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Constructing Cross-Device Ad Attribution Models for Integrated Performance Measurement

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Abstract- Cross-device advertising has become an integral component of digital marketing strategies, driven by the proliferation of devices and the non-linear paths consumers take before conversion. However, accurately attributing marketing performance across devices remains a significant challenge for marketers due to fragmented user identities, inconsistent engagement signals, and inadequate modeling frameworks. This paper proposes a unified cross-device attribution model that leverages deterministic and probabilistic identity resolution, combined with machine learning-based multi-touch attribution (MTA) algorithms. Using data from a global e-commerce platform, we examine the comparative effectiveness of rule-based, data-driven, and hybrid models in capturing true conversion paths. The study finds that hybrid models outperform conventional approaches in accuracy, flexibility, and actionable insights. Our findings have implications for marketers seeking to optimize budget allocation, personalize experiences, and achieve integrated campaign performance measurement.

Indexed Terms- Cross-device attribution, identity resolution, multi-touch modeling, conversion tracking, machine learning, digital marketing

I. INTRODUCTION

In an era of ubiquitous connectivity, consumers routinely engage with brands across multiple devices smartphones, tablets, laptops, smart TVs throughout their decision-making journey. This shift has transformed the traditional linear conversion funnel into a dynamic, multichannel ecosystem [1]. For marketers, the central challenge lies in accurately tracing and measuring these complex user journeys to determine the true effectiveness of advertising touchpoints. Cross-device ad attribution seeks to link user interactions across disparate devices to provide a cohesive view of marketing performance [2].

However, constructing robust cross-device attribution models is fraught with technical, analytical, and ethical complexities. User identity resolution across devices can be probabilistic (based on behavioral patterns) or deterministic (based on login data), each with trade-offs in scalability and precision [3]. Attribution modeling further complicates measurement, as rule-based heuristics like "last-touch" often fail to reflect actual influence, while data-driven models require significant data infrastructure and expertise. Moreover, privacy regulations and platform restrictions (e.g., Apple's IDFA changes) continue to alter the landscape of user tracking and data availability [4].

This paper aims to bridge these gaps by proposing and validating a hybrid attribution framework that integrates identity stitching techniques with advanced multi-touch attribution (MTA) algorithms. We evaluate the framework using real-world campaign data to compare accuracy, transparency, and business utility. Our study contributes to both academic discourse and industry practice by offering a scalable, ethically aligned approach to integrated performance measurement.

II. LITERATURE REVIEW

The rise of multichannel and multi-device digital engagement has necessitated robust and integrated ad attribution models capable of capturing complex customer journeys. Traditional attribution methods, often constrained by device silos and single-touch logic, fail to represent the nonlinear and multi-touch realities of consumer behavior in contemporary digital ecosystems [5]. This literature review critically examines foundational theories, evolving frameworks, modeling approaches, and empirical findings relevant to constructing cross-device ad attribution models for integrated performance measurement.

2.1 Theoretical Foundations of Attribution

Attribution theory, initially rooted in psychology and behavioral economics, posits that individuals interpret outcomes based on perceived causes [6], [7]. In digital marketing, this translates into identifying which marketing touchpoints influenced a consumer's conversion decision. Early attribution models applied last-click or first-click heuristics, assuming linear decision-making processes [8], [9]. However, these assumptions have been widely challenged by empirical evidence showing that consumers interact with multiple channels and devices before converting [10], [11].

The theory of planned behavior and the elaboration likelihood model provide further theoretical context, emphasizing the influence of contextual cues, frequency, and device type on consumer decision pathways [12], [13]. These theories underscore the importance of adopting probabilistic and algorithmic models that can accommodate the stochastic nature of consumer journeys.

2.2 Evolution of Attribution Models

The progression from rule-based models to algorithmic and data-driven approaches marks a significant paradigm shift in attribution modeling. Early models such as first-touch, last-touch, and linear distribution fail to reflect the differential impact of each touchpoint in a multichannel environment [14], [15]. Multi-touch attribution (MTA) models emerged to address this limitation by distributing conversion credit across multiple engagements. However, MTA models often fall short in cross-device scenarios due to identity resolution challenges and data fragmentation [16], [17].

Markov chain modeling has gained traction for its ability to capture transition probabilities between touchpoints and account for the removal effect of channels [18], [19]. Shapley value-based models, rooted in cooperative game theory, allocate credit by assessing the marginal contribution of each touchpoint across all permutations [20], [21]. These models offer fairness and transparency but can be computationally intensive in high-dimensional environments.

2.3 Cross-Device Tracking and Identity Resolution

A central challenge in constructing cross-device attribution models is the accurate linking of user identities across devices and sessions. Deterministic approaches, such as login data or CRM-based identifiers, offer high accuracy but limited scalability [20]. Probabilistic matching, which uses IP addresses, device fingerprints, and behavioral signals, extends reach but introduces uncertainty and potential bias [22], [23].

Recent advancements in graph-based identity resolution have improved the precision of cross-device tracking by modeling relationships between devices, accounts, and interactions as nodes and edges in a user graph. Deep learning architectures, particularly variational autoencoders and attention-based models, have been applied to learn latent representations of user behaviors for cross-device mapping [24], [25]. Nevertheless, concerns regarding data privacy and compliance with regulations such as GDPR and CCPA remain pressing [26].

2.4 Multichannel Data Integration and Measurement

Effective cross-device attribution relies on the seamless integration of multichannel data sources, including web analytics, mobile app interactions, social media engagements, email marketing, and offline channels such as call centers and in-store visits [27], [28]. Data lakes and customer data platforms (CDPs) have emerged as essential infrastructure for unifying disparate datasets into cohesive customer profiles [29], [30].

However, data sparsity and inconsistency across touchpoints present significant challenges. Research highlights the value of employing data imputation techniques, temporal alignment models, and event standardization protocols to enhance data quality for attribution modeling [31], [32]. Moreover, the integration of real-time data streams has enabled the development of near real-time attribution models, which are crucial for dynamic campaign optimization [33].

2.5 Attribution Algorithms and Machine Learning Approaches

Recent studies advocate for machine learning-based attribution models that leverage supervised and unsupervised learning to derive attribution weights from historical data [34], [35]. Logistic regression, gradient boosting machines, and support vector machines are commonly used due to their interpretability and predictive accuracy [36], [37].

Neural network-based models, particularly recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, have shown promise in modeling sequential user behavior across devices [38], [39]. These architectures can capture temporal dependencies and nonlinear interactions that traditional models overlook. Reinforcement learning approaches, where attribution is framed as a reward optimization problem, have also gained attention for their ability to dynamically adapt to evolving consumer behavior [40], [41].

Ensemble learning, which combines multiple models to enhance robustness and accuracy, has been employed in large-scale attribution systems used by digital advertising platforms. The incorporation of attention mechanisms allows these models to weigh the influence of touchpoints differentially, aligning computational logic with marketing intuition [42].

2.6 Model Evaluation and Attribution Validation

Evaluating attribution model performance requires metrics that go beyond predictive accuracy. Incrementality tests, such as uplift modeling and A/B testing, assess the causal impact of marketing interventions on conversion outcomes [43]. Attribution validation frameworks emphasize business relevance, model interpretability, and alignment with strategic goals [44], [45].

Research suggests that combining statistical validity with domain knowledge improves stakeholder trust and model adoption [46], [47]. Calibration techniques and post-modeling audits are also recommended to address potential biases introduced by skewed data distributions or algorithmic artifacts [48].

2.7 Ethical and Regulatory Considerations

Cross-device attribution raises significant ethical and legal concerns, particularly regarding data privacy, user consent, and algorithmic transparency. The use of personally identifiable information (PII) for identity resolution necessitates strict adherence to data protection laws [49], [50].

Scholars advocate privacy-preserving attribution methods, including federated learning, differential privacy, and homomorphic encryption. These approaches allow model training without exposing raw data, thereby enhancing compliance and user trust. Transparent model documentation, user opt-out mechanisms, and ethical review boards are also proposed as best practices in responsible attribution modeling [51], [52].

2.8 Applications and Industry Implementations

Major advertising platforms such as Google Ads, Facebook, and Amazon have developed proprietary cross-device attribution systems that integrate deterministic and probabilistic tracking [53], [54]. These platforms employ closed-loop measurement and attribution windows to provide advertisers with granular insights into multidevice performance.

Case studies in sectors such as retail, travel, and financial services demonstrate substantial improvements in ROI, cost-per-acquisition (CPA), and customer lifetime value (CLV) through the adoption of cross-device attribution strategies [55], [56]. However, there remains a knowledge gap in the transferability of these systems to smaller enterprises with limited data infrastructure [57].

2.9 Research Gaps and Future Directions

Despite advancements, significant research gaps persist. There is limited consensus on standardized methodologies for evaluating cross-device attribution models across contexts. More empirical studies are needed to test the scalability, fairness, and efficiency of emerging algorithms [58], [59].

Hybrid models that combine causal inference, machine learning, and econometric approaches are proposed as promising directions for future work [60], [61]. Additionally, the emergence of edge computing and Internet of Things (IoT) devices introduces new frontiers in cross-device tracking that require fresh theoretical and methodological perspectives [62].

Academic literature also calls for greater focus on interpretability, especially in black-box models, to ensure alignment with regulatory standards and stakeholder usability [63]. Interdisciplinary collaboration between computer science, marketing, ethics, and law is increasingly necessary to develop holistic attribution solutions.

2.10 Summary of Literature Synthesis

This review synthesizes a decade of research and practice in cross-device attribution modeling. It highlights the transition from heuristic to algorithmic frameworks, the integration of advanced tracking and identity resolution techniques, and the increasing reliance on machine learning and probabilistic logic. While promising developments have been made, challenges related to data integration, ethical compliance, model validation, and domain generalizability remain. Addressing these gaps will be critical in advancing the science and practice of cross-device ad attribution.

The next section outlines the methodological approach used to construct and evaluate a novel cross-device attribution model for integrated performance measurement.

III. METHODOLOGY

This section details the methodological framework adopted for constructing a cross-device ad attribution model tailored to integrated performance measurement. The approach encompasses data acquisition, preprocessing, identity resolution, model design, training, validation, and implementation, aligned with ethical and regulatory compliance frameworks. The methodology adheres to principles of transparency, reproducibility, and scalability to ensure both academic rigor and practical applicability in real-world advertising environments.

3.1 Research Design and Objectives

The study adopted a quantitative-experimental design, combining retrospective data analysis and predictive modeling to simulate and validate ad attribution in multichannel, cross-device contexts. The core objective was to develop a machine learning-based attribution model that dynamically allocates conversion credit to touchpoints across devices. Key research questions guiding the methodology include:

- How can disparate device-level interactions be effectively unified into a cohesive user journey?
- Which algorithmic approach best reflects the actual influence of each touchpoint?
- What evaluation metrics are suitable for validating model accuracy and business impact?

To address these, the research followed a multi-phase methodology encompassing data engineering, model development, and attribution validation.

3.2 Data Sources and Acquisition

Data were obtained from a digital advertising platform managing multi-device campaigns across web, mobile, and app channels over a 12-month period. The dataset included anonymized user-level logs containing session IDs, timestamps, device types, IP addresses, clickstream events, campaign IDs, and conversion markers [64], [65]. A total of 20 million interaction records from 3 million unique users were analyzed. Data access and handling complied with GDPR and CCPA standards, including user consent verification, pseudonymization, and encryption at rest and in transit [66], [67]. Data governance protocols were implemented to ensure ethical use and prevent re-identification.

3.3 Data Preprocessing and Feature Engineering

Preprocessing steps involved cleaning, deduplication, and normalization of event logs to ensure temporal and structural consistency. Device types were categorized into desktop, smartphone, tablet, and smart TV. Events were timestamp-aligned using Coordinated Universal

Time (UTC) and grouped into sessions based on inactivity thresholds of 30 minutes [68], [69].

Feature engineering included extraction of:

- Temporal features (hour of day, day of week)
- Engagement metrics (dwell time, scroll depth)
- Device transition patterns (e.g., mobile-to-desktop)
- Campaign metadata (channel type, creative ID)

Categorical variables were one-hot encoded, and continuous features were normalized using z-score standardization. Missing values were addressed via multiple imputation using k-nearest neighbors [70], [71].

3.4 Cross-Device Identity Resolution

A hybrid identity resolution strategy was employed. Deterministic matching used hashed login credentials, CRM IDs, and device IDs. Probabilistic matching utilized IP clustering, device fingerprinting, and behavioral similarity scoring [72].

Graph-based identity resolution was implemented using Neo4j to build user-device graphs. Nodes represented devices, while edges represented observed transitions or co-occurrences. A deep learning-based link prediction algorithm (GraphSAGE) was applied to infer probable connections across sparse graphs [73]. Precision-recall trade-offs were managed using threshold tuning.

3.5 Model Design and Algorithm Selection

The attribution model was built on a Long Short-Term Memory (LSTM) neural network, chosen for its ability to learn sequential dependencies in multistep user journeys. The input sequence consisted of encoded touchpoints, while the output was a probabilistic score indicating each touchpoint's contribution to conversion [74], [75].

To compare effectiveness, four models were tested:

1. Logistic Regression (baseline)
2. Gradient Boosting Machine (GBM)
3. Shapley Value Attribution
4. LSTM Neural Network

The LSTM architecture included:

- Input layer with embedding dimension of 128
- Two LSTM layers with 64 units each
- Dropout layer (0.2)
- Dense output layer with softmax activation for probability distribution

Hyperparameters were tuned using Bayesian optimization with 5-fold cross-validation [76], [77].

3.6 Model Training and Implementation

The model was trained on 80% of the dataset, with the remaining 20% reserved for testing. The Adam optimizer was used with a learning rate of 0.001 and categorical cross-entropy loss. Early stopping was applied to prevent overfitting [78], [79].

A batch size of 512 and 30 epochs yielded optimal performance. Model training was executed on a TensorFlow-GPU instance with NVIDIA RTX A6000 accelerators. Each training epoch took approximately 40 seconds, and the full training cycle completed in under 30 minutes.

The trained model was deployed using TensorFlow Serving and integrated into an ad tech platform via REST APIs. Attribution outputs were visualized on dashboards using Power BI for stakeholder interpretation [80], [81].

3.7 Evaluation Metrics and Attribution Validation

Model evaluation used both statistical and business-relevant metrics:

- Precision, Recall, F1-Score
- Area Under the Receiver Operating Characteristic Curve (AUC-ROC)
- Attribution Lift (conversion rate uplift from high-attribution touchpoints)
- Cross-device recall (accuracy in identity resolution)

Incrementality was assessed using uplift modeling, comparing test and control groups exposed to key touchpoints. Attribution validity was confirmed through backtesting against observed conversion patterns and revenue impact [82].

3.8 Ethical Considerations

All modeling and data practices adhered to ethical AI principles. Differential privacy mechanisms were explored but not applied in the final model due to trade-offs in accuracy. However, data minimization and audit trails were enforced. An independent ethics panel reviewed the study design [83], [84].

3.9 Methodological Limitations

Limitations include potential bias in probabilistic identity resolution, underrepresentation of offline touchpoints, and the black-box nature of deep learning models. Despite these, rigorous validation and triangulation across models enhanced reliability. Future research should explore explainable AI methods and multimodal data fusion for attribution modeling.

The following section presents the empirical results of the model's performance across evaluation metrics, identity resolution accuracy, and attribution impact.

IV. RESULTS

This section presents the empirical findings derived from the application of the proposed cross-device ad attribution model. Results are organized according to the model's performance on evaluation metrics, identity resolution accuracy, and its practical attribution impact on campaign performance.

4.1 Model Performance Metrics

Among the four attribution models tested Logistic Regression, GBM, Shapley Value, and LSTM the LSTM model consistently outperformed others across all key metrics. The final evaluation metrics on the test dataset are summarized as follows:

Table 1: Evaluation metrics

Model	Precision	Recall	F1-Score	AUC-ROC
Logistic Regression	0.62	0.58	0.60	0.66
GBM	0.71	0.69	0.70	0.78
Shapley Value	0.74	0.72	0.73	0.81
LSTM	0.86	0.84	0.85	0.93

The LSTM model demonstrated superior ability to recognize sequential dependencies in user touchpoints, resulting in the highest AUC-ROC and F1-Score values. The Shapley model also performed well due to its robust interpretability, though it was computationally more intensive.

4.2 Attribution Accuracy and Cross-Device Recall

The cross-device recall metric, which measures how accurately user identities are reconstructed across devices, yielded the following results:

- Deterministic resolution accuracy: 96.3%
- Probabilistic resolution accuracy: 89.7%
- Combined hybrid strategy: 92.8%

These results validate the effectiveness of the graph-based identity resolution framework. The use of GraphSAGE for link prediction significantly improved connection inference in sparse data scenarios, particularly in low-frequency device transitions.

4.3 Attribution Lift and Business Impact

To assess real-world impact, attribution lift was measured by comparing conversion rates between user segments influenced by high-attribution touchpoints versus low-attribution ones. The findings include:

- Conversion rate uplift from top 10% of attributed touchpoints: +27.4%

- ROI improvement on optimized media spend: +18.6%
- Reduction in customer acquisition cost (CAC): −12.1%

These figures indicate substantial gains in campaign efficiency when attribution-informed optimization was applied. The LSTM model's attributions enabled more targeted budget reallocation and strategic prioritization of high-impact channels.

4.4 Visualizations and Stakeholder Interpretation

Power BI dashboards were used to translate model outputs into business-friendly visualizations. Key stakeholder deliverables included:

- Attribution waterfall charts showing credit distribution across devices
- Conversion funnel overlays annotated with attribution weights
- Geo-device interaction heatmaps

These tools improved cross-functional understanding of customer journeys and supported evidence-based decision-making for media planners.

4.5 Backtesting and Incrementality Analysis

Backtesting showed a close alignment between predicted attribution paths and observed conversion sequences. Incrementality analysis through uplift modeling further validated attribution robustness:

- Uplift model accuracy: 83.2%
- Statistically significant lift ($p < 0.01$) for attribution-optimized interventions

The results reinforce confidence in using the attribution model for strategic planning and investment justification.

4.6 Error Analysis and Edge Cases

Misclassifications were predominantly found in:

- Short sessions (< 5 seconds) with ambiguous intent
- Device clusters with high IP variability (e.g., shared networks)
- Creative IDs reused across multiple campaigns

Subsequent refinements are being considered to improve attribution in these edge scenarios, including context-aware embeddings and campaign-specific priors.

4.7 Summary of Key Results

- LSTM model delivered highest predictive performance across metrics
- Hybrid identity resolution achieved 92.8% cross-device accuracy
- Attribution-informed optimization produced measurable business lift
- Stakeholder tools enhanced interpretability and adoption

The next section discusses implications of these findings, limitations, and directions for future research.

V. DISCUSSION

The findings from the results section provide strong empirical support for the efficacy of advanced cross-device ad attribution frameworks. In this discussion, we interpret these findings in the broader context of performance marketing, evaluate their implications for practical deployment, and address key limitations and future research opportunities.

5.1 Interpretation of Model Performance

The LSTM model's superior performance validates the central hypothesis that temporal sequencing and context of user interactions across devices are critical for accurate attribution modeling. Its 0.93 AUC-ROC reflects a high degree of model discriminability, outperforming traditional rule-based and regression approaches. This confirms previous assertions in the literature that deep learning models particularly those using recurrent architectures are better suited to capture sequential behavior in multichannel environments [85].

Notably, the Shapley Value model, while slightly lower in predictive power, offered enhanced interpretability, which is crucial for stakeholder trust and regulatory compliance [86]. As such, a hybrid deployment involving LSTM for predictive scoring and Shapley modeling for explainability could present a balanced solution.

5.2 Value of Hybrid Identity Resolution

The hybrid identity resolution approach achieved a 92.8% cross-device accuracy, bridging deterministic and probabilistic methodologies. This is significant because previous studies have shown that pure deterministic strategies often fail to generalize across fragmented digital ecosystems, while purely probabilistic methods may yield higher false positives. The graph-based enhancements, specifically GraphSAGE, demonstrated value in identifying latent user connections in sparse data environments—a known limitation of prior approaches.

These results support an emerging industry trend toward hybrid identity strategies, combining hashed emails, device graphs, and contextual signals to resolve cross-device personas more effectively [87], [88].

5.3 Campaign Optimization Impact

The +27.4% conversion uplift and 18.6% ROI improvement suggest that attribution-informed media spend reallocation can significantly enhance campaign performance. These results align with marketing science research indicating that accurate attribution facilitates higher marginal returns on advertising.

This is particularly relevant in today's fragmented ad ecosystem where users traverse mobile, desktop, connected TV, and IoT touchpoints. The attribution model enabled marketers to shift investment toward under-recognized but high-impact touchpoints, addressing budget cannibalization and channel siloing problems identified in previous studies.

5.4 Visualization and Stakeholder Engagement

Power BI dashboards played a key role in facilitating cross-functional understanding. Attribution waterfall charts and geo-device heatmaps were particularly effective in enabling non-technical stakeholders to comprehend model outcomes. This corroborates studies showing that explainable AI tools increase adoption rates among marketing executives.

Further, integration of model outputs into existing business intelligence tools minimizes change management friction a common barrier in digital transformation initiatives [89], [90].

5.5 Backtesting and Incrementality Insights

The 83.2% uplift model accuracy and statistically significant lift underscore the attribution model's real-world validity. Incrementality testing a key validation technique revealed that interventions based on attribution insights drive causally linked outcomes.

This distinguishes the framework from traditional heuristics-based models, which often conflate correlation with causation. It also addresses advertiser concerns regarding attribution bias, especially in environments with complex retargeting and frequency capping mechanisms[91].

5.6 Limitations and Edge Case Considerations

While the model showed strong generalizability, challenges remain in edge scenarios. These include short sessions (< 5 seconds), shared IP networks, and recycled creative identifiers. Such contexts introduce ambiguity that even deep models struggle to disambiguate.

Potential solutions include incorporating session-based embeddings, improving device fingerprinting accuracy, and adopting campaign-specific metadata. Privacy-compliant user feedback loops, such as consented clickstream augmentation, may also enhance training data quality [91].

Another limitation lies in real-time inference latency. While LSTM models are effective, they may be computationally intensive during inference at scale. Optimization through model distillation or edge inference strategies could mitigate this issue [92].

5.7 Implications for Industry Practitioners

For advertisers, the implementation of this framework offers a path toward truly integrated performance measurement. Unlike siloed approaches that assign credit at the channel level, the proposed model accounts for user-level behavior across devices and campaigns, aligning with customer-centric marketing strategies [93].

For technology vendors, the framework's modular design enables flexible integration into existing demand-side platforms (DSPs), customer data platforms (CDPs), and marketing automation tools.

5.8 Future Research Directions

Several avenues warrant further exploration:

- Federated learning techniques could improve model training while preserving user privacy.
- Reinforcement learning-based attribution could dynamically adjust credit assignment based on campaign outcomes.
- Multimodal modeling (e.g., combining video, text, and behavior data) may enhance understanding of intent and context.
- Blockchain-enhanced identity frameworks may improve transparency and user control.

Finally, regulatory shifts such as GDPR and CCPA necessitate ongoing alignment of attribution models with evolving compliance requirements [94].

5.9 Summary of Discussion Points

- LSTM models show superior performance for sequential attribution
- Hybrid identity resolution enhances cross-device recognition
- Attribution insights drive real-world business gains
- Visualization tools improve adoption and interpretability
- Limitations include short sessions, shared networks, and inference latency
- Future work should explore privacy-preserving, real-time, and multimodal solutions

The next section concludes with a synthesis of findings and strategic recommendations for academic and industry stakeholders [95].

CONCLUSION

This study developed and evaluated a comprehensive cross-device ad attribution framework that integrates advanced behavioral modeling, hybrid identity resolution, and real-time analytics to enable accurate and actionable performance measurement. The empirical results and subsequent analysis highlight both the theoretical robustness and practical utility of this integrated attribution model[96].

6.1 Summary of Key Contributions

Foremost among the contributions is the demonstration that deep learning models, specifically LSTM-based architectures, substantially outperform traditional rule-based and regression models in identifying user journeys across multiple devices. The high AUC-ROC value of 0.93 confirms the model's discriminative power. Importantly, the inclusion of Shapley Values for model interpretability ensures that performance does not come at the cost of transparency, a crucial consideration in privacy-centric marketing environments [97].

Furthermore, the hybrid identity resolution framework demonstrated 92.8% accuracy in associating cross-device behavior, leveraging a combination of deterministic identifiers and probabilistic inference supported by graph-based enhancements such as GraphSAGE. This dual approach not only improves accuracy but also reflects current industry trends toward nuanced identity strategies [98].

The model also led to measurable business impact: a 27.4% increase in conversion rate and 18.6% ROI uplift through optimized media spend allocation. These performance gains validate the practical relevance of advanced attribution strategies in today's multichannel marketing ecosystem.

6.2 Strategic Implications

From a strategic standpoint, this research highlights the necessity of transitioning from siloed, last-touch attribution models to integrated, user-centric approaches. The adoption of cross-device attribution frameworks allows for granular performance evaluation that reflects actual consumer behavior rather than generalized heuristics [99].

Marketers equipped with such models can make more informed decisions about budget allocation, creative optimization, and customer engagement strategies. Technology providers and platforms stand to benefit by integrating modular attribution tools into existing analytics pipelines, driving broader industry adoption.

Moreover, the visualization component of the framework built using Power BI and focused on interpretability served as a catalyst for cross-departmental collaboration and stakeholder alignment. These dashboards translated complex model outputs into actionable insights, promoting executive buy-in and facilitating change management [100].

6.3 Limitations and Risk Considerations

Despite its strengths, the framework is not without limitations. Real-time latency from deep learning inference, ambiguity in shared device environments, and session sparsity in short interactions remain unresolved challenges. Future implementations may require model distillation or edge-based inference to maintain real-time responsiveness.

Another important consideration is regulatory compliance. With increasing scrutiny from GDPR, CCPA, and other emerging global data privacy laws, attribution systems must be designed with privacy-by-design principles and transparency as foundational elements.

6.4 Future Research Opportunities

Several directions exist for extending this work. Federated learning can enable privacy-preserving attribution modeling across decentralized data silos. Reinforcement learning may be employed to dynamically adjust attribution logic based on real-time performance metrics. Multimodal data fusion integrating behavioral, contextual, and multimedia signals holds potential for more comprehensive customer understanding.

Additionally, incorporating blockchain technology for decentralized identity management could enhance data transparency and user control, aligning with ethical data use practices. Finally, comparative studies across verticals (e.g., retail, finance, healthcare) would provide domain-specific benchmarks for attribution model effectiveness.

6.5 Concluding Remarks

In conclusion, this paper presents a robust and adaptable cross-device ad attribution model that merges methodological rigor with real-world applicability. Through advanced behavioral analytics, hybrid identity resolution, and interpretable outputs, the proposed framework offers a viable solution for performance marketers seeking to navigate the complexities of multichannel digital ecosystems.

As digital interactions continue to evolve across an expanding array of devices and platforms, accurate and ethical attribution remains a cornerstone of sustainable marketing success. This research contributes a foundational step in that direction and opens multiple pathways for future exploration.

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