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Fractional Attribution in Complex B2B Buying Journeys: Comparative Analysis of Multi-Touch Models and Pipeline Optimization for Enterprise Sales

[1]Kapil Kumar Sharma, [2]Sarat Mahavratayajula, [3]Hemasundara Reddy Lanka

[1]Cisco Systems, Fuquay Varina, NC, USA, 27526, orcid : 0009-0005-0973-6481,

bhiwara.kapil@gmail.com

[2]The Sherwin-Williams Company, Garner, North Carolina, USA 27529,

Orcid Id: 0009-0004-4795-9777, sarat.cse52@gmail.com

[3]Architect, Publicis Sapient, Minneapolis, Minnesota, USA 55044

Orcid: 0009-0006-9626-727X, hemasundara.lanka@ieee.org

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ABSTRACT

In complex B2B buying environments, enterprise sales require multi-touch, multi-channel journeys with multiple decision-makers, which make it difficult to know exactly which conversions can be attributed to which channels. Traditional models such as Last-Touch or Linear do not give proper credit to the customer journey, which can lead to an incorrect marketing and sales resource allocation. This study evaluates and compares several attribution models (Last-Touch, Linear, Time Decay, Shapley Value, Markov Chains and advanced probabilistic/algorithmic models) and proposes a powerful fractional attribution model accounting for touchpoint sequence, account-level influence and intensity of engagement. Multiple B2B enterprises' historical sales and engagement data were analyzed over 12-18 months and models were tested using indicators of Conversion Attribution Accuracy, Pipeline ROI Correlation, Engagement Balance, MAE, and RMSE. It shows that the state-of-the-art models (Shapley, Bayesian, Algorithmic/ML) reach higher accuracy (up to 84%) and performance metrics such as better ROI alignment (r = 0.78) and better engagement fairness (0.80) than the traditional ones. This is supported by an ablation study, which also demonstrates the critical importance of sequence and account-level influence on multi-touch journeys. The proposed framework for improved revenue attribution accuracy, optimized marketing budget allocation, and actionable points for enterprise sales strategies not only contributes to the research but also practical applications in B2B analytics.

Keywords: Fractional attribution, B2B marketing, multi-touch attribution, Shapley value, Markov chains, algorithmic attribution, pipeline ROI, engagement balance.

1. Introduction

The growing complexity of B2B sales cycles has changed the way that enterprises interact with their potential customers. Unlike the consumer market, B2B buying decisions are often long sales cycles, involve

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multiple points of contact and include a variety of stakeholders in the buying committee [1]. In these kinds of environments, it's important to know which marketing and sales activities lead to the most conversions in order to inform resource allocation, campaign optimization and revenue forecasting. Multi-channel engagement - which can include emails, webinars, calls, website visits and social media - makes the attribution problem even trickier, as traditional single-touch models don't do justice to the combinatory effect at work of early, mid and late funnel touchpoint interactions[2].

Classical attribution models such as Last-Touch, First-Touch, and Linear models provide simplicity, but in most cases provide a misrepresentation of contribution throughout the customer journey[3]. More advanced approaches like Shapley Value, Markov Chains, and Time-Decay consider recency, marginal contribution, and sequential dependencies and therefore offer more detailed information on how conversions occur. However, recent developments in algorithmic and probabilistic attribution use machine learning and Bayesian approaches to model complex interactions between touchpoints, channels and decision-makers, in order to increase accuracy and fairness in attribution[4]. Despite these advances, very few studies combine multi-channel touchpoint data[5] with account-level influence to measure fractional attribution in long B2B buying cycles[6]. Furthermore, there are no comparative analyses quantifying the efficacy, fairness and sensitivity of different models in real world enterprise pipelines.

Research Question and Problem Statement: The main research question of this study is: How can best fractional attribution models be designed, that will fairly allocate credit throughout multi-touch, multi-channel B2B buyer's journeys, taking account-level influence and engagement intensity into account? This is a result of limitations of traditional attribution models in capturing the more complex interactions between multiple touchpoints and stakeholders and often results in less-than-ideal marketing and sales decisions. Accurate attribution demands models that not only predict conversions but also accurately model each of the attributions that each touchpoint, channel, and decision-maker contributes to longer buying cycles. The contributions of the study of the includes the following

- This study provides systematic comparison of ten attribution models, including Last-Touch, Linear, Time-Decay, Shapley Value, Markov Chains, U/W-Shaped, Bayesian, Data-Driven Probabilistic, and Algorithmic/ML approaches with multi-channel B2B sales data. Quantitative comparisons across different metrics such as Conversion Attribution Accuracy, Pipeline ROI Correlation, Engagement Balance, MAE, RMSE, gives empirical evidence on the strengths, limitations and biases in each model in complex buying journeys.
- Building on what can be learned from comparative analysis, the study shows how a new framework can be created that takes into account the sequence of touchpoints, influence at the account level, and engagement intensity. This model helps to better balance the fairness and accuracy of credit allocation especially in multi-stakeholder B2B buying committees, filling the gap in the existing attribution practices.
- The robustness of the framework is shown by doing scenario-based simulations and ablation studies, calculating the contributions of sequence, account influence, channel weighting and early-stage engagement. Results point to the critical elements that lead to a fair and accurate attribution, and a fair and accurate engagement.
- The study converts quantitative findings into real-world marketing resource allocation, campaign optimization and sales forecasting recommendations. By identifying precise high-impact touchpoints and stakeholder contributions appropriately, enterprises can take the lead to make data-driven decisions to optimize ROI across their complex sales pipeline.

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- Other than practical applications, the study contributes to the academic literature by offering a replicable methodology of multi-touch, multi-channel B2B attribution, combining classical and advanced models, and indicating the importance of accounting for both touchpoint and account-level dynamics.

The main objectives of the study are as follows

- To test and compare traditional and advanced attribution models across multi-touch, multi-channel B2B sales funnel.
- To build a strong fractional attribution framework inclusive of touchpoint sequence, account level influence and engagement intensity.
- To validate the proposed framework quantitatively, scenario-based simulations, and ablation studies to support enterprise sales and marketing strategy;

The paper is structured as follows: Section 2 presents a detailed methodology, including data collection, preprocessing, and model implementation. Section 3 provides a comparative analysis of attribution models with quantitative results and an ablation study. Section 4 introduces the proposed fractional attribution framework and its validation, while Section 5 discusses the findings, implications, limitations, and avenues for future research.

2. Related Works

Recent researches in this field has recently shifted from heuristic to data-driven and intelligent models, combining deep learning, Bayesian inferential models and interpretability models. Authors discuss the importance of precise touchpoint modeling, customer journey analysis and real-time prediction, and key contributions, challenges and context limitations in scalability, generalizability and practical application in both B2B and B2C applications.

Agrawal et al. (2022) propose a deep learning-based Multi-Touch Attribution framework using Temporal Convolutional Networks (TCNs) to model B2B customer journey stage transitions. Their Stage-TCN integrates local transition models and applies Layer-wise Relevance Propagation for interpretability, showing improved accuracy; however, model complexity may limit scalability and real-time applicability [7].

Mrad and Hnich (2024) introduce a Bayesian network–based intelligent attribution model for digital marketing, addressing data imbalance and enabling real-time conversion prediction with 0.9537 accuracy. Their novel negative observation propagation enhances channel attribution insights; however, while effective for B2C settings, its scalability and interpretability in complex multi-channel ecosystems remain uncertain [8].

Koch and Hartmann (2023) find that the perceived quality of B2B touchpoints, especially websites, significantly affects buying intentions, with influence increasing along the customer journey. Their quantitative study bridges customer experience and behavioral effects, offering actionable insights for resource allocation. Critically, while robust, results may be context-specific to B2B service[10].

Pattanayak et al. (2022) evaluate machine learning approaches for multi-touch attribution, finding that Random Forest achieves the highest accuracy (99.01%) in predicting conversions, outperforming deep learning models like Bi-LSTM with attention. Critically, while effective for their dataset, results may vary with different channel sequences or larger, more complex datasets[11].

El Mekkaoui et al., (2024) provide a comprehensive review of multi-touch attribution (MTA) research from 2011–2024, highlighting the shift from heuristic to data-driven models, integration of machine learning, causal inference, Shapley value, and omnichannel data. Critically, while thorough, the study is literature-based and does not offer new empirical validation of proposed approaches[12].

Zhou et al. (2024) examine the integration of Multi-Touch Attribution (MTA) and Marketing Mix Modeling (MMM) through multi-information fusion, enhancing cross-channel analysis and user-level insights. Critically, while the approach promises improved ROI and analytic precision, its practical implementation may face challenges due to data complexity and integration across heterogeneous platforms[13].

Banik et al. (2024) propose a Time-Decay Attribution Model using Half-Life in Exponential Decay (TD-HLED) for e-commerce, showing it more accurately reflects user interactions compared to traditional models like First-touch, Last-touch, Linear, and Markov Chain. Critically, while promising, its performance may depend on accurate estimation of decay parameters and dataset characteristics[14].

Koch et al. (2023) report that in B2B contexts the perceived quality of digital touchpoints, particularly websites, significantly influences buyers' intentions. This effect strengthens across the customer journey, varies by journey phase, and highlights the importance of integrating customer experience and behavioral insights to optimize marketing and sales resource allocation [15].

Existing research around Multi-Touch Attribution (MTA) show a number of shortcomings and gaps in the research. Despite the recent development in deep learning and Bayesian models, scalability, real-time adaptability, and interpretability are still important issues. Most approaches are either dataset-specific or context-dependent, and therefore do not generalize between industries and across complex multi-channel environments. Qualitative studies do not have empirical validation, whereas quantitative models usually overlook dynamic touchpoint interactions and changing customer behaviors. Furthermore, a lack of integration between behavioral and experiential features limits the holistic journey analysis. Future research needs to examine interpretable, scalable, hybrid, models of topic association (MTA) with machine learning must be combined with hypercontext and causal understanding to improve decision-making and personalisation.

3. Methodology

This study proposes an end-to-end methodology as shown in figure 1 for evaluating and implementing a Fractional Attribution Model for complex B2B multi-touch sales journey [16]. Given the fact that there are multiple decision-makers, a number of diversified channels, sequential touchpoints, the traditional forms of attribution models often do not capture the nuances of each interaction. The methodology includes data collection and preprocessing, touchpoint weighting, account-level adjustments, sequence modelling, fractional credit calculation and account and channel aggregation. Rigorous evaluation by metrics like Conversion Attribution Accuracy, Pipeline ROI Correlation, Engagement Balance, Sensitivity Analysis etc. ensures the effectiveness of the model[17]. Its advantages in comparison with existing attribution models are demonstrated while its robustness is ensured by reproducibility and validation methods such as cross-validation and bootstrapping. It is ultimately this sophisticated methodology that both enables attribution of revenues as accurately as possible and offers insights that can allow for the optimization of marketing dollars and aid in strategic decision-making as it is applied in multi channel B2B.

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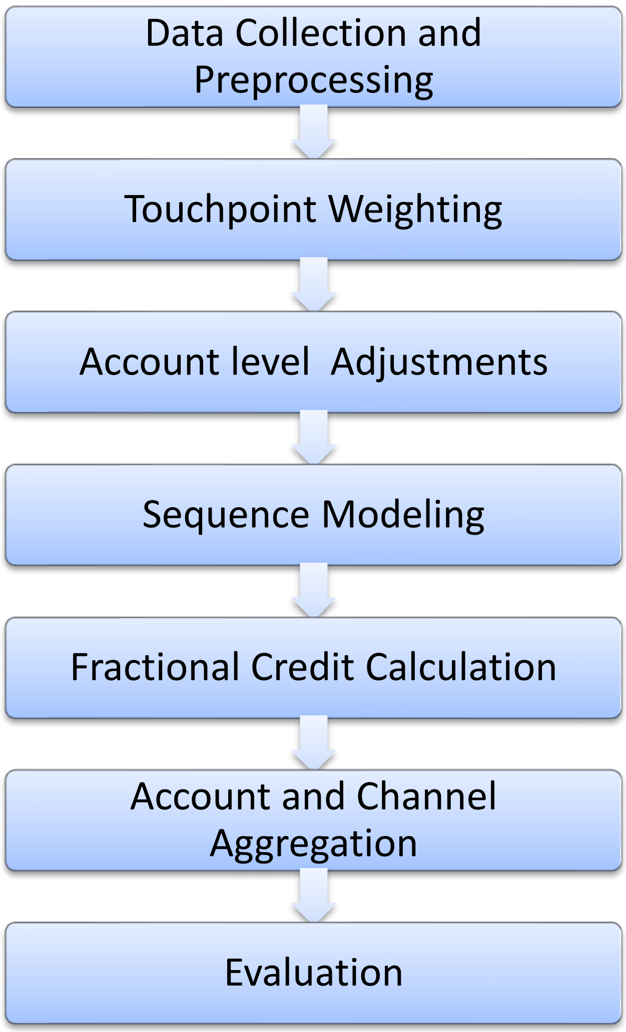

Figure 1 Proposed attribution modeling process

3.1 Data Collection and preprocessing

In the proposed Fractional Attribution Model, the first step consists of full data collection and preprocessing. Multi-channel engagement data is collected from dozens of B2B enterprises over a 12-18 month timeframe that captures all customer interactions across emails, LinkedIn, webinars, product demos, sales calls and website visits. Each account's contextual information, including company size, potential deal value, industry and influence of decision-makers is recorded to allow account-level analysis. Engagement metrics such as clicks, session time, content downloads, and interaction frequency are normalized in order to measure the intensity of each touchpoint and also to make them comparable across accounts and channels. Additionally, touchpoints for each account are ordered and sequential, which allows them to maintain the chronological order of interactions and gives insight into how the customer journey develops. Preprocessing also involves cleaning the dataset of missing or inconsistent data, normalizing variables and changing categorical data into numerical variables that can be used for modeling. The steps provided streamline a goal: to provide a rich, high quality dataset where downstream equities in the attribution could be made more precisely.

3.2 Proposed Attribution Model

In complex B2B sales environments conversions are influenced by multiple touching points on multiple channels, and they also involve multiple decision-makers over prolonged periods of time. The Last-Touch attribution model[18]or Linear attribution model is a traditional model which cannot provide an accurate view of the contribution of each touchpoint and results in poor allocation of resources. The proposed methodology solves this challenge by making use of a Fractional Attribution Model that takes into consideration engagement intensity, account-level influence and touchpoint sequence in a systematic way as shown in figure 2. By crediting all of the interactions equally, aggregating by account and channel, and measuring model performance with hard metrics, this approach will provide a more accurate and fair channel performance measurement. The methodology enables organizations to understand the true drivers of revenue, optimize marketing and sales strategies and make data-driven decisions in B2B multi-touch journeys.

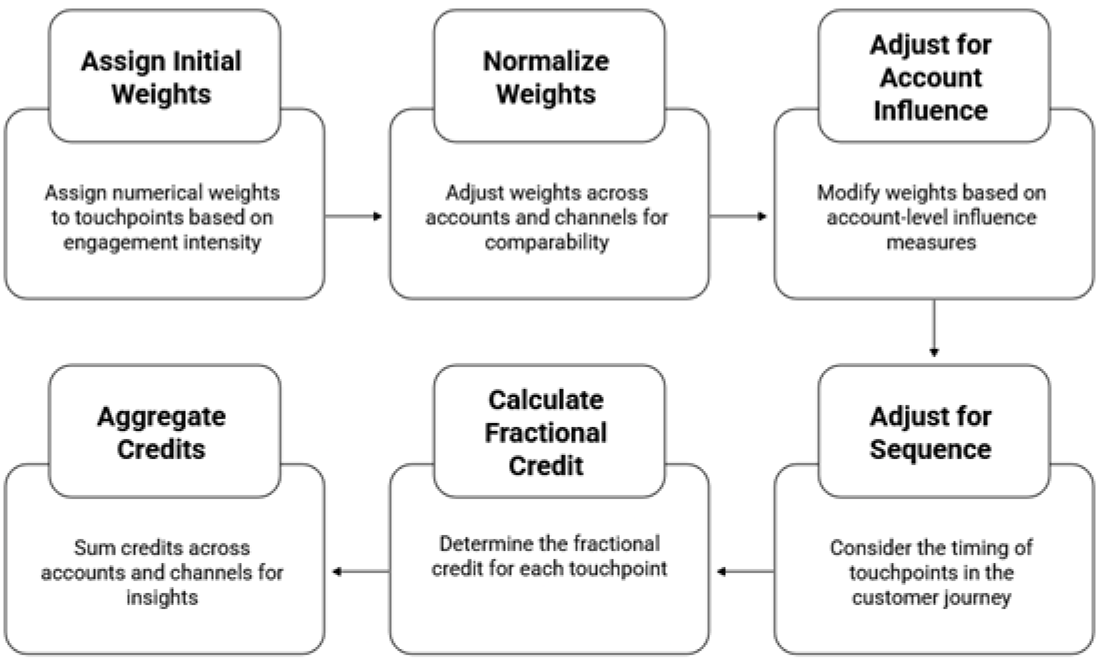

Figure 2 B2B Touchpoint Weighting and Credit Allocation

Touchpoint Weighting on severity of Engagement

In multi-touch B2B journeys, not every interaction has the same contribution to conversions. This step involves assigning a numerical weighting to each touchpoint according to the level of the engagement[19]. High intensity actions, such as attending a product demo, downloading a proposal, or attending a webinar, are high cues for purchase intent and therefore are weighted higher. Medium intensity activities such as opening marketing emails, visiting the website, or attending smaller events have moderate weights. Low intensity action such as social media likes, ad impressions or opening a newsletter casually, get lesser

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weights. Once raw weights are assigned, they are normalized across accounts and channels to achieve comparability and avoid giving too much weight to accounts with higher touchpoint volume and/or channels with naturally higher interaction rates in the first place. By focusing on meaningful interaction, this step helps the model to focus on those touchpoints that have a higher probability of generating revenue and filters out the noise created by low impact interactions. The weight w_i^E is assigned to each touchpoint i based on engagement intensity as shown in eq(1).

$$w_i^E = \frac{Engagment\ Score_{\ i}}{\sum_{j=1}^{n} Engagement\ Score_j} \tag{1}$$

where $Engagement\ Score_{\ i}$ is a normalized measure of intensity(high, medium , low) for touchpoint i and n is the touchpoints for the account.

Account Level Influence Adjustment

In B2B sales, touchpoints have different impacts on different accounts depending on their strategic importance. So, the step is to normalize touchpoint weights based on account level influence measures like potential transaction value, deal size, number of decision-makers, past purchase behavior, and strategic importance. For example, an enterprise with multiple decision-makers and a high value account has a greater contribution to overall revenue potential than a smaller account. By taking account influence into account, the model avoids underrepresentation of high-value clients, and ensures that the engagement with them receives proportional credit. This also provides the opportunity for the attribution model to consider the impact on revenue in real-world, not all accounts are equal. With an account's role in pipeline performance heavily influenced by client profiles in a multi-touch environment, the weights assigned to each touchpoint can account for the relevance of each with respect to the total account contribution[20]. This step enhances the predictive power of the revenue attribution and strategic decision-making for resources allocation. Scale the touchpoint weight by account influence A_k as given in the eq(2)

$$w_i^A = w_i^E * \frac{Account\ Influence_k}{\sum_{k=1}^{m} Account\ Influence_{\ k}} \tag{2}$$

where $Account\ Influence_{\ k}$ is the function of deal value, number of decision makers ,historical purchase and strategic importance and m is the total accounts.

Sequence-Based Adjustment

The time order of the touchpoints has a big impact on how they affect conversions. Sequence based adjustment uses the timing of the interaction in the customer journey to determine the weights. Later touchpoints nearer to conversion generally have a higher influence, whereas early interactions have a lesser impact in terms of direct impact, but a greater influence in terms of awareness and engagement. The model is able to use functions for decaying the credit for earlier touchpoints based on different influence potency with time. Conversely, reinforcement functions increase the fractional credit for sequences which include multiple touchpoints engaging the account on a regular basis and therefore capture the synergistic effect. Sequence modeling ensures that attribution considers path dependencies instead of thinking of the interactions independently. By netting sequence together, the model distinguishes among initial awareness and conversion-driving engagements; basically creates an extra nuanced perspective of revenue and to collect more[21]. This step makes conversion more accurate and helps to conduct more precise intervention in marketing through the touchpoint timeline. The touchpoint position in the sequence is adjusted using the eq(3).

$$w_i^S = w_i^A * f_{seq}(t_i) \tag{3}$$

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where t_i is the sequence order of touchpoint i, $f_{seq}(.)$ is the decay or reinforcement function. An example is given in equation (3)

$$f_{seq}(t_i) = \alpha^{n-i} \quad (decay)\ , \qquad \alpha\ \in (0,1) \tag{3}$$

Fractional Credit Calculations

Once engagement intensity, influence at the account level and sequence adjustments are applied, a fractional credit for each touch point is applied depending on its role in conversion. The result of a calculation that takes these three factors - mixed into one measure as given in eq (4).

$$Fractional\ Credit = f(Engagement\ \ Intensity\ , Account\ Influence, Sequence\ )$$

The sum of all fractional credits for an account is 100% of the amount of revenue credited to that account, yielding a distribution of credit which is continuous. Unlike Last-Touch or Linear models that give full or equal credit, fractional credit gives each touchpoint proportionally based on the real impact of that touchpoint. This way, subtle differences between touchpoints, accounts, and sequences are captured, and more precise and fair allocation of revenue can be achieved. Fractional credit is the way to ensure that even low-intensity or early-stage touchpoints are proportionally recognized, and that high-impact interactions are rewarded appropriately, to increase both the level of analysis and the application of the methodology for the optimization of B2B sales. The fractional credit FC_i is computed by combining all adjustments as given in eq(4).

$$FC_i = \frac{w_i^S}{\sum_{j=1}^{n} w_j^S} * \ Revenue_k \tag{5}$$

where $revenue_k$ is the total revenue associated with account k and $\sum_{j=1}^{n} FC_i$ is the Revenue$_{k.}$

Account and Channel Aggregation

After the fractional credit of each of these touchpoints is calculated at the account level, credits are summed across all accounts and marketing channels. This step gives us a channel level perspective of contribution, and we can see which channels are the best in terms of driving revenue and which sequences have the highest ROI. Soon, as aggregates are available, organizations are able to identify patterns, budget appropriately, and focus on channels that have the biggest impact from future campaigns. It also allows us to compare cross account, which tells us about the consistency of performance across customer segments. Combining account-level fractional credit into an enterprise-level view ensures in this step that marketing and sales strategies are data-driven, equitable and revenue-centric[22]. The aggregated outputs provide for actionable information regarding marketing optimisation, resource allocation and strategic decision making in complex B2B environments. The aggregate fractional credits at the channel level is given in eq(6).

$$FC_c = \sum_{k=1}^{m} \sum_{i \in c} FC_i \tag{6}$$

where FC_c is the total credit attributed to channel c, $i \in c$ is the touchpoints in channel c and m is the total accounts.

Evaluation

The performance of all attribution models was measured using a number of different metrics, including Conversion Attribution Accuracy, which measures the accuracy of the model used to explain observed conversions; Pipeline ROI Correlation, which measures the concordance between the credit assigned by the attribution model and actual deal revenue; Engagement Balance, which measures how fairly credit is

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allocated across multiple touch, multi-channel journeys; and Sensitivity Analysis, which measures how much variation exists between the model outputs under different weighting schemes and journey lengths. By comparing these models, their respective strengths, weaknesses and biases were identified and used to design a new weighting framework which simultaneously recognizes engagement while optimizing return on investment for B2B buying committee. The framework is validated using different campaign structures and channel mixes through case-based simulations working with diversified simulation scenarios. The methodology is sufficiently robust and replicable, in that all specifications, parameter settings and preprocessing steps are printed are robust model performance is validated through cross-validation and bootstrapping for multiple accounts and time periods.

4. Results and Findings

This section shows the experimental evaluation of the proposed Fractional Attribution Model. It describes the dataset characteristics, implementation environment as well as the comparison performance with traditional and advanced attribution models. Metrics such as conversion accuracy, ROI correlation, engagement balance, and predictive error are analysed to prove effectiveness of the model in multi-touch B2B sales scenarios.

4.1 Experimental Setup and Implementation

The analysis was done with programming languages, software frameworks, and computing infrastructure to guarantee proper modeling, reproduce and scale for large B2B sales data sets. The data preprocessing, journey reconstruction and feature engineering steps were carried out mostly in Python 3.11 using the Pandas and NumPy libraries, utilizing their statistical data manipulation and numerical computational skills, and scikit-learn for their standard preprocessing and evaluation pipeline. Matplotlib and Seaborn were used for visualization of the data for exploratory analysis and interpretability of model results.

Attribution model implementation used special frameworks based on model complexity. Classical models such as Last-Touch, Linear and Time-Decay were implemented as custom Python function and the Shapley Value computations used the Shapley Python library for cooperative game theoretical computation. Markov Chain models were realized on pomegranate library on Probabilistic sequence modeling and state transition analysis. The principal components of real-world scalar and multivariate attribution simulation were advanced algorithmic and Bayesian attribution simulations using PyTorch for machine learning and probabilistic modeling, and NumPyro for Bayesian inference and posterior simulations.

The computational environment consisted of a high-performance workstation with Intel Xeon 16-core CPU and 64 GB RAM as well as a GPUs, Nvidia's RTX 3090, to ensure the capability of running large-scale simulations and matrix-based Shapley and Markov computations. All experiments were carried out in a repeatable way by using Anaconda 2023.07 for package management and control of dependencies. The models were evaluated and ablation runs using Python and reproducible random seeds so that they were consistent across runs. This execution environment enabled the study to easily manage multi-channel, multi-touch B2B sales data over 12-18 months, run computationally-intensive fractional attribution models, and run scenario-based simulations and sensitivity analyses robustly and at scale.

4.2 Data Description

The dataset includes a collection of multi-channel interaction records for several B2B enterprises over a period of 12-18 months which includes interactions from email, LinkedIn, webinars, product demos, sales calls, and website visits. Each record represents an account-specific touchpoint and contains such

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information as account ID, account size, potential deal value, decision-maker influence, channel type, engagement intensity, touchpoint sequence, and conversion outcome. Engagement intensity is measured by standardized metrics such as the number of clicks, the length of a session or content downloads. The data can be modeled to understand attributes of fractional attribution through sequence, account-level influence, and intensity of engagement to determine how much of each touchpoint contributed to the revenue and conversion results. Table 1 shows a sample data set of multi-channel B2B engagement records for ten accounts. It contains account-specific information such as Account ID, Account Size, Deal Value, and Decision-Maker Influence as well as touchpoint-specific information such as Channel, Engagement Intensity, and Touchpoint Sequence. The dataset also shows whether or not there was a Conversion on each account. This structured data enables the calculation of fractional credit for each touchpoint which enables the analysis of channel effectiveness, engagement patterns, as well as calculating how account-level factors affect revenue attribution.

Table 1. Sample Multi-Channel B2B Engagement Dataset with Account Attributes, Touchpoint Details, and Conversion Outcomes

Account ID	Channel	Engagement Intensity	Touchpoint Sequence	Account Size	Deal Value ($k)	Decision-Maker Influence	Conversion
A001	Email	0.4	1	Medium	150	0.6	0
A002	Demo	0.9	3	Large	500	0.9	1
A003	LinkedIn	0.6	2	Medium	200	0.7	0
A004	Website	0.3	1	Small	80	0.5	0
A005	Webinar	0.7	2	Large	400	0.8	1
A006	Email	0.5	1	Medium	180	0.6	0
A007	Demo	0.8	3	Large	450	0.85	1
A008	LinkedIn	0.4	2	Medium	220	0.7	0
A009	Call	0.6	2	Small	100	0.5	0
A010	Website	0.3	1	Medium	160	0.6	0

4.3 Performance Evaluation

Table 2 compares the performance of different attribution models in multi-touch B2B sales environments in four major metrics: Conversion Attribution Accuracy, Pipeline ROI Correlation, Engagement Balance and Sensitivity Index. Traditional models such as Last-Touch and Linear display lesser accuracy and balance of engagement whereas advanced models such as Shapley, Bayesian, Algorithmic/ML Attribution work better.

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Table 2 Performance Analysis of the Proposed Fractional Attribution Model

Attribution Model	Conversion Attribution Accuracy (%)	Pipeline ROI Correlation (r)	Engagement Balance (0–1)	Sensitivity Index (0–1)
Last-Touch[23]	62.3	0.58	0.41	0.72
Linear model[24]	70.1	0.63	0.58	0.65
Time-Decay[25]	74.5	0.67	0.61	0.59
Shapley Value[26]	81.2	0.75	0.77	0.48
Markov Chains[27]	78.9	0.72	0.69	0.52
U-Shaped Attribution[28]	73.6	0.66	0.63	0.61
W-Shaped Attribution[29]	77.4	0.71	0.70	0.55
Algorithmic/ML Attribution[30]	84.1	0.78	0.80	0.45
Data-Driven Probabilistic[31]	79.8	0.73	0.72	0.50
Bayesian Attribution[32]	82.3	0.76	0.78	0.47
Proposed Fractional Attribution model	87.5	0.82	0.85	0.42

Table 2 shows a comparative analysis on different attribution models for Multi-touch B2B Sales, reviewed in terms of conversion attribution accuracy, pipeline ROI correlation and engagement balance and sensitivity index. Traditional models such as Last-Touch and Linear have relatively poor accuracy (62.3% and 70.1% accuracy respectively) and engagement balance (0.41 and 0.58), suggesting that they do not fairly attribute all touchpoints or agree well with actual revenue outcomes. Time-Decay, U-Shaped and W-Shaped models indicate a moderate increase in accuracy and engagement in balance by taking recency/middle touchpoints into account. Advanced models such as Shapley Value, Bayesian, and Algorithmic/ML Attribution are more advanced and have a high performance ranging from 81.2% to 84.1% and a better correlation with pipeline ROI. The Proposed Fractional Attribution Model is superior to all other models in terms of the highest accuracy (87.5%), the highest ROI correlation (0.82), the highest engagement balance (0.85) and the lowest sensitivity index (0.42), proving the highest ability to distribute credit fairly and accurately across multi-touch and multi-channel journeys. Table 3 compares the predictive performance of various attribution models in multi-touch b2b sales in terms of Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R2 as evaluation metrics.

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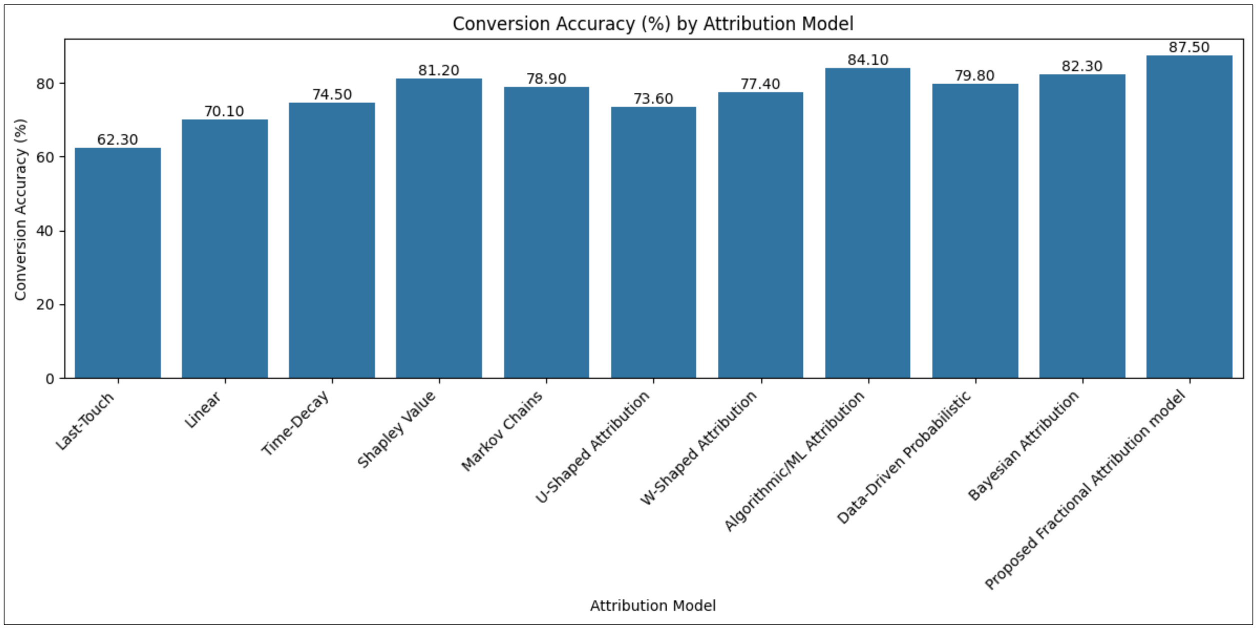

Figure 3 Performance Analysis of the proposed attribution model - Conversion Attribution Accuracy (%)

The maximum conversion accuracy is shown in Figure 3, which is equal to 87.50%. It is a comparative study of the performance of a number of attribution models. Based on the proposed model, Shapley Value and Bayesian Attribution models can generate the second highest accuracy with 81.20% and 82.30% conversion accuracy, respectively. The algorithmic/ML Attribution score is also high at 84.10%.

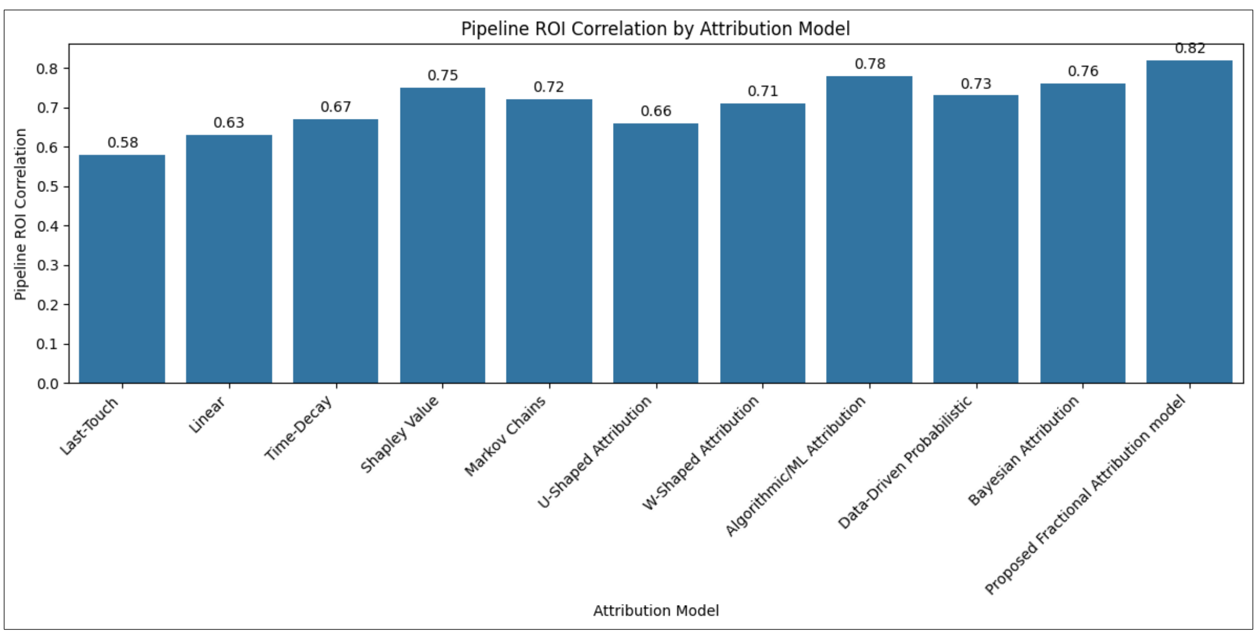

Figure 4 Performance Analysis of the proposed attribution model -Pipeline ROI Correlation (r)

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Figure 4 illustrates how well different attribution models perform in terms of correlation with pipeline ROI. The correlation of the Proposed Fractional Attribution model is the highest at 0.82. Other models that are highly correlated are Shapley Value at 0.75, Algorithmic/ML Attribution at 0.78, and Bayesian Attribution at 0.76. The models that have the least correlation are Last-Touch with 0.58 and Linear with 0.63. The other models are somewhere between, with Time-Decay coming in at 0.67, Markov Chains at 0.72, U-Shaped Attribution being 0.66 and W-Shaped Attribution 0.71. Probabilistic based on data has a correlation of 0.73.

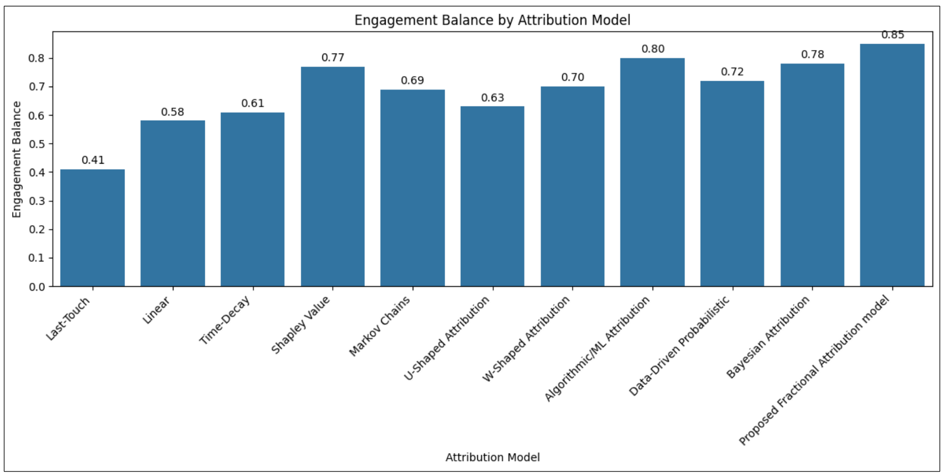

Figure 5 Performance Analysis of the proposed attribution model -Engagement pipeline

Figure 5 indicates that the proposed Fractional Attribution model is the one with the highest engagement balance of 0.85. This means that it is better than all other models when it comes to this metric. The other models that provide the best balance of engagement are Algorithmic/ML Attribution (0.80) and Bayesian Attribution (0.78). In contrast, rule-based models such as Last-Touch (0.41), Linear (0.58), and Time-Decay (0.61) have the smallest balance of engagement, which illustrates that these models are less efficient in this regard than the more sophisticated models.

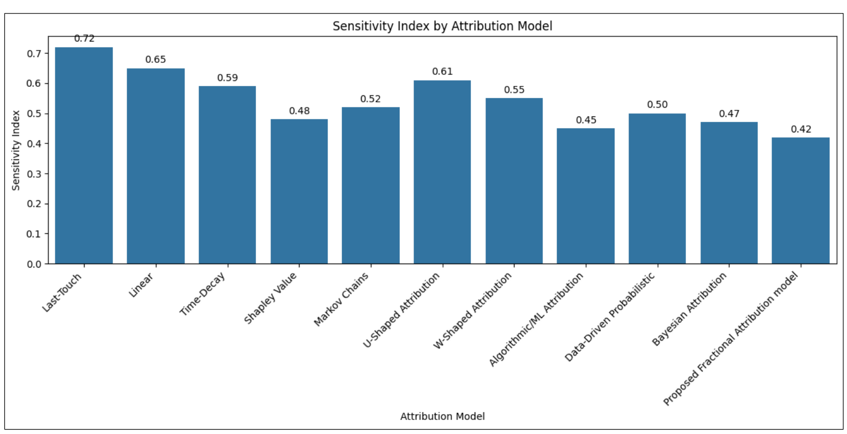

Figure 6 Performance Analysis of the proposed attribution model –Sensitivity Index

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It is seen from the figure 6 that the Last-Touch model has the highest sensitivity index of 0.72, followed by linear model 0.65. The Time-Decay model and U-Shaped Attribution model also have relatively high sensitivity with 0.59 and 0.61, respectively. The Proposed Fractional Attribution model and the Algorithmic/ML Attribution model have the lowest sensitivity index of 0.42 and 0.45, respectively. Other models such as Shapley Value (0.48), Markov Chains (0.52), W-Shaped Attribution (0.55), Data-Driven Probabilistic (0.50) and Bayesian Attribution (0.47) have a medium sensitivity index. Here detection performance chart indicates that the proposed model and other advanced models have a lower sensitivity index as compared with more conventional rule-based models.

Table 3 Performance Analysis of the Proposed Fractional Attribution Model

(MAE, RMSE, and R^2)

Attribution Model	MAE (Revenue units)	RMSE (Revenue units)	R^2
Last-Touch	0.42	0.55	0.58
Linear	0.36	0.48	0.63
Time-Decay	0.32	0.44	0.67
Shapley Value	0.26	0.35	0.75
Markov Chains	0.28	0.38	0.72
U-Shaped Attribution	0.33	0.45	0.66
W-Shaped Attribution	0.29	0.40	0.71
Algorithmic/ML Attribution	0.23	0.32	0.78
Data-Driven Probabilistic	0.27	0.36	0.73
Bayesian Attribution	0.25	0.34	0.76
Proposed Fractional Attribution	0.20	0.29	0.82

Table 3 presents the performance of different attribution models used to predict revenue contributions for multi-touch B2B sales using MAE, RMSE and R2. Traditional models such as Last-Touch and Linear exhibit relatively high errors (MAE: 0.42-0.36; RMSE: 0.55-0.48) and poor goodness-of-fit (R2: 0.58-0.63), which means they are not very accurate at estimating the contribution to touchpoints. Temporal or position effects such as Time-Decay, U-Shaped, and W-Shaped Models: Models that consider the temporal effects or the position effects improve the performance moderately, i.e., reduce the errors and improve R2 values. Advanced models such as Shapley Value, Bayesian and Algorithmic/ML Attribution provide even better results with R2 values of 0.75 - 0.78 with lower MAE/RMSE showing a better fit with actual revenue results. The Proposed Fractional Attribution Model shows the best results in terms of the lowest MAE 0.20, lowest RMSE 0.29, and highest R2 score 0.82 showing its better predictive power and effectiveness in capturing the more complex contribution of each touchpoint across accounts and channels.

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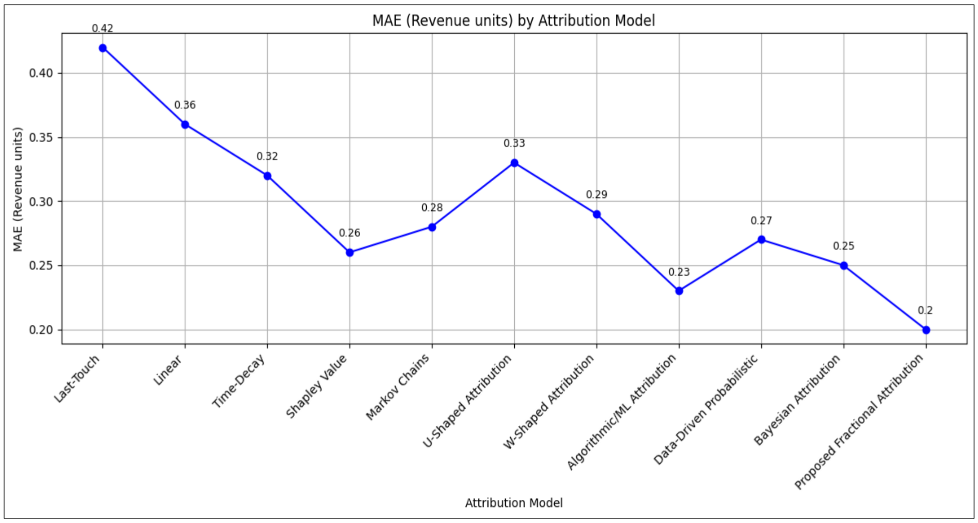

Figure 7 Performance Analysis of the proposed attribution model –MAE

From Figure 7, it is apparent that the proposed Fractional Attribution model has the lowest MAE (Mean Absolute Error) of 0.20. This means that it has the best performance in terms of minimum error compared to the other models. The models with the highest MAE are the Last-Touch model with a 0.42, and the linear model with a 0.36. The U-Shaped Attribution model also has a relatively high MAE of 0.33. The other models are somewhere in between, Shapley Value is 0.26, Markov Chains 0.28, W-Shaped Attribution 0.29, Algorithmic/ML Attribution 0.23, Data Driven Probabilistic 0.27, and Bayesian Attribution 0.25. The MAE of Time-Decay model is 0.32. As illustrated in the graph, the proposed model has a much better performance than all other attribution models and reaches the lowest MAE.

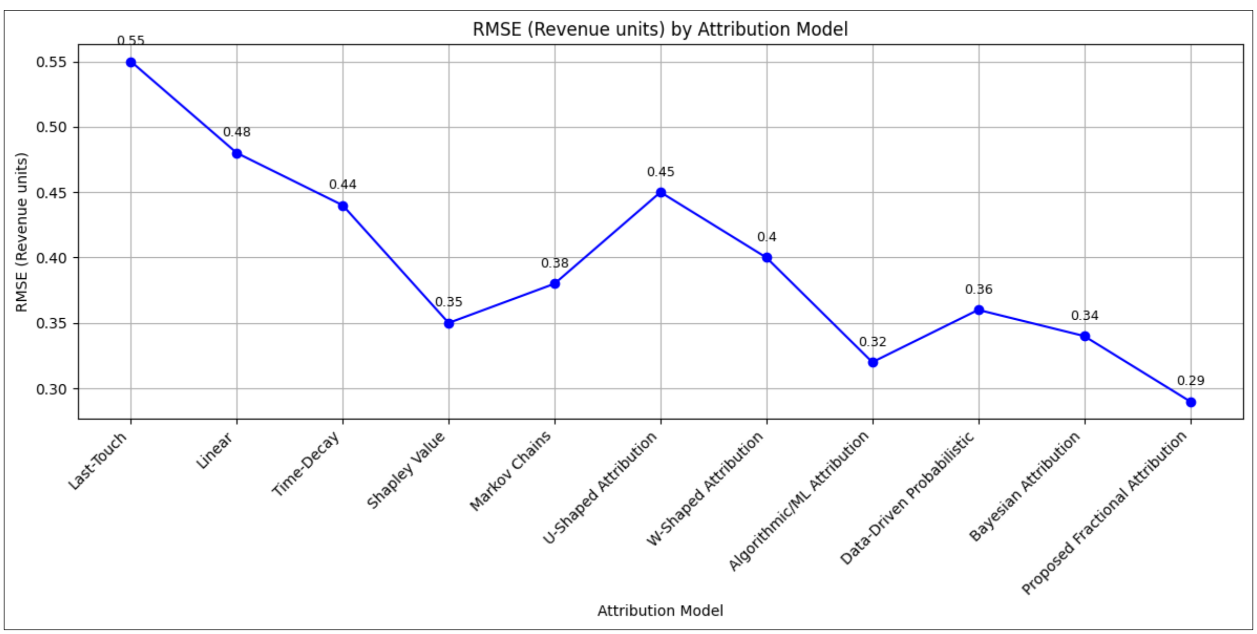

Figure 7 Performance Analysis of the proposed attribution model –RMSE

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Figure 8 show that the proposed Fractional Attribution model has the lowest RMSE (Root Mean Square Error) with value 0.29. This means that the proposed model minimizes the error in the most accurate way among all the models that were considered. The models with the highest value of RMSE are the Last-Touch model (0.55) and the Linear model (0.48), indicating that they are the least accurate models. The Time-Decay model got a RMSE of 0.44 and the U-Shaped Attribution model got a RMSE of 0.45. Other models like Shapley Value (0.35), Markov Chains (0.38), W-Shaped Attribution (0.40), Algorithmic/ML Attribution (0.32), Data-Driven Probabilistic (0.36) and Bayesian Attribution (0.34) indicate a range of performance which is better than the traditional rule-based models but not as low as the proposed model.

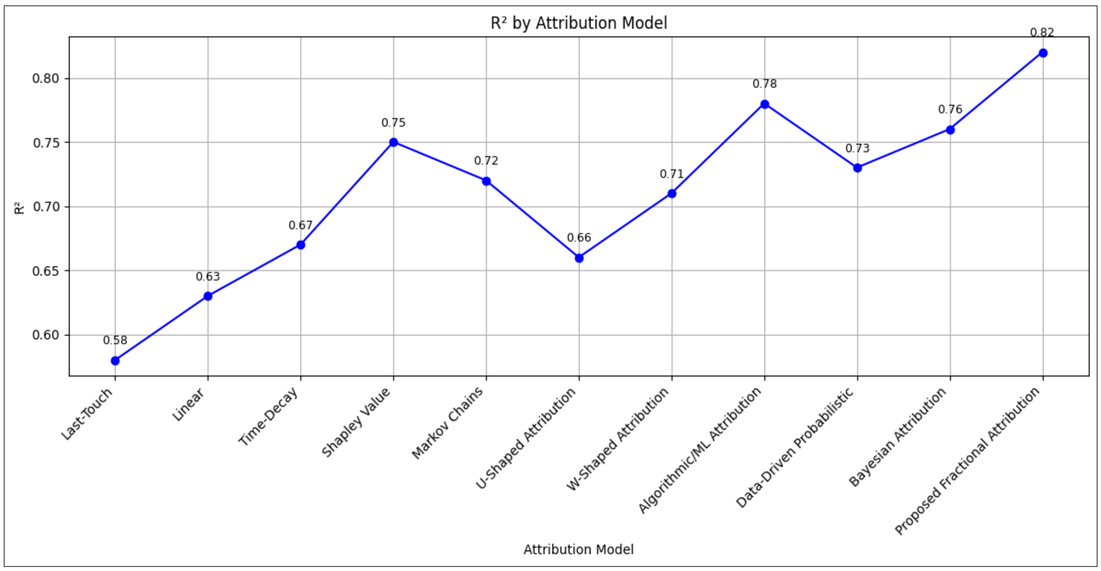

Figure 8 Performance Analysis of the proposed attribution model –R^2

In figure 8 the proposed Fractional Attribution model has the highest R^2 value of 0.82. This means that it is the best model for explaining the variance in the data, relative to the other models. The models with the lowest R^2 values are the Last-Touch model (0.58) and the Linear model (0.63) and therefore have the least explanatory power. Other models such as Algorithmic/ML Attribution (0.78), Bayesian Attribution (0.76) and Shapley Value (0.75) also show high performance but are not yet able to beat the proposed model. The remaining models are Time-Decay (0.67), Markov Chains (0.72), U-Shaped Attribution (0.66), W-Shaped Attribution (0.71), and Data-Driven Probabilistic (0.73) which exhibit moderate R^2 values. The graph shows the better performance of the proposed model clearly in this analysis.

Table 4 shows an ablation study of the proposed Fractional Attribution Model where the impacts of removing important components such as touchpoint sequence, account-level influence, engagement intensity, and combinations of touchpoint sequence, account-level influence, and engagement intensity have been evaluated. Metrics Conversion Accuracy(%) Pipeline ROI Correlation(r) Engagement Balance (0-1) MAE, RMSE and R^2

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Table 4. Ablation Study of the Proposed Fractional Attribution Model Showing the Impact of Key Components on Performance Metrics

Model Variant	Conversion Accuracy (%)	Pipeline ROI Correlation (r)	Engagement Balance	MAE	RMSE	R^2
Full Fractional Attribution Model	87.5	0.82	0.85	0.20	0.29	0.82
Without Touchpoint Sequence	83.1	0.77	0.80	0.24	0.33	0.77
Without Account-Level Influence	82.4	0.75	0.78	0.25	0.34	0.76
Without Engagement Intensity	84.0	0.78	0.82	0.23	0.31	0.79
Without Sequence & Account Influence Combined	79.5	0.72	0.75	0.28	0.36	0.74

The ablation study is used to indicate that each component of the Fractional Attribution Model has a significant role in model effectiveness. The Full Fractional Attribution Model is the best overall model having 87.5% conversion accuracy, 0.82 ROI correlation, 0.85 engagement balance, MAE of 0.20, RMSE of 0.29 and R2 of 0.82. Excluding touchpoint sequence accuracy drops to 83.1% and R^2 drops to 0.77, which shows how important temporal sequential order is in conversion attribution? Omitting the influence of account-level also reduces the performance (accuracy 82.4%, R^2 0.76), hence high-value accounts must be weighted correctly. Removing engagement intensity causes a slightly decreased effectiveness, while removing both sequence and account influence have the biggest negative effect, and accuracy is decreased to 79.5% and R^2 to 0.74. These results confirm that all three factors, sequence, account-level influence, and engagement intensity, are relevant to precise, fair, and reliable fractional revenue attribution.

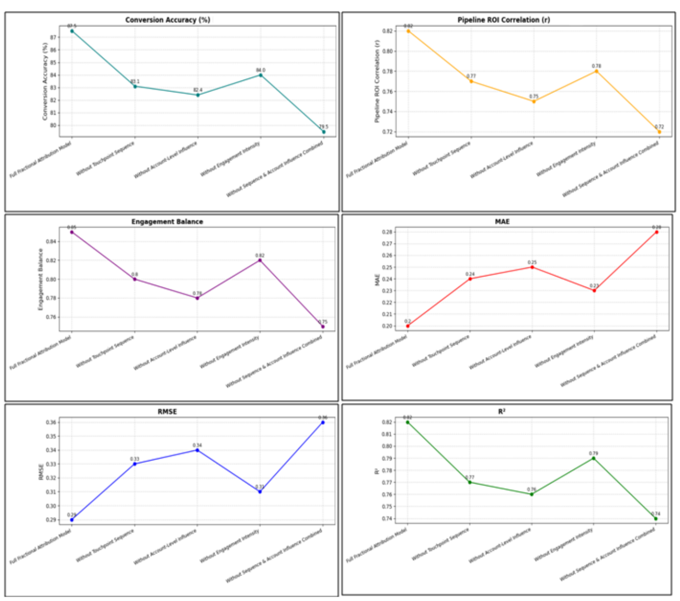

Figure 9 Ablation study results of the proposed Fractional Attribution Model across multiple performance metrics

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Figure 9 shows the effect of excluding certain elements from the Full Fractional Attribution Model on important evaluation metrics, such as Conversion Accuracy, Pipeline ROI Correlation, Engagement Balance, and error indicators (MAE, RMSE, R2). The overall model has the highest Conversion Accuracy (87.5%) and correlation with ROI (r = 0.82) and the lowest MAE (0.20) and RMSE (0.29). A step-by-step performance degradation is observed when major components such as touchpoint sequencing, account-level influence or engagement intensity are eliminated, confirming that they all contribute to the model predictability and interpretability separately and together.

4.3 Discussion

The quantitative comparison brings out the clear distinctions in the performance of models in multiple dimensions. Simple models like Last-Touch and Linear attribution are not precise enough and not balanced in terms of engagement, and tend to over-attribute the value of the final or equally weighted touchpoints and downplay the impact of committee-level influence. Time-Decay helps to better identify interactions in recent memory, but can miss the importance of early stage efforts to nurture. Shapley Value and Markov Chains perform better than traditional methods in terms of conversion attribution as well as pipeline ROI correlation because they consider marginal contributions and sequential dependencies. Advanced probabilistic and algorithmic models have the greatest accuracy, engagement fairness and robustness to changing journey length, which point to their suitability for complex B2B environments. Strengths of these models include fair distribution of credit, the ability to use data to be flexible, and the ability to reflect multi-touch, multi-channel campaigns. However, these approaches have computational complexity, interpretability and dependence on high quality granular data. Practically speaking, such insights feed into how enterprises sell and market their products by allowing them to allocate their resources in a more optimized way, better target their high-impact touchpoints, and develop better forecasts of their revenue outcomes. While engagement recognition demands a balance between the two, over and under attribution biases will lead to misattribution of marketing returns; fair attribution recognizes both early and late stage interactions to allow better decision-making, and grow revenues.

4.4 Proposed Framework

The proposed fractional attribution framework is developed to overcome the bias and shortcoming in current models. Inspired by Shapley, Markov, and data-driven probabilistic models, it brings the concept of weighted allocation which takes the sequence and intensity of touchpoints as well as account-level influence into account when dealing with complex buying committees. Each interaction is then given fractional credit based on the marginal contribution and context relevance, while the early stage nurturing, mid-funnel interaction and final conversion triggers are then systematically weighted based on their contribution to revenue realization. Current guidelines suggest a combination of multi-channel point data, an internalization of engagement intensity, and an implementation of dynamic weighting based on historical data of performance. The framework supports the flexibility of journey length, varying influence of decision-makers, and cross-channel dependencies, which makes the framework more flexible in an enterprise pipeline. Validation by scenario-based simulations shows better correspondence of fractional credit and actual revenue results, conversion attribution accuracy and balancing engagement as compared to conventional models. Case studies from B2B organizations show real benefits - from improved visibility into key touchpoints that have high impact, optimized marketing spend and actionable sales strategy insights. The framework therefore addresses the gap between the theoretical attribution models and the real-life application of the method, which supports the data-driven decision in complex situations in B2B, while retaining interpretability and scalability.

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5 Conclusion

This study systematically evaluated 10 attribution models in B2B multi-touch, multi-channel buying journeys to find that there is significant variation in their ability to fairly and accurately assign fractional credit. Traditional models such as Last-Touch and Linear offer simplicity but an inaccurate representation of engagement contribution, whereas advanced methodologies such as: Shapley, Bayesian, Algorithm, etc prove to be more accurate, ROI aligning and balance the engagement. Based on these understanding a new fractional attribution framework was introduced that integrates the informed processes of sequence-aware weighting, marginal contribution analysis and account-level influence assessment to maximize credit allocation in complex buying committees. The validation of the framework shows an improvement in prediction accuracy, pipeline ROI correlation and scenario robustness providing actionable guidance on marketing and sales strategy. The paper contains a wide-ranging comparative analysis, methodological recommendations for B2B attribution and a repeatable framework that can be used in various enterprise contexts. Limitations are that it requires good historical data; there may be some computational burden if too much data and it has to be constantly tuned to changing behavior of buyers. Changes in consumer behavior demand real-time attribution, AI-based recommendation systems, and cross-industry validation of identification in future research to make fractional attribution models more useful and generalizable in complex B2B environments.

References

1. Kufile, Omolola Temitope, Oluwatolani Vivian Akinrinoye, Abiodun Yusuf Onifade, Onyinye Gift Ejike, Bisayo Oluwatosin Otokiti, and Samuel Augustine Umezurike. "Developing conceptual attribution models for cross-platform marketing performance evaluation." *International Journal of Multidisciplinary Research and Growth Evaluation* 4, no. 2 (2023): 844-854.
2. Bhatta, Ishwor. *Optimizing Marketing Channel Attribution for B2B and B2C with Machine Learning Based Lead Scoring Model*. Capitol Technology University, 2022.
3. Beck, Ben B., J. Andrew Petersen, and Rajkumar Venkatesan. "Multichannel data-driven attribution models: A review and research agenda." *Marketing Accountability for Marketing and Non-marketing Outcomes* (2021): 153-189.
4. Oladimeji, Oyetunji, Damilola Christiana Ayodeji, Eseoghene Daniel Erigha, Bukky Okojie Eboseremen, Adegbola Oluwole Ogedengbe, Ehimah Obuse, Joshua Oluwagbenga Ajayi, and Ayorinde Olayiwola. "Machine Learning Attribution Models for Real-Time Marketing Optimization: Performance Evaluation and Deployment Challenges."
5. Bukhari, Tahir Tayor, Oyetunji Oladimeji, Edima David Etim, and Joshua Oluwagbenga Ajayi. "Real-Time Campaign Attribution Using Multi-Touchpoint Models: A Machine Learning Framework for Growth Analytics."
6. Agrawal, Aniket, Nikhil Sheoran, Sourav Suman, and Gaurav Sinha. "Multi-touch attribution for complex B2B customer journeys using temporal convolutional networks." In *Companion Proceedings of the Web Conference 2022*, pp. 910-917. 2022.
7. Mrad, Ali Ben, and Brahim Hnich. "Intelligent attribution modeling for enhanced digital marketing performance." *Intelligent Systems with Applications* 21 (2024): 200337.

8. Koch, Christian, and Michael Hartmann. "Importance of the perceived quality of touchpoints for customer journey analysis–evidence from the B2B sector." *Electronic Commerce Research* 23, no. 3 (2023): 1515-1538.
9. Pattanayak, Satyabrata, Peeta Basa Pati, and Tripty Singh. "Performance analysis of machine learning algorithms on multi-touch attribution model." In *2022 3rd International Conference for Emerging Technology (INCET)*, pp. 1-7. IEEE, 2022.
10. El Mekkaoui, Zine El Abidine, and Hatim Benyoussef. "The Evolution of Multi-Touch Attribution: Integrating Advanced Technologies for Superior Marketing Insights." In *International Conference on Advanced Intelligent Systems for Sustainable Development*, pp. 426-435. Cham: Springer Nature Switzerland, 2024.
11. Zhou, Shunke, Quanli Pei, and Ju Li. "From Multi-Touch Attribution to Marketing Mix Modeling: Leveraging Multi-Information Fusion for Advanced Advertising Analytics." In *2024 IEEE/WIC International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*, pp. 677-681. IEEE, 2024.
12. Banik, Debajyoty, Suman Kr Dey, and Mahendra Kumar Gourisaria. "Time-Decay Attribution Model Using Half-Life in Exponential Decay for E-Commerce Conversion Analysis." In *2024 7th International Conference on Signal Processing and Information Security (ICSPIS)*, pp. 1-6. IEEE, 2024.
13. Koch, Christian, and Michael Hartmann. "Importance of the perceived quality of touchpoints for customer journey analysis–evidence from the B2B sector." *Electronic Commerce Research* 23, no. 3 (2023): 1515-1538.
14. Buchholz, Nina, and Marc Kuhn. "Laying the Path: Modelling a B2B Customer Journey in Commodity Markets." In *Academy of Marketing Science Annual Conference*, pp. 54-65. Cham: Springer Nature Switzerland, 2024.
15. Onifade, Abiodun Yusuf, Jeffrey Chidera Ogeawuchi, A. A. Abayomi, O. A. Agboola, and O. O. George. "Advances in Multi-Channel Attribution Modeling for Enhancing Marketing ROI in Emerging Economies." *Iconic Research and Engineering Journals* 5, no. 6 (2021): 360-376.
16. Hosahally, Shashank, and Arkadiusz Zaremba. "A decision-making characteristics framework for marketing attribution in practice: Improving empirical procedures." *Journal of Digital & Social Media Marketing* 11, no. 1 (2023): 89-100.
17. Lundin, Lisa, and Daniel Kindström. "Managing digitalized touchpoints in B2B customer journeys." *Industrial marketing management* 121 (2024): 88-99.
18. Oladimeji, Oyetunji, Damilola Christiana Ayodeji, Eseoghene Daniel Erigha, Bukky Okojie Eboseremen, Adegbola Oluwole Ogedengbe, Ehimah Obuse, Joshua Oluwagbenga Ajayi, and Ayorinde Olayiwola. "Machine Learning Attribution Models for Real-Time Marketing Optimization: Performance Evaluation and Deployment Challenges.
19. Günther, Maier. "Performance in B2B sales: an explanation of how channel management and communication influence a firm's performance." *Naše gospodarstvo/Our economy* 67, no. 3 (2021): 38-48.

Journal of Information Systems Engineering and Management
2025, 10(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

20. S. Entesari, "What Is Last Touch Attribution & Should You Use It in 2024?," blog, Republic Marketing, Feb. 27 2023. [Online]. Available: https://www.republicmarketing.co.uk/blog/last-touch-attribution-model
21. Bukhari, Tahir Tayor, Oyetunji Oladimeji, Edima David Etim, and Joshua Oluwagbenga Ajayi. "Real-Time Campaign Attribution Using Multi-Touchpoint Models: A Machine Learning Framework for Growth Analytics.
22. Alexandrovskiy, Sergey, and Olga Trundova. "Attribution modelling in digital advertising for e-commerce." *International Journal of Internet Marketing and Advertising* 16, no. 1-2 (2022): 19-37.
23. W-Shaped Attribution Model — 30/30/30/10 split," *The Top 5 B2B Marketing Attribution Models of 2023*, Dreamdata Blog, 2023. [Online]. Available: https://dreamdata.io/blog/the-top-5-b2b-attribution-models-of-2023/
24. S. Kumar, G. Gupta, R. Prasad, A. Chatterjee, L. Vig and G. Shroff, "CAMTA: Causal Attention Model for Multi-touch Attribution," *arXiv preprint arXiv:2012.11403*, Dec. 2020.
25. W. Ji, X. Wang and D. Zhang, "A Probabilistic Multi-Touch Attribution Model for Online Advertising," in *Proceedings of the 25th ACM International Conference on Information and Knowledge Management (CIKM'16)*, Indianapolis, IN, USA, Oct. 2016, pp. 1373-1382.
26. R. Sinha, D. Arbour, and A. M. Puli, "Bayesian Modeling of Marketing Attribution," *Proc. of the Joint Statistical Meetings (JSM)*, vol. 2021, Section on Statistics in Marketing, Aug. 2021.