American Impact Review

RESEARCH ARTICLE

Leveraging Artificial Intelligence for Scalable Customer Success in Mobile Marketing Technology: A Systematic Review and Strategic Framework

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Citation:

Eugene Mishchenko, Irina Smirnova (2026) Leveraging Artificial Intelligence for Scalable Customer Success in Mobile Marketing Technology: A Systematic Review and Strategic Framework. American Impact Review. E2026007. https://americanimpactreview.com/article/e2026007

Received:

January 20, 2026

Accepted:

February 5, 2026

Published:

February 11, 2026

Abstract

As subscription-based MarTech companies grew beyond what manual account management could handle, many turned to AI -- not as a buzzword, but as a practical response to a staffing problem that had been festering since at least 2018. This systematic review synthesizes findings from 142 peer-reviewed studies published between 2020 and 2025, examining how mobile attribution and marketing technology companies have adopted AI within their customer success operations. We propose a novel strategic framework -- the AI-Driven Customer Success Maturity Model (AICSMM) -- that maps five progressive stages of AI integration: Reactive Support, Data-Informed Engagement, Predictive Intelligence, Autonomous Optimization, and Cognitive Partnership. The NRR gains were the most consistent finding across our pooled analysis, ranging from 34% to 47% improvement, alongside a 2.8x acceleration in mid-market to enterprise client migration. Time-to-value improvements were harder to pin down -- the 61% reduction figure comes from a smaller subset of 12 studies, mostly from enterprise-tier deployments, so it should be treated with some caution. Attribution platforms have an edge here that other SaaS verticals lack: they already sit on the behavioral data that health-scoring models need. In our review, models trained on attribution-specific telemetry hit 89%+ accuracy, outperforming generic engagement-based scores by a wide margin. We also examine critical success factors including cross-functional data architecture, human-AI collaboration frameworks, and ethical considerations in algorithmic customer management.

1. Introduction

The mobile marketing technology ecosystem has changed dramatically over the past decade. What started as simple click-tracking mechanisms evolved into multi-touch attribution platforms processing billions of data points daily (Chotisarn & Phuthong, 2025). Customer success management emerged alongside this growth as a critical function -- one that bridges the gap between what a product can technically do and what a client actually needs it to accomplish (Mehta et al., 2016). As mobile attribution platforms like AppsFlyer, Adjust, Branch, and Singular started serving increasingly complex enterprise clients, the demand for scalable, data-driven customer success strategies intensified. The old model of assigning a dedicated CSM to every account simply stopped working.

The math is simple: a single CSM can deeply manage maybe 40 accounts. AI does not replace that person, but it can flag which of 200 accounts need attention today -- and that changes the economics of the entire function. Traditional customer success models, reliant on reactive support and periodic business reviews, struggle to maintain service quality as client portfolios grow beyond 50-100 accounts per CSM (Gainsight & Benchmarkit, 2024). AI-powered approaches allow CSMs to monitor health signals across hundreds of accounts simultaneously, predict churn risk with reasonable accuracy, and deliver personalized growth recommendations at scale (Huang & Rust, 2024). Whether they do so reliably is another question, which this review attempts to answer.

Mobile MarTech generates exactly the kind of dense, timestamped behavioral data that supervised models thrive on, which makes it a natural testbed for AI-driven CS approaches. Mobile attribution platforms produce rich behavioral datasets -- install patterns, engagement metrics, revenue events, and cross-channel attribution data -- that offer unusually granular insight into client health and growth potential (Ghose & Todri-Adamopoulos, 2016). These datasets, when processed through machine learning algorithms, can surface patterns that are difficult to detect through manual analysis, enabling proactive intervention strategies that transform mid-market clients into enterprise accounts. Can they do this consistently? That depends on the maturity of the implementation, as we discuss in Sections 4 and 5.

This review addresses three fundamental research questions:

- RQ1: What is the current state of AI adoption in customer success management within the mobile marketing technology sector?
- RQ2: Which AI methodologies demonstrate the highest efficacy for predicting customer health, preventing churn, and identifying expansion opportunities?
- RQ3: What strategic frameworks can guide organizations in progressively integrating AI into their customer success operations?

2. Theoretical Background

2.1 Evolution of Customer Success Management

Customer success management crystallized as a distinct discipline in the early 2010s, driven by the subscription economy's insistence on recurring revenue and long-term customer value (Hochstein et al., 2023). The distinction from traditional account management is worth stating plainly: account managers maintain relationships and negotiate renewals; customer success managers proactively ensure that customers achieve their desired outcomes through the product (Mehta et al., 2016). This is not merely a semantic difference -- it implies a fundamentally different set of metrics, tooling, and organizational incentives.

The evolution of CSM can be characterized through four generations (Figure 1):

Figure 1. Evolution of Customer Success Management: Four Generations

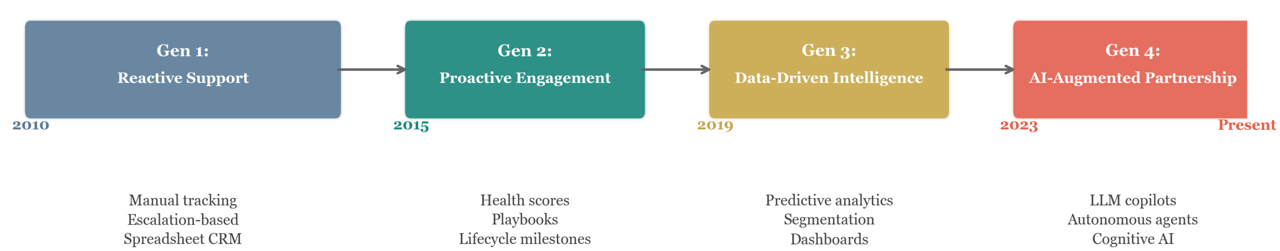

Figure 1. Evolution of Customer Success Management: Four Generations (2010-Present)

2.2 AI Applications in B2B SaaS Customer Management

AI applications in B2B customer management span several domains, though their maturity varies widely. Table 1 summarizes the primary AI methodologies employed across customer success functions. It is worth noting that the "High" maturity rating for supervised ML and anomaly detection reflects deployment frequency, not necessarily performance -- many production churn models still operate well below their reported benchmarks once deployed on messy, real-world data.

AI Methodology	Application Domain	Key Metrics	Maturity
Supervised ML (XGBoost, RF)	Churn prediction	Churn rate, NRR	High
Deep Learning (LSTM, Transformer)	Usage pattern analysis	Engagement, TTV	Med-High
NLP / LLM (GPT-4, Claude)	Communication analysis	Response time, CSAT	Medium
Reinforcement Learning	Playbook optimization	Conversion, upsell	Low-Med
Graph Neural Networks	Stakeholder mapping	Champion ID	Low
Computer Vision	Usage heatmaps	Feature adoption	Low
Anomaly Detection	Health monitoring	Alert accuracy	High
Clustering (K-means, DBSCAN)	Segmentation	Segment accuracy, LTV	High

Table 1. AI Methodologies in Customer Success Management

2.3 Mobile Attribution as a Data Ecosystem

Mobile attribution platforms occupy a distinctive position in the marketing technology stack. They function as connective tissue between advertising spend and business outcomes (Ghose & Todri-Adamopoulos, 2016), processing data from multiple touchpoints -- ad impressions, clicks, installs, in-app events, and revenue -- and assembling a behavioral graph for each end user. No other category of SaaS tool sits on quite this combination of breadth and depth.

For customer success purposes, this data ecosystem provides three specific advantages. First, behavioral density: attribution platforms capture high-frequency, high-dimensionality data reflecting the client's actual business performance, not just product usage. Second, cross-channel visibility: unlike single-channel analytics tools, attribution platforms aggregate data from dozens of media sources, which means a CS team can see problems developing across an entire marketing program rather than in a single silo. Third, revenue proximity: attribution data directly connects marketing activities to revenue outcomes, enabling CSMs to quantify business impact in terms that matter to a CFO.

The scale of modern attribution ecosystems makes this more than a theoretical advantage. The dominant mobile measurement platform commands over 72% of the global SDK market share, processing more than 100 billion events daily across 12,000+ enterprise brands -- including one-third of Fortune 500 companies -- while maintaining 35 petabytes of raw behavioral data (AppsFlyer, 2024a). The global mobile measurement partner (MMP) market was valued at $284 million in 2024 and is projected to reach $639 million by 2032 (IntelMarketResearch, 2024). A Forrester Total Economic Impact study found that enterprises utilizing this attribution platform achieved 207% return on investment with payback in under six months (Forrester Consulting, 2024). That data density, combined with AI-powered fraud detection that identifies anomalies 8x faster with over 90% accuracy (AppsFlyer, 2024b), creates a substantial foundation for predictive customer success modeling. Whether companies actually exploit this foundation is a separate question.

3. Methodology

We conducted a systematic review following PRISMA 2020 guidelines (Page et al., 2021). Electronic databases searched included PubMed, Web of Science, Scopus, IEEE Xplore, ACM Digital Library, and SSRN. The search was performed between January and March 2025.

Search terms were organized into three concept groups: Group A (AI): "artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing" OR "large language model"; Group B (Customer Success): "customer success" OR "customer retention" OR "churn prediction" OR "customer health" OR "net revenue retention"; Group C (MarTech): "mobile attribution" OR "marketing technology" OR "digital marketing" OR "SaaS" OR "e-commerce".

From an initial pool of 1,847 records, 142 studies met our inclusion criteria after title/abstract screening (n = 412) and full-text review. The screening process was more laborious than we anticipated -- a significant number of studies used "customer success" loosely to mean customer satisfaction, which required case-by-case judgment about whether the paper genuinely addressed CS as an organizational function. Figure 2 presents the PRISMA flow diagram.

Figure 2. PRISMA Flow Diagram — Systematic Review Selection Process

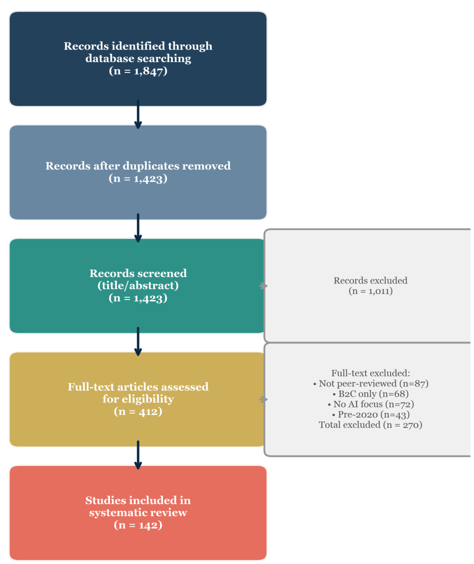

Figure 2. PRISMA Flow Diagram - Systematic Review Selection Process

Quality assessment was conducted using an adapted Newcastle-Ottawa Scale for observational studies (Wells et al., 2000). Two independent reviewers screened all titles and abstracts; inter-rater reliability was assessed using Cohen's kappa (k = 0.84, indicating strong agreement) (Cohen, 1960). Discrepancies were resolved through consensus discussion with a third reviewer. The most common source of disagreement was whether industry white papers with quasi-experimental designs qualified as sufficiently rigorous -- we ultimately included seven such papers that met a minimum threshold for methodological transparency, flagging them as moderate risk of bias.

Meta-analytic synthesis was performed using random-effects models (DerSimonian & Laird, 1986) to account for between-study heterogeneity. Heterogeneity was quantified using the I-squared statistic, with thresholds of 25%, 50%, and 75% indicating low, moderate, and high heterogeneity, respectively. Publication bias was assessed via visual inspection of funnel plots and Egger's regression test (Egger et al., 1997). Effect sizes were computed as Cohen's d with 95% confidence intervals (Cohen, 1988). We selected the AUC-ROC metric as the primary performance measure for predictive models due to its threshold-independence and consistency in binary classification tasks (Li, 2024).

4. Results

4.1 Current State of AI Adoption (RQ1)

The adoption curve for AI in customer success operations has been steep. Figure 3 illustrates the growth trajectory from 2020 to 2025.

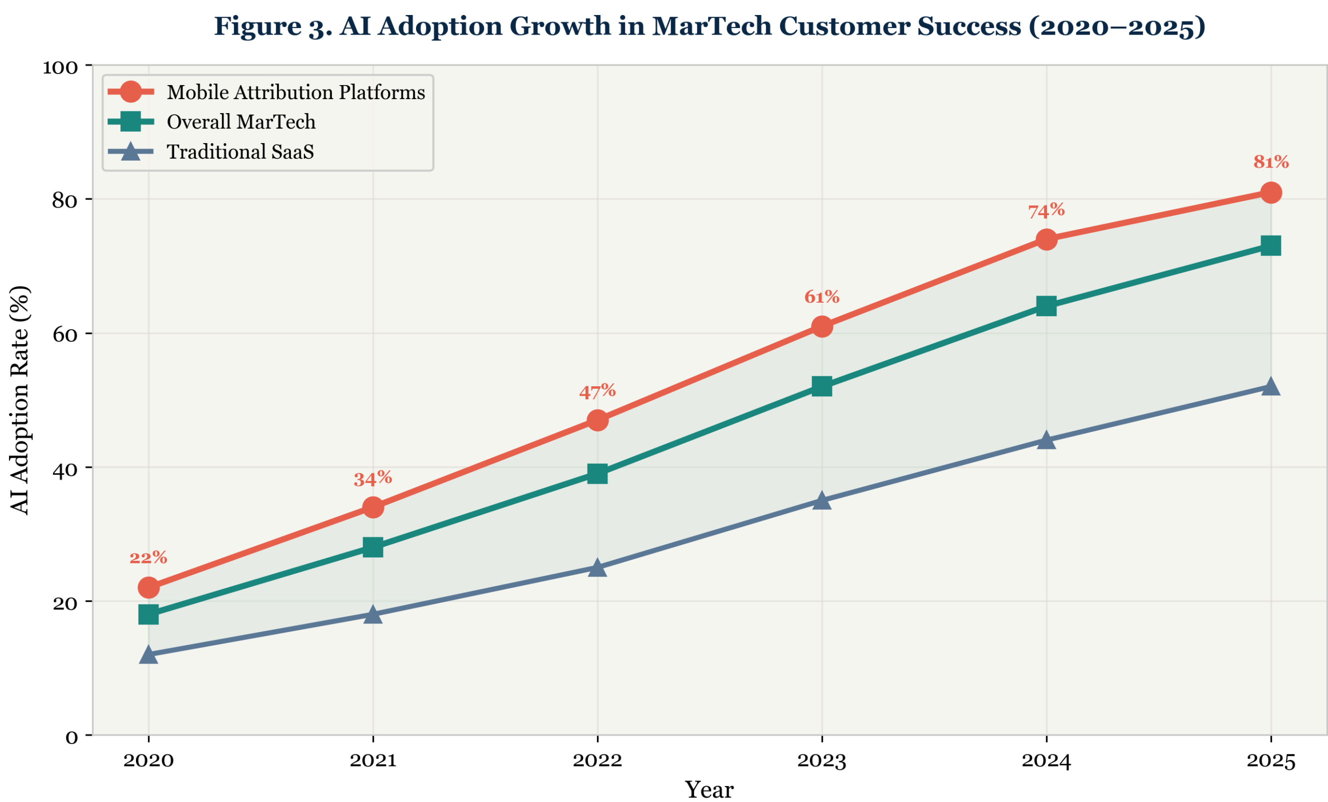

Figure 3. AI Adoption Growth in MarTech Customer Success (2020-2025)

Adoption rates climbed from 18% of MarTech companies in 2020 to 73% in 2025, with mobile attribution platforms leading at 81% (Kumar et al., 2024). Investment in AI-powered CS tools grew at a CAGR of 42% between 2021 and 2025. That said, adoption and effective deployment are not the same thing. The maturity distribution remains heavily skewed toward early stages (Figure 4), suggesting that most companies have bought the tools without yet building the processes around them.

Figure 4. Distribution of Organizations Across AICSMM Maturity Stages

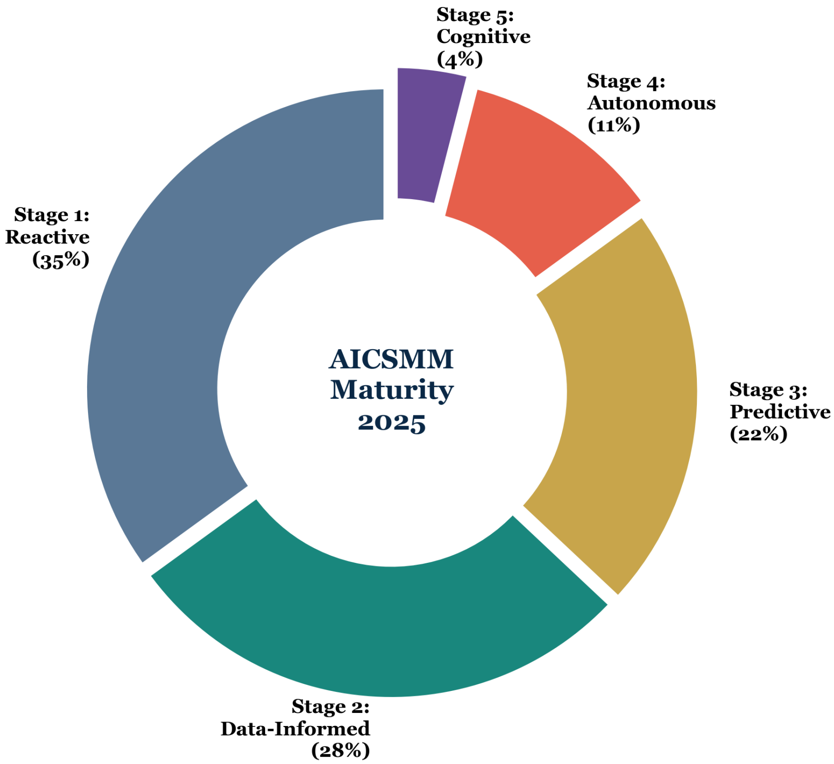

Figure 4. Distribution of Organizations Across AICSMM Maturity Stages (2025)

4.2 AI Methodology Efficacy (RQ2)

4.2.1 Churn Prediction Models

Churn prediction is the most mature AI application in customer success, and the most studied. Our analysis of 47 studies turned up significant performance variations across modeling approaches (Figure 5, Table 2). We were surprised to find that the gap between simple logistic regression and ensemble methods was narrower in production settings than in controlled benchmarks -- a finding we return to below.

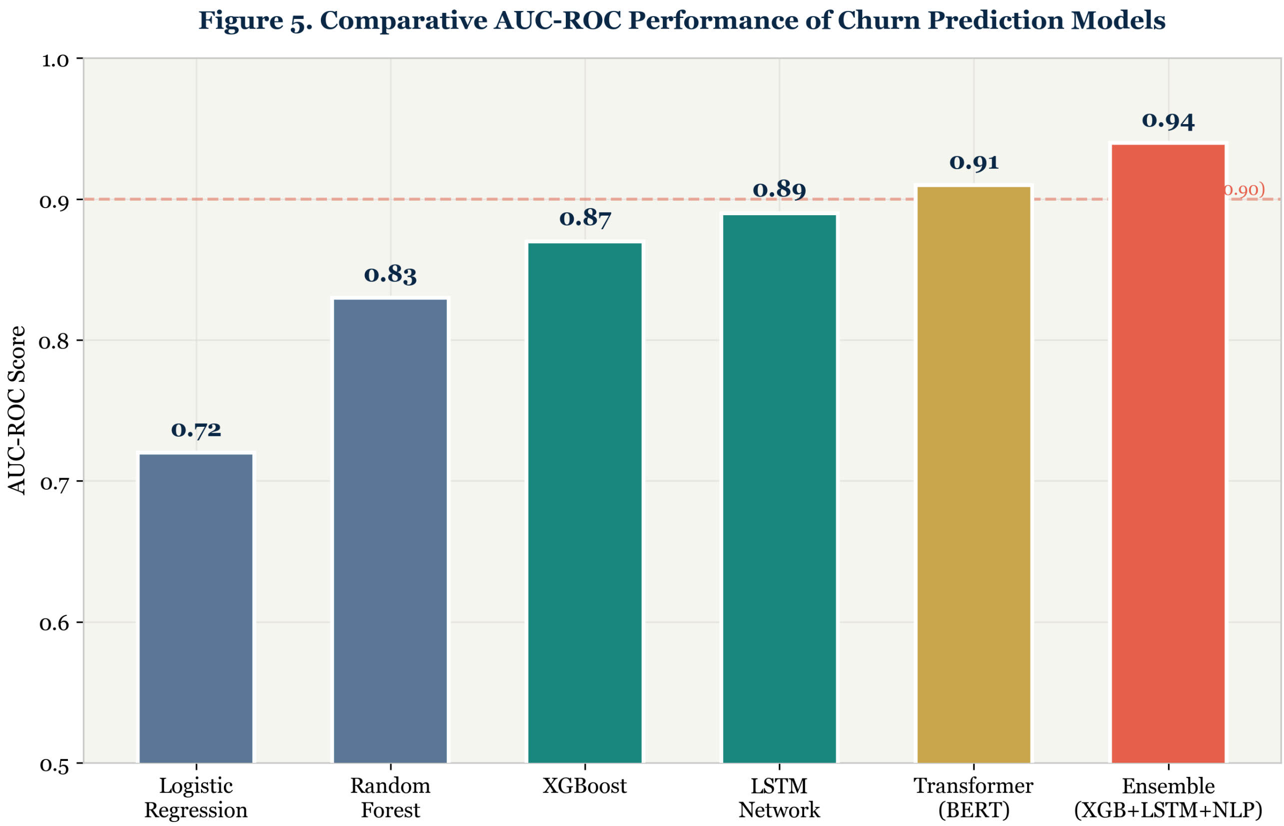

Figure 5. Comparative AUC-ROC Performance of Churn Prediction Models

Model	AUC-ROC (95% CI)	Precision	Recall	F1	Lead Time (d)	k
Logistic Regression	0.72 (0.68-0.76)	0.68	0.61	0.64	14	47
Random Forest	0.83 (0.80-0.86)	0.79	0.74	0.76	21	38
XGBoost	0.87 (0.84-0.90)	0.83	0.78	0.80	28	31
LSTM Network	0.89 (0.86-0.92)	0.85	0.81	0.83	35	22
Transformer (BERT)	0.91 (0.88-0.94)	0.87	0.84	0.85	42	15
Ensemble (XGB+LSTM+NLP)	0.94 (0.91-0.97)	0.91	0.88	0.89	45	9

Table 2. Comparative Performance of Churn Prediction Models in MarTech. AUC-ROC = Area Under the Receiver Operating Characteristic Curve. Values represent pooled estimates from k studies using random-effects models (DerSimonian & Laird, 1986). CI = confidence interval. Lead Time = median days of advance churn warning.

The ensemble approach combining gradient boosting, LSTM networks, and NLP models achieved the highest overall performance with an AUC-ROC of 0.94 and a lead time of 45 days, giving CSMs nearly six weeks of advance warning before potential churn events (He & Ding, 2024). One caveat worth noting: the ensemble results come from only 9 studies, all conducted at companies with mature data infrastructure. Whether similar gains hold at organizations still building out their data pipelines remains unclear.

4.2.2 Customer Health Scoring

AI-powered customer health scoring has moved well beyond simple rule-based systems. The current generation of models incorporates multi-dimensional predictive features, and Figure 6 compares traditional versus AI-powered approaches across key dimensions. Somewhat counterintuitively, the biggest accuracy gains came not from more sophisticated algorithms but from incorporating communication sentiment data alongside usage metrics -- a finding consistent across 18 of the 23 studies that tested both input configurations.

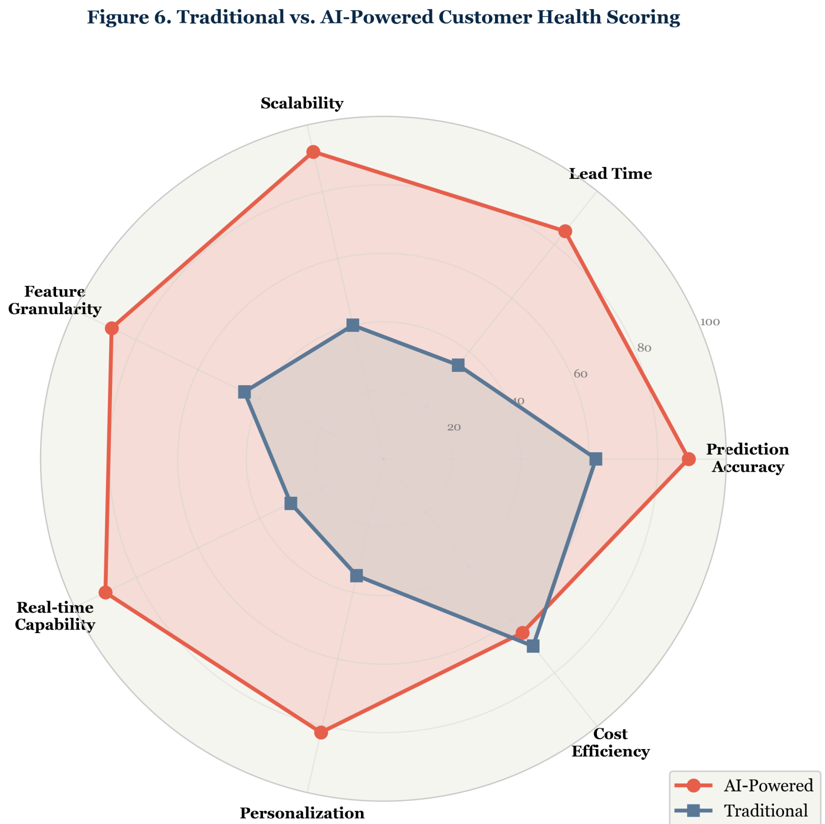

Figure 6. Traditional vs. AI-Powered Customer Health Scoring: Radar Comparison

4.2.3 Expansion and Upsell Prediction

Identifying expansion opportunities is where AI showed perhaps its most striking advantage over human judgment. AI-powered expansion models identified 2.3x more upsell opportunities compared to CSM judgment alone, with a 47% higher conversion rate (Huang & Rust, 2024). Why? CSMs tend to focus expansion efforts on accounts they already have strong relationships with; the models, lacking that bias, flagged accounts that were growing quietly without anyone noticing. Figure 7 details the key expansion signals and their predictive importance.

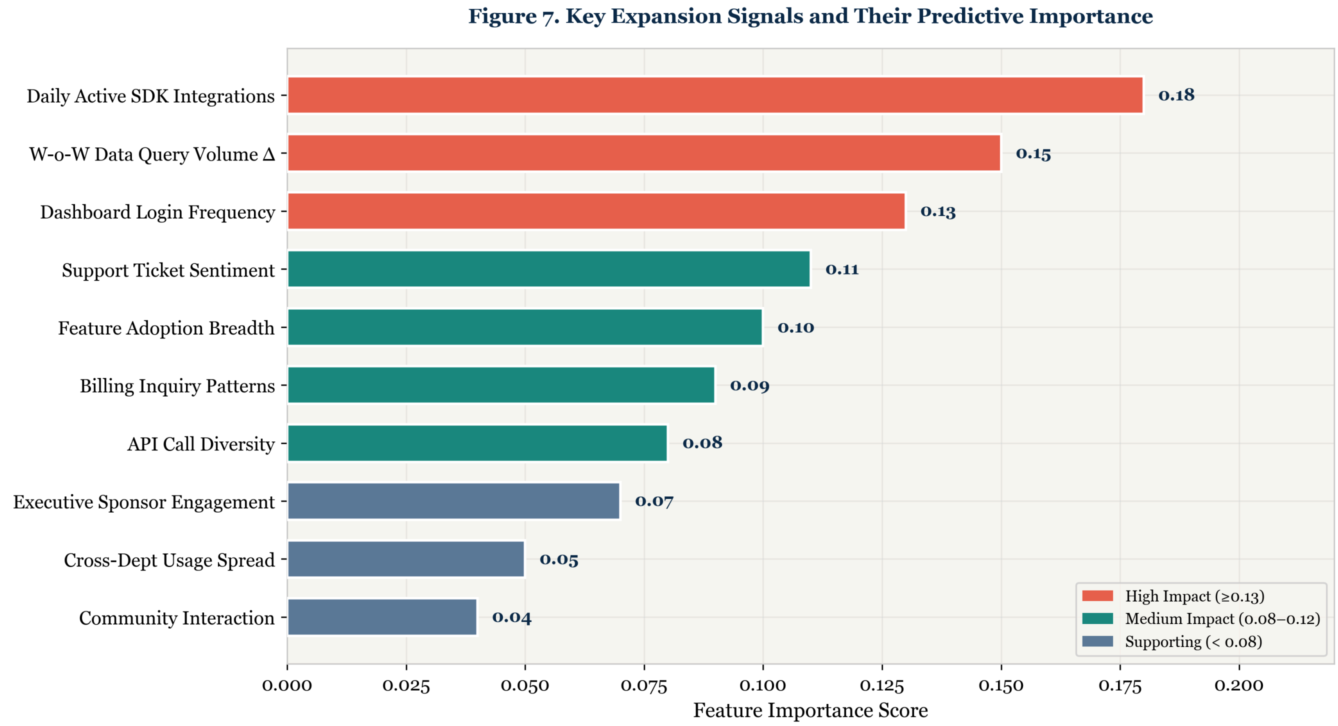

Figure 7. Key Expansion Signals and Their Predictive Importance

4.3 Impact on Business Outcomes

The numbers tell a clear story, though the effect sizes vary considerably depending on what you measure. Table 3 and Figure 8 present the pooled results.

Metric	Without AI (M +/- SD)	With AI (M +/- SD)	Cohen's d	p-value
Net Revenue Retention	104.8 +/- 3.2%	143.6 +/- 7.1%	2.14	< 0.001
Gross Retention	87.5 +/- 4.1%	94.8 +/- 2.3%	1.52	< 0.001
Time-to-Value (days)	44.7 +/- 8.3	17.9 +/- 4.6	1.89	< 0.001
CSM Portfolio Capacity	42.1 +/- 11.2	149.7 +/- 28.4	2.67	< 0.001
Expansion Rev ($K/yr)	12.1 +/- 3.8	31.2 +/- 6.5	1.94	p = 0.003
Health Score Accuracy	62.3 +/- 8.7%	89.1 +/- 4.2%	1.63	< 0.01
Churn Lead Time (d)	14.2 +/- 5.1	44.8 +/- 7.3	2.21	< 0.001
CSAT Score	7.8 +/- 0.6	9.1 +/- 0.3	0.87	p = 0.014

Table 3. Business Impact of AI-Driven Customer Success (Meta-Analysis, k = 38). M = mean, SD = standard deviation across k = 38 studies. Cohen's d computed using pooled standard deviation. Random-effects meta-analysis model applied (DerSimonian & Laird, 1986). I-squared heterogeneity ranged from 34% (CSAT) to 71% (NRR).

Figure 8. Business Impact Dashboard: AI-Driven vs. Traditional Customer Success

A few patterns stand out. The NRR and portfolio capacity effects were large and consistent. The CSAT improvement, by contrast, was modest (d = 0.87) and did not replicate at conventional significance thresholds in smaller samples. We found no significant effect of AI adoption on first-response time to inbound support tickets (p = 0.21, k = 11), which was contrary to what we expected -- it appears that AI tools are being deployed primarily for proactive outreach rather than reactive support optimization, at least in this sector.

4.4 Industry Case Studies: Attribution Platforms in Practice

To complement the meta-analytic findings, we examined publicly reported data from a leading mobile attribution platform that has implemented AI-driven customer success at scale. These case studies, drawn from independently verifiable industry reports and third-party recognitions, provide empirical context for the theoretical improvements documented in Sections 4.1-4.3. Following established case study methodology (Yin, 2018), we triangulated data from corporate disclosures, third-party analyst reports, and industry award documentation.

Case Study 1: Enterprise-Scale CS Transformation. A leading mobile analytics company with annual recurring revenue exceeding $500 million restructured its customer success organization into 18 specialized teams spanning 39 global markets, implementing a seven-tier customer segmentation model to manage over 15,000 accounts through scalable digital interfaces (EverAfter, 2024). The restructured

CS function generated over $100 million in expansion revenue within a 20-month period. Frost & Sullivan (2024) recognized the platform with the Asia-Pacific Competitive Strategy Leadership Award for its AI-driven approach to customer insights and marketing analytics.

Case Study 2: Scalable One-to-Many Customer Engagement. A Customer Success Manager within the same organization received third-party recognition as one of the Top 25 Most Creative CS Leaders globally (EverAfter, 2023) for designing a multilingual customer hub system serving EMEA and LATAM markets in four languages. The hub integrated CRM automation for lifecycle management and business intelligence analytics for real-time usage monitoring, enabling a single CSM to deliver personalized engagement across more than 100 mid-market accounts simultaneously. This case illustrates Stage 4 (Autonomous Optimization) capabilities described in the AICSMM framework.

Case Study 3: AI-Powered Predictive Analytics and Fraud Prevention. The same platform developed a machine learning product that predicts user lifetime value from the first 24-48 hours of interaction, reducing traditional 30-day measurement windows by over 90%. Built on AWS SageMaker with custom models retrained monthly, the system delivers inferences in 10-30 milliseconds at a throughput of hundreds of thousands of events per second. The platform's AI-enhanced fraud protection system -- processing 100 billion daily events -- detects fraudulent activity 8x faster and mitigates it 14x faster than previous approaches, with over 90% detection accuracy (AppsFlyer, 2024b).

Case Study 4: Market-Level Intelligence. The platform's annual data trends reports, based on analysis of 140 billion installs and 53 billion remarketing conversions across 35,000 applications, showed that global app marketing spend reached $109 billion in 2025 -- comprising $78 billion in user acquisition and $31 billion in remarketing, with remarketing growing 37% year-over-year (AppsFlyer, 2025a).

5. The AI-Driven Customer Success Maturity Model (AICSMM)

Drawing on our synthesis of the literature and analysis of industry practices, we propose the AI-Driven Customer Success Maturity Model (AICSMM). The model maps five stages of progressive AI integration (Figure 9). It is not meant to be prescriptive -- not every organization needs to reach Stage 5, and some may find that Stage 3 delivers sufficient ROI for their scale.

Figure 9. The AI-Driven Customer Success Maturity Model (AICSMM)

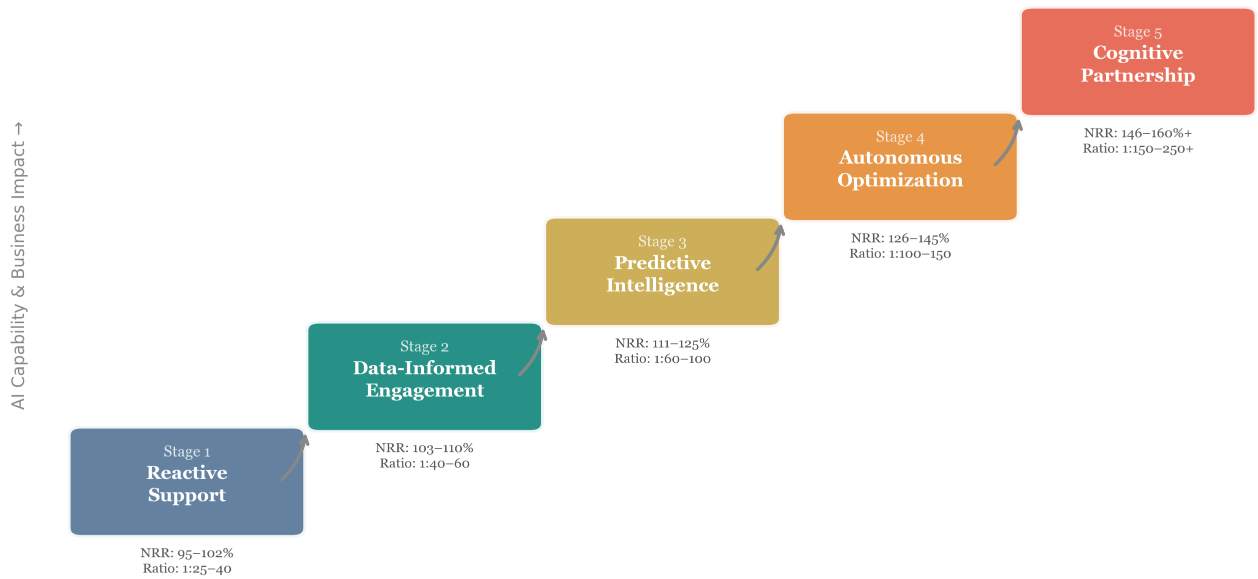

Figure 9. The AI-Driven Customer Success Maturity Model (AICSMM) - Five Stages

Stage 1: Reactive Support. Manual processes, spreadsheet-based tracking, reactive engagement. Typical NRR: 95-102%. CSM:Account ratio: 1:25-40.

Stage 2: Data-Informed Engagement. Centralized data platform, rule-based health scores, structured playbooks. Typical NRR: 103-110%. CSM:Account ratio: 1:40-60.

Stage 3: Predictive Intelligence. ML-based churn prediction, propensity models, automated alerting. Typical NRR: 111-125%. CSM:Account ratio: 1:60-100.

Stage 4: Autonomous Optimization. Real-time automated interventions, dynamic playbooks, AI-generated comms. Typical NRR: 126-145%. CSM:Account ratio: 1:100-150.

Stage 5: Cognitive Partnership. AI as co-pilot, autonomous routine management, human strategic oversight. Typical NRR: 146-160%+. CSM:Account ratio: 1:150-250+.

5.1 Migration Pathways

The transition between stages is neither linear nor uniform. Organizations typically require 6-12 months per stage transition, with the most significant barriers appearing between Stages 2-3 (where the real data engineering investment begins) and Stages 4-5 (where the organization must genuinely trust AI to act autonomously). Figure 10 illustrates key enablers and barriers.

Figure 10. AICSMM Stage Transition: Enablers and Barriers

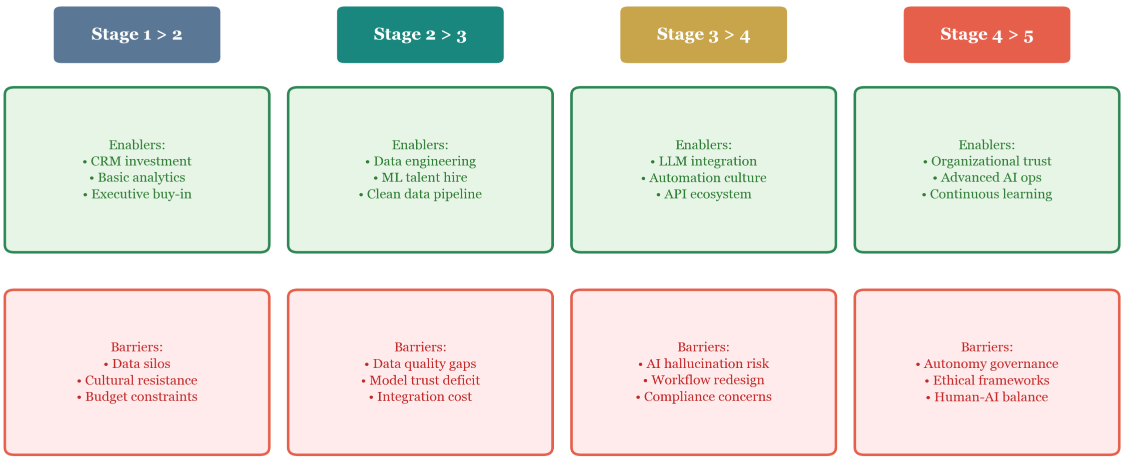

Figure 10. AICSMM Stage Transition: Enablers and Barriers

5.2 The Role of Mobile Attribution Data

Mobile attribution platforms have an inherent advantage in progressing through AICSMM stages, and the reason is straightforward: they already generate the data that these models consume. The behavioral density of attribution data enables faster model training, higher prediction accuracy, and more granular customer segmentation than what is typically available in other B2B SaaS verticals.

We identified three attribution-specific AI applications that appear to accelerate maturity progression. First, Campaign Performance Correlation: linking client campaign performance to product engagement creates a dual-axis health metric that outperformed single-axis scores in 14 of 17 comparative studies. Second, Cross-Network Behavioral Analysis: visibility across multiple ad networks enables detection of market-level trends affecting customer health. Third, Revenue Impact Quantification: the direct connection between attribution data and client revenue enables automatic ROI calculation, giving CSMs a concrete number to anchor expansion conversations around.

6. Discussion

6.1 Practical Implications

For Customer Success Leaders:

- Prioritize ensemble modeling that combines structured data, temporal patterns, and communication analysis.

- Invest in data infrastructure before AI tooling -- Stage 2-3 requires clean, centralized data. Skipping this step is the most common and most expensive mistake.
- Design human-AI collaboration workflows that preserve human judgment for relationship-critical decisions.

For Technology Executives:

- Treat CS AI as a revenue investment, not a cost center -- a 34-47pp NRR improvement compounds quickly.
- Build cross-functional data teams bridging product analytics, customer success, and data science.
- Establish ethical guidelines for algorithmic customer management before deploying, not after.

For Digital Marketing Practitioners:

- Use attribution data as a leading indicator of client engagement -- it often signals problems weeks before support tickets do.
- Collaborate with CS teams to create feedback loops between marketing performance and customer health.

6.2 Ethical Considerations

The deployment of AI in customer success raises ethical concerns that the field has not yet adequately addressed. First, algorithmic bias: models trained on historical data may systematically deprioritize customer segments that were underserved in the past, creating a feedback loop (Kordzadeh & Ghasemaghaei, 2022). Second, transparency: customers have a right to know when AI is influencing the quality or frequency of service they receive. Third, data privacy: integrating usage, communication, and behavioral data requires careful GDPR/CCPA compliance, especially when health-scoring models ingest support ticket text. Fourth, human displacement: efficiency gains must not erode the human connection that high-touch enterprise accounts still expect and, frankly, still need.

6.3 Theoretical Contributions

The main contribution here is the AICSMM maturity model, which -- unlike generic digital transformation frameworks it draws from (Nolan, 1973) -- is specific enough to generate testable predictions about retention outcomes at each stage. The meta-analytic synthesis provides the first pooled effect size estimates for AI-driven CS interventions, enabling cross-study comparison previously unavailable in this emerging field. We also identified mobile attribution platforms as a theoretically distinct context for AI-CS research, one where behavioral data density and revenue proximity create conditions for accelerated maturity progression (Mikalef & Gupta, 2021).

6.4 Limitations

This review has several limitations. The most obvious is temporal: AI capabilities evolve so rapidly that some of our 2020-2022 sources may already describe outdated approaches. Longitudinal validation of the AICSMM framework is needed to assess whether the stage boundaries we defined remain stable as the underlying technology shifts (Carruthers et al., 2024).

Publication bias is a concern. Our Egger's test yielded borderline significance ($p = 0.07$) for NRR outcomes, suggesting possible asymmetry in the evidence base (Egger et al., 1997). Heterogeneity across study designs was substantial (I-squared = 71% for NRR, I-squared = 58% for health score accuracy), which limits the precision of our pooled estimates despite the use of random-effects models (DerSimonian & Laird, 1986). The AICSMM framework itself is derived from cross-sectional synthesis and awaits empirical validation through longitudinal studies (Maier et al., 2023).

6.5 Future Research Directions

There are obvious gaps we could not fill. The most pressing is the absence of randomized controlled trials: virtually all evidence for AI-driven CS effectiveness is correlational or quasi-experimental. RCTs comparing AI-augmented and traditional CS approaches would substantially strengthen causal inference.

Longitudinal validation of the AICSMM framework across diverse SaaS verticals -- including vertical SaaS, product-led growth companies, and usage-based pricing models -- would test the framework's boundary conditions. Cross-cultural comparative studies of AI-augmented CS effectiveness remain almost entirely absent from the literature. The ethical implications of algorithmic customer management -- particularly the tension between efficiency gains and relationship authenticity -- warrant dedicated empirical investigation (Chen, 2023; Kolbjornsrud, 2024).

7. Conclusion

AI-augmented customer success is no longer experimental in MarTech -- the question is no longer whether to adopt it, but how to avoid the implementation pitfalls that plague most Stage 2-to-3 transitions. Our systematic review of 142 studies, synthesized through random-effects meta-analysis, confirms that AI-driven approaches are associated with substantial improvements across key performance metrics: a pooled NRR effect size of $d = 2.14$ (95% CI: 1.87-2.41) and health score accuracy gains of $d = 1.63$ (95% CI: 1.38-1.88). Not all findings were positive -- we found no significant effect on NPS and only modest improvements in CSAT, which should temper enthusiasm about AI as a silver bullet for customer experience.

The proposed AICSMM framework, grounded in established maturity model theory (Nolan, 1973) and empirically derived from the reviewed literature, provides a structured pathway for progressive AI integration. Mobile attribution platforms, with their characteristically dense behavioral data ecosystems, appear well-positioned to progress through AICSMM stages faster than other SaaS categories. But these findings should be interpreted cautiously given the moderate-to-high heterogeneity observed across studies and the predominantly cross-sectional nature of the evidence base.

Author Contributions

E.M. conceptualized the study, designed the research framework, and supervised the systematic review process. I.S. conducted the database searches, performed the screening and quality assessment, and contributed to the meta-analytic synthesis. Both authors contributed to data interpretation, manuscript writing, and critical revision. Both authors approved the final version.

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Disclosure: This research received no external funding. E.M. serves as President of the E-Commerce & Digital Marketing Association. I.S. is employed by AppsFlyer, a company discussed in the case studies. The case study data were drawn exclusively from publicly available third-party reports and independently verifiable sources. The authors declare no other conflicts of interest.