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MODERN SAAS PLATFORMS FOR BID MANAGEMENT IN AMAZON ADVERTISING CAMPAIGNS

Dmytro Balan

CEO of THINKAD INC
Boca Raton, Florida, USA

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ABSTRACT

This article examines the characteristics of contemporary SaaS platforms for automated bid and budget management in Amazon Advertising, built upon Machine-Learning-as-a-Service (MLaaS). We describe a three-tier architecture (Back-end, ML Modules, Front-end) and detail three core components: dynamic bid optimization, hybrid keyword recommendation, and budget-allocation forecasting. Our findings support the hypothesis that integrating MLaaS modules into a unified SaaS ecosystem enhances advertising effectiveness for small and medium-sized businesses. We discuss the study's contributions, practical significance, and avenues for future development. Methodologically, the research is grounded in a comparative analysis of existing literature on SaaS bid-management platforms for Amazon Advertising, which enabled a comprehensive exploration of current platform features.

Information on modern SaaS bid-management solutions for Amazon campaigns will be of greatest interest to researchers and practitioners in digital marketing and e-commerce—particularly programmatic-advertising specialists, business-data analysts, and doctoral students investigating algorithmic pricing strategies and auction-optimization techniques. Moreover, cloud-solution engineers and scholars in related fields (econometrics, machine learning, and operations research) will find value in the theoretical models and empirical methods presented for improving automated advertising systems.

KEYWORDS: MLaaS; SaaS platform; bid management; Amazon Advertising; dynamic bid optimization; keyword recommendation; budget forecasting.

1. INTRODUCTION

Small and medium-sized businesses (SMBs) are increasingly investing in Amazon Ads campaigns; however, limited budgets and a lack of expertise often result in high ACoS (Advertising Cost of Sales) and suboptimal allocation of funds [1, 2]. At the same time, rising competition on the platform

demands that sellers employ flexible, automated tools for bid and keyword management.

The aim of this study is to analyze an MLaaS-based SaaS platform for automated bid management, budget allocation, and keyword recommendations in Amazon Advertising, and to assess its impact on SMB advertising metrics.

The scientific novelty of this work lies in the first-ever proposal of a three-tier cloud architecture (Back-end / ML Modules / Front-end) for bid management in Amazon Ads, integrating MLaaS modules.

The author's hypothesis is that integrating MLaaS modules—for bid optimization, budget allocation, and keyword recommendation—into a unified SaaS platform will enable SMBs, via automation, to reduce ACoS and increase ROI compared with manual management.

Methodologically, this research is grounded in a comparative analysis of existing publications that examine the features of SaaS platforms for bid management in Amazon Advertising campaigns, thereby providing a comprehensive overview of current platform characteristics.

2. MATERIALS AND METHODS

Agarwal S. et al. [1] propose using classical UCB strategies and Thompson sampling for real-time adaptive budget reallocation in advertising, demonstrating higher ROI compared to heuristic methods. Lin Y., Wang Y., and Zhou E. [7] extend this paradigm to a risk-averse linear contextual bandit by incorporating CVaR (Conditional Value at Risk) constraints, thereby limiting the probability of large financial losses during aggressive exploration of new bidding strategies. Gan M. and Kwon O. C. [8] show how external knowledge graphs can be integrated into ad-variant selection, enriching contextual features with semantic product and user-preference information to improve recommendation accuracy and accelerate algorithm convergence.

Alongside algorithmic innovations, architectural design and the delivery of analytics as a service (SaaS/MLaaS) are equally important. Pereira I. et al. [2] describe a modular MLaaS approach comprising data-preprocessing components, an orchestration pipeline, and dynamic model deployment, ensuring reliability and scalability for marketing campaigns of clients of all sizes. Raghavan R. S., KR J., and Nargundkar R. V. [6] analyse the impact of the SaaS model on software procurement processes, concluding that subscription pricing lowers entry barriers but introduces vendor lock-in and dependence on the provider's update cadence. Pothuri S. [9] focuses on security in cloud-based marketing-analytics solutions, proposing an architecture with multilayer encryption, client isolation in virtual private clouds, and automated auditing to minimise data-leak risk at scale.

A separate group of studies addresses recommendation systems and optimal send-time prediction models. Rebelo M. Â. et al. [3] propose a cascade-hybrid architecture: an initial content-based filter performs coarse assortment reduction, followed by collaborative filtering to refine the final recommendation list for retail applications. Araújo C. et al. [4] develop an LSTM-based model that captures user-behavior patterns over specific time windows, boosting email open rates by 8 % compared to static send-time rules.

Infrastructure- and methodology-focused research is also critical. Merkel D. et al. [5] demonstrate Docker containers' potential for ensuring consistency between development and production environments—minimising integration deadlines for new algorithms and accelerating time-to-market in marketing platforms. Nguyen T. [10] highlights the use of lean methodology in B2B SaaS startups during market entry, stressing the importance of rapid customer feedback cycles and a minimum viable product (MVP) for early testing of bidding-management and customer-acquisition hypotheses.

Overall, the literature exhibits a clear trend toward merging advanced algorithmic approaches with SaaS/MLaaS cloud architectures; however, transparency and interpretability of complex models—particularly LSTM and hybrid systems—remain under-addressed, hindering adoption in heavily regulated industries. Finally, there is a lack of unified methodologies for multichannel bid optimization and cross-channel attribution analysis, representing promising directions for future research.

3. RESULTS AND DISCUSSION

The solution is built on a three-layer architecture that delivers modularity, scalability, and reliability for dynamic bid and budget management in Amazon Ads campaigns [2]:

Layer 1 – Back-end. Responsible for secure data storage and transport, message-queue management, and safe database access. An External API handles incoming and outgoing requests from the front-end and ML modules, while ActiveMQ provides asynchronous data exchange between components.

Layer 2 – ML Modules. Comprises containerized (Docker) services for three core functions:

- Dynamic Bid Optimization – computes the optimal bid for each ad group, factoring in target ACoS and current budget;
- Keyword Recommendation – a cascade-hybrid recommender built on collaborative filtering with similarity pruning;
- Budget Allocation Prediction – a stacking ensemble of regressors (Random Forest, SVR, linear regression) to forecast daily and monthly budgets [2].

Models are trained following a process akin to CRISP-DM and deployed as Docker containers to ensure reproducibility and straightforward scalability [1, 3].

Layer 3 – Front-end. Provides marketers with a web interface to configure automated workflows, visualize KPIs (ACoS, ROI, CTR, spend), monitor ML-module performance, and manually adjust campaign parameters [2].

Below, Table 1 compares the key components at each layer.

Table 1
Components of the MLaaS-SaaS Layers [1, 2]

Layer	Components	Primary Functions	Technologies & Standards
Back-end	<ul style="list-style-type: none"> • External API • ActiveMQ • Secure DB 	<ul style="list-style-type: none"> • Request ingestion and routing • Asynchronous data exchange • Secure historical data storage 	Java Spring Boot, OpenAPI 3.1, ActiveMQ, PostgreSQL
ML Modules	<ul style="list-style-type: none"> • Bid Optimization • Keyword Rec. • Budget Predictor • Docker Registry 	<ul style="list-style-type: none"> • Model training per CRISP-DM • Real-time prediction generation • Automated container updates 	Python, scikit-learn, TensorFlow, Docker, Kubernetes
Front-end	<ul style="list-style-type: none"> • Web Application • Dashboards • API Client 	<ul style="list-style-type: none"> • Campaign configuration • Metric visualization • Automation-scenario management 	React.js, D3.js, REST API

This multilayered design enables:

- Isolation of ML logic from business code and the user interface, simplifying maintenance and CI/CD;
- Horizontal scaling of individual modules according to load;
- Rapid integration with the Amazon Advertising Partner API for campaign statistics and bid updates.

In sum, the MLaaS-SaaS architecture establishes a resilient platform capable of adapting SMB advertising strategies in real time under conditions of intense competition and limited resources [2, 4]. In the ThinkAd platform, three interrelated MLaaS modules implement the full cycle of automated campaign management in Amazon Ads. All modules are designed according to the CRISP-DM

methodology and deployed in Docker containers to ensure reproducibility and easy scalability [1, 2]. The Dynamic Bid Optimization module calculates, in real time, the optimal CPC for each ad group to maintain target ACoS and make efficient use of the daily budget. Inputs include historical bids and clicks, daily spend, conversions, KPI targets (target ACoS), seasonality (day of week and hour), and external demand indicators. After data cleaning, aggregation over time windows, and lag-feature construction, a stacking ensemble of regressors (Random Forest, Gradient Boosting Machines, linear regression) is trained using past forecast errors as additional features [4, 10]. Exploration–exploitation balance is managed via the Upper Confidence Bound (UCB) algorithm [1, 7], and the output is a JSON document of recommended CPC bids, which is automatically applied through the Amazon Ads API. The Keyword Recommendation module generates a personalized set of phrases for each campaign by analyzing historical purchase data and competitive behavior. It starts from a client–phrase matrix (impression frequency, click cost, conversions) and product metadata (category, price, seasonality). First, each client–phrase pair is scored based on volume, cost, and temporal factors [3, 5]; next, a cascade-hybrid algorithm is applied: initial candidate selection via collaborative filtering (ALS), followed by content-based similarity pruning to discard irrelevant phrases [6]. Hyperparameters are tuned by grid search to maximize average CTR and minimize overlap among phrases. The final result is a ranked list of up to 30 keywords, with priority scores and predicted ROI, provided in CSV format [8, 9].

The Budget Allocation Prediction module computes the optimal distribution of the total ad budget among campaign groups (by product and segment) over 7- and 30-day horizons. Inputs include daily spend and performance by group, seasonal and marketing events, and historical investment and ROI data. The process begins with feature engineering—calculating rolling averages, creating seasonal indicators, and dummy variables for promotions (Black Friday, Prime Day). Modeling uses a stacking ensemble: level-1 regressors are Random Forest, Support Vector Regression, and k-Nearest Neighbors; a level-2 meta-learner (linear regression) is then trained on these outputs [2, 5]. The model retrains every 24 hours and is evaluated by RMSE and MAPE on a held-out validation set. The result is a JSON response with recommended budgets for each interval (daily/weekly), ready for automatic upload via API.

Table 2 summarizes the key modules.

Table 2
Summary of Key Modules [2, 5, 7]

Module	ML Method	Main Inputs	Optimization Goals / Metrics	Output
Dynamic Bid Optimization	Stacking regressors + UCB	CPC history, clicks, spend, target ACoS, seasonality	Minimize ACoS, maximize ROI	Recommended CPC bids per ad group
Keyword Recommendation	Cascade-hybrid (ALS + similarity pruning)	Client–phrase matrix, product metadata, seasonality	Increase CTR, reduce CPC	Top 30 keywords with priorities and ROI forecast
Budget Allocation Prediction	Stacking (RF, SVR, k-NN + linear regression)	Spend, ROI, seasonal factors, promotions	RMSE/MAPE of budget forecast	Budget distribution per campaign for 7/30 days

Each module integrates into a unified MLaaS ecosystem: the Back-end manages queues and storage, the ML modules handle training and prediction, and the Front-end delivers a user interface for monitoring and configuring automation. This modular design provides flexibility in scaling and rapid adaptation to shifts in the market environment.

The study then examines the implementation details of ThinkAd for bid management in Amazon Advertising campaigns. As a pilot project, the proposed MLaaS-SaaS architecture was deployed on the ThinkAd platform—an official Amazon Advertising partner recognized as Best SaaS Ecommerce Platform 2025 by the ECDMA Global Association. Below are the main implementation steps and key outcomes.

Integration with the Amazon Advertising API was developed at the server component level, enabling two-way data exchange for impressions, clicks, spend, and conversions, as well as real-time automatic bid adjustments. To build the automated data pipeline, data collection, validation, and preprocessing stages were established; the processed data is then fed into the ML modules, and the resulting predictions are recorded in a unified database for subsequent analysis and reporting. Continuous integration and delivery (CI/CD) of the ML modules are managed by testing all model changes on a

dedicated staging environment and deploying them in Docker and Kubernetes containers, ensuring environment consistency and system scalability [2].

The ThinkAd deployment—leveraging containerized models and API integration with the Amazon Advertising Partner API—yielded practical results across a sample of over 100 SMB clients. Table 3 presents the platform’s performance against industry benchmarks.

Table 3
Results of ThinkAd implementation and industry benchmarks

Metric	Value
Reduction in ACoS	22–26%
Increase in ad-driven sales	+200%
Uplift in CTR	+125–361%
Time saved on routine tasks	10–20 h/week
Monthly ad-driven profit growth	from \$250,000 to \$700,000
Share of Amazon sellers using AI for marketing	14%
Average time saved by AI tools (all Amazon tasks)	15–20 h/week

Compared with these benchmarks, ThinkAd clients reported a 22–26% reduction in ACoS and more than a twofold increase in ROI. The hybrid keyword-recommendation module—which combines statistical and semantic methods—boosted keyword relevance and delivered a CTR uplift of 125–361%, enabling more precise targeting and reduction of wasted impressions. Budget-allocation forecasting, based on time-series models and optimization techniques, ensured even spend pacing throughout the month; algorithmic daily-limit adjustments prevented early-campaign overspend and achieved stable returns on investment.

These results confirm the high effectiveness of the proposed MLaaS-SaaS architecture. Comprehensive automation of bid, keyword, and budget management in Amazon Ads gives small

businesses a competitive edge—delivering significant metric improvements with minimal resource expenditure.

4. CONCLUSION

This work presents a comprehensive MLaaS-SaaS architecture for automating Amazon Ads campaign management, comprising three complementary modules: dynamic bid optimization, hybrid keyword recommendation, and budget-allocation forecasting. Its implementation on the ThinkAd platform—built on containerized models and integrated with the Amazon Advertising Partner API—delivered highly practical results across more than 100 SMB clients.

The data demonstrate that centralized, MLaaS-based bid-management automation outperforms traditional manual tuning approaches. The scientific novelty lies in formalizing a three-tier architecture, combining multiple ML algorithms, and validating their effectiveness in real-world deployments.

Future research should expand this framework by incorporating Multi-Armed Bandit algorithms to balance exploration and exploitation, and by integrating large language models for generating ad creatives and seasonal recommendations. These enhancements promise further ROI gains and cost reductions in the rapidly evolving digital-advertising environment.

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