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Review Article

Marketing Funnel Optimization in Mobile App Analytics: A Systematic Review

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Abstract

Mobile apps have revolutionized digital marketing and created a need for systematic optimization of user acquisition, engagement, retention, and monetization. However, research on mobile funnel optimization remains fragmented across marketing, information systems, and computational analytics. This systematic literature review investigates the question: What are the changes in conceptual, attribution, experimentation, machine learning, and privacy-aware approaches to support the optimization of the marketing funnel in mobile app environments? We performed a systematic literature review using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework. Peer-reviewed journal articles and conference papers published in English between 2015 and 2025 were searched in the Scopus database. The search identified 168 records, of which 27 studies met the predefined eligibility criteria and were included in the thematic synthesis. The synthesis indicates a shift from linear funnel conceptualizations toward adaptive lifecycle models encompassing awareness, consideration, acquisition, onboarding, engagement, and monetization. Attribution research is shifting from heuristic to multichannel, probabilistic, game-theoretic, and incremental approaches. The reviewed studies also show an increasing adoption of techniques such as causal experimentation, machine learning, contextual bandits, and reinforcement learning for adaptive optimization. Privacy concerns, such as App Tracking Transparency and the General Data Protection Regulation, also influence mobile measurement by restricting user-level signals and elevating the significance of privacy-preserving and probabilistic methods. The review considers mobile funnel optimization as a lifecycle, with attribution, experimentation, algorithmic optimization, and privacy governance working together throughout the funnel. The proposed literature-derived framework integrates these fragmented research streams and identifies directions for future empirical research in mobile app analytics.

Categories: Digital Marketing, Marketing and Market Issues in Business

Keywords: mobile app analytics, marketing funnel optimization, attribution modeling, reinforcement learning, differential privacy, marketing experimentation

Introduction And Background

The global mobile application ecosystem has become one of the most economically significant digital environments of the twenty-first century. By 2024, the aggregate consumer spending on mobile apps topped 170 billion dollars a year, and over 255 billion downloads had taken place across the globe (Sensor Tower, 2024). Such numbers demonstrate a structural change in the way consumers learn about, compare, and buy digital services - a change that puts increasing pressure on app publishers to streamline every part of the user experience, such as initial touchpoint discovery and long-

term monetization. Importantly, this optimization imperative is playing out against the context of increasing user acquisition expense, disintegrating measurement ecosystems triggered by privacy regulation, and the algorithmic complexity of platform-controlled distribution channels (Palomares et al., 2021).

The academic analysis of marketing funnel optimization can be traced back to classical persuasion models like AIDA (Awareness-Interest-Desire-Action) and its offshoot, which framed consumer decision-making as a one-way, stage-based process (Barry and Howard, 1990). However, with the advent of digital multichannel spaces, these linear models have become structurally ineffective. Recent research highlights the fact that consumer experiences are nonlinear, mediated by platforms, and often involve re-engagement loops that do not follow funnel-like developments (Lemon and Verhoef, 2016). The increasing prevalence of omnichannel interactions further complicates consumer decision-making pathways. Consumers frequently move across multiple digital and physical touchpoints during information search and purchase processes, creating nonlinear pathways that challenge traditional stage-based funnel assumptions. Such cross-channel behavior reinforces the need for adaptive analytical frameworks capable of capturing dynamic customer journeys across interconnected engagement environments (Gu and Tayi, 2017). This reorganization is especially consequential in mobile settings, where platform architecture, algorithmic discovery processes, and real-time behavioral cues are configured to influence user paths in a manner that cannot be explained by traditional funnel models.

Although the core role of mobile app analytics has been established in both research and practice, the literature remains fragmented across multiple disciplines. Attribution theory and causal experimentation techniques have primarily been investigated within marketing research, reinforcement learning, and probabilistic modelling have largely emerged from computer science, while privacy governance and platform-related issues have been examined in information systems research. In addition, practitioner reports provide supplementary context on operational aspects of user acquisition, retention, and monetization. This disciplinary fragmentation limits the integration of conceptual, methodological, and practical perspectives, making it difficult to obtain a comprehensive understanding of mobile marketing funnel optimization (Lamberton and Stephen, 2016) (Beck et al., 2021). Consequently, there is a need for a systematic synthesis that consolidates these diverse research streams into a coherent conceptual framework to support future research and practice.

This review fills that gap by offering a synthesis of evidence-based research on mobile marketing funnel optimization in five thematic areas, namely: (1) the conceptual underpinnings of the mobile marketing funnel and its difference from web-based counterparts; (2) attribution modeling and multichannel credit assignment; (3) causal inference and controlled experimentation across funnel stages; (4) machine learning and reinforcement learning in adaptive budget allocation and conversion optimization; (5) privacy regulation, data governance, and ethical aspects of mobile measurement. The review focuses on peer-reviewed academic literature, while practitioner technical documentation is used only as supplementary background to contextualize recent developments in mobile analytics. By so doing, it addresses calls to review scholarship that balances academic rigor and practical relevance in the fast-changing discipline of digital marketing analytics (Lamberton and Stephen, 2016).

This review aims to synthesize and critically evaluate the literature on marketing funnel optimization in mobile app analytics. Specifically, it examines the evolution of mobile marketing funnel conceptualizations from linear to adaptive lifecycle models and reviews attribution modeling approaches for tracking and optimizing user journeys in mobile environments. It further analyzes the application of experimentation, and evidence-based optimization techniques across funnel stages, evaluates the role of machine learning and reinforcement learning in adaptive funnel optimization, and examines the implications of privacy regulations and platform governance for mobile measurement, attribution, and optimization practices. Finally, the review synthesizes these research streams into an integrated conceptual framework for mobile marketing funnel optimization.

The remainder of this article is structured as follows. Section "Review Design and Approach" describes the systematic review methodology, including the review design, search strategy, study selection, data extraction, and analysis procedure. Section "Conceptual Foundations of the Mobile Marketing Funnel" discusses the conceptual foundations of the mobile marketing funnel. Sections "Attribution Modeling in Mobile Funnel Optimization", "Causal Inference and

Experimentation Across Funnel Stages", "Machine Learning and Reinforcement Learning for Funnel Optimization", and "Privacy, Data Governance, and Ethical Constraints in Mobile Funnel Optimization" examine attribution modeling, experimentation and evidence-based optimization, machine learning and reinforcement learning, and privacy and governance considerations, respectively. Section "Synthesis: Toward a Unified Framework for Mobile Funnel Optimization" synthesizes these findings into an integrated conceptual framework for mobile funnel optimization. Section "Limitations" presents the limitations of the review, Section "Future Research Directions" outlines future research directions, and Section 10 concludes the study by summarizing the key findings and contributions.

Review

Review design and approach

This study uses the systematic literature review (SLR) to critically synthesize and summarize the literature on the optimization of the marketing funnel in mobile app analytics. The review was carried out according to the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) 2020 guidelines to guarantee methodological transparency, reproducibility, and consistency across the process of study identification, screening, and synthesis (Page et al., 2021).

Research on mobile funnel optimization is dispersed across multiple disciplines, including marketing, information systems, artificial intelligence, and mobile analytics. The SLR approach allows for a structured, transparent, and reproducible synthesis of evidence and minimizes the possibility of selective interpretation. To ensure consistency in the identification, screening, eligibility assessment, and reporting, PRISMA 2020 guidelines were used. To reduce selection bias, inclusion and exclusion criteria were defined before the search process, duplicate records were eliminated, and studies were sequentially screened in the title, abstract, and full-text review. In addition, methodological quality and relevance were evaluated with pre-established evaluation criteria to increase the robustness of the synthesis.

The review emphasizes different analytical architectures of mobile marketing funnels that are evolving, namely: attribution modeling, experimentation and evidence-based optimization frameworks, machine learning-based optimization, reinforcement learning applications, and privacy-aware analytics in mobile ecosystems. The interdisciplinary character of the domain requires a review in various areas: digital marketing, information systems, computer science, artificial intelligence, and mobile advertising research.

The review does not merely describe the previous research, but it takes a thematic-synthesis approach to uncover the prevailing research paths, methodological advances, unresolved analytical issues, and new research gaps related to adaptive mobile funnel optimization.

Data Source and Search Strategy

Given the interdisciplinary nature of research on mobile analytics, artificial intelligence, digital marketing, and information systems, Scopus was selected as the sole database because of its broad coverage of peer-reviewed journals, conference proceedings, and interdisciplinary publications. Scopus has been widely used in SLRs owing to its extensive indexing, citation coverage, and ability to retrieve high-quality research across multiple disciplines. Although PRISMA 2020 recommends comprehensive literature searches that may include multiple databases, the present review intentionally employed Scopus as a single source to ensure methodological consistency and a transparent, reproducible screening process. This decision is acknowledged as a limitation of the review and is discussed in the Limitations section.

The search process aimed to include current research on mobile funnel optimization, so only papers from the last ten years, from 2015 to 2025, were considered. The Scopus database search was conducted in February 2026. Journal articles and conference papers in English were the only articles included to achieve methodological uniformity and scholarly validity.

Boolean operators and combinations of keywords in the TITLE-ABS-KEY fields in Scopus were used as the search strategy. The search query was engineered to deliver a balance between broadness and thematic targeting of retrieved content, across mobile analytics, conversion optimization, customer journey modeling, engagement optimization, and mobile monetization ecosystems. The search terms were selected using a concept-based approach to represent the mobile application domain, marketing funnel and customer journey, and funnel optimization objectives. A detailed justification of the selected search terms is provided in Appendix A. The main search term used during the study was the following:

TITLE-ABS-KEY
((
"mobile app*" OR "mobile marketing" OR "mobile analytics" OR "mobile advertising" OR "app analytics" OR "mobile user engagement")
AND
(
"marketing funnel" OR "conversion funnel" OR "user journey" OR "customer journey" OR "funnel optimization" OR "conversion optimization" OR "user acquisition" OR "user retention" OR "app monetization"
))

The search strategy was further optimized in the initial retrieval and screening phase to generate more relevant themes with a wide conceptual coverage for each of the four categories: an attribution system, an experimentation methodology, adaptive optimization, and a privacy-aware analytical approach.

Screening and Selection Criteria

The study selection process was based on a multi-stage screening process using PRISMA methodology. First, 168 records were obtained from the Scopus database. Then the filters for the year of publication, document type, language, and thematic relevance were applied. There were 132 studies left after filtering. Duplicate studies were then excluded, leaving 124 studies for the title and abstract screening.

In the title and abstract screening phase, the concepts were assessed for their relevance to mobile marketing funnels, mobile analytics ecosystems, attribution methods, experimentation frameworks, machine learning-driven optimization, and privacy-protective measurement systems. At this stage, studies that were not analytically relevant to funnel optimization, or focused primarily on non-mobile environments or non-relevant application domains were excluded.

Full-text eligibility assessments, based on predefined inclusion and exclusion criteria, were performed for the remaining studies.

The studies were included if they:

• were peer-reviewed journal articles or conference papers;

• were published between 2015 and 2025;

• focused on mobile applications, mobile advertising, mobile analytics, or mobile engagement ecosystems;

• addressed funnel optimization, attribution modeling, experimentation, personalization, machine learning, reinforcement learning, or privacy-aware analytics; and

• provided sufficient conceptual, methodological, or empirical relevance to mobile funnel optimization.

Studies were excluded if they:

• focused exclusively on non-mobile digital ecosystems;

• lacked direct analytical relevance to mobile funnel optimization;

• represented editorials, abstracts, notes, or non-peer-reviewed reports; or

• did not provide adequate methodological or conceptual detail for thematic synthesis.

Practitioner reports, industry white papers, and technical documentation were used only as supplementary background sources and were not included in the formal evidence synthesis or thematic analysis. After the full-text review, 27 studies, which had met all of the eligibility criteria, were included in the final synthesis. The entire study identification, screening, eligibility assessment, and inclusion process is shown in the PRISMA flow diagram presented in Figure *1*.

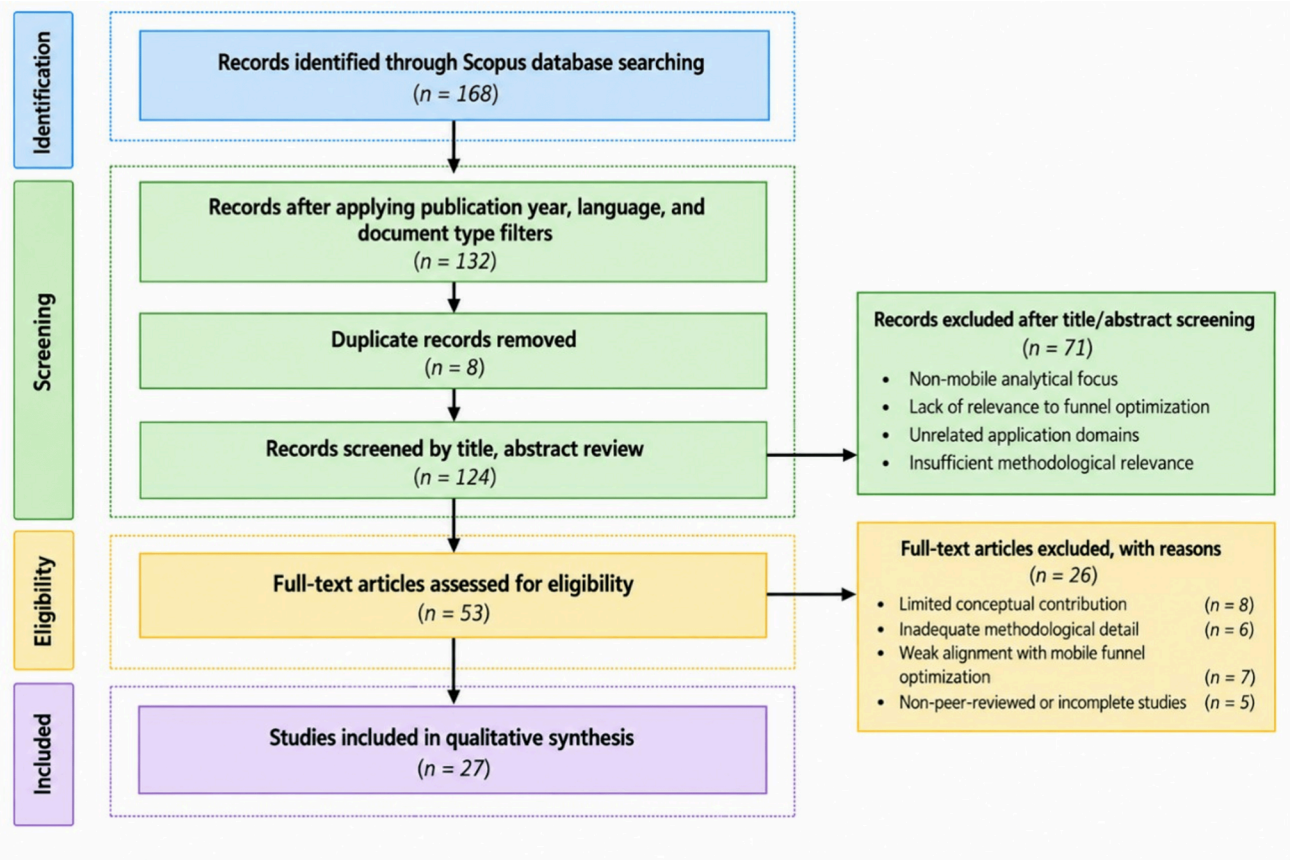


FIGURE 1: PRISMA Flow Diagram of the Study Selection Process

Source: Authors' analysis based on the Scopus dataset.
PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Data Extraction, Quality Assessment, and Analysis Procedure

The selected studies were analyzed and information was collected systematically using a structured data extraction framework. The variables retrieved were publication year, goals of the research, funnel stages covered, methods of attribution, methods of experimentation, optimization techniques, use of machine learning, privacy considerations, and the main results.

To enhance analytical consistency and interpretive rigor, the included studies were critically evaluated during the data extraction and thematic synthesis process based on the clarity of the research objectives, methodological approach, analytical focus, empirical relevance, and applicability to mobile marketing funnel optimization. Potential publication bias was considered during the interpretation of the findings, recognizing that studies reporting significant or positive optimization outcomes are generally more likely to be published than studies reporting null or negative findings.

During the eligibility assessment, studies with insufficient methodological detail or limited relevance to the review objectives were excluded based on the predefined inclusion and exclusion criteria. The methodological characteristics and limitations of the included studies were considered qualitatively during the interpretation of the synthesized

findings.

The literature obtained was then analyzed by the thematic synthesis method. Literature was categorized into major themes based on the main themes of the author keywords, abstracts, methodological orientations, and study aims, namely funnel conceptualization, attribution modeling, experimentation and evidence-based optimization, machine learning-based optimization, reinforcement learning-based optimization, and frameworks for privacy and governance.

Descriptive analytical methods were used in addition to thematic synthesis to analyze the publication trend and thematic distributions among the studies included. The distribution of the studied literature by year of publication is shown in Figure *2*. Figure *3* presents the frequency of the research themes identified across the included studies. The thematic distribution was as follows: funnel conceptualization (10 studies), attribution modeling (12 studies), experimentation and evidence-based optimization (5 studies), machine learning and reinforcement learning (10 studies), and privacy and governance (5 studies). Because individual studies often addressed multiple thematic areas, a single study could contribute to more than one theme. The descriptive analysis showed a significant surge in research efforts since 2020, especially in the areas of engagement-oriented optimization and machine-learning-based personalization frameworks. However, comparatively less research has specifically focused on causal attribution consistency and experimentation methodologies, highlighting an unexplored area in the field of mobile marketing that needs robust causal measurement and validation frameworks.

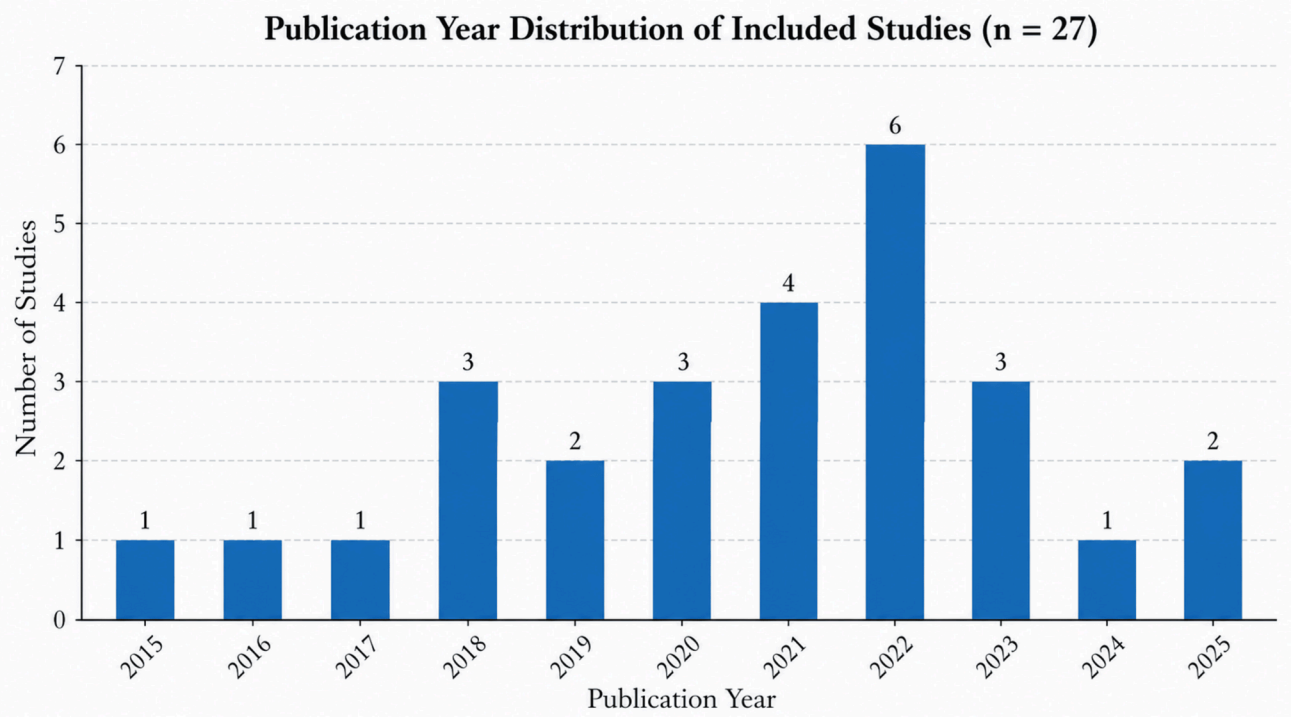


FIGURE 2: Publication Year Distribution of the Included Studies

Source: Authors' creation.

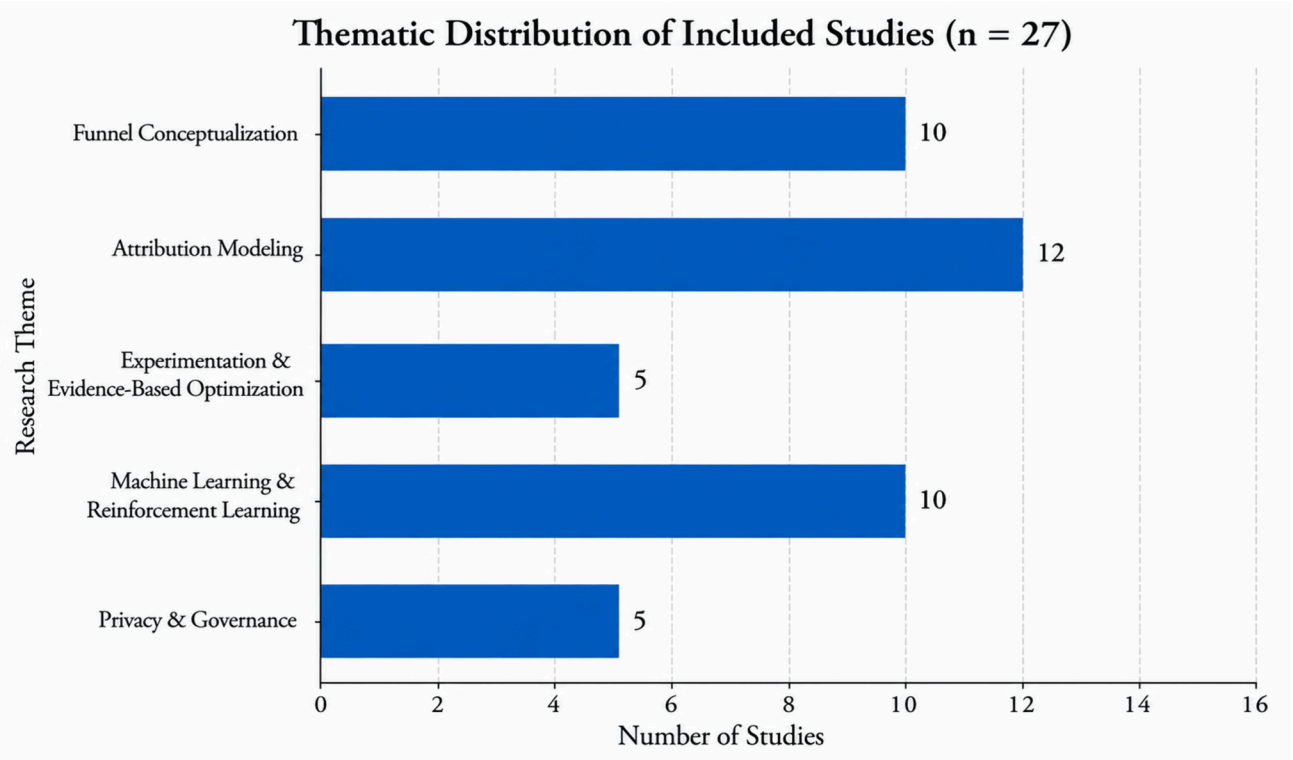


FIGURE 3: Thematic Distribution of Research Themes Across Included Studies

Source: Authors' creation.

Table *1* summarizes the characteristics and principal contributions of the studies discussed in the review, including foundational references. The included studies were categorized into five thematic areas: funnel conceptualization, attribution modeling, experimentation and evidence-based optimization, machine learning and reinforcement learning, and privacy and governance. Together, these studies provide the conceptual, methodological, and empirical foundation for the integrated framework developed in this review.

Author(s)	Theme	Study Type	Key Contribution
(Barry and Howard, 1990)	Funnel Conceptualization	Conceptual Review	Critiqued hierarchy-of-effects models and highlighted limitations of linear consumer decision frameworks.
(Lemon and Verhoef, 2016)	Funnel Conceptualization	Conceptual Framework	Developed a customer journey framework emphasizing multichannel and nonlinear consumer interactions.
(Lamberton and Stephen, 2016)	Funnel Conceptualization	Literature Review	Synthesized developments in digital, social, and mobile marketing and identified future research directions.
(Gu and Tayi, 2017)	Funnel Conceptualization	Analytical Modeling	Examined pseudo-showrooming behavior and optimal omnichannel channel-placement strategies.
(Kannan et al., 2016)	Funnel Conceptualization	Conceptual Paper	Discussed path-to-purchase processes and attribution challenges in digital marketing ecosystems.
(Mondal and Chakrabarti, 2021)	Funnel Conceptualization	Empirical Study	Identified determinants of branded mobile app abandonment behavior using interpretive structural modeling.
(Enache et al., 2025)	Funnel Conceptualization	Empirical Study	Applied customer lifetime value concepts to mobile app environments and user value assessment.
(Abrar and Herzog, 2025)	Funnel Conceptualization	Methodological Study	Developed ML- and NLP-based models for app search ranking prediction and app store optimization.
(Chiba et al., 2025)	Funnel Conceptualization	Empirical Study	Investigated the effects of app title length restrictions on consumer decision-making and app discovery.

(Grewal et al., 2016)	Funnel Conceptualization	Conceptual Framework	Proposed a research agenda for mobile advertising effectiveness and mobile consumer engagement.
(De Haan et al., 2016)	Attribution Modeling	Empirical Study	Compared the effectiveness of online advertising formats using multiple-channel attribution approaches.
(Singal et al., 2019)	Attribution Modeling	Theoretical Study	Developed an axiomatic Shapley-value framework for attribution and credit allocation.
(Mrad and Hnich, 2024)	Attribution Modeling	Methodological Study	Proposed intelligent attribution models for improved digital marketing performance measurement.
(Beck et al., 2021)	Attribution Modeling	Review Article	Reviewed multichannel attribution methodologies and identified future research directions.
(Barajas and Bhamidipati, 2021)	Experimentation & Evidence-Based Optimization	Experimental Study	Enhanced incrementality testing through double-blind experimental designs in programmatic advertising.
(Zhang et al., 2024)	Experimentation & Evidence-Based Optimization	Methodological Study	Proposed temporal uplift modeling for estimating heterogeneous treatment effects in marketing interventions.
(Lemmens et al., 2025)	Experimentation & Evidence-Based Optimization	Review Article	Synthesized personalization, targeting, experimentation, learning, and optimization practices in marketing systems.
(Witarsyaha et al., 2025)	Experimentation & Evidence-Based Optimization	Empirical Study	Combined causal analysis and predictive modeling to evaluate digital marketing effectiveness.
(He and Rao, 2024)	Experimentation & Evidence-Based Optimization	Review Article	Synthesized contemporary causal inference methodologies and

			applications in marketing research.
(Han and Gabor, 2020)	Machine Learning & Reinforcement Learning	Computational Study	Applied contextual bandit algorithms to advertising budget allocation problems.
(Cai et al., 2023)	Machine Learning & Reinforcement Learning	Deep Reinforcement Learning Study	Proposed constrained offline deep reinforcement learning for marketing budget optimization.
(Adikari and Dutta, 2021)	Machine Learning & Reinforcement Learning	Optimization Study	Developed adaptive ad network selection methods for publisher revenue optimization in mobile apps.
(McGuigan et al., 2023)	Privacy & Governance	Qualitative Study	Examined industry responses and governance implications of the transition toward privacy-preserving advertising ecosystems.
(Kollnig et al., 2022)	Privacy & Governance	Empirical Study	Assessed the impact of Apple's App Tracking Transparency framework on mobile tracking practices.
(Subramanian, 2023)	Privacy & Governance	Methodological Study	Demonstrated differential privacy techniques for privacy-preserving analytics.
(Latif et al., 2020)	Privacy & Governance	Technical Study	Introduced differential privacy mechanisms for mobile application analytics systems.
(McGuigan et al., 2025)	Privacy & Governance	Conceptual Study	Investigated the meanings, mechanisms, and governance implications of privacy-preserving advertising technologies.

TABLE 1: Characteristics and Key Contributions of Included Studies

Source: Authors' synthesis based on the studies included in the systematic literature review.
ML, Machine Learning; NLP, Natural Language Processing

Conceptual foundations of the mobile marketing funnel

The marketing funnel has been conceptualized to have developed significantly since the old AIDA model into more dynamic and lifecycle-oriented models, which represent the current trends in digital consumption. Although AIDA has presented a linear view of persuasion and purchase, later research has focused on nonlinear, multi-touch customer experiences with multiple channel and device interactions. Kannan et al. claim that the current path-to-purchase activity is always fragmented, and the attribution and journey analysis should be conducted holistically and not at the stage level (Kannan et al., 2016). This re-conceptualization is especially relevant to mobile settings, where users move across app stores, in-app experiences, and external platforms and then complete transactional events.

Mobile funnels have three structural and behavioral differences from web-based counterparts that have a significant impact on measurement and optimization needs. To begin with, discovery is platform-controlled: app store algorithms, keyword ranking, and metadata restrictions have a direct effect on visibility and acquisition at the initial funnel level. Studies of app store optimization show that the ranking of determinants like the structure of keywords, the title, and the features of natural language processing has a very strong influence on user discovery results (Abrar et al., 2025). App title design and metadata characteristics can significantly influence visibility and user discovery outcomes within app marketplaces (Chiba et al., 2025). Compared to traditional web traffic, which is mediated by open search ecosystems, mobile awareness and consideration phases are significantly limited by platform structures that publishers are unable to directly manage.

Second, mobile funnels are very vulnerable to abandonment and retention processes. As shown by Mondal and Chakrabarti, interrelated structural antecedents such as perceived usefulness, ease of use, trust, and value realization cause branded application abandonment (Mondal and Chakrabarti, 2021). Their structural modeling approach to interpretation indicates that mobile engagement is delicate and dependent on the quality of experience at an early stage (Mondal and Chakrabarti, 2021). This volatility is confirmed by industry standards, which indicate that over 70 percent of applications that are installed are abandoned within 30 days of installation (CleverTap, 2024). Based on this, funnel analysis in mobile settings should go beyond acquisition metrics and include onboarding performance, initial engagement quality, and churn indicators as part of the performance measurements.

Third, monetization and long-term value play a central role and not a terminal role in mobile ecosystems. Instead of viewing conversion as a single point, modern models incorporate Customer Lifetime Value (CLV) as a fundamental performance measure. Enache et al. show that mobile-specific CLV models, which take into consideration correlated purchase and dropout behavior, make more accurate predictions of long-term profitability than traditional conversion-rate-based metrics (Enache et al., 2025). Such a view reinvents funnel optimization as a sustainable value creation exercise throughout the user lifecycle, as opposed to a conversion rate maximization exercise in the short term.

Based on these theoretical and empirical observations, the mobile marketing funnel can be theorized to consist of six related steps, namely: Awareness, Consideration, Acquisition, Onboarding, Engagement, and Monetization. Perception and mindfulness are conditioned by the visibility of app stores and platform-mediated discovery processes (Chiba et al., 2025). Installation and first-launch behaviors are reflected in acquisition, whereas first-value realization and permission acceptance are determined by onboarding, thus affecting early retention (Mondal and Chakrabarti, 2021). Engagement will include repeat sessions and use of features, and monetization will go beyond the first purchase to include long-term value addition throughout the user lifecycle.

The mobile funnel is also cyclical, meaning that users may repeatedly move between consideration, acquisition, engagement, retention, and monetization stages through continuous interactions rather than progressing through the funnel only once, in contrast to the linear AIDA formulations, and it is also feedback-driven. The consideration step can be repeated by the user with the help of push notifications, in-app messages, or promotional messages, and monetization results can transform acquisition strategies with lifetime value-based bidding algorithms. According to Kannan et al., measurement and optimization can only be effective with a comprehensive picture of the customer journey and not

individual conversion touchpoints (Kannan et al., 2016). The mobile marketing funnel can then best be viewed as an adaptive lifecycle system, constrained by platform considerations, algorithmic visibility systems, and economic incentives through retention.

Attribution modeling in mobile funnel optimization

Attribution modeling is the analytical foundation of marketing funnel optimization, since it defines how the credit for conversion results is distributed among touchpoints in the user journey (Beck et al., 2021). Attribution is methodologically complicated and strategically decisive in mobile environments where users engage with a variety of paid, owned, and organic channels before installing an app or making an in-app purchase (Grewal et al., 2016). The initial practice of digital attribution was based on heuristic rules-the majority being last-click or first-touch credit attribution-which are inherently inadequate in capturing the dynamism and multi-stage nature of path-to-purchase behavior in mobile ecosystems with cross-device interactions and platform-mediated discovery (Beck et al., 2021).

De Haan et al. empirically examined the effectiveness of different online advertising formats within a multichannel attribution framework (De Haan et al., 2016). Their findings demonstrated that estimates of channel effectiveness and return on investment vary according to the attribution approach employed, highlighting the limitations of relying on heuristic or single-touch attribution measures. These findings emphasize the importance of multichannel attribution approaches for more informed evaluation of marketing performance and budget allocation.

Although multichannel statistical models enhance the accuracy of descriptive allocation, they are prone to correlation bias when causal identification is not achieved. On a theoretical basis, Singal et al. operationalized attribution based on an axiomatic model, proposing a counterfactual-adjusted Shapley value model (Singal et al., 2019). Meeting the axioms of fairness and consistency, as developed in cooperative game theory, Shapley-based approaches can be used to theoretically justify credit allocation across interacting channels, an improvement that has a direct practical application in mobile app marketing, where multiple touchpoints frequently co-occur in tight acquisition timeframes (Singal et al., 2019).

More recent works combine probabilistic and machine learning methods to overcome signal sparsity and data constraints in mobile ecosystems due to privacy. Mrad and Hnich suggest a smart attribution model that utilizes Bayesian networks and negative observation propagation to enhance the prediction of conversion and credit allocation (Mrad and Hnich, 2024). Their empirical findings show that probabilistic modeling increases the strength of attribution in the case of incomplete deterministic event records - a situation that is becoming more common in post-ATT settings where persistent device identifiers are no longer consistently available (Mrad and Hnich, 2024).

In line with these scholarly developments, attribution research has increasingly emphasized incrementality and lift-based measurement. Incremental cost-per-action effects can be estimated using auction-based identification strategies, including ghost-bidding approaches that model counterfactual exposure without requiring complete randomized withholding of advertisements. Such approaches are particularly relevant in large-scale programmatic advertising environments where conventional controlled experiments may be operationally difficult to implement (Barajas and Bhamidipati, 2021).

Taken together, the existing literature demonstrates that there are three fundamental paradigms of mobile attribution modeling, namely, heuristic attribution (e.g., last-click), multichannel statistical attribution (e.g., regression-based or Shapley models), and causal or incrementality-based attribution. Heuristic models have the benefit of operational simplicity but with systematic bias; multichannel models have fairer allocation but still may be based on correlational inference; causal and lift-based methods are theoretically rigorous in measurement but have much higher implementation costs and experimentation infrastructure requirements. Within the mobile setting, all three paradigms will also have to grapple with platform-enforced restrictions, such as the unavailability of identifiers, the existence of aggregated reporting requirements, and privacy-aware measurement protocols, forcing them to resort to hybrid strategies that integrate probabilistic modeling, counterfactual reasoning, and experimental validation. Table *2* summarizes the major attribution paradigms used in mobile marketing ecosystems, highlighting their methodological

characteristics, operational strengths, analytical limitations, and robustness under privacy-constrained environments. The comparison demonstrates the transition from heuristic and correlational attribution approaches toward causal and probabilistic frameworks capable of operating under increasingly restricted measurement architectures.

Paradigm	Method Examples	Strengths	Limitations	Privacy Robustness	Key References
Heuristic	Last-click, First-touch	Operational simplicity	Systematic bias	Low	(De Haan et al., 2016)
Statistical Multichannel	Regression-based, Markov models	Improved allocation fairness	Correlational inference	Moderate	(De Haan et al., 2016)
Axiomatic / Game-Theoretic	Shapley value attribution	Fairness axioms satisfied	Computational complexity	Moderate	(Singal et al., 2019)
Causal / Incrementality	Lift tests, Ghost bidding	Counterfactual validity	High infrastructure cost	High	(Barajas and Bhamidipati, 2021)
Probabilistic / Bayesian	Bayesian networks	Robust to signal sparsity	Model dependence	High	(Mrad and Hnich, 2024)

TABLE 2: Comparative Characteristics of Attribution Paradigms in Mobile Ecosystems

Source: Authors' synthesis based on (De Haan et al., 2016), (Singal et al., 2019), (Barajas and Bhamidipati, 2021), and (Mrad and Hnich, 2024).

Operational definition of privacy robustness: Privacy robustness is defined as an attribution approach's utility in a limited user-level tracking scenario. Low means that the data show high dependence on granular tracking, Moderate means partial adaptability to aggregated data, and High means that the data show greater reliance on aggregated, experimental, counterfactual, or probabilistic approaches. Ratings are not validated quantitative scores.

Causal inference and experimentation across funnel stages

Attribution modeling assigns credit to observed touchpoints. Causal inference and controlled experimentation can be used to determine whether particular marketing interventions produce real incremental behavioral effects or not (Witarsyaha et al., 2025). The ability to differentiate causal influences and spurious relationships is methodologically indispensable and practically significant in mobile funnel optimization, in which decisions are made to determine the costs of acquisition, the rate of activation, the depth of engagement, and the monetization patterns. Observational performance measures such as click-through rates and post-exposure conversion rates systematically overestimate the effects of treatments because they are subject to selection bias and confounding factors of self-selected exposure. The resulting transition to incrementality testing and causal machine learning is consequently a methodological breakthrough in mobile marketing analytics (He and Rao, 2024).

Another important methodological input in this field is the auction-based incrementality estimation framework by Barajas and Bhamidipati. Their double-blind ghost bidding method approximates incremental cost-per-action effects in programmatic advertising settings by modeling counterfactual exposure situations without entirely withholding the delivery of ads (Barajas and Bhamidipati, 2021). This can be used to achieve causal measurement at scale without

disrupting live revenue operations, which is especially desirable in mobile acquisition settings where real-time bidding ecosystems make fully randomized field experiments operationally expensive or impossible (Barajas and Bhamidipati, 2021).

Recent developments in causal machine learning have also generalized experimental designs to allow time-dependent and dynamic treatment effects. A temporal uplift modeling framework suggested by Zhang et al. to model delayed and decadent effects of marketing interventions is an attribute of modeling that is especially relevant to retention-oriented strategies where onboarding triggers or loyalty incentives can induce lagged behavioral changes (Zhang et al., 2024). In contrast to the homogeneous and immediate response assumed in the case of static A/B testing, temporal uplift models approximate the change in treatment impact over time, which significantly increases the accuracy of decisions related to the optimization of activation and engagement (Zhang et al., 2024).

On a more abstract level, Lemmens et al. combine personalization and causal experimentation into a single framework of policy learning (Lemmens et al., 2025). Their experiment-learn-optimize paradigm re-conceptualizes funnel management as an iterative and adaptive learning process as opposed to a series of discrete campaigns, which is in line with the nonlinear and temporally distributed nature of mobile user journeys (Lemmens et al., 2025). Mobile marketing experimentation is further limited by the shift to aggregated reporting architecture, which limits granular user-level tracking in favor of cohort-based or modeled attribution signals. In this type of setting, lift-based experimentation obtains methodological priority because it allows causal validation without the need to use persistent identifiers.

In combination, the literature outlines three complementary methods of causal evaluation in mobile funnel optimization: randomized controlled experiments, such as large-scale A/B testing and field trials; quasi-experimental and auction-based incrementality estimation; and causal machine learning models including temporal uplift and adaptive policy learning. With mobile ecosystems becoming privacy-restricted and algorithmically mediated, causal experimentation becomes an essential pillar of rigorous, data-driven funnel optimization. One of the key findings of the literature reviewed is the increasing use of causal experimentation to measure the effectiveness of marketing at different points in the mobile funnel. The experiment-learn-optimize cycle is shown in Figure *4* and is the basis of incrementality-based decision making. Marketing interventions are exposed at random, then the outcome is measured and the uplift is estimated to get the real impact of the interventions. Evidence generated then leads to policy updates and subsequent interventions, establishing a feedback loop that enables data-driven optimization of acquisition, engagement, retention, and monetization strategies.

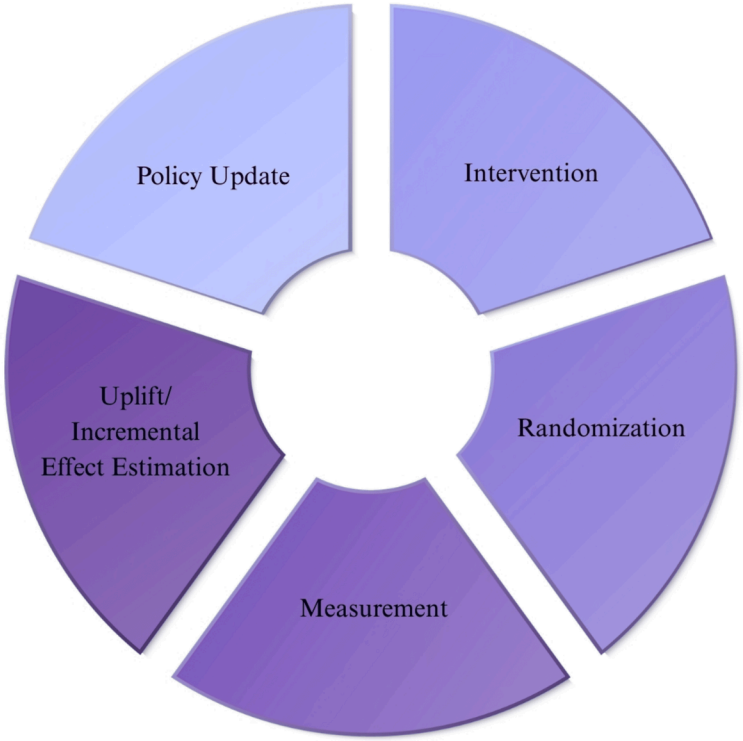


FIGURE 4: Experiment–Learn–Optimize Cycle in Mobile Funnel Management

Source: Authors' creation.

Machine learning and reinforcement learning for funnel optimization

With the dynamic and multichannel nature of mobile marketing funnels, fixed rule-based optimization approaches cannot be used to capture real-time changes in user behavior, channel performance, and cost structure. Machine learning and reinforcement learning have since become important techniques of adaptive funnel optimization, especially in budget allocation, channel selection, and decision-making at the monetization stage. Unlike traditional attribution models that passively attribute credit to observed results, reinforcement learning-based systems actively learn the best policies by making decisions sequentially under uncertainty, which allows prospective rather than reactive optimization.

Han and Gabor made one of the earliest contributions in this direction by developing a contextual bandit framework for advertisement budget allocation (Han and Gabor, 2020). Their methodology allows dynamic spending on marketing by continuously training the anticipated response of each channel given the observed contextual features, such as user demographics, session timing attributes, and previous engagement cues. Unlike fixed heuristics or budget allocations that are manually adjusted, contextual bandits update allocation strategies with real-time performance feedback, allowing quick adjustment to changing advertising conditions. Empirical findings indicate quantifiable improvements in return on investment compared to rule-based allocation standards (Han and Gabor, 2020).

Contextual bandits can be used to support online learning, but operational environments often place exploration limitations that can be explained by financial risk, policy restrictions of the platform, and the opportunity cost of suboptimal allocation during learning. Cai et al. overcome this difficulty by using an offline constrained deep reinforcement learning model of marketing budget allocation (Cai et al., 2023). Their model can attain high-quality objective performance by learning optimal allocation policies using historical logged data and incorporating explicit budget and risk constraints through constrained optimization, a feature that is essential in large-scale mobile applications where unlimited online experimentation can create substantial revenue volatility (Cai et al., 2023).

Monetization-stage ad network selection is also optimized using machine learning. Adikari and Dutta suggest an adaptive ad network selection algorithm that identifies the advertising network that maximizes revenue on a case-by-case basis in each instance of a mobile app (Adikari and Dutta, 2021). Their structure enhances publisher returns by dynamically directing impressions to the most effective network, showing that reinforcement learning-inspired selection mechanisms can increase monetization results without altering upstream acquisition policies (Adikari and Dutta, 2021).

The contributions are all parts of three parallel strands of machine learning-based funnel optimization, namely contextual bandit methods to learn adaptive spend allocation; risk-aware budget policy learning through constrained deep reinforcement learning; and monetization-stage impression routing by adaptive selection algorithms. More importantly, reinforcement learning-based models treat funnel management as a series of decisions and thus internalize cross-stage dependencies, such as acquisition volume affecting onboarding load, which subsequently impacts the degree of engagement and monetization potential, instead of maximizing stage-level metrics. Another significant weakness, however, is that most current reinforcement learning applications in this field have been tested in controlled or simulated settings; application to live mobile ecosystems leads to non-stationarity, reward sparsity, and partial observability, which are active research problems. Table *3* shows the relationship between causal inference and machine learning analytical techniques at each stage of the mobile marketing funnel. The table highlights the growing use of experimentation frameworks, reinforcement learning techniques, and adaptive optimization models in mobile acquisition, onboarding, engagement, budget allocation, and monetization processes.

Funnel Stage	Analytical Method	Objective	Constraints	Key References
Acquisition	Incrementality testing	True CPA lift	Auction complexity	(Barajas and Bhamidipati, 2021)
Awareness	App Store Optimization (ML/NLP)	Ranking improvement	Platform constraints	(Abrar and Herzog, 2025)
Onboarding	A/B Testing	Activation uplift	Heterogeneous effects	(Zhang et al., 2024)
Engagement	Temporal uplift modeling	Retention optimization	Delayed reward effects	(Zhang et al., 2024)
Budget Allocation	Contextual Bandits	ROI maximization	Exploration risk	(Han and Gabor, 2020)
Budget Allocation (Constrained)	Offline Deep RL	Risk-aware policy learning	Logged data limitations	(Cai et al., 2023)
Monetization	Adaptive Ad Network Selection	Revenue maximization	Platform mediation	(Adikari and Dutta, 2021)

TABLE 3: Mapping Causal Inference and Machine Learning Methods to Funnel Stages

Source: Authors' synthesis based on (Barajas and Bhamidipati, 2021), (Abrar and Herzog, 2025), (Zhang et al., 2024), (Zhang et al., 2024), (Han and Gabor, 2020), (Cai et al., 2023), and (Adikari and Dutta, 2021)
CPA, Cost per Action; ML, Machine Learning; NLP, Natural Language Processing; RL, Reinforcement Learning; ROI, Return on Investment

Privacy, data governance, and ethical constraints in mobile funnel optimization

The development of mobile marketing analytics is becoming increasingly preconditioned by privacy regulation, platform governance frameworks, and socio-technical changes in the allocation of data control. With the gradual replacement of identifier-based tracking functionality, the measurement and optimization of mobile marketing funnels must be performed in a strictly regulated environment and architecture. Privacy is ceasing to be a fringe compliance concern; it is a structural factor in how attribution, experimentation, and personalization may be scaled. Funnel optimization models therefore have to address performance goals and data minimization needs in a way that balances the requirements of aggregation with the accountability concepts inherent in existing legal and platform governance frameworks.

One of the most significant changes in mobile measurement was the launch of the App Tracking Transparency (ATT) system by Apple in 2021. The empirical measurement of ecosystem-level impacts of ATT by Kollnig et al. reported significant decreases in the prevalence of tracking and heterogeneous opt-in rates across categories of apps (Kollnig et al., 2022). The results of their study indicate that the weakening of persistent device identifiers is a major dampening of deterministic attribution signals, especially in cross-app and cross-device tracking, and highlight the importance of switching to probabilistic modeling, aggregated reporting, and experimental validation as the main measurement techniques (Kollnig et al., 2022).

In addition to technical limitations at the platform level, privacy transitions are manifestations of a wider set of governance dynamics, which should be analyzed both sociologically and technically. The article by McGuigan et al. captures the story of the privacy pivot in the advertising technology sector, in which companies make rhetorical promises of privacy but at the same time create measurement workarounds (McGuigan et al., 2023). Their qualitative results reveal ongoing conflicts between the need to comply with regulations and the need to achieve business performance (McGuigan et al., 2023). McGuigan et al. build on this criticism, stating that so-called privacy-preserving attribution mechanisms incorporate normative governance decisions into technical design decisions that encode choices concerning informational visibility, accountability frameworks, and market power, which should be expressly subject to scholarly analysis (McGuigan et al., 2025).

Technically, differential privacy (DP) has become a conceptual framework that can be used to balance analytical utility and privacy protection. Subramanian shows that DP can be directly applied to funnel stage analysis because, at the population level, differentially private analytics can maintain insights, and at the individual level, it guarantees that the data of a specific individual is not leaked (Subramanian, 2023). Latif et al. also build a mobile-specific differential privacy pipeline, empirically analyze utility-privacy trade-offs in dynamic content settings, and show that it is technically feasible to implement DP mechanisms directly into mobile telemetry infrastructures (Latif et al., 2020).

Together, these changes suggest that privacy limitations are reorganizing the entire measurement stack on which mobile funnel optimization is based. User-level tracking is increasingly being replaced by aggregated reporting, probabilistic inference, and cohort-based analysis; attribution is no longer fully observed but partially modeled; and optimization algorithms are forced to work on privacy-compliant signals that are noisier and less granular than their counterparts. Moreover, the heterogeneity of platforms in the iOS and Android ecosystems, which are run by different privacy architectures, complicates the comparison of funnels across platforms and requires adaptive analytics architectures capable of operating under different measurement regimes. The normative assumptions inherent in privacy-protective measurement solutions, as McGuigan et al. (McGuigan et al., 2025) warn, should be subject to long-term critical academic scrutiny as well as technical optimization. Table *4* provides an overview of the primary privacy governance mechanisms that affect modern mobile marketing analytics and their implications for attribution, experimentation, and optimization systems. The comparison shows how privacy rules and platform-level governance models are increasingly transforming mobile measurement ecosystems from deterministic tracking to probabilistic modeling, aggregated reporting, and privacy-preserving analytical approaches.

Mechanism	Jurisdiction/Platform	Measurement Impact	Modeling Response	Key References
App Tracking Transparency (ATT)	Apple iOS	Reduced Identifier for Advertisers access	Probabilistic modeling	(Kollnig et al., 2022)
General Data Protection Regulation (GDPR)	European Union	Consent and data minimization	Differential privacy	(Subramanian, 2023) (Latif et al., 2020)
Industry "Privacy Pivot"	AdTech ecosystem	Governance reframing	Hybrid attribution	(McGuigan et al., 2023) (McGuigan et al., 2025)

TABLE 4: Privacy Governance Mechanisms and Their Analytical Implications for Mobile Funnel Optimization

Source: Authors' synthesis based on (Kollnig et al., 2022), (Subramanian, 2023), (Latif et al., 2020), (McGuigan et al., 2023), and (McGuigan et al., 2025)

Synthesis: Toward a unified framework for mobile funnel optimization

The four thematic areas discussed in the previous sections such as funnel conceptualization, attribution modeling, causal experimentation, and machine learning-driven optimization are highly interdependent and together form a system of mobile marketing analytics. An overview of the literature reviewed shows that there are four major themes that describe the current situation in the field and outline the limits of new academic research.

The reviewed studies collectively indicate that mobile funnel optimization should be understood as an integrated and adaptive lifecycle system rather than a collection of independent analytical activities. Figure *5* shows the "adaptive lifecycle framework" compiled from the literature, depicting the relationships among attribution systems, experimentation methodologies, machine learning-driven optimization, and privacy governance mechanisms throughout the key phases of the mobile funnel. The framework offers a conceptual understanding of the interdependencies that define today's mobile analytics environments and provides the foundation for the synthesis results presented below.

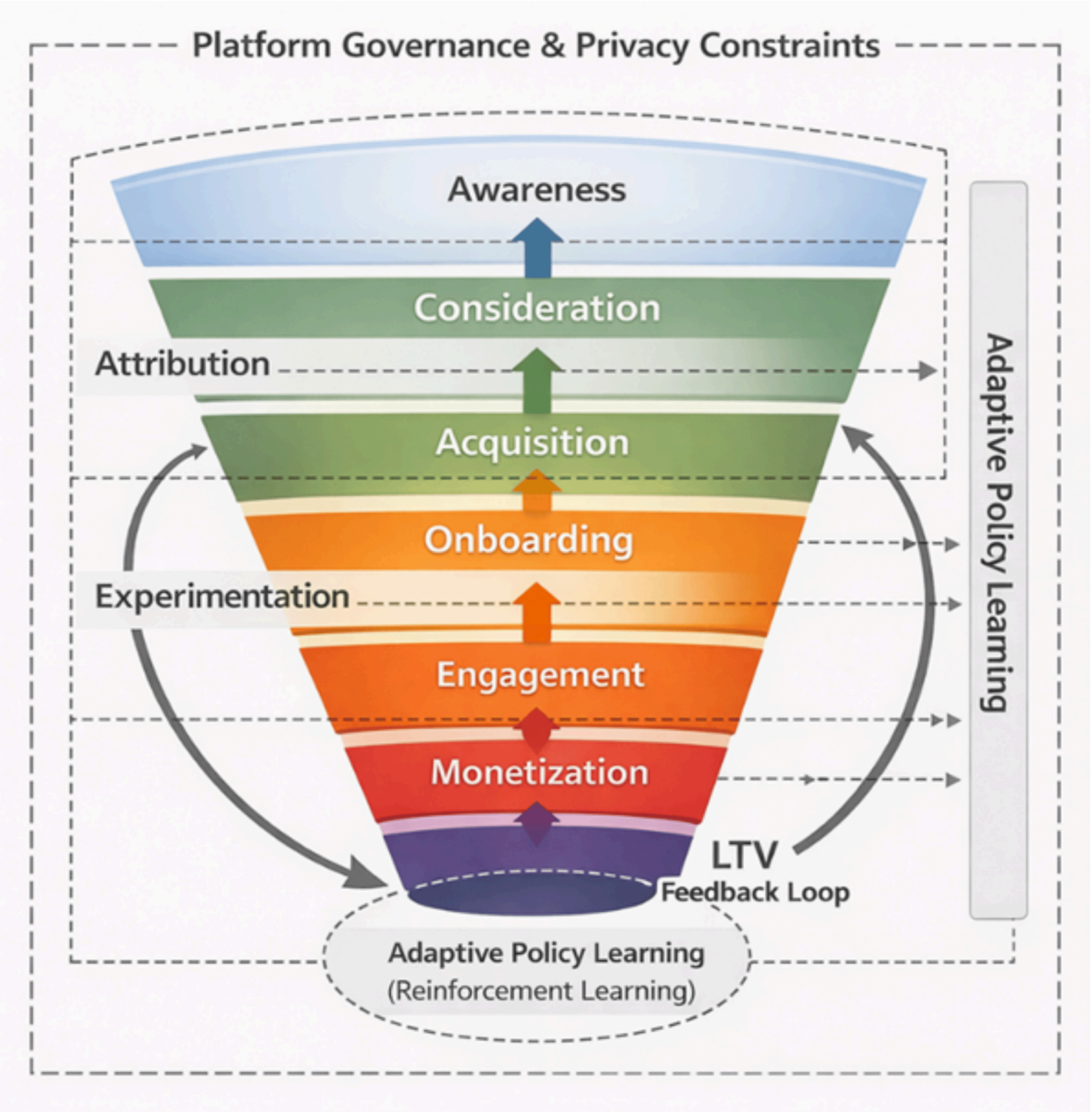


FIGURE 5: Literature-Derived Conceptual Framework for Adaptive Mobile Marketing Funnel Optimization

Source: Authors' synthesis based on the included studies.

To begin with, the shift in the mode of static to adaptive analytical models is a common pathway in all the reviewed fields. This is reflected in attribution as the gradual replacement of heuristic last-click models by dynamic and probabilistic and causal models. In optimization, it manifests itself in the transition of budget allocation by rules to reinforcement learning policies that are constantly updated on real-time environmental feedback. In experimentation, it is manifested in the development of one-time A/B tests to iterative policy learning systems. This convergence suggests that the mobile funnel optimization is reaching a stage of constant, algorithmic control - a paradigm where human decision-making is more and more mediated and enhanced by adaptive computational systems.

Second, the privacy governance is an architectural limitation that mediates all other functions of analysis. The measurement environment that has emerged after ATT and General Data Protection Regulation has successfully necessitated a methodological shift that has been long advocated on statistical grounds but has seldom been implemented in practice: the systematic substitution of granular user-level tracking by aggregated, modeled, and experimentally validated measurement. Privacy limitations are therefore an unwanted driver of methodological rigor that drives the use of DP, causal experimentation, and probabilistic attribution because less technically and legally viable simpler methods of observation are no longer possible.

Third, there is an endemic conflict between the sophistication of methods and operational viability in the field. Causal and reinforcement learning-based methods are analytically more valid but require large technical infrastructure, experimental capabilities, and data volume that may be structurally unavailable to smaller publishers. This asymmetry has equity implications: theoretically optimal measurement methodologies can systematically favor large platforms and well-funded advertisers, which can create or increase competitive distortions in mobile app markets.

Fourth, the literature continues to emphasize the necessity of lifecycle-consistent rather than stage-isolated optimization frameworks. The mobile funnel is not a linear chain of discrete conversion events but an adaptive system in which a decision made at one stage is passed to all other stages. The quality of acquisition onboarding conditions the onboarding conversion rate, the onboarding depth conditions the engagement intensity, the engagement patterns predict the monetization potential, and the lifetime value is estimated recursively and informs acquisition bidding decisions. Stage-isolated optimization - done without consideration of these cross-stage dependencies - is vulnerable to producing locally efficient but globally inefficient results, a theoretical problem with important practical implications for resource allocation and long-run revenue performance.

Limitations

This review has some limitations that should be taken into account when interpreting the results. First, the literature search was conducted in the Scopus database, which may have missed other relevant studies not indexed in Scopus. Second, only English-language publications were included, which may have excluded research conducted elsewhere and in other languages. The proposed framework was developed based on the literature reviewed and has not been empirically tested or evaluated by experts. Therefore, its applicability and the relationships among its elements should be validated in different contexts of mobile applications.

Furthermore, mobile marketing analytics is a constantly shifting landscape, with privacy laws, platform management, attribution models, and AI-driven optimizations continually evolving. As such, new technologies and industry advances may not be fully captured in the peer-reviewed academic literature. Interpretative judgment is also part of the thematic synthesis, especially in an interdisciplinary field where attribution, experimentation, machine learning, and privacy-aware analytics intersect. Hence, studies may be included in more than one thematic category.

The review may also be influenced by publication bias, since studies with positive or significant optimization results are more likely to be published than studies with null or negative results. Lastly, the selected studies were diverse in their research designs, data sources, analysis methods, and measurement techniques. This heterogeneity made it difficult to compare results directly across studies and made it impossible to conduct a formal meta-analysis.

Future research directions

The synthesis provided in this review reveals five priority areas of research that merit long-term academic consideration. To begin with, standardization of cross-platform measurements is required immediately: the fragmentation of iOS, Android, and new platform ecosystems, which are controlled by different privacy architectures and reporting regimes, limits the ability to perform funnel analysis and report consistently. Second, the discipline needs long-term lifecycle and CLV modeling frameworks that are not limited to short-term conversion metrics but incorporate correlated purchase, engagement, and churn dynamics, as suggested by Enache et al. in real-time bidding and budget allocation systems (Enache et al., 2025). Third, the moral aspects of automated funnel management are not theorized; future research should explore the limits of algorithmic personalization and engagement maximization at which platform interests and user

health and freedom come into conflict. Fourth, automated campaign management AI governance frameworks, which address accountability, explainability, and liability in reinforcement learning-based optimization systems, constitute a gap at the interface of marketing ethics and platform regulation. Fifth, the geographic clustering of existing literature in North American and Western European markets should be systematically explored in relation to funnel dynamics, attribution issues, and privacy constraints in high-growth new markets in South and Southeast Asia, sub-Saharan Africa, and Latin America.

Conclusions

This systematic review aimed to bring together the literature on the optimization of the marketing funnel in the field of mobile app analytics, covering the conceptualization of the marketing funnel, attribution modeling, experimentation and evidence-based optimization, machine learning and reinforcement learning, and the governance of privacy. In terms of conceptualization of the funnel, the literature reviewed shows that the funnel has evolved from a linear, stage-based funnel to a nonlinear, lifecycle-based funnel, with acquisition, onboarding, engagement, retention, and monetization all connected. Regarding attribution, the evidence shows a trend from heuristic and single-touch approaches to multichannel, game-theoretic, probabilistic, and incrementality-oriented approaches, which offer a more holistic picture of user journeys.

Causal and counterfactual methods are emphasized as important tools to separate incremental effects from observational associations across funnel interventions, especially in the context of experimentation and evidence-based optimization. Machine learning and reinforcement learning also enable adaptive decision-making, such as estimating treatment effects, allocating budgets, and optimizing ads, to further extend funnel optimization. Meanwhile, the privacy and governance literature shows that limitations on user-level tracking and shifts in platform governance are increasingly shaping the ways attribution, experimentation, and optimization can be achieved in mobile contexts. The review synthesizes these insights and presents mobile funnel optimization as an adaptive lifecycle system with the interaction of attribution, experimentation, algorithmic optimization, and privacy governance at various points in the user journey. The proposed literature-based conceptual framework brings these previously disjointed research streams together and serves as a foundation for future interdisciplinary research. However, the framework has not been tested independently, and further research is needed to empirically test the relationships and applicability of the framework in various mobile application contexts.

Appendices

Appendix A

A concept-based approach was used to develop the search strategy, in which keywords were chosen to represent the three main concepts of the review: (i) the mobile application domain, (ii) the marketing funnel and customer journey, and (iii) funnel optimization objectives (Table *5*). This method allowed for thorough and comprehensive retrieval of relevant studies while also providing a transparent and reproducible search process.

Search Concept	Keywords Included	Rationale
Mobile application domain	"mobile app*", "mobile marketing", "mobile analytics", "mobile advertising", "app analytics", "mobile user engagement"	Captures studies focusing on mobile applications, marketing activities, analytics, advertising, and user engagement.
Marketing funnel and customer journey	"marketing funnel", "conversion funnel", "user journey", "customer journey"	Represents the conceptual progression of users through the marketing funnel.
Funnel optimization objectives	"funnel optimization", "conversion optimization", "user acquisition", "user retention", "app monetization"	Covers the primary optimization objectives addressed in mobile marketing funnel research.

TABLE 5: Justification of Search Terms

Keywords are grouped by search concept according to their role in identifying literature on mobile applications, marketing funnels, and funnel optimization.

The search strategy focused on general conceptual terms rather than specific techniques or performance measures. Therefore, keywords such as A/B testing, push notification, customer acquisition cost, lifetime value, churn prediction, or app store optimization were not considered as individual keywords, as they are part of the broader picture of funnel optimization, user acquisition, user retention, or app monetization. Adding these terms one by one would have greatly expanded the number of retrieved studies but would not have significantly increased the number of relevant studies.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Acquisition, analysis, or interpretation of data: Aditi Shintre, Sudipkumar Ghanvat, Shreya Joshi, Rohan Jamdagni

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Critical review of the manuscript for important intellectual content: Aditi Shintre, Sudipkumar Ghanvat, Rohan Jamdagni

Concept and design: Sudipkumar Ghanvat, Rohan Jamdagni

Supervision: Sudipkumar Ghanvat

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Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following:

- **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work.
- **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted

work.

- **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The materials supporting this literature review, including the literature search strategy and study-selection information, are available from the corresponding author upon reasonable request. No code was developed or used in this review.

References

1. Abrar M, Herzog NJ: App search ranking prediction towards enhanced app store optimization using ML and NLP. Franklin Open. 2025, 12:100292. 10.1016/j.fraope.2025.100292
2. Adikari S, Dutta K: Adaptive ad network selection for publisher-return optimization in mobile-app advertising. Decision Sciences. 2021, 52:986-1017. 10.1111/deci.12500
3. Barajas J, Bhamidipati N: Incrementality testing in programmatic advertising: Enhanced precision with double-blind designs. Proceedings of the Web Conference 2021. 2021, 2818-2827. 10.1145/3442381.3450106
4. Barry TE, Howard DJ: A review and critique of the hierarchy of effects in advertising. International Journal of Advertising. 1990, 9:121-135. 10.1080/02650487.1990.11107138
5. Beck BB, Petersen JA, Venkatesan R: Multichannel data-driven attribution models: A review and research agenda. Marketing Accountability for Marketing and Non-marketing Outcomes. Kumar V, Stewart DW (ed): Emerald Publishing Limited, Bingley, UK; 2021. 18:153-189. 10.1108/S1548-643520210000018007
6. Cai T, Jiang J, Zhang W, et al.: Marketing budget allocation with offline constrained deep reinforcement learning. WSDM '23: Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining. 2023, 186-194. 10.1145/3539597.3570486
7. Chiba S, Liu Y-H, Sher C-Y, Tsai M-H: Can length limit for app titles benefit consumers?. Analytics. 2025, 5:3. 10.3390/analytics5010003
8. CleverTap: Mobile App Engagement and User Retention. 2024, Accessed: May 5, 2026: https://clevertap.com/l/mobile-engagement-guide/.
9. De Haan E, Wiesel T, Pauwels K: The effectiveness of different forms of online advertising for purchase conversion in a multiple-channel attribution framework. International Journal of Research in Marketing. 2016, 33:491-507. 10.1016/j.ijresmar.2015.12.001
10. Enache A, Friberg R, Wiklander M: Customer lifetime value applied to mobile apps. Information Economics and Policy. 2025, 70:101131. 10.1016/j.infoecopol.2025.101131
11. Grewal D, Bart Y, Spann M, Zubcsek PP: Mobile advertising: A framework and research agenda. Journal of Interactive Marketing. 2016, 34:3-14. 10.1016/j.intmar.2016.03.003
12. Gu Z, Tayi GK: Consumer pseudo-showrooming and omni-channel placement strategies. MIS Quarterly. 2017, 41:583-606. 10.25300/misq/2017/41.2.11
13. Han B, Gabor J: Contextual bandits for advertising budget allocation. Proceedings of the ADKDD. 2020, 1-14.
14. He Z, Rao VR: Methods for causal inference in marketing. Foundations and Trends® in Marketing. 2024, 18:176-309. 10.1561/1700000080
15. Kannan PK, Reinartz W, Verhoef PC: The path to purchase and attribution modeling: Introduction to special section. International Journal of Research in Marketing. 2016, 33:449-456. 10.1016/j.ijresmar.2016.07.001
16. Kollnig K, Shuba A, Van Kleek M, Binns R, Shadbolt N: Goodbye tracking? Impact of iOS app tracking transparency and privacy labels. FAccT '22: Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency. 2022, 508-520. 10.1145/3531146.3533116
17. Lamberton C, Stephen AT: A thematic exploration of digital, social media, and mobile marketing: Research evolution from 2000 to 2015 and an agenda for future inquiry. Journal of Marketing. 2016, 80:146-172. 10.1509/jm.15.0415

18. Latif S, Hao Y, Zhang H, Bassily R, Rountev A: Introducing differential privacy mechanisms for mobile app analytics of dynamic content. 2020 IEEE International Conference on Software Maintenance and Evolution (ICSME), Adelaide, SA, Australia. 2020, 267-277. 10.1109/ICSME46990.2020.00034

19. Lemmens A, Roos J, Gabel S, et al.: Personalization and targeting: how to experiment, learn & optimize. International Journal of Research in Marketing. 2025, 43:537-559. 10.1016/j.ijresmar.2025.07.004

20. Lemon KN, Verhoef PC: Understanding customer experience throughout the customer journey. Journal of Marketing. 2016, 80:69-96. 10.1509/jm.15.0420

21. McGuigan L, Sivan-Sevilla I, Parham P, Shvartzshnaider Y: Private attributes: The meanings and mechanisms of "privacy-preserving" adtech. New Media & Society. 2025, 27:2703-2724. 10.1177/14614448231213267

22. McGuigan L, West SM, Sivan-Sevilla I, Parham P: The after party: Cynical resignation in Adtech's pivot to privacy. Big Data & Society. 2023, 10:1-14. 10.1177/20539517231203665

23. Mondal J, Chakrabarti S: The abandonment behaviour of the branded app consumer: A study using interpretive structural modelling approach. Journal of Retailing and Consumer Services. 2021, 63:102695. 10.1016/j.jretconser.2021.102695

24. Mrad AB, Hnich B: Intelligent attribution modeling for enhanced digital marketing performance. Intelligent Systems with Applications. 2024, 21:200337. 10.1016/j.iswa.2024.200337

25. Page MJ, McKenzie JE, Bossuyt PM, et al.: The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021, 372:n71. 10.1136/bmj.n71

26. Palomares I, Martínez-Cámara E, Montes R, et al.: A panoramic view and swot analysis of artificial intelligence for achieving the sustainable development goals by 2030: progress and prospects. Applied Intelligence. 2021, 51:6497-6527. 10.1007/s10489-021-02264-y

27. Sensor Tower: State of Mobile 2024. 2024, Accessed: June 1, 2026: https://sensortower.com/state-of-mobile-2024.

28. Singal R, Besbes O, Desir A, Goyal V, Iyengar G: Shapley meets uniform: An axiomatic framework for attribution in online advertising. WWW '19: The World Wide Web Conference. 2019, 1713-1723. 10.1145/3308558.3313731

29. Subramanian R: Have the cake and eat it too: Differential Privacy enables privacy and precise analytics. Journal of Big Data. 2023, 10:117. 10.1186/s40537-023-00712-9

30. Witarsyaha D, Wijaya YV, Oktavianiva R: Evaluating the effectiveness of digital marketing channels: A causal inference and predictive modeling approach. Smart Computing Paradigms: Human-Centric Systems for Sustainable Development. Bhateja V, Hoong ALS, William YGS, Omar Z (ed): Springer, Cham, Switzerland; 2025. 1685:269-283. 10.1007/978-3-032-08253-4_24

31. Zhang X, Wang K, Wang Z, et al.: Temporal uplift modeling for online marketing. KDD '24: Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. 2024, 6247-6256. 10.1145/3637528.3671560

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