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Artificial Intelligence In Digital Marketing Management: A Comparative Study Of Advertising Platforms

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Abstract
Artificial intelligence (AI) has revolutionized digital advertising by shifting away from insights based on rules, media buying, audience modeling, and real-time budget allocation, and continually predicting audiences, automating creative assembly, and automating media buying. However, when comparing platforms, it is sometimes based on isolated information from the vendor, which can be hard to move from goal to goal. Drawing on the published impact of peer-reviewed advertising research and platform features from the five top ad ecosystems – Google Ads, Meta Ads, LinkedIn Ads, TikTok Ads and Amazon Ads – this study wants to provide a structured comparison of the different ad ecosystems from a managerial perspective. A secondary research approach was used in a comparative manner. Seven criteria were synthesized from the literature: intent capture, targeting/personalization, Automation, Measurement, Creative intelligence, business-to-business suitability, and managerial control. All criteria were marked on a five-point anchored scale and explained by capability, radar, heatmap, portfolio, and maturity models (MM). The analysis showed that none of the platforms automatically dominated. Google Ads and Amazon Ads are best suited for ads featuring a clearly evident commercial intent, while Meta Ads and TikTok Ads are better suited for an environment focused on discovery or creative learning, and LinkedIn Ads is best suited for an environment focused on the professional identity and B2B context. Automation in all ecosystems is accelerating and scaling up, but it is diminishing management discretion to mysterious optimization systems. Thus, the best approach is a controlled portfolio in which the platforms are chosen according to the journey role, required data quality, creative needs, and risk appetite. This study proposes an auditable management decision-making process and research agenda with topics related to incrementality, algorithmic transparency, privacy, and human-AI collaboration.

Keywords: artificial intelligence; digital marketing management; advertising platforms; programmatic advertising; personalization; marketing analytics; generative AI

Introduction

Today, digital advertising is controlled by systems that determine the likelihood of some sort of advertiser desired action: click, conversion, purchase, lead, and so on. Auctions, growth audience, attributions, fraud detection, content creation, and recommendations are just a few of the key parts of an auction driven by AI. The business impact of the platform goes beyond simple automation, as platforms increasingly become the filter for target markets, what combinations of creatives are displayed, evidence of success, and how the marginal budget is being spent. Consequently, marketing has subconsciously come to involve the regulation of algorithmic intermediary practices. AI is a collection of capabilities, not a single technology, as described in the literature. Patterns are identified, and predictions are made using machine learning, natural language processing interprets and produces text, computer vision classifies and produces imagery, recommends ordering of content and products, and generative models produce copy and imagery, audio, and video. These capabilities are advantageous for segmentation, personalization, customer interactions, forecasting, and content production. On the other hand, AI research has showcased its utility as a complement to managerial decision-making, as posited by Davenport et al. (2020), and digital marketing, budgeting optimization, consumer behavior, and competitor strategy are some of the recurring themes in the AI research history that Ziakis and Vlachopoulou (2023) identify.

All advertising platforms pursue these capabilities differently because they all have different user contexts and data contexts. Google Ads is fully structured by users' search, browsing, video viewing, mapping, application use and coming back to publisher inventory; the benefit of Google Ads is the voice of information or purchase intent. Meta Ads will work in social identity, interest, relationship and engagement graphs and will be discoverable on Facebook, Instagram, Messenger and partner surfaces. To cater to the needs of business-to-business markets, LinkedIn Ads focuses on professionals, their identity, their organization, their industry, their job function, and their seniority. Brief video clips, creators culture, and quick feedback are the inextricable characteristics of TikTok Ads. Amazon Ads is located near product search, and transaction data, all while connecting ads with retail media and marketplace outcomes. The only thing we can really compare is their ability to engage and nurture real-life customers.They are ONLY comparable based on their ability to engage and nurture real-life customers; we don't really have anything else to compare fairly.

Some platforms are able to generate low-cost leads while others generate high-cost leads, and according to accounts, a high-cost lead could have long-term value, but a low-cost attention-based lead may not generate any. The observed performance is related to the advertiser's first-party data maturity, unique users, conversion windows, attribution rules, auction pressure, and creative format. Optimization using AI can exacerbate this issue because optimization learns towards the easiest-to-see event. If there is a shallow proxy, the system can optimize the wrong business option and be efficient. Studies on the AI model of marketing also yield a trust zone.AI-integrated marketing studies also reveal a zone of trust. While personalization may contribute to increased relevance and decreased search costs, it can have the opposite effect of increased relevance when it comes to consumers when the data collected is not from the consumer's expected source or when explanations are lacking. Acatrinei et al. (2025) indicated that among the factors that foster trust and acceptance of transparency and perceived benefits, perceived risk weakens them. According to Beyari and Hashem (2025), personalization and content optimization by artificial intelligence can help bolster customer experience, but will only play out under specific conditions, namely privacy and skills. These tensions make the best platform not just the most automated platform, but the platform whose automation can be adjusted to comply with lawful data use, consumer expectations of the platform, quality of the data measured, and humans as fiduciaries.

The addition of Generative AI increases this comparison. This will reduce variant costs and enable campaigns to personalize messages and graphics for specific audiences and placements. Grewal et al. (2025) remind readers that the quality of the outputs will rely on the input quality and the right level of human augmentation. Advertising exposure at the extreme level that is sometimes seen may cause faster experimentation, it may also lead to over-exposure, factual errors, drift in the brand, or to synthesized persuading that is not easily identifiable by the users. Creative throughput without review standards and with no clear accountability for final claims is of little value unless accompanied by the experience that comes from review and provenance.

Experience gained through review, provenance and testing discipline, and clear accountability for final claims is a valuable component of creative throughput. This study addresses the lack of a comprehensive cross-platform solution that ties together the skills needed for AI with the skills that managers need. Although previous research has covered a wide range of the impact of AI on marketing or assessed particular consumer reactions, managers still need to determine where each platform fits into a portfolio of campaigns.

This study seeks to answer the following questions: What are the advertising platforms with significant artificial intelligence functionality? Which part of the platforms will legitimate search, discovery, B2B, video-led, and commerce goals? As automation grows, what governance actions are taken to maintain managerial control? This study had two aims. First, it brings together five platforms and analyzes them based on seven criteria, which conform to the published literature reviews of the peer. Second, the transformation of the comparison into an investment portfolio and maturity model that managers can use before investing in media. This contribution does not represent an assertion of the general superiority of performance. Rather, it is a clear and repeatable framework for thinking about platforms that do not confuse platform capability, strategic context, and readiness for governance.

Materials and Methods

This study emphasized secondary research. The unit of analysis is the advertising platform ecosystem, as opposed to a specific campaign. To showcase a full range of digital ad logics, researchers selected five platforms: intent-led search and advertising video (Google Ads), social discovery advertising (Meta Ads), professional networking advertising (LinkedIn Ads), entertainment-led short-form video advertising (TikTok Ads), and retail media advertising (Amazon

Ads). The results are based on the capabilities of the platforms in the current market and are not dependent on confidential auction data from the previous year. They are not intended to indicate whether the performance of any advertiser will be predicted by any measure of the other platforms.

Peer-reviewed journal articles published by MDPI, Taylor & Francis, and Springer Nature were included in the conceptual evidence base. The literature was chosen to be directly related to AI in marketing, personalization, generative AI, customer experience, predictive analytics, ethics, or collaboration between humans and AI. Bibliographic details and DOIs were checked against the publishers' records. The capability descriptions for the platforms were considered "contextual inputs," while the evaluative criteria were abstracted from scholarly literature. This separation minimizes the possibility of receiving promotional portrayals as separate pieces of information. Seven criteria were identified in this study. Intent capture refers to how likely it is that the observed action indicates a current information or commerce need. Targeting and personalization leverage contextual, behavioral, demographic, professional, and commerce data. The elements of automation include bidding, audience expansion, placement, recommendations, and campaign orchestration. Measurement" is a metric for tracking conversions, experimenting, supporting the process of attribution, and making connections between media exposure and business results. Creative intelligence includes automated assembly, optimization, and generative assistance. B2B fit refers to access to the context of the world of business and/or professionals or organizations. Managerial control is the hands-on capability of restricting, monitoring, and directing automated decisions.

A five-point anchored scale was used, in which the value of 1 represented limited capability, 2 emerging capability, 3 functional capability, 4 strong capability, and 5 distinctive capability. Scores are comparative analytical ratings generated based on defined criteria and should not be treated as vendor benchmarks or representations of returns on ad spend. An unstated bias towards a campaign type is avoided in the headline capability model by assigning equal weights to questionnaire items. The manager should consider converting equal weights to objective-specific weights to make it more practical. Leaders in the business-to-business lead generation industry, for instance, might be more influenced by the business context and the quality of the leads, while direct-to-consumer commerce might focus on intent, creative velocity, and transaction measurement. The analysis was conducted in four steps as follows.

The analysis was performed in the following four stages. The first coding of the evidence was performed using the seven criteria. Second, an anchored rating with a written explanation was provided for each platform. Third, the ratings were analyzed using five different models: the mean capability index, a multi-dimensional radar, a criterion heat map, a reach–intent portfolio model, and a model of managerial maturity. Fourth, the construct validity of the interpretations was assessed by basing recommendations on the context of the platform, not on numerical differences in the scores. Inferential significance tests were not performed because the scores were not observations but rather structured judgments. Explicit definitions, common anchors, and sensitivity-oriented interpretation provided useful support for reliability. The norms assume that the differences are not significant if they are less than approximately 0.3 points. Triangulation of studies involving both strategy and personalization, consumer acceptance, generative content, and ethics further enhanced validity. There was no human subject involvement, private records, or information disclosed for this study. This is because the data are only available for the ratings and rationales reported in this manuscript.

Results and Discussion

Table 1 presents the platform-level comparison. The scores should be read as strategic profiles. A high value indicates a distinctive capability within the comparison, not guaranteed campaign efficiency.

Platform	Primary logic	Distinctive AI value	Best-aligned objectives	Principal caution
Google Ads	Intent and cross-surface reach	Query interpretation, predictive bidding, asset and placement optimization	Demand capture, local action, video reach, application growth	Automation may broaden queries or placements beyond managerial intuition
Meta Ads	Social discovery and identity graph	Audience modeling, creative delivery, conversion prediction	Awareness, consideration, direct response, retargeting	Attribution and privacy changes can weaken observable signals
LinkedIn Ads	Professional identity and organizations	Lead prediction and professional audience optimization	B2B demand generation, account-based marketing, recruitment	Higher media costs and smaller audience pools

TikTok Ads	Entertainment and creator-led discovery	Content recommendation, creative pattern learning, automated video support	Youth reach, product discovery, cultural participation	Creative fatigue and brand-safety sensitivity
Amazon Ads	Retail search and transaction context	Product relevance, commerce prediction, retail-media optimization	Marketplace sales, product launch, category defense	Closed-ecosystem measurement and marketplace dependence

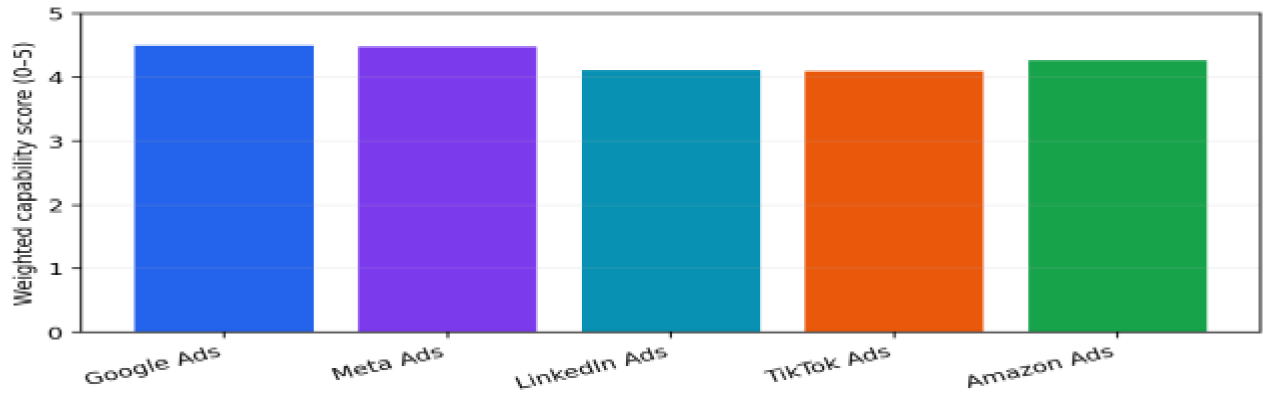

Figure 1. Equal-weight AI-enabled capability index. Scores are analytical ratings, not audited performance statistics.

Google Ads and Meta Ads are slightly ahead with the equal-weight index among both options, but the width of the difference confirms that it should be done on a case-by-case basis. Google Ads is great because it has an explicit intent and a wide inventory design. Meta Ads provides the benefit of large-scale social discovery, coupled with test-tested and reliable predictive delivery and flexible creative testing. Amazon Ads works well when searching for products and making transactions are relevant. It is a type of LinkedIn Facebook ad that loses in the width and depth of its consumer audience but gains in the depth of its professional appeal. TikTok Ads demonstrates content consumption into fast discovery emphasizing that it requires a steady stream of native creative. In the radar model shown in Figure 2, the average is not the most informative measure. Google Ads has the most well-rounded profile and the most powerful intent. Meta Ads is top for targeting and personalization, while creative intelligence is still a strong area. Unlike most advertising platforms, LinkedIn Ads allows for business-to-business fit and control over professional audience definitions. TikTok Ads has proven to be the leader in this space when it comes to potential for creative AI and content learning. Amazon Ads offers commerce measurement, but cross-channel transparency can be limited to a degree.

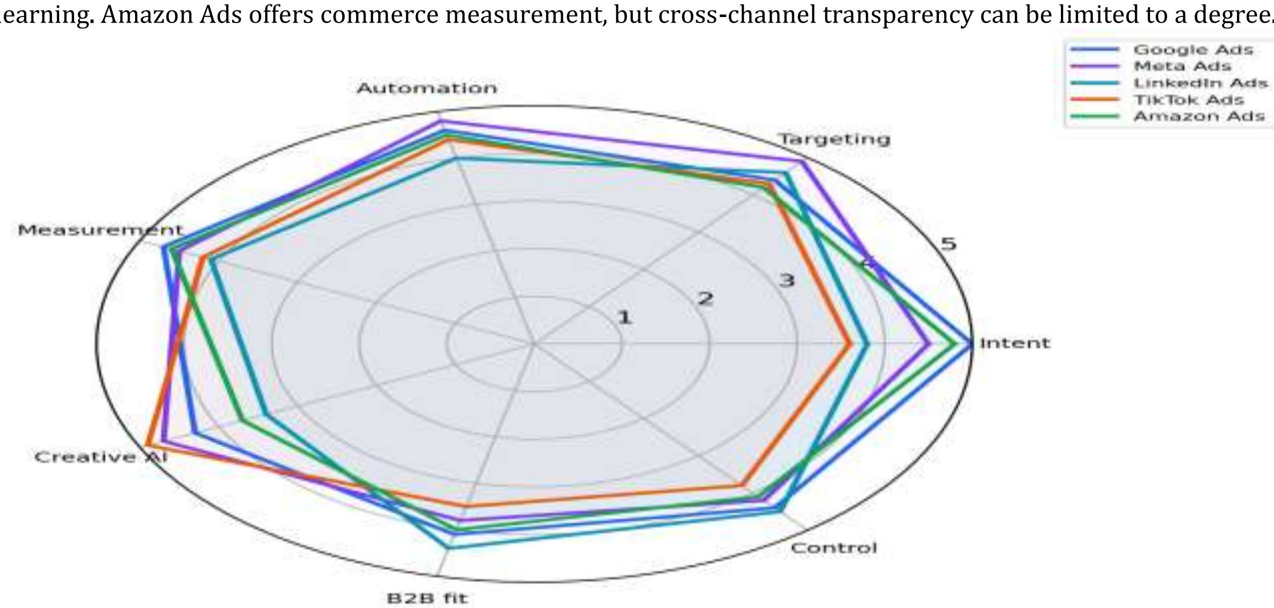

Figure 2. Seven-criterion strategic radar model for the five advertising platforms.

Table 2 provides the ratings used in the underlying table and helps with the ratification of comparisons. The ratings have been added to get the discussion going for managers; they should be modified based on local evidence that may differ from the general profile.

Platform	Intent	Targeting	Automation	Measurement	Creative AI	B2B fit	Control	Mean
Google Ads	5.0	4.4	4.6	4.7	4.3	4.1	4.4	4.50
Meta Ads	4.5	4.9	4.8	4.5	4.7	3.8	4.2	4.49
LinkedIn Ads	3.8	4.6	4.0	4.1	3.4	4.4	4.5	4.11
TikTok Ads	3.6	4.3	4.4	4.2	4.9	3.5	3.8	4.10
Amazon Ads	4.8	4.2	4.5	4.6	3.7	4.0	4.1	4.27

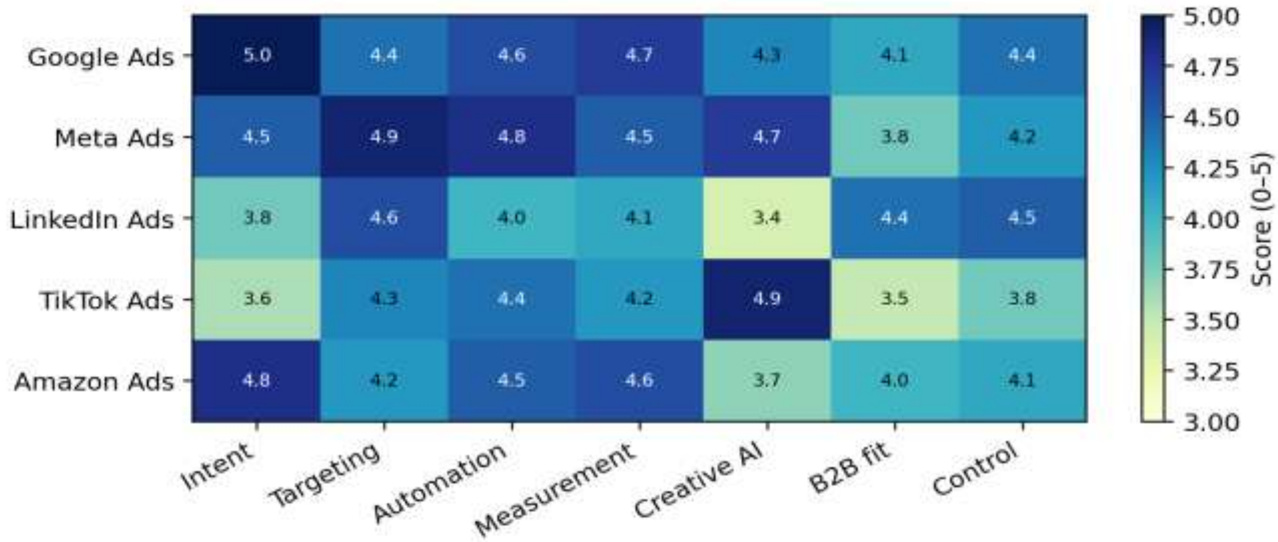

Figure 3. Criterion heat map showing relative strengths and capability gaps.

AI changes campaign management through a feedback loop. Managers define objectives, supply data and assets, establish constraints, and select conversion events. Platform systems then predict outcomes, allocate impressions, assemble content, and update estimates from observed responses. The quality of the loop depends on the target variable. A purchase, qualified lead, retained customer, or contribution margin provides a stronger business signal than a click or landing-page view. When sufficient high-quality outcomes are unavailable, automated systems may learn slowly or overfit to noisy proxies.

This observation explains the central role of data readiness. First-party consented data can improve identity matching, value-based bidding, suppression, and customer-lifecycle management. However, more data is not automatically better. Data must be current, lawful, representative, and connected to meaningful outcomes. Historical conversion data can reproduce earlier targeting patterns; incomplete customer records can bias predicted value; and aggressive audience expansion can make it difficult to determine which strategic assumptions remain valid. Reed et al. (2025) emphasize that bias mitigation requires a structured framework rather than reliance on technical optimization alone.

The reach–intent portfolio in Figure 4 offers a more useful selection logic than ranking platforms from first to fifth. Google Ads occupies the high-reach, high-intent position because search and other Google surfaces connect broad access with observed demand. Amazon Ads has strong commercial intent but its effective reach depends on marketplace category and geography. Meta Ads offers high scale and rich discovery, although intent is often inferred rather than explicitly stated. LinkedIn Ads provides strong professional intent in a smaller addressable universe. TikTok Ads provides substantial discovery reach, while immediate purchase intent varies by product, creator fit, and creative execution.

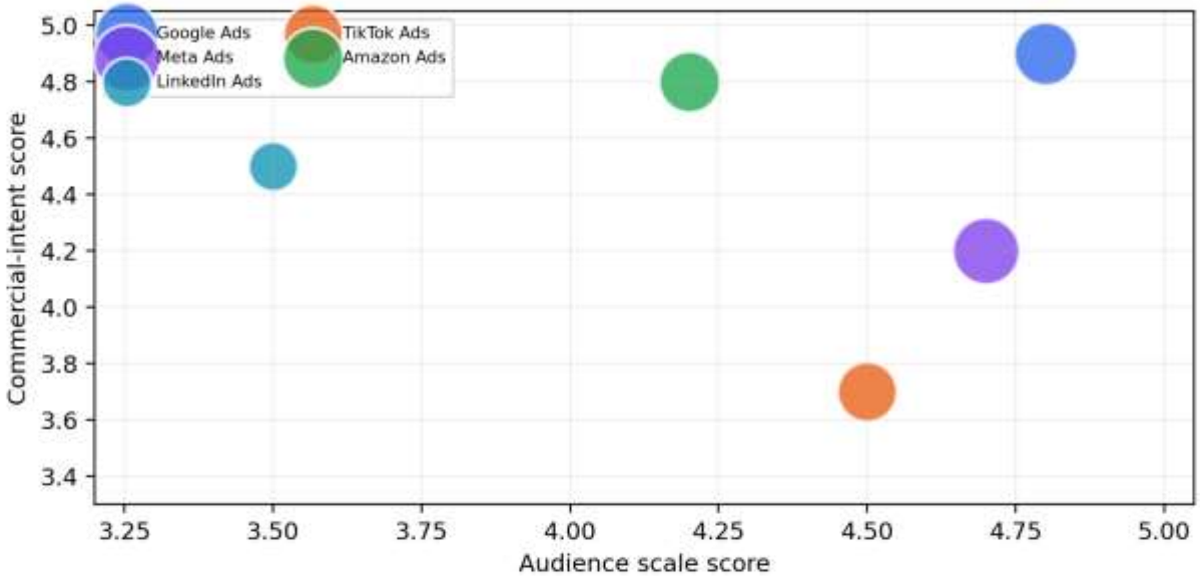

Figure 4. Reach–intent portfolio model. Bubble size represents relative automation and creative-learning opportunity.

The results are presented as goals for allocation in Table 3 below. The difference between primary and supporting is when they are tested; supporting is a complement of primary, and objective specific measurement is used for recording primary.

Managerial objective	Primary platform role	Supporting platform role	AI-enabled tactic	Decision metric
Capture existing demand	Google Ads; Amazon Ads for marketplace demand	Meta retargeting	Value-based bidding and query/product relevance	Incremental profit, qualified conversion rate
Create consumer demand	Meta Ads; TikTok Ads	YouTube within Google Ads	Creative variation, audience learning, sequential exposure	Incremental reach, brand lift, assisted conversion
Generate B2B pipeline	LinkedIn Ads	Google Search; Meta for remarketing	Professional targeting, lead scoring, conversion-value feedback	Qualified pipeline, cost per opportunity
Launch a new product	TikTok/Meta for discovery; Amazon for commerce	Google video and search	Generative variants, trend learning, retail optimization	New-to-brand buyers, trial, contribution margin
Retain or reactivate customers	Meta/Google customer-list activation	Amazon audiences where available	Suppression, propensity and lifetime-value modeling	Incremental repeat purchase, retention value

The results demonstrated a lesser dependency on any single attribution system, as well as a portfolio approach. Search can record generated demand via social media and videos; retail media can convert a sale that is off-platform first; and a professional-network impression can influence a sale later on via branded search. This overlap in reported conversions is due to the fact that each platform uses its own identity and attribution rules. Therefore, platform metrics need to be reconciled with independent analytics, customer relationship management records, the results of geo or holdout experiments, and financial metrics. The intent of measurement is to inform decisions; it is not just to provide a full report. The area of recent change is most apparent in creative intelligence. Generative tools can write text, scale and expand images, produce video variations, and align assets to the placement. Generative AI is an exciting opportunity for digital marketing, as described by Islam et al. (2024); however, when it comes to content, the focus shifts from production to judgement. Marketers must choose propositions that are true, differentiated, compliant, and consistent with the brand. More recently, Huh et al. (2023) placed generative systems as a pivotal advancement in advertising research and practice. However, the value of personalization is still dampened by consumer acceptance issues. When a relevant suggestion seems to suggest the "right answer," that can be less stressful than it is when a non-relevant personalization appears to be "stalking" them. Transparency is not about hacking or exposing proprietary algorithms; it is about giving appropriate notice, clear and easily digestible choices, limiting data collected, and telling people the truth when synthetic content could misinform. Similarly, "perceived transparency" fosters trust, as demonstrated by Acatinei et al. (2025).

The management implication is that privacy, fairness, and disclosure - these also need to work as performance indicators – can be a negative motivator for engagement as well as compliance. Automation also alters the roles of organizations. Media specialists have more time for signal design and experimentation, creative systems, and exception handling, and they have less time involved in manual bid changes. Analysts must determine the difference between correlation and incrementality. Brand teams must establish standards for artificial content. Legal and privacy experts must be included prior to activating data, not once a campaign is launched. It is up to senior managers to establish rules for risk appetite and escalation. Both Davenport et al. (2020) and Grewal et al. (2025) have argued from an augmentation perspective, arguing that humans are responsible for goals, constraints, interpretation, and consequences. The following five-stage maturity model is shown in figure 5. When data are "ready," companies develop definitions of business value, naming conventions, event quality, and consent. It was used on a small scale during the pilot phase. In the Learning stage, experiments compare Objectives, Signals, Creative Hypotheses. After there is causal and financial evidence, scale-based budgets and asset production increase. Governance continues to be a complementary set of capabilities, such as access management, documentation, brand protection, biased review, and incident mitigation. When there is initially a lack of trust and control, these simple factors hinder efficiency; however, governance generally follows the implementation of the technology, and therefore, the gap narrows as the company matures.

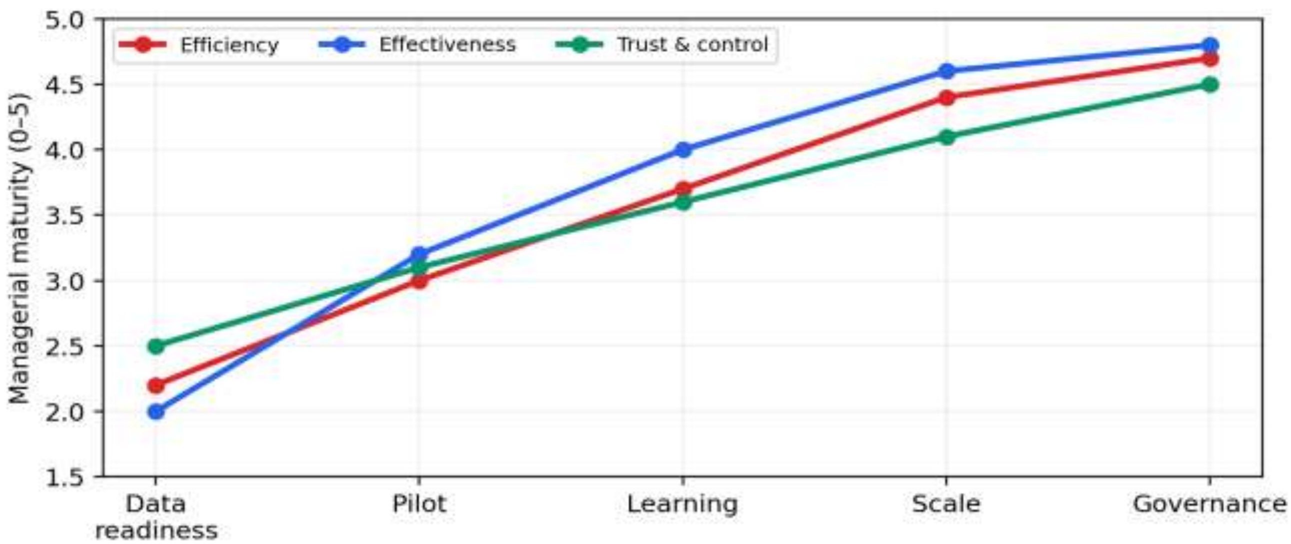

Figure 5. AI advertising management maturity model across efficiency, effectiveness, and trust.

Based on the findings of the comparison, six managerial rules can be offered. The platforms are first considered for their role in the journey and not their popularity, because if they are popular, the focus should be on what they offer. Therefore, set up a goal for the furthest goal possible that you have. Third, maintain an allowance for testing, which an automated approach will not be able to pay for without clear proof. Fourth, it plays a smaller role as a dashboard in tracking incrementality. Finally, creative and data quality are considered as a combination of inputs to the machine learning model. Sixthly, continue to control what can be claimed, what audiences are excluded, what contexts are sensitive, and budget risk. These rules enslave AI from being a media buying agent to a decision-supporting system that is in charge, transforming AI from an autonomous media buyer to a governed decision-supporting system. A platform as active institutional actor implies theoretical consequences and sometimes leads to research shifting focus. Using the platform as an active institutional actor has theoretical consequences and can sometimes result in a research paradigm shift. Traditional media planning emphasizes the audience, message, medium, and frequency. An adaptive decision layer is added to audience boundaries, message combinations, and price through the hindsight of AI-driven advertising.

A campaign's outcomes are the result of a dynamic interplay among the advertiser's inputs, as well as consumers' actions, performance targets, auction mechanics, and metric rules. However, comparative studies should also focus on the role of the platform's architecture in shaping managerial agency and market access because of possible differences in the impact of AI on performance. The present study also sheds light on the dynamic nature of platform advantages. A unique set of data can have diminished utility when privacy is tightened; new generative user–friendliness can reduce the creative ROI for competitors; and shifting privacy default settings can affect data interpretation when managing campaigns. The right management action is not retain customers forever, but a looped evaluation cycle.The solution to the management is not to keep a customer forever but an evaluation cycle that can be repeated. Quarterly assessments of signal quality, marginal returns, learning agendas, creative fatigue, discrepancies in measurements, and incidents related to governance. Budget shifts must be correlated with the predetermined evidence threshold and not based on recommendations from the vendor or anyone else.

Limitations and Scope for Future Research

A limitation of this study is that the methodology adopted was secondary, and the data were comparative. These ratings are a depiction of platform characteristics and may not reflect causal platform performance; they will vary across country, sector, budget, product margin, creative quality/strength, attribution window, and organizational capability. Platform characteristics and operations tend to evolve rapidly, and the profiles are not technical specifications but merely current analyses. Equal weighting enhances transparency but may not necessarily align with an advertiser's priorities. Although there may be huge variations in performance across the different categories of search, display, video, feed, marketplace, and partner inventory, each platform is approached here as one ecosystem. The framework could be applied to campaign-level data in future research with matched objectives, creative standards, and conversion definitions. Field experiments informed by data from multiple countries may provide a rough approximation of how many sales, profits, or long-term value customers create on a platform in multiple countries. Platform attribution and randomized holdouts, as well as marketing-mix models and customer-level causal inference, should be explored in future research for comparison with platform attribution.

Small and medium-sized businesses may not have the same number of events and expertise assumed when using automated optimizations. Future studies should focus on the relationship between generative creativity and authenticity, how it is understood if people disclose, the diversity of representation, and brand memory gained over time. Audiences need to be expanded or value optimized; both actions will lead to additional benefits. However, an audit is required to check for differential exposure to audiences or differential exclusion. Factors to examine in privacy-preserving measurement, data clean rooms, synthetic data, and on-device learning, in terms of their impact on effectiveness and accountability, should also be studied by researchers. Finally, longitudinal studies are needed to determine which blends of managerial ability and AI autonomy yield resilient performance instead of the short-term benefit of metrics.

Conclusion

This study demonstrates how AI brings a level of adaptation to advertising and selling platforms. This positioning is ideal for Google Ads for observable intent and demand across diverse surfaces, Meta Ads for social discovery and personalization and for flexible learning through creative formats, LinkedIn Ads for professional identity and business-to-business (B2B) marketing, TikTok Ads for cool, creator-led discovery and immediate video feedback, and Amazon Ads for retail intent and optimising for transactions that are close at hand. These differences are not meant to be compared as definitive differences. The Governed Platform Portfolio is the best management approach. They should set business-value outcomes, check for data quality, assign each platform its role in the journey, test for incrementality, and expand only if there is financial evidence. While generative AI can enhance creative learning, proper assessment and review by human users are necessary to maintain truthfulness, differentiation, fairness, and privacy while ensuring brand responsibilities. This will be achieved by designing better objectives, signals, experiments, and governance in automation.

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