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AI IMPLEMENTATION IN MARKETING OF U.S. COMPANIES: EVIDENCE, CASE STUDIES, AND FORECASTS FOR RETAIL AND HEALTHCARE

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Abstract

Artificial intelligence (AI) has transformed U.S. marketing from periodic to continuous, algorithmic decision-making. The clear business impact stems from firms' access to data, enabling them to create individualized customer experiences at scale. This article examines AI implementation in marketing at retail and healthcare U.S companies. These economically significant sectors have different data access, regulations, and risk profiles. We blend peer-reviewed research on marketing AI. The goal is to see how they complement authoritative market statistics and proven case studies. The paper analyzes how AI creates marketing value through personalization systems, automated targeting, predictive analytics, and emerging agentic commerce. Retail implementations by Amazon, Starbucks, Walmart, Target, and Sephora demonstrate mature personalization and conversational commerce. In contrast, healthcare cases span provider marketing, payer engagement, and life sciences HCP (health care professionals) activation. The article also addresses the different ways to measure impact. This includes extra sales, lift, attribution, and market mix modelling. We examine team capabilities in terms of data governance, MLOps, and cross-functional operating models. We examine sector-specific concerns, including HIPAA regulations, clinical risk, and trust requirements. Finally, forward-looking analysis examines generative AI as a production layer for marketing operations, and the rise of AI agents that may drive or halt a major aspect of online sales. Main takeaways hold for both retail and health. AI marketing outcomes do not depend on a single tool. Instead, they need integrated systems combining data quality, experiment-driven learning, responsible governance, and human oversight.

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Keywords: Artificial intelligence; marketing analytics; personalization; generative AI; retail marketing; healthcare marketing; retail media networks; agentic commerce; customer engagement; privacy and regulation; incremental lift; marketing measurement.

1. Introduction

Marketing in the United States has moved from one-off campaigns to those driven by AI algorithms that run nonstop. These AI marketing systems shape who and how offers, messages, and communications happen. They also evaluate how every budget amount is spent across channels. Moreover, this impact goes from technology-native firms to even everyday business tasks. This is a part of the widespread integration of AI into business operations rather than a niche change exclusive to tech-native companies. Stanford AI Index reports that 78% of organizations used AI in 2024, up from 55% in 2023 [1]. The marketing implications are direct. When AI use spreads to everyday tasks, marketing has access to more data, which boosts tracking and speeds up actions.

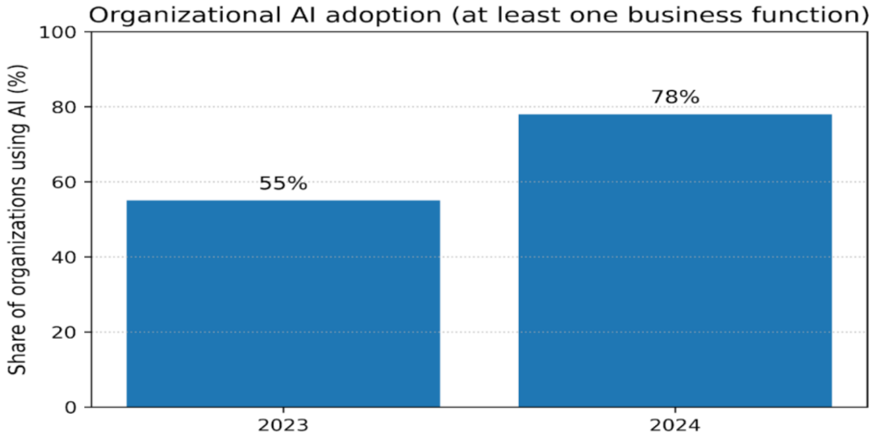

Figure 1 . Organizational AI adoption (share of organizations reporting AI use), 2023-2024. Source: Stanford HAI Index Report, 2025 [1]

Marketing teams are picking up speed because of generative AI and low-friction access to cloud-based tools. A September 2024 American Marketing Association survey found that 90% of marketers use generative AI tools at work. [2]. Also, about 71% used them weekly or more. Generative AI goes beyond AI adoption

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and analytics. It's also about creative production and workflow automation. Marketers can make copy variations. They can generate fresh ideas and even prototype audience messaging within minutes. Marketers can summarize campaign performance. Meanwhile, platforms are also collecting increasing amounts of data for targeting. This is why Meta announced in October 2025 that it will use interactions with its generative AI features. This is another signal of its importance for personalizing content and ad recommendations, effective December 16, 2025 [3]. These developments signal a shift from 'AI as a tool' to 'AI as infrastructure' in marketing ecosystems.

AI adoption is not the only thing growing. There's also mounting governance pressure. U.S. consumer protection regulators say AI-enabled marketing must comply with existing laws. The Federal Trade Commission (FTC) announced Operation AI Comply in September 2024. These moves target deceptive AI claims and AI-enabled schemes [4]. Marketers and executives now face two core issues. One, they need to deploy AI to improve relevance and efficiency. Secondly, they must ensure that claims, targeting, and AI-generated content are compliant and transparent, and that they avoid deception. However, for marketers, this can equally create an uncomfortable paradox. The same AI that optimizes engagement could also enhance deception. It's important to remember that a chatbot might not realize it's leading users astray while trying to reduce prediction errors. That's why human oversight is crucial as the final safeguard.

This article explores the role of AI in marketing at U.S. companies, particularly in high-impact sectors such as retail and healthcare. Retail is a well-established space for AI marketing, characterized by frequent transactions, abundant behavioral data, and quick feedback loops—think conversion rates, shopping carts, and returns. On the other hand, healthcare presents a different set of challenges. Here, we must navigate sensitive data, adhere to strict privacy regulations, and deal with lengthy decision-making processes.

Adoption of domain-specific AI has accelerated. Menlo Ventures reports that 22% of healthcare organizations have implemented domain-specific AI tools, with health systems leading with 27% adoption [5]. Comparing these sectors reveals how AI changes marketing strategy, measurement, and governance.

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Research objectives. We aim to: (1) highlight the AI tools and capabilities that U.S. firms use for marketing; (2) examine how they adopt AI in marketing and the economic benefits derived through market indicators; (3) analyze representative case studies within retail and healthcare; (4) evaluate emerging trends like retail media networks and agentic commerce; and (5) offer steps for leaders and researchers on using AI responsibly and track results correctly. Our approach aligns with recent studies on the effects of business on marketing. It stresses real results, field details, and real-world limits.

2. Related Work and Conceptual Foundations

Academic research on AI and marketing has been increasing. Right now, several systematic reviews document shifts from rule-based automation to machine learning, and then to the new generative AI and agentic systems. Vlačić, Corbo, Costa e Silva, and Dabić (2021) reviewed over 164 articles and highlighted themes such as adoption and acceptance, data protection and ethics, institutional support, and changing competencies of marketing professionals. [6]. This work matters in real-world applications because it shows that AI in marketing is about more than just tech. Instead, AI is changing how we interact with each other and our society. It also highlights that succeeding with AI depends on the organization's readiness, good governance, and stakeholder trust.

Classic marketing theory centers on segmentation, targeting, and positioning. AI changes its scale and granularity. Predictive models support micro-segments and individualized treatment. They tune offers or messages for individual users, not broad cohorts. Recommender systems play a key role in personalizing product discovery and merchandising. With algorithmic bids and rankings, capturing attention in the digital landscape has become more competitive than ever. Modern marketing AI fits into platform networks. It’s possible to hit the same buyer through owned channels like web, apps, and email. At the same time, there are also paid ones to cover search, social, and retail media. Beyond that, there are also service channels like chat and call centers. Connected identity and consent systems can govern each of these.

Generative AI changes the production function of marketing. Instead of automating routing, it’s also possible to generate the text, images, and

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conversational experiences. This quickens creative tweaks. It also lowers costs for localization and content variation. At the same time, generative AI does have risks. There's the issue with hallucinations, leaking sensitive data into prompts, and brand inconsistencies. Recent strategy-focused writing argues that gen AI is changing market research. The research, in particular, postulates that generative AI makes it easier to collect and synthesize data. Beyond that, it also creates synthetic personas or 'digital twins' to explore consumer reactions more quickly. [7]. These tools demand new measurement and validation frameworks because the data-generating process is partly synthetic.

Another frontier is the shift toward agentic marketing and agentic commerce, where AI systems move from recommendation to action. Agentic systems can initiate or complete transactions, negotiate bundles, or optimize logistics and checkout in the background. This is not only 'in trend' in the industry.

It is also reflected in academic priorities: the Journal of the Academy of Marketing Science announced a 2026 call for papers on 'AI-Driven Marketing: Agents, Interfaces, and Ecosystems', emphasizing that AI systems are becoming actors that reshape value creation and capturing in marketing exchange [8]. Thus, a contemporary article on AI marketing must address the analytics, personalization, and how agents transform demand, discovery, and channel power.

3. Methodology

Our study uses a structured narrative review. It also blends secondary data sources. First, we build on peer reviews [6] to identify established constructs, mechanisms, and open questions in marketing AI. Second, we weave key indicators and primary articles from trusted institutions such as Stanford HAI, HHS, the FTC, and the IAB to provide as much nuance as possible on adoption and governance. Third, we analyze use cases from U.S. companies that have publicly shared details about their AI marketing.

Case selection criteria. Cases qualify if they demonstrate relevance to marketing implementation, have high-quality documentation from primary sources, and represent their sector's adoption patterns. Regarding Retail, we pick Amazon (recommendations and generative shopping assistant), Walmart (agentic assistant and AI-first shopping), Target (AI-powered shopping experiences and

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conversational commerce integrations), Starbucks (loyalty personalization), and Sephora (AI-assisted engagement). On the Healthcare side, we cover Penn Medicine (AI-supported campaign optimization), CVS Health (AI-native consumer engagement initiatives), and a life-sciences case study with measurable prescription lift and additional revenue via HCP activation [9].

Forecast visualization method. For market-size forecasts with only start points, endpoints, and compound annual growth rates (CAGR), we focus on yearly values with CAGR interpolation (geometric growth). This approach preserves the published endpoints. It also provides a smooth path for year-by-year visualization. We also treat these parts as visuals of the published forecasts and do not see them as our own economic models. Regarding future claims with scenario ranges, we share the ranges the sources publish and discuss what they mean, rather than using single points.

3.1 Methodological Limitations

This study synthesizes publicly available case evidence and market forecasts. It does not include primary interviews with marketing executives, which could have revealed unpublished failures or strategic pivots. It also does not include proprietary data, which most firms treat AI ROI as confidential. Finally, there are no independent replications of reported metrics. We rely solely on vendor and media disclosures. Additionally, our case selection may suffer from survivorship bias, as most companies publicize only successful implementations while failed ones remain internal. Future work should actively seek out discontinued AI initiatives to understand failure modes.

4. AI Implementation in Retail Marketing

Retail marketing is leading in AI marketing, especially given the regularity of deals and customer actions. Digital commerce produces rich behavioral logs (search queries, clicks, dwell time, cart activity, returns). As a result, it’s easier to enable continuous learning systems for optimizing targeting and conversion. This also happens in the same way for omnichannel retailers, which connect loyalty programs and mobile apps to offline purchases. With AI in marketing, there are

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more avenues to tie in-store and online experiences together, with more room for personalization.

4.1 Adoption signals and capability maturity

Clear signs show that retail is shifting from experimenting with AI to full rollout. Deloitte reports that 26% of retail executives have already focused on personalization through AI capabilities, and another 35% expect to have personalized AI recommendations within the next year [10]. Previously, NVIDIA's 2026 State of AI in Retail and CPG survey found that 58% of their organizations are actively deploying AI solutions, which is up from 42% in 2024 [11]. Also, 33% are assessing AI solutions, indicating a stabilization in evaluation activity following last year's broader exploratory phase at 47%. Both surveys differ. But they all point to the same conclusion: retail AI adoption is growing across many different tasks.

An earlier NVIDIA survey also indicates that adoption is not limited to a single application [12]. Among retailers already using AI, more than 80% reported deploying three or more AI use cases. Half cited, they also have six or more use cases in production. This pattern is vital to marketing because customer experience is an end-to-end system. Personalization, pricing, inventory visibility, and service responsiveness depend on one another. For example, a promotional campaign would increase demand but harm customer experience if there is no alignment between inventory and fulfilment. Implementing AI in marketing also grows hand in hand with AI in operations.

Market-scale indicators already point to fast AI growth in retail. MarketsandMarkets predicts that the global AI in retail market will grow from USD 31.12 billion in 2024 to USD 164.74 billion by 2030 (CAGR 32.0%) [13]. While these values are global, U.S. firms represent a large share of demand and innovation. Beyond that, the forecast also shows the pace of investment and vendor ecosystem growth for U.S. retail marketing leaders.

Figure 2 Global AI forecast for the retail market, 2024-2030 (CAGR interpolation). Source: MarketsandMarkets (2024) press release endpoints [13].

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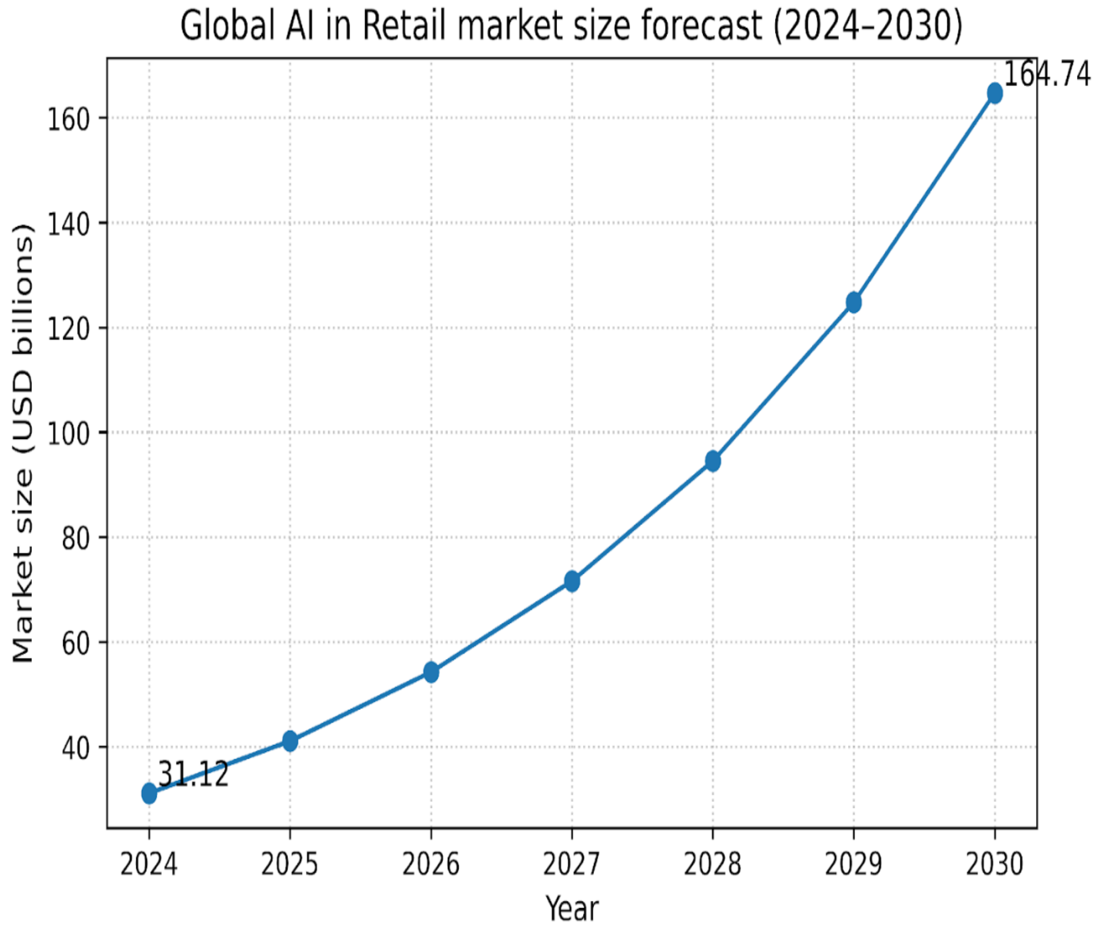

4.2 Core marketing use cases in retail.

Retailers use AI across different marketing steps from discovery to conversion to retention. Common applications include personalized recommendations, semantic search and discovery, bid optimization for retail media networks, dynamic promotions, lifecycle marketing, and service automation. Generative AI boosts these areas by speeding up creative work and powering conversational interfaces that guide shopping decisions.

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Table 1 Common AI-enabled marketing use cases in retail

Item	Description
Personalized recommendations	Tools for helping customers go from browsing to buying, enhancing cross-selling and upselling, ranking products, personalizing emails, and app experiences.
Search and discovery	Semantic search, vector retrieval, conversational search, and visual search for higher findability.
Retail media and targeting	Strategies for selecting audiences, optimizing bids, and measuring success within retailer ad networks.
Promotions and pricing	Tailored offers, optimizing promotions, and dynamic pricing that adapts to inventory levels while keeping things in check.
Lifecycle marketing	Models to predict customer behavior and churn, triggering reminders for restocking, guiding loyalty journeys, and crafting win-back offers.
Service automation	Chatbots and virtual assistants are ready to help with product inquiries, order statuses, returns, and provide guided selling experiences.
Creative generation	Using generative AI to create various copy options, product descriptions, images, and to localize content on a large scale.

4.3 Personalization as a primary growth lever

Highly personalized marketing stands out as AI's top win in retail. This is because it increases relevance and reduces search costs for consumers. McKinsey reported in 2013 that 35% of what consumers purchase on Amazon and 75% of what they watch on Netflix comes from product recommendations based on algorithms and predictive models [14]. The impact actually varies by measurement approach and category. But even so, the point remains that recommender systems have become economically material when integrated into discovery, merchandising, and lifecycle communication.

When measuring impact, we see that retail personalization benefits from short feedback loops and experimentation. This is why Retailers test personalization using randomized controlled experiments (A/B tests). Often, they would compare the treatment and control groups for recommendations, creative variations, or promotional targeting. This allows learning under realistic conditions. It also provides a safeguard against 'AI placebo' - the perception of improvement without causal evidence.

4.4 Retail media networks, first-party data, and privacy-driven targeting

A defining trend in U.S. retail marketing is the rise of retail media networks (RMNs) and commerce media. These networks convert retailer first-party data and onsite inventory into advertising products, enabling closed-loop measurement from ad exposure to purchase. The U.S. digital advertising industry reached approximately $258.6 billion in revenue in 2024, with retail media accounting for $53.7 billion (20.8% of total), up 23% year over year [15]. This growth comes from signal loss in traditional ad targeting and an increasing need for privacy-compliant first-party data strategies [15].

RMNs also grow in their optimization capacity thanks to AI in marketing. They offer high-intent contexts, such as search and category browsing. They also offer rich conversion data and new inventory types (sponsored products, display, video). eMarketer also reports that U.S. retail media spending reached $60 billion in 2025 and $100 billion by 2028 [16]. This means that retailers now run like media platforms. AI now serves as the coordination layer for targeting, creative rotation, and bid optimization across on-site and off-site inventory.

This shift also means Brands now have a new competitive environment. If retail media spend more on a small number of RMNs, the advantage goes to firms with superior optimization tooling, better attribution, and stronger supply chain reliability that improves post-click experience. AI-enabled metrics and creative systems set the top giants apart. This also holds for retailers and brands that buy retail media.

4.5 Generative AI in retail marketing operations

Generative AI is increasingly used to accelerate creative iteration and connect insights to execution. The AMA survey indicates near-ubiquitous experimentation among marketers and high-frequency use among weekly users (AMA, 2024). In retail, generative AI is used for product copy, campaign variants, localization, customer service scripts, and brand-safe summarization of review content. Paired

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with experimentation infrastructure (A/B tests and bandits), generative AI creates a 'test and scale' loop: AI generates options, platforms test them, and performance signals guide subsequent generation. Of course, 'using generative AI' can mean anything from asking ChatGPT to brainstorm taglines to deploying production-grade content engines. The 90% figure likely captures a wide spectrum—from serious integration to casual experimentation. What matters for business impact is not adoption breadth but deployment depth.

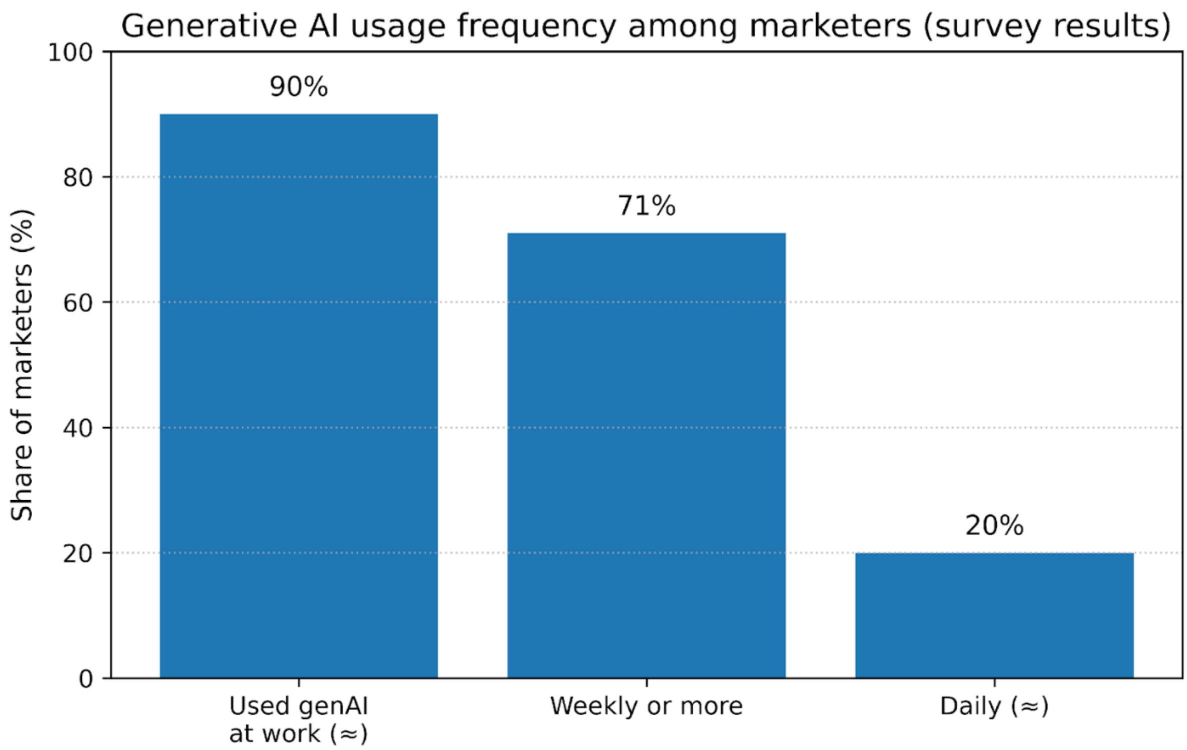

Figure 3 Generative AI usage among marketers (survey, September 2024). [2]

4.6 Conversational and agentic shopping assistants

Another retail trend is integrating large language models (LLMs) into shopping experiences. One of the earliest forms of this was when Amazon rolled out Rufus. This generative AI shopping assistant sits within the Amazon shopping app. This tool helps customers make more informed purchase decisions. [17]. Another example is Walmart's Sparky. This AI shopping assistant pulls reviews and

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provides suggestions to customers based on events. The tool also helps customers plan and streamline their purchases. Walmart calls it "agentic" shopping [17].

Target announced new AI-powered shopping features and, notably, partnerships that enable conversational commerce experiences through LLM platforms such as ChatGPT and Google Gemini, allowing curated browsing and checkout in assistant environments. [18] [19] [20]. These initiatives mark a shift from keyword searches and static pages to conversational, agent-mediated journeys in marketing.

These initiatives illustrate a strategic shift: the marketing interface layer is moving from keyword search and static pages to conversational, agent-mediated journeys. This means marketers are now dealing with different content requirements and measurements. Presently, there is a need for assistants who can accurately compare, summarize, and recommend. These agents also need trust signals, such as reviews, return policies, and fulfillment reliability, to inform their decision-making. To also optimize, changes start with data quality (product attributes, images, inventory) and move toward retention. In the case of retention, agents may prefer retailers that reduce friction and provide reliable fulfillment. This creates new forms of competitive advantage but also ties brands closer to platforms.

4.7 Case studies in retail marketing implementation.

Amazon: recommendation-driven merchandising and generative discovery. Amazon runs on algorithmic personalization across on-site ranking, recommendation, and lifecycle messaging. McKinsey estimates that the recommender system has significantly influenced conversion and cart size at scale [14]. In 2024, Amazon added Rufus, a generative AI assistant, to the shopping system. [21]. The combined pattern is significant. On one aspect, the traditional recommender system optimizes ranking and cross-sells. In contrast, the LLM-based assistant explains, compares, and helps customers find quality products. Together, they move marketing from 'show' to 'converse.' This, in turn, increases the role of interactive persuasion and reduces search costs.

Starbucks: loyalty personalization as a closed-loop system. Starbucks' Deep Brew platform shows how AI-powered personalization fits into loyalty and mobile app

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ecosystems. A CIO report in 2025 found that Deep Brew uses app and transaction data to analyze customer preferences and peak times. This action alone increased ROI by 30% and customer engagement by 15% [22]. Although these figures originate from industry reports rather than peer-reviewed evaluations, they back the core idea. They reinforce the narrative that when a retailer has a high-frequency loyalty channel, they can continually optimize and measure personalized offers to create a closed-loop marketing system. Starbucks' mobile order-ahead feature creates a tight loop between offer, redemption, and next purchase. Unlike traditional loyalty programs that batch offers weekly, Deep Brew can adjust daily based on visit patterns, weather, and local inventory—creating relevance that generic campaigns cannot match.

Walmart and Target: omnichannel assistants and 'AI-first' commerce integrations. Walmart positions Sparky as a pathway to agentic shopping. They also talk about plans to expand its core features, including reordering and multimodal inputs. [17]. Walmart also plans to partner with ChatGPT to allow customers shop through the ChatGPT platform for faster checkouts [23]. Similarly, Target rolled out conversational commerce integrations. This includes ChatGPT in-app experiences and easy Google Assistant checkouts [19] [20].

These strategies suggest that major U.S. retailers are preparing for scenarios in which customers discover or make transactions via AI assistants rather than thorough search.

Sephora: AI-assisted engagement and assisted selling. Beauty retail is suitable for AI because people value highly individualized preferences and fit. Sephora has used AI-assisted experiences, such as virtual try-on and personalized recommendations, to reduce uncertainty and increase conversion rates. Strategically, these tools gather data like shades tried or styles saved. Then the data is fed into lifecycle messaging. This illustrates a broader principle. Thus, AI establishes customer touchpoints and data tracking simultaneously, providing more avenues for even better personalization.

4.8 Measurement, attribution, and ROI in AI-enabled retail marketing.

These implementations showcase AI’s capabilities. But capabilities mean little without rigorous proof of impact. Retail is well-positioned to measure the business impact of AI. This is because we can observe outcomes such as click-through rates, conversion rates, average order value, return rates, and repeat purchase rates at high frequency. Yet measurements can be difficult. This is because AI changes even the decision process itself. For example, recommender systems alter what customers see, dynamic pricing can alter demand, and generative interfaces can change how people search and evaluate products. It is harder to have a central methodology that can separate true AI impact from the selection biases. Another example that illustrates this is the propensity model's targeting of high-intent customers who appear successful. It won't change their behavior. Consequently, leading retailers are treating measurement as a priority. They are running random tests, conducting counterfactual evaluations, and setting up governance rules to assess the real-life impact of AI.

Considering the tactical level, it is easy to see how experimentation can be applied to recommendation logic (model A vs model B), ranking features, creative variants, coupon personalization, and marketing timing. For RMNs, retailers, and advertisers, incrementality is often evaluated through geo-tests, holdout groups, or randomized ad exposure, where feasible. That said, at the strategic level, marketing mix modeling (MMM) remains important for budget allocation because it can incorporate offline channels and longer time windows. AI has begun to augment MMM by enabling faster scenario evaluation and higher-dimensional feature sets. Still, the same caution applies: models should be validated on holdouts and interpreted as decision support rather than as causal truth.

An additional complexity is that AI-driven marketing can shift costs as well as revenue. The NVIDIA State of AI in Retail and CPG survey reports that among respondents using AI, 69% believe AI has contributed to increased annual revenue. Also, 72% believe AI has decreased operating costs and changed shares by 5%-15% or more [12].

The survey reports do not prove causation, but they suggest sharp demand forecasts cut stockouts and waste. Precise targeting lowers customer acquisition costs and boosts conversion rates. For top journal-quality reviews, the implication is that both outcome and mechanism metrics are reported. For example, lower

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stockout frequency, lower customer acquisition costs, better conversions with steady traffic, and easier explanation of the measurement design.

Finally, as retail moves toward conversational and agentic shopping. Hence, measurement (metrics) must adapt. Traditional KPIs like keyword rankings and click paths won't provide as much information. This will happen because discovery now occurs within AI assistants, which shorten conversion funnels. Retailers will need new metrics, such as assistant-to-cart conversion, assistant response quality, and share of agent-referred sessions. This will boost the case for data standardization. Therefore, product metadata quality, inventory accuracy, and fulfillment reliability will no longer be the only operational variables. There will be equal room for studying marketing inputs that shape how agents recommend and close deals.

5. AI Implementation in Healthcare Marketing

Healthcare marketing differs from retail in its objectives, data constraints, and risk. Here, strict laws govern every process. Health outcomes carry real consequences, and patient trust is essential. Still, the U.S healthcare feels more like shopping now. Patients can now pick providers. They also use online tools for searching, booking, and talking to providers. This "digital front door" has changed incentives for health systems, insurers, and life sciences firms. It has also created an avenue for these entities to invest in AI for patient engagement. Moreover, their adoption is also influenced by labor shortages and pressure on administrative overhead margins.

5.1 Adoption signals and domain-specific AI acceleration

Menlo Ventures reports that 22% of healthcare organizations now use specialized AI tools. This is seven times more than in 2024. Regarding the systems they are using, health systems lead at 27% adoption. This is followed by outpatient providers (18%) and payers (14%) [5]. The report also notes that adoption across the entire economy is around 9%. Therefore, adoption dynamics matter for marketing because specialized AI systems fit into patient engagement workflows such as contact centers, bookings, clinical documentation, and service growth planning.

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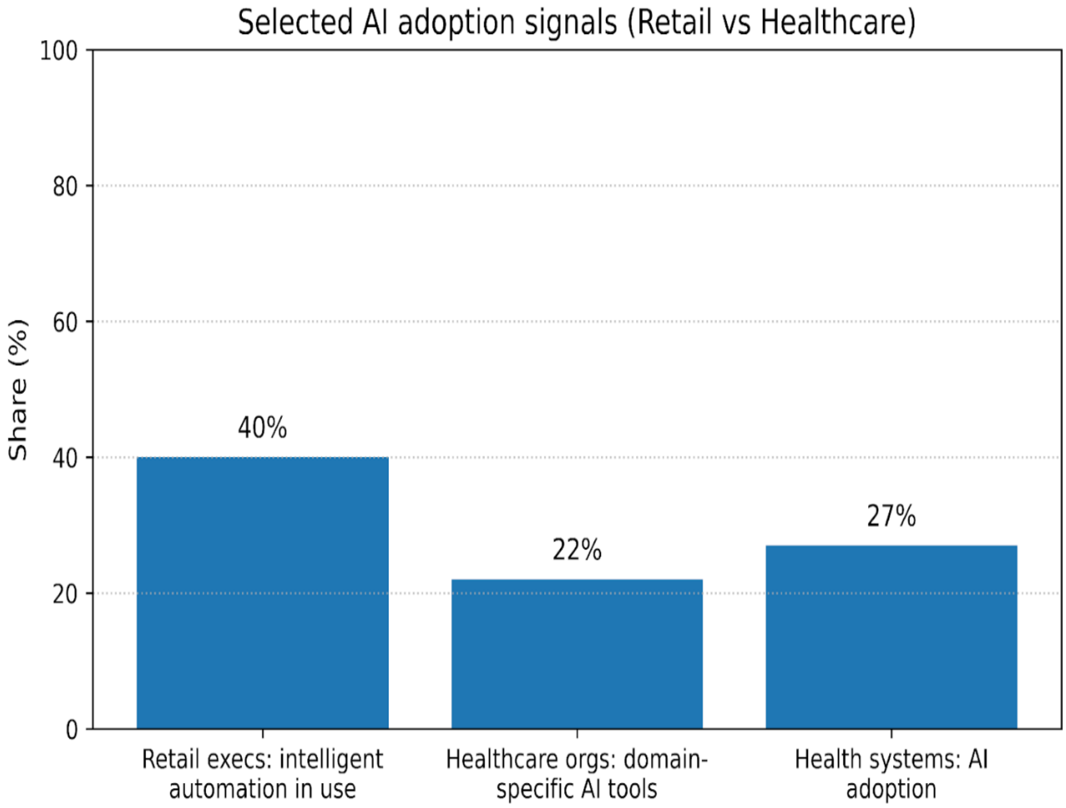

Figure 4 Selected AI adoption signals in retail and healthcare (directional indicators; metrics are not directly comparable across sources) [5]

5.2 Core marketing use cases in healthcare

Healthcare marketing AI focuses more on engagement and guidance over impulse conversion. Healthcare marketers deploy AI across several domains. Patient acquisition strategies use AI-driven local search optimization and call center routing to match inquiries with appropriate service lines. Preventive care programs leverage predictive models to identify patients who are overdue for screenings and to personalize outreach within HIPAA guidelines. Operational AI reduces no-shows through risk scoring and automated reminders. Finally, life sciences firms use contextual point-of-care messaging to activate HCPs within EHR workflows.

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Table 2 Common AI-enabled marketing and engagement use cases in healthcare

Item	Description
Patient acquisition	AI-driven local search optimization, call center routing, and targeted digital campaigns for service lines.
Patient navigation	Conversational assistants that help patients find care, understand benefits, and schedule appointments.
Preventive outreach	Predictive models to identify patients due for screening and personalize reminders (within compliance boundaries).
No-show and adherence	Risk scoring for missed appointments and personalized follow-up workflows.
Reputation and sentiment	NLP analysis of patient reviews and feedback to identify service issues and improve messaging.
HCP activation	Predictive audience activation and contextual point-of-care messaging in EHR workflows.

5.3 Regulatory boundary: marketing vs care operations.

In the U.S., the HIPAA Privacy Rule defines 'marketing' as any communication about a product or service that encourages recipients to purchase or use it. It generally requires the patient to authorize the sharing of protected health information (PHI) for marketing purposes. There are also important exceptions, such as treatment and health care operations [24]. This boundary also limits how AI can be used for personalization. Many effective targeting efforts can only occur after the patient has authorized access or through the use of non-identifying information or care-linked communication. For example, a cancer patient using ChatGPT to check treatment options doesn't want to feel targeted by the algorithms. They want information that respects the gravity and privacy of their search. This is why healthcare AI must err on the side of caution, even when retail-style hyper-personalization could, in theory, improve relevance.

5.4 Provider case study

Penn Medicine (AI-supported campaign optimization). Fathom Digital Marketing shared a case study about their client, Penn Medicine, which used AI tools like Perplexity for search-term analysis and Akkio and ChatGPT for ad copy creation. The brand was able to save time, and witness 11% increase in click-through rates [25]. Still, the case emphasized that AI was used as a "thought partner" rather than a fully automated copywriter. Thus, it reinforces the best practice to prioritize human experts to ensure clinical accuracy, tone, and trust. At the same time, AI accelerates analysis and iteration.

5.5 Payer and pharmacy engagement: toward AI-native consumer platforms.

Large U.S. healthcare giants are using AI across retail, payer, and clinical touchpoints for consumer engagement. For example, CVS Health built an 'AI-native consumer engagement platform' to link pharmacy, benefits management, insurance, and care delivery businesses into a single digital interface [26]. CVS also stresses responsible AI use in improving member experiences and simplifying the plan journey [27]. While public quantitative outcomes are limited in these disclosures, the strategic direction is important for marketing. When organizations unify touchpoints, they can personalize communications across channels and measure outcomes across the member lifecycle.

5.6 Life-sciences case study: AI-enabled HCP activation for a next-generation CGM sensor.

OptimizeRx documents a life-sciences campaign in which an AI-powered platform dynamically identified and engaged high-value HCPs across EHR and social channels. This helped them to drive early adoption of an advanced continuous glucose monitor (CGM) sensor. The case reports lifted scripts 8.5% in reached doctors, added 1,086 prescribers, 12,473 new prescriptions, and USD 12.8 million extra sales [9]. This case shows how point-of-care contextual messaging and predictive audience activation in clinical workflows has been expanding. Nonetheless, even as the 8.5% lift and $12.8M revenue figures are impressive, the case study does not disclose whether a randomized control group was used or whether the lift calculations adjusted for baseline growth trends in

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CGM adoption. In specialty pharma, prescription patterns can also shift because of formulary changes, clinical guidelines updates or competitor supply issues. All of these can inflate the observed lift if not properly controlled. For academic rigor, future healthcare marketing cases should also report: (1) experimental design (RCT vs. observational), (2) baseline trends, (3) campaign costs for ROI context, and (4) sustained vs. one-time lift.

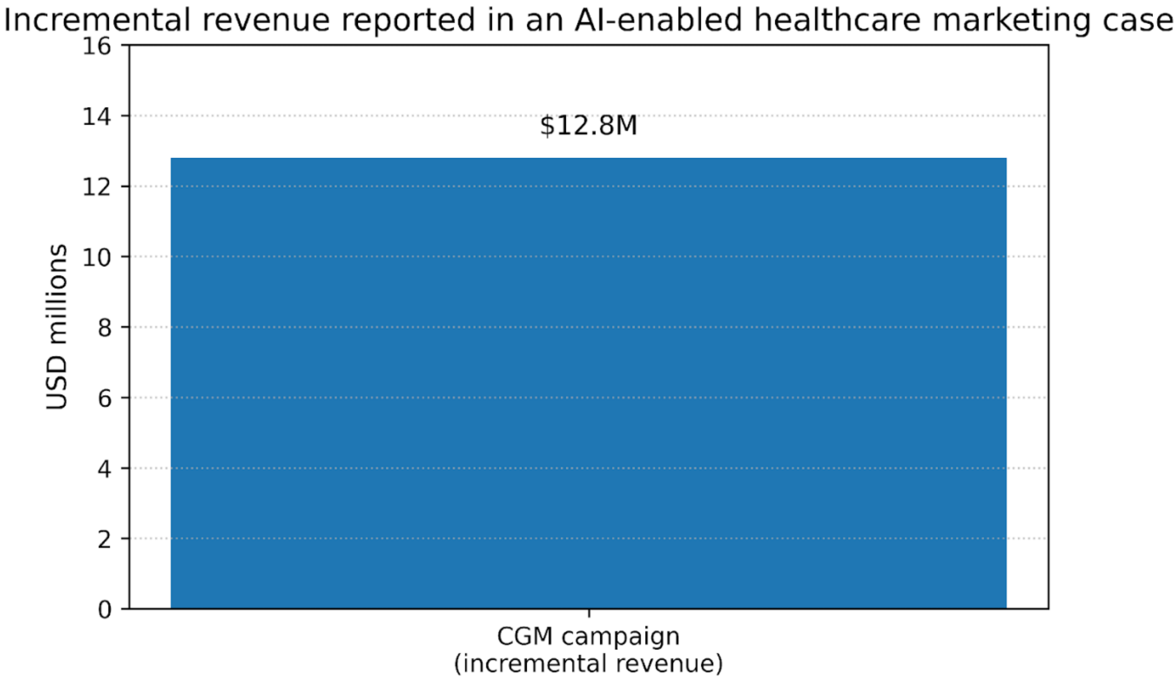

Figure 5 Incremental revenue reported in an AI-enabled healthcare marketing case (CGM campaign). [9]

5.7 Measurement and trust constraints in healthcare.

Healthcare marketing faces longer measurement horizons than retail. This is because demand is shaped by seasonality, capacity, insurance coverage, and physician referral patterns. Moreover, the healthcare sector has stronger trust limitations. This means AI-generated messages that are too personal would trigger privacy fears. Healthcare marketers stress the need to only improve relevant areas, such as providing guides and easy access instead of aggressive sells. Thus, in healthcare, top AI setups focus on low compliant data use, and clear consent

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boundaries. Top setups equally focus on explainable targeting logic and strong human oversight for clinical or sensitive content.

5.8 Generative and agentic AI for the healthcare digital front door

A new trend in the U.S. is that patients are now turning to digital tools to make decisions. They use search engines, provider directories, review sites, and online booking platforms. This digital front door creates a marketing and access funnel that acts like an e-commerce funnel. But the stakes run higher and with tight rules. Generative AI helps by allowing users chat to find clinics or services. It also helps them summarize complex information, such as preparation steps or insurance details. Generative AI also reduces friction in booking and follow-ups. Healthcare still has many guardrails. The cost of misinformation is high. Plus, too much personalization can feel intrusive when it comes to private health conditions.

Healthcare organizations use layers for safety. They build knowledge-grounded assistants from approved sources. They hand off to human agents when needed. They also set default values for sensitive topics. Beyond that, there are also boundaries for ad personalization. For example, Meta says, it won't feed conversations about health to ads [3]. Health providers skip social ads for sensitive targeting. Still, these rules show the norm. Here, personalization must fit the context and avoid mining sensitive data.

Patient engagement platforms show the path ahead. CVS plans on an AI-native consumer engagement platform connecting interactions across pharmacy, benefits, insurance, and care [26]. This tie-in allows for steady messages over time. This includes medication reminders, care nudges, benefit breakdowns, and service ideas. All of this runs across channels with clear consent governance. Conceptually, this actually resembles retail loyalty plans. But that stricter data demands still stand out. Menlo Ventures suggests AI engagement better serves healthcare as part of the core workflow than as an add-on [5]. It is only natural that healthcare marketing AI prioritize metrics that reflect access and quality. Such metrics include reduced no-show rates, improved scheduling completion, better call center resolution, improved patient satisfaction, and service-line growth. Proving causality is harder than in retail due to the limitations of referrals and insurance pathways. However, quasi-experimental methods such as matched

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controls, stepped-wedge rollouts, and geographic experiments can yield credible estimates. There's also a need to document all compliance boundaries. The HIPAA Privacy Act also requires marketing to share health data. Even so, there are exceptions regarding treatment and heath care operations [24]. AI must be designed using personalization logic that sticks to permitted categories or requires getting clear consent.

As healthcare AI matures, 'point solution fatigue' is becoming a limiting factor [28]. This means that isolated chatbots or content generators will not deliver sustainable value for marketing. Only deep workflow integration with accountability checks can yield better outcomes. In high-performing organization, digital systems are treated as systems. Thus, marketing, access operations, IT, and compliance share performance metrics and continuously improve the experience. This operating model will shape the next phase of AI-enabled healthcare marketing in the United States.

6. Cross-Sector Comparative Analysis

Retail and healthcare share the same AI marketing mechanisms. They both require prediction, personalization, automation, and continuous optimization. They differ in terms of data access, tolerance for error, and regulatory constraints. Retail gets higher-frequency behavioral signals and faster feedback loops. Thus, conversion outcomes in Retail happens in minutes or days. Healthcare marketing often has longer decision cycles (weeks to months). It also has more complex attribution paths and multiple clinical touchpoints). The marketers and brand they represent also faces a huge risk of losing their reputation if outreach appears intrusive or inaccurate.

These differences shape AI implementation. Retail companies can easily push towards real-time personalization and purchase funnel optimizations at a faster pace. This is because their target consumers expect experiments and errors don't cost a lot. Healthcare firms would always remain conservative. Errors carry significant risks, and data use is always regulated. As a result, healthcare marketing AI can be implemented in fewer workflows. In fact, for most healthcare businesses, implementation would only occur in search and scheduling optimization, call center routing, and approved patient education.

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Measurement approaches also differ and matter just as much. Retail tests can target and set short goals to evaluate targeting and creatives with quick gains. Healthcare measurements require a long-term approach. It must also adjust for seasons and capacity as well.

For example, Life-sciences HCP marketing can measure prescription lift. But casual inference is still challenging because of channel spillovers and patient mix. This suggests that cross-sector learning should focus on methods: healthcare can benefit from retail's experimentation culture, while retail can learn from healthcare's governance discipline.

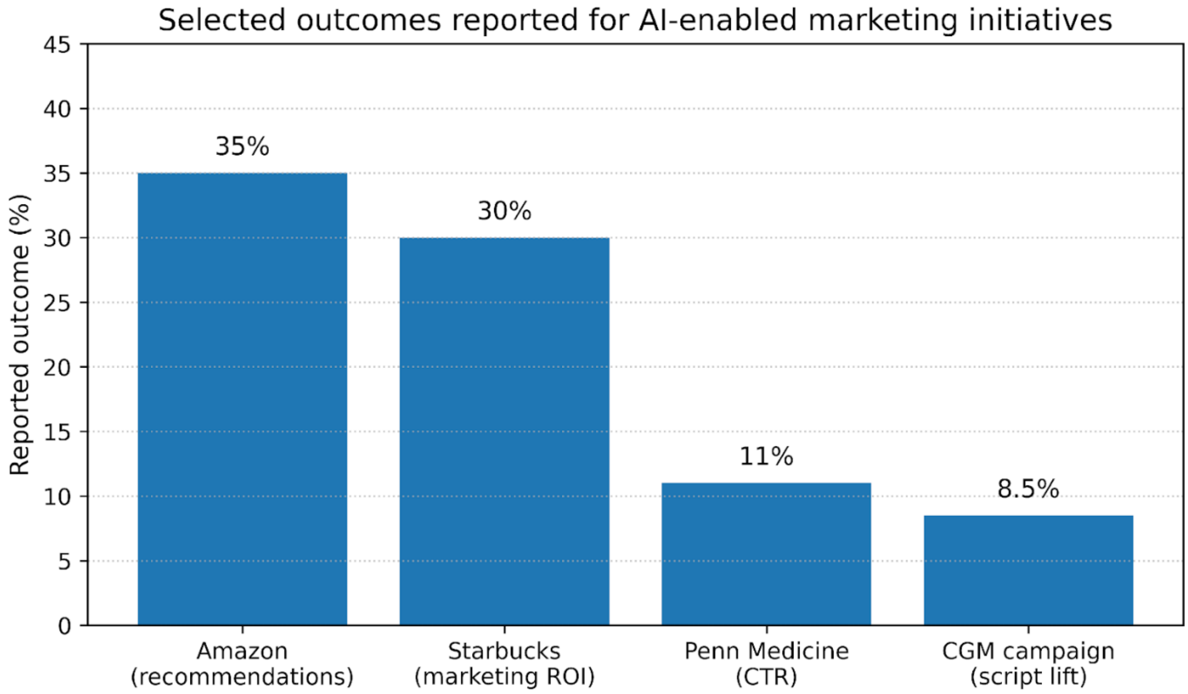

Figure 6 Selected reported outcomes associated with AI-enabled marketing initiatives (percent metrics [14] [22] [9]

Another cross-sector insight that stands out is that the performance of operations and marketing AI is closely linked. In retail, inventory accuracy and quick shipping can lift sales and customer loyalty. Healthcare, in turn, turns ad interest into appointment availability, clinician capacity, and scheduling usability. Thus,

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AI marketing should be treated as a system optimization problem rather than a narrow advertising problem.

Table 3 Comparative Implementation Framework: Retail versus Healthcare AI Marketing

Dimension	Retail	Healthcare
Feedback Loop	Hours to days	Weeks to months
Data Richness	High (clickstream, purchase, reviews)	Moderate (fragmented across systems0
Consent Model	Opt-out (with privacy registrations)	Opt-in (HIPAA authorization)
Error Tolerance	High (bad recommendation = Lost sale)	Low (bad targeting = trust damage)
Primary KPI	Conversion, AOV, LTV	Utilization, satisfaction, outcomes
Personalization Boundary	Aggressive (1:1 messaging)	Conservative (cohort-level, approved content)
Measurement Gold Standard	A/B tests with holdouts	Quasi-experimental designs

Table 3 shows the structural differences in complete detail. It explains why retail can iterate faster while healthcare must govern harder. Retail's high error tolerance enables rapid A/B testing, and failed experiments only cost pennies. Healthcare's low error tolerance demands pre-launch clinical and legal review. Thus, this slow deployment reduces reputational risks.

7. Implementation Challenges and Cautionary Tales

Not all AI marketing implementations deliver promised results. Retail and healthcare both also face common pitfalls:

Personalization backfire: Over-personalization can feel invasive. In 2012, a major U.S. retailer faced backlash when its pregnancy prediction model sent

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baby-related ads to a teenager before her family knew she was pregnant—a cautionary tale about inferring sensitive states from behavioral data.

Cold-start problems: Recommender systems struggle with new products or new customers who lack browsing history. Retailers that over-rely on collaborative filtering may under-serve emerging trends or niche tastes.

Attribution inflation: As noted in Section 4.8, propensity models can create 'AI placebo'—campaigns that appear successful because they target high-intent customers who would have converted anyway. Without proper holdout testing, marketers risk crediting AI for organic demand.

Regulatory missteps: In healthcare, even well-intentioned personalization can violate HIPAA if not carefully scoped. An example is the case against Flo Health, which was a class action alleging unauthorized sharing of personal information for advertising purposes. [29].

8. Market Outlook, Predictions, and Emerging Trends

Having compared the retail and healthcare AI impacts, we now turn to where the sectors and AI marketing are heading. AI sits at the heart of the marketing technology setup. Marketsand Markets forecasts that the global AI for sales and marketing market will expand from USD 57.99 billion in 2025 to USD 240.58 billion by 2030 (CAGR 32.9%) [29]. This market includes CRM augmentation, content generation, chatbots, AI agents, forecasting tools, and campaign management analytics. Even as these tools are not U.S.-specific, they show that the vendor ecosystem supporting U.S. marketing teams is expanding rapidly.

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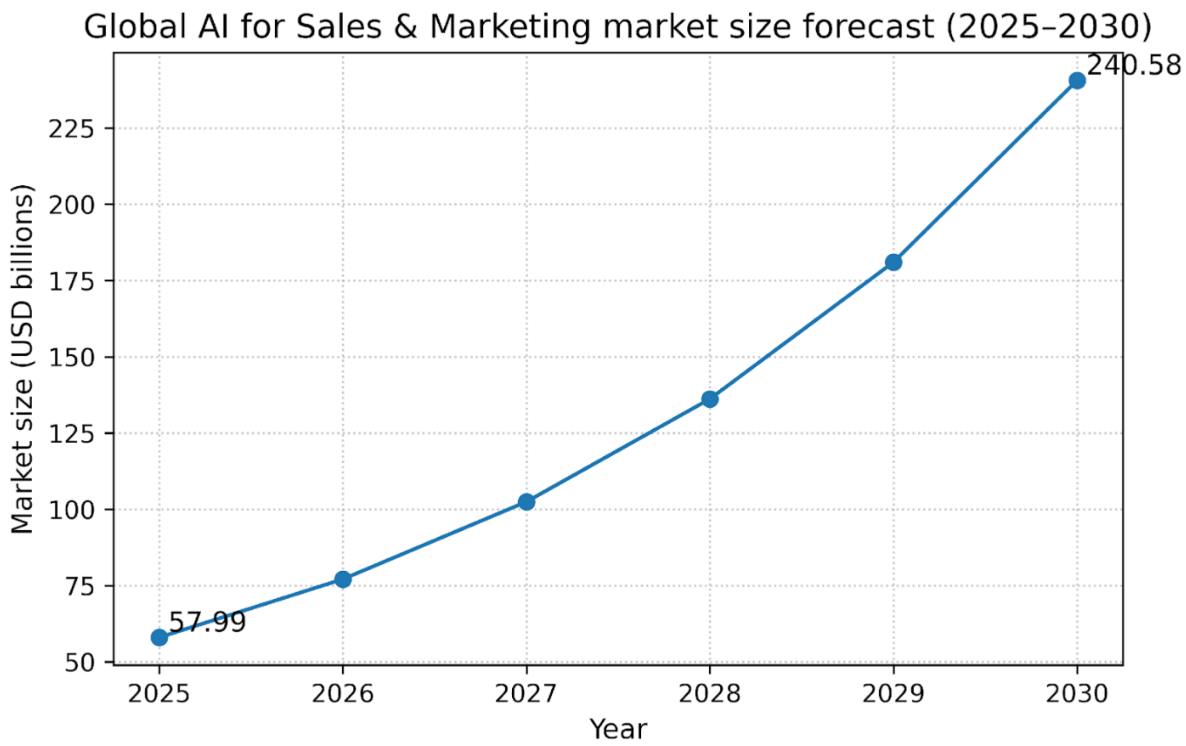

Figure 7Global AI for sales and marketing market forecast, 2025-2030 (CAGR interpolation) [13]).

7.1 From automation to transformation in digital advertising.

The IAB reports that the U.S. digital advertising industry grew by 14.9% year over year in 2024. This highlights AI-driven advertising as a key trend for 2025. We equally note the evolution from automation to 'transformative' capabilities due to generative and agentic models [15]. This suggests that AI's contribution to marketing outcomes will expand from incremental optimization (e.g., better targeting) to interface and business model changes (e.g., conversational ads, shoppable AI results, and agent-to-agent transactions).

7.2 Agentic commerce and the next interface for marketing.

A major emerging trend is the shift from AI-assisted shopping (recommendations and search) to agentic commerce. This, Agents now initiate and complete transactions. Bain estimates that the U.S. agentic commerce market could reach USD 300-500 billion by 2030. This represents roughly 15-25% of overall U.S. e-

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commerce [30]. Morgan Stanley provides a similar but slightly lower range, projecting USD 190-385 billion and a 10-20% share by 2030 [31]. For marketers, agentic commerce implies a shift in optimization targets. Campaigns will increasingly be evaluated by how they influence both human and agent decision processes. Such includes product metadata, trust signals, and fulfillment reliability. Whether Americans will trust AI agents to spend their money on groceries—let alone high-stakes purchases like mattresses or medical devices—remains an open, profoundly human question. Early adopters may embrace convenience; skeptics may see surveillance. The answer will shape e-commerce over the next decade.

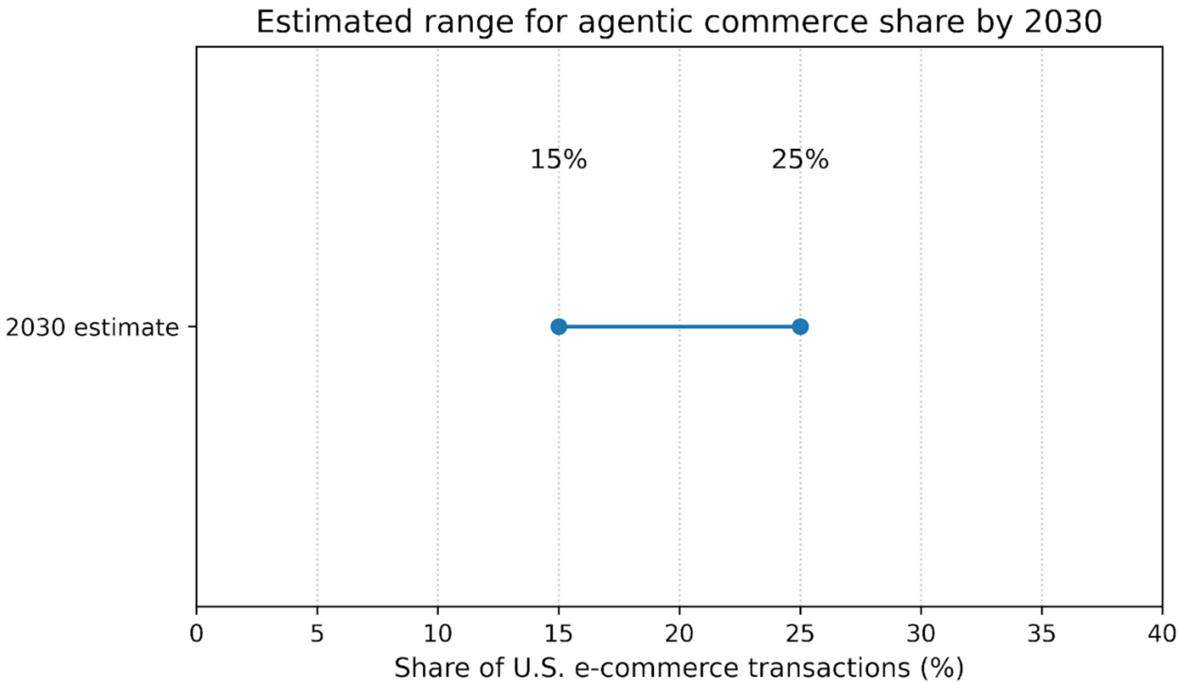

Figure 8 Estimated share of U.S. e-commerce attributable to agentic commerce by 2030 (range). Source: Bain (2025).

Agentic commerce is shaking up retailers, brands, and platforms. If agents choose among retailers based on price, delivery speed, and reliability, then operational excellence becomes a marketing variable. If agents are hosted by platforms (e.g., LLM providers) rather than retailers, retailers lose direct control over them. Thus,

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it forces retailers to negotiate new distribution models and invest in 'agent-optimized' merchandising.

7.3 Platform policy shifts and privacy dynamics. AI-driven personalization uses fresh user signals.

Meta's policy update indicates that generative AI chats will inform ad and content recommendations starting December 16, 2025 [3]. Yet, privacy regulations and signal loss push first-party data strategies. IAB calls privacy and regulation a big 2025 shift with focus on owned data, contextual targeting, and consent-based tools [15]. Such dynamics show that AI marketing advantage will increasingly depend on the quality of first-party data, consent governance, and privacy-safe tracking.

7.4 Health AI integration and 'point solution fatigue.'

As healthcare AI scales, organizations face integration and workflow challenges. An AXIOS 2025 report cited burnout from the use of isolated tools in health AI. Stakeholders demand tangible values and integrated workflows in its place [28]. Such is also seen in marketing AI. Standalone content generators or ad tools that aren't integrated with scheduling, access, and care delivery systems won't deliver as many positive outcomes. The only way to achieve sustainable impact is through workflow-level integration.

7.5 Scenario outlook for 2026-2030.

Given how platforms change, and Agentic commerce is growing, forecasts can only be presented as scenarios rather than isolated guesses. We outline three practical scenarios for the U.S. retail and healthcare marketing landscape through 2030. In all scenarios, generative AI reduces the cost of content and analysis. Marketing teams can now run more experiments. The key uncertainties are consumer trust in delegating decisions to agents, evolving platform and regulatory policies on personalization data, and the availability of high-quality first-party data and interoperable workflows.

Conservative scenario: AI would remain a helper. In retail, conversational assistants (e.g., Rufus or Sparky) are widely used for research and comparison.

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But users would still ultimately make their own purchase decisions. It also means that the shopping journey would still require multiple steps. Moreover, as Retail media continues to grow, measurements will remain fragmented. Still, RMNs rely heavily on onsite conversion data. Healthcare limits generative assistants to guides and FAQs with tight rules and frequent escalation to humans. Specialized AI systems will continue to expand. [5]). But tools overload and fatigue may slow deployment unless vendors can show how easily they fit into different workflows. [28].

Base scenario: AI becomes the primary place for discovery and planning. In retail, assistant-mediated journeys drive a meaningful share of discovery. There's also a subset of categories (replenishment, household goods) that shift toward agentic execution. Such is consistent with the ranges proposed by Bain and Morgan Stanley [30] [31]. Retailers respond by improving product data quality, fulfillment reliability, and agent-friendly merchandising. In healthcare, digital front doors become conversational by default for scheduling and service navigation. Retrieval-augmented systems get grounded in approved content. The main competitive differentiator becomes access friction. Systems that reduce scheduling delays and improve patient experience translate marketing demand into action.

Accelerated scenario: End-to-end agentic transactions scale quickly. Agent-hosted commerce takes a large share of e-commerce transactions. This compresses the marketing funnel into a single conversational interaction. Marketing optimization pivots to agent ecosystems. This means there are more agent recommendations, structured product reputation signals, and negotiation of distribution terms with assistant platforms. In healthcare, consumer engagement platforms link payer, pharmacy, and provider interactions. This allows for lifecycle orchestration at scale. [26]. Under this scenario, governance and regulation matter most. Remember, FTC cracks down on deceptive AI claims [4]. Stricter privacy expectations constrain aggressive personalization, which increases the value of trustworthy brands with strong consent governance.

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9. Governance, Ethics, and Regulation

AI use in marketing needs rules that align performance goals with laws and ethics. In the U.S., consumer protection regulators have targeted deceptive AI claims and the misuse of AI to boost false ads. The FTC's Operation AI Comply demonstrates that enforcement will focus on both 'AI washing' (overstated capability claims) and AI-enabled deception, such as fake reviews [4]. For marketers, this implies that AI claims must be substantiated, that AI-generated endorsements require strict controls, and that marketing organizations should maintain documentation of model use and review processes.

Healthcare brings additional privacy and ad-targeting rules. The HIPAA Privacy Rule's marketing definition and authorization requirements set limits on the use of PHI (HHS, 2013). Practical compliance patterns include: strict segmentation of PHI and marketing datasets; use of de-identified or aggregated data for modeling when feasible; business associate agreements with vendors; and explicit consent management. Ethical implementation requires fairness and inclusivity: models used to target outreach or prioritize resources should be audited for bias to avoid systematically excluding vulnerable groups from beneficial communications.

Across both sectors, responsible AI in marketing can be operationalized through model risk management (validation, monitoring, drift detection) and human-in-the-loop review for high-stakes content and automated decisions. There is also the need for transparency in customer interactions (disclosing chatbot use and AI-generated content where appropriate). Organizations also need security controls to protect training data and model outputs, as well as procurement and vendor governance that clarify data usage, retention, and model training rights. Governance complexity increases as systems become agentic and begin taking actions rather than merely making recommendations.

10. Managerial Implications and Implementation Roadmap

Successful AI marketing implementation tends to follow a common set of stacks. The specific tools differ by sector, but the layers remain the same. Data foundation, model layer, activation layer, experimentation and measurement, and an operating model that connects marketing, data science, IT, and compliance.

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Table 4 AI marketing capability stack (cross-sectors)

Item	Description
Data foundation	Unified identity where permitted, clean event streams, consent metadata, taxonomy for products/services, and governance.
Model layer	Propensity/churn models, recommenders, NLP for intent, forecasting, evaluation, and monitoring.
Activation layer	Orchestration across channels with real-time decisioning; integration into service workflows (chat/call/EHR).
Experimentation and measurement	A/B testing, incrementality, attribution, marketing mix modeling, and causal inference methods.
Operating model	Cross-functional teams, clear ownership, MLOps, and governance with legal/compliance embedded.

Retail groups focus on high-leverage personalization opportunities, such as homepage ranking, product detail recommendations, and lifecycle triggers. It's important to tie generative content pipelines to real results to avoid producing volume without value. Healthcare teams should focus on improving patient access compliance, including search, navigation, and scheduling. There's also a need for AI to focus on efficiency and relevance rather than hyper-personalization. Such could trigger privacy concerns. In both sectors, robust strategies start with narrow, measurable use cases, validate lift, and scale through an operating model that includes compliance and risk review from the beginning.

Measurement recommendations. For high-level decision makers, three measurement principles are especially important: (1) separate correlation from causality through experiments or quasi-experiments where possible, (2) evaluate AI performance in terms of business outcomes (incremental revenue, retention, or utilization) rather than proxy metrics alone, and (3) maintain guardrails to avoid optimizing short-term metrics at the expense of long-term trust (e.g., excessive personalization, price discrimination perceptions, or fatigue from high-frequency messaging).

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11. Limitations and Future Research Agenda

11.1 Study Limitations

This article pulls from secondary sources and documented case evidence. It does not present new primary data collection or controlled experimental evaluation across firms. Some reported case outcomes are based on industry reporting and should be interpreted cautiously.

Data and access constraints. We rely on publicly disclosed cases, which introduces survivorship bias. Most companies only announce successful implementations and keep failed projects confidential. The reported outcomes from Starbucks (30% ROI boost), Penn Medicine (11% CTR lift), and OptimizeRx ($12.8M incremental revenue) originate from industry sources rather than peer-reviewed studies. Methods and baselines are not always fully disclosed, limiting our ability to assess internal validity or replicability.

Measurement transparency gaps. None of the retail or healthcare cases examined were from randomized controlled trials with proper holdout groups. The Starbucks Deep Brew case does not specify whether the 30% increase in ROI accounts for baseline loyalty-program growth or seasonal demand. The OptimizeRx CGM campaign does not disclose campaign costs (preventing a true ROI calculation), nor does it address whether the 8.5% prescription lift accounts for concurrent market trends, such as competitor stockouts, formulary changes, or updated clinical guidelines for diabetes management. Without these details, we cannot definitively attribute observed outcomes to AI interventions versus confounding factors.

Scope boundaries. Our analysis focuses on U.S retail and healthcare. Findings may not generalize to other sectors (financial services, manufacturing). It also does not extend to other geographies with different regulatory environments, such as GDPR in Europe or emerging markets with limited data infrastructure. Additionally, we examine AI marketing outcomes but do not consider workforce displacement, organizational change management, long-term competitive dynamics, or other factors that may also play a notable role.

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Forecast interpretation. As noted in Section 3, market forecasts are visualizations of published endpoints. These are not independent econometric models. They are industry expectations and not validated predictions. The agentic commerce forecast, especially, depends on assumptions about consumer trust and platform adoption. All that remains empirically untested.

Despite its limitations, the secondary synthesis remains vital. It helps map mechanisms and implementation patterns in a domain evolving faster than academic publication cycles can track. The cases and trends we document establish a baseline for future primary research.

11.2 Critical Research Gaps and Future Directions

Our synthesis finds three critical research gaps that can guide future academic inquiries. We organize these gaps by explicitly linking them to the limitations observed in the current implementation.

Gap 1: Casual inference in multi-touchpoint marketing journeys

Current case studies report correlational metrics such as click-through rates, prescription lifts, and revenue gains. These reports happen without counterfactuals. For example, the Starbucks Deep Brew case reports a 30% ROI without disclosing the control group or the baseline trend. Similarly, the OptimizeRX CGM campaign reports 6.5% prescription lift. The report does not explain whether it exceeds natural adoption trends for the sensor category. This matters because, in multitouch journeys, customers encounter brand messages across owned (email, app), paid (search ads, retail media), and earned (reviews, word-of-mouth channels). AI often optimizes everything at once, making it harder to determine which intervention drove the outcome. Propensity models also compound the challenge by targeting only customers already likely to convert. Thus, it creates measurement artifacts that make AI appear effective simply because it focuses on high-intent users. Future research directions would benefit from randomized geo-experiments, synthetic control methods, attribution decomposition studies, and mechanism validation.

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Gap 2: Long-term trust dynamics and personalization boundaries

Our focus was on short-term performance lifts but not whether aggressive personalization erodes customer trust, satisfaction, or loyalty over time [32]. The retail cases focus on conversion gains but do not track sentiment shifts or churn patterns among heavily targeted segments. In healthcare, no case reported longitudinal monitoring of patient trust or whether AI-driven outreach affects willingness to return in the future. The stakes are high because personalization happens on the trust frontier. Consumers appreciate relevant offers but perceive hyper-personalization as invasive surveillance. The 2012 Target pregnancy prediction incident—where algorithmic inference revealed a teenager's pregnancy to her family before she disclosed it—illustrates the reputational and ethical risks of crossing this boundary. In healthcare, the stakes are higher: patients who feel "tracked" by their health system may disengage from preventive care or avoid disclosing sensitive information to providers. Therefore, none of the cases we reviewed measured trust degradation, privacy concerns, or long-term opt-out rates. Retail personalization studies focus on immediate conversion but ignore whether customers who receive daily AI-optimized offers eventually experience fatigue, resentment, or reduced brand affinity. Future directions should focus on longitudinal panel studies that measure satisfaction, churn, and qualitative sentiment among customers with varying levels of personalization. There's also the need for studies that test consumer reactions to AI disclosure. We also need healthcare-specific trust studies and investigations into whether tolerance for personalization varies by age, digital literacy, income, or cultural background. Sustainable AI marketing needs this research to investigate dynamic governance fully. These studies will help develop decision frameworks that balance short-term conversions with a long-term relationship framework.

Gap 3: Equity, Fairness, and Systematic Exclusion

None of the cases examined reported fairness audits or distributional impact analyses. We do not know whether AI-driven retail targeting excludes low-income shoppers from high-value promotions. We also don't know whether healthcare outreach underserves rural or non-English speaking patients. Finally, we don't know whether algorithmic optimization inversely amplifies existing inequities in

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access to beneficial offers or health information. AI marketing systems optimize for measurable outcomes. However, if certain populations have historically had lower engagement due to internet access issues, language barriers, or distrust, algorithms trained on such data may not prioritize them for future targeting. This creates a feedback loop of exclusion. Thus, underserved groups receive fewer offers, engage less, and the algorithms further reduce their focus on them. Nevertheless, this risk isn't specific to marketing. But research on algorithmic fairness would help, especially in healthcare. Future studies should conduct fairness audits across protected classes. There's also the need for counterfactual fairness studies, alongside equity-aware optimization. The FTC's Operation AI Comply signals that regulators are scrutinizing AI-enabled marketing for deception. Equity and fairness represent the next enforcement frontier. Firms that cannot demonstrate fairness audits and corrective actions may face legal risk under civil rights statutes (e.g., disparate impact claims) or consumer protection laws. Academic research that develops auditing methodologies and fairness benchmarks will be critical for both compliance and social responsibility.

12. Conclusion

Many US businesses are quickly adopting AI in their marketing workflows. It is changing the ways businesses create and capture value through personalization, automation, and predictive decisioning. Retail demonstrates mature, data-driven implementations in recommendations, retail media optimization, and AI-accelerated creative and conversational workflows. Healthcare is adopting domain-specific AI, with marketing applications increasingly integrated into compliant patient engagement and HCP activation within clinical workflows.

As AI marketing matures, competitive advantage shifts from who has the best algorithms to who builds the best system. That system must balance optimization with trust, personalization with privacy, and short-term conversion with long-term relationships. Both retail and healthcare systems must navigate these tensions to shape their futures and the broader evolution of AI-enabled commerce and care.

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