st–2nd touchpoints), thus serving as acquisition or supporting channels. Consequently, their contribution to the final conversion may be underestimated by traditional attribution models, such as the Last Touch approach. Email frequently functions as the initial point of contact that initiates user engagement (e.g., via newsletters) and, in certain instances, may independently lead to conversion within a single-step purchase path. Push notifications act as supplementary communication tools, predominantly occurring within the first two touchpoints. They typically function as reminders activated through mobile applications and have a relatively limited impact on conversion outcomes.

The Last Touch Attribution model evaluates the impact of channels based on their role in concluding the user journey before conversion, disregarding previous interactions. It is suitable for scenarios where the final contact is considered decisive. According to the analysis conducted in Python, the leading channel is House Ads, accounting for 60.23% of conversions as the last touchpoint due to its dominance at the second and third touchpoints. This channel frequently serves as the final element in the communication chain, effectively "closing" the deal. Facebook (14.62%), Instagram (10.82%), and Email (8.48%) play less significant roles. Notably, Email appears exclusively at the first touchpoint and is absent from the second, meaning that under the Last Touch model, conversions associated with Email are attributed only when it serves as the initiating contact.

Within the framework of a comparative analysis of three attribution models – Shapley Values, Linear Attribution, and Last Touch Attribution – certain differences in the distribution of marketing channel contributions were identified. These findings allow for a series of conclusions regarding user behavior, the effectiveness of marketing efforts, and the characteristics of each model. The results of the channel contribution comparison are presented in Table 3.

First, the Last Touch Attribution model places maximum emphasis on the final point of contact, assigning the entire value of the conversion to the last channel in the user's journey. This leads to an overestimation of channels that frequently conclude interactions, particularly House Ads, which receive the highest share (60.23%). However, this model neglects prior stages of the user journey. Second, the Linear Attribution model distributes value evenly across all channels in the conversion path, reducing the weight of the final touchpoint and increasing the contribution of channels that consistently appear in multi-touch sequences, such as Instagram and Email. These channels demonstrate higher contributions compared to the Last Touch model, as their supporting role in a multichannel context is recognized. Third, the Shapley Values model offers the most structured and mathematically grounded assessment by allocating the value of each channel according to its marginal contribution across all possible channel coalitions. This approach identifies channels whose effectiveness increases through interaction with others (e.g., Email, with a share of 13.36% under Shapley versus 8.48% under Last Touch), eliminates the "last-touch bias," provides a more realistic estimate of the weight of House Ads (50.49%), and consistently excludes low-impact channels such as Push, which maintains a minimal contribution across all models.

Thus, the differences in evaluation are determined by the conceptual assumptions of each model regarding the causal relationships between channels and conversion: Last Touch simplifies them to the final interaction; Linear distributes value evenly without considering context; Shapley assesses the actual impact, accounting for the sequence and interaction of channels. This is why Shapley Values is considered more appropriate for optimizing marketing budgets in complex multichannel environments.

Based on the implemented model, marketers gain valuable insights into the effectiveness of their marketing efforts and budget planning. Regarding the strongest conversion driver – House Ads (50.49%) – the following recommendations are appropriate: continue investing in internal advertising (in-app ads, banners, recommendation blocks within the interface); further unlock the channel's potential through enhanced personalization (e.g., adapting creatives based on past user interactions); use House Ads as a retargeting tool for users who have previously interacted with other channels (e.g., Email or Instagram); develop behavior-based scenarios (e.g., "House Ads only after email open").

Facebook (19.06%) – an effective support and engagement channel. It plays a role in both the upper and middle stages of the funnel, generating initial interest and maintaining the momentum of user transitions. Its contribution in coalitions is significant, especially in combination with House Ads. Recommendations for channel optimization: launch ad campaigns with detailed audience targeting (Lookalike Audiences based on conversion behavior); use Facebook as a "reminder" channel, especially in interaction sequences where it is not the first touchpoint; test video formats and interactive posts to increase engagement depth before the appearance of House Ads.

Email (13.36%) – a stable channel, yet requires systematic expansion of interactions. It does not function independently as a final trigger, but significantly amplifies the effect of combinations. The contribution in the Shapley model is higher than in Last Touch. Further integration of email marketing at the final stages of the user journey is needed. As a core CRM tool, Email should re-engage users who did not convert at earlier stages. Recommended actions: identify audience segments with a high likelihood of email response (e.g., based on Retention data); apply trigger-based campaigns such as abandoned cart, re-engagement, and onboarding; conduct A/B tests on subject lines, send times, and CTA formats (call-to-action).

Instagram (11.58%) received higher scores in traditional models but lower scores in the Shapley model. The nature of this channel points to high visibility but a relatively weak marginal effect, indicating a limited impact on final decision-making and its appearance alongside more influential channels. It primarily builds emotional connection and enhances user engagement. Practical recommendations: use Instagram mainly at the early stages of the funnel (awareness), with creatives that build brand perception; integrate it with House Ads or Facebook to support multichannel communication; run campaigns linking to a landing page (LP) rather than just the brand profile to increase the likelihood of final conversion.

Push notifications (5.51%) – a low-impact channel in need of relaunch. It shows the smallest contribution across all models. Its influence is insufficient and poorly structured. As the channel with the fewest impressions, it requires traffic growth for proper testing and assessment of its effectiveness. There's a rationale to revise the tactic or audience targeting. Recommendations for optimization: shift to more personalized push notifications (e.g., referencing prior user actions); limit frequency and apply A/B testing – whether to send push before or after email or other channels; measure open time and its influence on re-engagement.

Therefore, by leveraging the flexibility and precision of the Shapley model, a company can effectively assess the marginal effect of each touchpoint. This approach will mitigate dependence on traditional models, which consistently overvalue the final stages of user interaction with channels. Concurrently, it will facilitate a more efficient allocation of the marketing budget, as channels with negligible impact will no longer receive disproportionate funding. Basing decisions on the actual impact of channels, rather than merely their frequency or reach, will enable more precise planning of multichannel campaigns. Ultimately, this will empower the company to formulate a truly coherent marketing strategy, wherein each channel functions as part of a synchronized system geared towards effective user engagement.

Discussion and conclusions

The study addresses the problem of marketing attribution in the modern digital environment and proposes effective approaches for modeling channel impact using both traditional and adaptive methods. The theoretical foundations of marketing attribution are summarized, and a comparative analysis of its principal models is presented. It is established that traditional rule-based models (such as First/Last Click, Linear, and U-shaped), while popular due to their simplicity, present significant limitations in the context of complex multichannel interactions. These models fail to consider the sequence, context, and interdependencies between touchpoints, resulting in a distorted understanding of the actual contribution of channels. Particular attention is given to Markov chains as a stochastic method for assessing channel impact, as well as to the Shapley value model derived from cooperative game theory. Both approaches demonstrate a stronger capacity to account for channel interactions, user journey context, and multichannel effects – substantially outperforming rule-based models in digital marketing settings. The Shapley Values Attribution model was implemented in a Python environment using real-world data. This allowed for the reconstruction of detailed user journeys, the formation of channel coalitions, the calculation of the marginal contribution of each channel across all possible combinations, and the visualization of the results. As a result, the analysis identified the channels with the greatest marginal effect in driving conversions while avoiding the overvaluation of channels with high interaction frequency but minimal actual impact.

It is important to acknowledge that the findings presented in this study are derived from a single dataset; comparable approaches have been employed by other explorers (Mehta & Singhal, 2020; Ben Mrad & Hnich, 2024), who similarly conducted analyses on limited samples. To strengthen the external validity and generalizability of these results, future research should consider applying the proposed methodology to diverse datasets encompassing varying product verticals, temporal frameworks, and channel configurations. Such extensions would facilitate the evaluation of the model's robustness across different contexts and enhance confidence in the applicability of the conclusions drawn.

Notwithstanding the model's potential precision, critical questions remain concerning the practical interpretability of Shapley value–based attribution outcomes, particularly when juxtaposed with simpler, more conventional models favored by practitioners. Additionally, the feasibility of implementing this approach in small enterprises with constrained computational resources, alongside its limitations under conditions of fluctuating user behavior, warrants further investigation. Moreover, systematic comparisons with other publicly available empirical studies are recommended to enable a more comprehensive understanding of the influence exerted by individual marketing channels.

A comparative analysis of the results from rule-based models (Last Click, Linear Attribution) and the algorithmic Shapley-based approach confirmed that rule-based models tend to overly concentrate or oversimplify influence. In contrast, the Shapley model enabled an objective evaluation of channel contributions across different combinations, confirming its superior accuracy, flexibility, and predictive power in marketing analytics.

Based on the results, a meaningful interpretation of channel contributions was proposed. The roles of individual channels within the user journey were identified, key channels at different stages of the funnel were determined, and budget optimization opportunities were revealed. The findings not only confirmed the advantages of adaptive attribution models but also illustrated how accurate analytics can become a strategic asset in a world where every customer interaction matters. Future research will aim to expand the analysis by incorporating additional factors such as the temporal dynamics of interactions, acquisition costs across different channels, and user segmentation by behavioral and demographic characteristics. This will facilitate the development of more sophisticated and flexible attribution models that consider not only the contribution of channels to conversions, but also their effectiveness over time, across audience segments, and within budgetary constraints.

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References

Ben Mrad, A., & Hnich, B. (2024). Intelligent attribution modeling for enhanced digital marketing performance. *Intelligent Systems with Applications*, 21, 200337. https://doi.org/10.1016/j.iswa.2024.200337.

Cain, P. M. (2014). Brand management and the marketing mix model. *Journal of Marketing Analytics*, 2(1), 33–42.

Chornous G., & Fareniuk Y. (2021). Marketing mix modeling for pharmaceutical companies on the basis of data science technologies. *Access to science, business, innovation in digital economy*, 2(3), 274–289. https://doi.org/10.46656/access.2021.2.3(6)

Cooper, A. (2022, December 31). *How Shapley values work.* https://www.aidancooper.co.uk/how-shapley-values-work/

Dhar, S., & Singh, N. (2020). Attribution Modelling in Marketing: Literature Review and Research Agenda. *Academy of Marketing Studies Journal*, 24(4), 1–21. https://www.abacademies.org/articles/Attribution-modelling-in-marketing-Literature-review-and-Research-Agenda-1528-2678-24-4-313.pdf

Dorokhova, L., Kuusik, A., Dimitrov, R., Pentus, K., Dorokhov, O., & Petrova, M. (2023). Planning the digital marketing budget: computer modelling for decision making. *Access to science, business, innovation in the digital economy,* 4(2), 248–260. https://doi.org/10.46656/access.2023.4.2(7)

Gaur, J., & Bharti, K. (2020). Attribution Modelling in Marketing: Literature Review and Research Agenda. *Academy of Marketing Studies Journal,* 24(4), 1–21. https://www.abacademies.org/articles/attribution-modelling-in-marketing-literature-review-and-research-agenda-9492.html

Gujar, P., Paliwal, G., Panyam, S., & Kewalramani, C. (2024). The evolution of ads marketing mix modeling (MMM): From regression models to AI-powered planning for SMBs. *IEEE Technology and Engineering Management Society Journal*, 1(1), 1–6. https://doi.org/10.1109/TEMSCONLATAM61834.2024.10717768.

Hosahally, S., Bharadwaj, M., Zaremba, A., & Volkova, O. (2025). Measuring digital advertising in a post-cookie era: A study of marketing-mix models, attribution and incrementality. *Journal of Digital & Social Media Marketing*. 12(4), 348–373. https://doi.org/10.69554/wsat6359.

Kamena, R. (2021). Moving towards inferential attribution modelling in a world without third-party cookies. *Applied Marketing Analytics: The Peer-Reviewed Journal*. 7(2), 122–130. https://doi.org/10.69554/gltl7716.

Karray S., Martín-Herrán G., Sigué S.P. Managing advertising investments in marketing channels. *Journal of Retailing and Consumer Services*, 2022, 65, 102852. https://doi.org/10.1016/j.jretconser.2021.102852

Lee, J., Jung, O., Lee, Y., Kim, O., & Park, C. (2021). A Comparison and Interpretation of Machine Learning Algorithm for the Prediction of Online Purchase Conversion. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(5), 1472–1491. https://doi.org/10.3390/jtaer16050083

Li, Y., Xie, Y., & Zheng, Z. (2017). Modeling Multi-Channel Advertising Attribution Across Competitors. *Microeconomics: Intertemporal Consumer Choice & Savings eJournal*, (Working Paper No. 3047981, pp. 1–58). https://doi.org/10.2139/ssrn.3047981.

Mathew, M. (2016). Attribution: Untangling the web of confusion – a primer for marketers. *Applied Marketing Analytics: The Peer-Reviewed Journal,* 329–339. https://doi.org/10.69554/ijhx1689.

Mehta, K., & Singhal, E. (2020). Marketing channel attribution modelling: Markov chain analysis. *International Journal of Indian Culture and Business Management*, 21(1), 63–77. https://doi.org/10.1504/ijicbm.2020.10027991

Méndez-Suárez, M., & Monfort, A. (2021). *Marketing Attribution in Omnichannel Retailing,* Springer (114–120). https://doi.org/10.1007/978-3-030-76935-2_14.

Mulc, T., Anderson, M., Cubre, P., Zhang, H., Liu, I., & Kumar, S. (2025). *NNN: Next-Generation Neural Networks for Marketing Mix Modeling.* ArXiv, abs/2504.06212. https://doi.org/10.48550/arXiv.2504.06212.

Ravid, R. (2025). *Marketing Mix Modeling in Lemonade.* ArXiv, abs/2501.01276. https://doi.org/10.48550/arXiv.2501.01276.

Sciarrino, J., Friedman, J., Kirk, W. T., Mayers, C. A., & Prudente, J. J. (2025). Salespersons as media channel: Making marketing mix modelling work for business-to-business. *Journal of Digital & Social Media Marketing*, 12(4). https://doi.org/10.69554/WNIS8466

Seth, S., & Ramakrishnan, S. (2025). Innovations in Multi-Touch Attribution Models: Beyond Traditional Marketing Analytics in the Pharmaceutical Sector. *2025 International Conference on Emerging Smart Computing and Informatics (ESCI)* (pp. 1–5). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/ESCI63694.2025.10988316. https://doi.org/10.1109/ESCI63694.2025.10988316.

Sharma, P., Meena, J., & Ibrahim, S. (2017). Media mix modeling comparison of interaction model to simple log-linear model. *Asian Journal of Pharmaceutical and Clinical Research*, 10, 390. 10.22159/ajpcr.2017.v10s1.19763.

Sun, Y. (2023). *Marketing attribution models: A survey of techniques used in the industry.* Statsig. https://www.statsig.com/blog/marketing-attribution-models-tech-survey

Yusup, M., Wijono, S., Manongga, D., Sembiring, I., Prasetyo, S. Y., & Wellen, T. (2024). Systematic Literature Review: The Role of Artificial Intelligence in Digital Marketing. *Journal Sensi,* 10(1), 56–66. https://doi.org/10.33050/sensi.v10i1.3117

Zhao, K., Mahboobi, S. J., & Bagheri, S. R. (2022). Some game theoretic marketing attribution models. *Annals of Operations Research,* 322, 153–179. https://doi.org/10.1007/s10479-022-04944-5

Zhou, S., Pei, Q., & Li, J. (2024). *From Multi-Touch Attribution to Marketing Mix Modeling: Leveraging Multi-Information Fusion for Advanced Advertising Analytics. IEEE/WIC International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)* (pp. 677–681).). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/WI-IAT62293.2024.00109.

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МОДЕЛЮВАННЯ АТРИБУЦІЇ НА ОСНОВІ ДАНИХ У ЦИФРОВОМУ МАРКЕТИНГУ

В с т у п . ***У сучасному цифровому середовищі маркетингові комунікації стали багатоканальними, персоналізованими та динамічними, що зумовлює зростаючу потребу у точному вимірюванні ефективності кожної взаємодії користувача з брендом. Традиційні правила маркетингової атрибуції, які надають усю цінність одній точці контакту, вже не забезпечують належного рівня аналітичної точності. У відповідь на ці виклики все ширше застосовують економіко-математичні методи, зокрема й моделі на основі ланцюгів Маркова та значень Шеплі, що дають змогу аргументовано й кількісно обґрунтовано розподіляти цінність між усіма каналами.***

М е т о д и . ***Методологія дослідження ґрунтується на поєднанні загальнонаукових і спеціалізованих методів. Зокрема, використано теоретичне моделювання, порівняльний аналіз, а також стохастичне моделювання (ланцюги Маркова) та теорію кооперативних ігор (значення Шеплі).***

Р е з у л ь т а т и . ***У цьому дослідженні вивчено проблему маркетингової атрибуції в цифровому середовищі, доведено обмеженість традиційних моделей та обґрунтовано переваги адаптивних підходів, таких як ланцюги Маркова та значення Шеплі. Практична реалізація та порівняльний аналіз моделі на основі значень Шеплі підтвердили її вищу точність і здатність об'єктивно оцінювати внесок кожного каналу, що дозволило сформулювати цінні рекомендації для оптимізації маркетингових стратегій.***

В и с н о в к и . ***Розроблено та впроваджено модель атрибуції на основі значень Шеплі, що дає змогу враховувати маржинальний внесок каналів у всіх можливих комбінаціях взаємодій, на відміну від традиційних моделей маркетингової атрибуції, що засновані на правилах. Результати дослідження можуть бути використані компаніями для точнішого оцінювання ефективності маркетингових каналів, оптимізації бюджету та підвищення рентабельності інвестицій у цифрову рекламу.***

К л ю ч о в і с л о в а : ***маркетингова атрибуція, цифровий маркетинг, атрибуція на основі даних, значення Шеплі, ланцюги Маркова, мультиканальна аналітика, Python.***

Автори заявляють про відсутність конфлікту інтересів. Спонсори не брали участі в розробленні дослідження; у зборі, аналізі чи інтерпретації даних; у написанні рукопису; в рішенні про публікацію результатів.

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