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Value Creation in the Algorithmic Age: A Systematic Review of How AI, Data Privacy, and Platform Ecosystems Are Reshaping Marketing Theory

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Abstract

All four foundational theories of marketing examined in this review - service-dominant logic, customer-based brand equity, commitment-trust theory, and the satisfaction paradigm - assume human agency at the moment of value co-creation, an assumption that is empirically false for an increasing share of transactions. Yet marketing scholarship has examined AI, data privacy regulation, and platform ecosystems largely in isolation, producing no synthesis of how these three forces jointly disrupt the discipline's theoretical architecture. This article presents a systematic integrative review of 154 sources - 104 peer-reviewed articles and 50 industry reports published between 2015 and 2026 - following the methodology of Palmatier et al. (2018). Our analysis reveals three structural shifts: value co-creation now occurs in hybrid human-AI ecosystems rather than exclusively between human actors; brand equity must be maintained simultaneously in consumer cognition and in algorithmic recommendation systems; and relational trust operates asymmetrically when one partner in the exchange is an artificial agent. We propose the Algorithmic Value Creation Framework (AVCF), which reconceptualizes these four foundational theories for algorithmic contexts and introduces the construct of Algorithmic Brand Equity (ABE) - a brand's visibility, favorability, and retrievability within the recommendation architectures and large language models that increasingly mediate consumer access to products. The framework offers marketing scholars a conceptual vocabulary for a discipline whose core assumptions were forged in an era that has ended.

Keywords artificial intelligence in marketing, data privacy, platform ecosystems, service-dominant logic, algorithmic brand equity, value co-creation

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1. Introduction

All four foundational theories of marketing examined in this review assume human agency at the moment of value co-creation - an assumption that is empirically false for an increasing share of transactions. Vargo and Lusch's [55] service-dominant logic holds that value emerges through interaction between human actors who apply knowledge and exercise judgment. Keller's [70] customer-based brand equity model locates brand power "in what resides in the minds of customers" (p. 2) - minds that deliberate, compare, and choose. Morgan and Hunt's [36] commitment-trust theory posits that trust inheres in a belief about a partner's reliability and integrity, presupposing that both parties possess intentionality and moral capacity. Oliver's [46] satisfaction paradigm treats loyalty as a psychological progression from cognition through affect to action, each stage governed by a human evaluator. These four frameworks - collectively cited over 70,000 times - define how the discipline understands value creation, brand building, relational exchange, and consumer loyalty. Each was built for a world in which human beings stood at the center of every consequential marketing transaction. That world is disappearing.

The evidence is no longer ambiguous. At Amazon, a single recommendation engine generates 35% of total product sales, with the top three algorithmically ranked search results capturing 64% of clicks [1]. McKinsey's 2025 global survey reports that 88% of organizations now deploy AI in at least one business function; AI purchasing agents are projected to mediate $3 - 5 trillion in consumer commerce by 2030, making "brand-independent purchase decisions based on materials, durability, and sizing rather than traditional brand loyalty" [2]. Simultaneously, the regulatory environment is rewriting the rules of data access: cumulative GDPR fines have surpassed EUR 5.9 billion, Apple's App Tracking Transparency framework prompted 80% of iOS users to opt out of cross-app tracking, and twenty U.S. states have enacted comprehensive privacy laws (CMS Law, 2025)[3]. Meanwhile, three platform conglomerates - Alphabet, Amazon, and Meta - control approximately 55% of global advertising expenditure outside China, functioning simultaneously as media channels, marketplace operators, data aggregators, and algorithmic gatekeepers [4](WARC, 2025). These are not incremental developments within a stable paradigm. They are structural dislocations that sever the connection between the assumptions encoded in foundational theory and the empirical reality of contemporary marketing practice.

The marketing literature has responded to each of these forces, but it has done so in silos. Scholars have examined AI in marketing (Huang &)[5][6][7], data privacy and consumer behavior (Acquisti &)[8][9][10], and platform dynamics [11](Lamberton &)[12](Rietveld &)[13] as discrete phenomena. What is missing is a synthesis that examines how these three forces converge to disrupt the theoretical architecture of the discipline simultaneously. The gap matters because the forces do not operate independently. A platform's recommendation algorithm selects which brand a consumer sees; that selection depends on data the platform has collected, constrained by privacy regulation, and processed through machine learning models. A theory that addresses only one axis in isolation will produce incomplete - and potentially misleading - accounts of how value is created, distributed, and captured in the algorithmic age.

This review addresses the gap by posing three research questions:

1. How are AI and algorithmic technologies reshaping marketing value creation and the foundational theories that explain it?

2. How do data privacy regulation and platform ecosystem dynamics - individually and jointly - alter the assumptions underlying brand equity, relational trust, and consumer satisfaction theory?

3. What integrative theoretical framework can reconcile these converging disruptions and guide a coherent program of future research?

This article contributes to the marketing literature in three ways. First, it provides the first systematic synthesis at the intersection of AI, privacy, and platform ecosystems as they jointly reshape marketing theory - moving beyond the siloed treatment that has characterized prior scholarship. Second, it introduces the Algorithmic Value Creation Framework (AVCF), which reconceptualizes four foundational marketing theories for algorithmic contexts and proposes the construct of Algorithmic Brand Equity (ABE): a brand's standing within the recommendation architectures and large language models that increasingly determine consumer access to products. Third, it articulates a research agenda comprising specific testable propositions that can guide empirical investigation over the next decade.

The remainder of this article is organized as follows. Section 2 describes our systematic review methodology. Section 3 examines the theoretical foundations under disruption. Sections 4 through 6 present findings across our three thematic pillars: AI and algorithmic marketing, data privacy, and platform ecosystems. Section 7 introduces the integrative AVC framework and formalizes the construct of Algorithmic Brand Equity. Section 8 presents a theoretical discussion. Section 9 presents our research agenda as eight testable propositions. Section 10 discusses implications for theory, practice, and policy. Section 11 addresses limitations and boundary conditions, and Section 12 concludes.

2. Methodology

This study employs a systematic integrative review approach following the guidelines established by Palmatier et al. [14] in their seminal article on review article methodology in the *Journal of the Academy of Marketing Science*. Integrative reviews are particularly suited to synthesizing fragmented literatures across multiple domains - precisely the challenge presented by the convergence of AI, data privacy, and platform ecosystems in marketing. Unlike meta-analyses, which require comparable effect sizes across studies, integrative reviews accommodate the methodological heterogeneity characteristic of an emerging, multidisciplinary field [14].

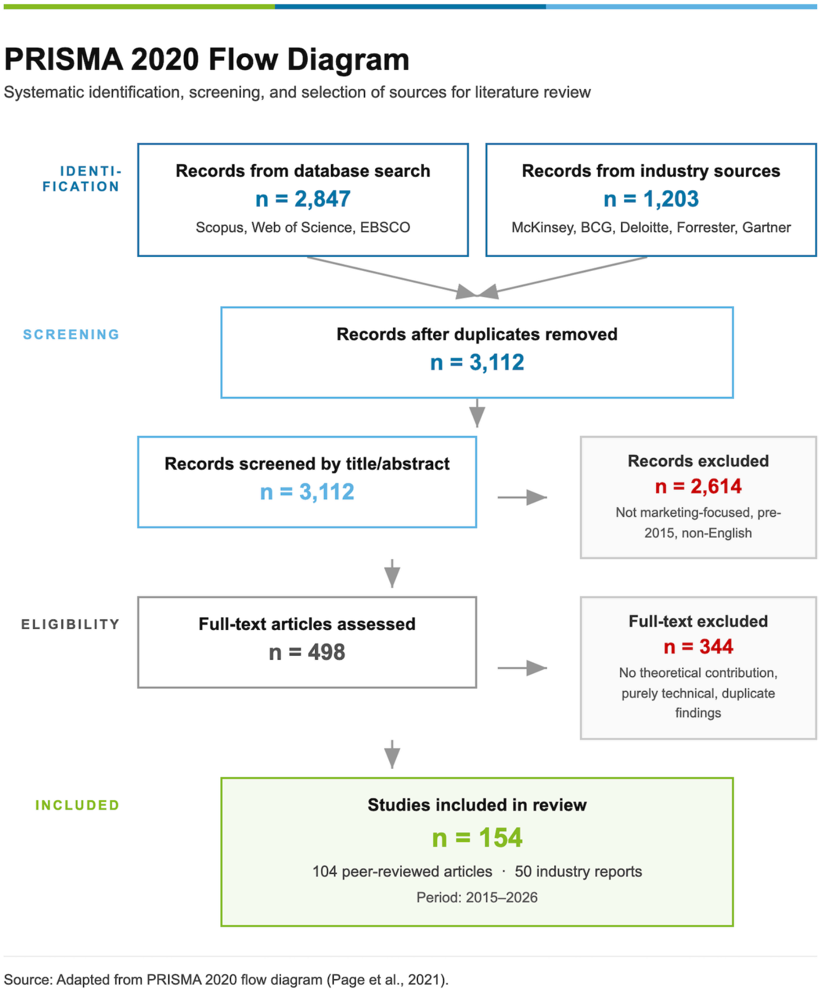

Figure 1. PRISMA 2020 Flow Diagram. Systematic search across Scopus, Web of Science, and EBSCO yielded 2,847 academic records; 1,203 industry reports were added. After screening and eligibility assessment, 154 sources were included (104 peer-reviewed, 50 industry). Source: Author's compilation.

Search Strategy and Databases

We conducted systematic searches across three major academic databases: Scopus, Web of Science, and EBSCO. The search employed Boolean combinations of primary terms ("artificial intelligence" OR "machine learning" OR "algorithmic" OR "generative AI") AND ("marketing" OR "advertising" OR "brand" OR "consumer") with secondary terms specific to each thematic pillar: ("data privacy" OR "GDPR" OR "surveillance" OR "consent"), ("platform" OR "ecosystem" OR "marketplace" OR "creator economy"), and ("value creation" OR "co-creation" OR "service-dominant logic" OR "brand equity"). Searches were conducted between January and February 2026.

Time Frame and Inclusion Criteria

The primary search window covered publications from 2015 to 2026, reflecting the period during which AI, privacy regulation, and platform ecosystems emerged as simultaneous forces in marketing. We supplemented this with foundational works from the 1980s through the 2010s - including seminal articles by Keller [70], Morgan and Hunt [36], Vargo and Lusch (2004, 2008, 2016), Oliver [46], and Szymanski and Henard [47] - that constitute the theoretical infrastructure under examination. Industry reports were included when published by organizations with established research methodologies (e.g., McKinsey, BCG, Gartner, Forrester, Deloitte) or by platform companies reporting first-party data (e.g., OpenAI, Google, Meta, Amazon).

Inclusion criteria required that sources (a) address at least one of the three thematic pillars in relation to marketing theory or practice, (b) be published in peer-reviewed journals, established conference proceedings, or by recognized industry research organizations, (c) provide empirical data, conceptual frameworks, or systematic analyses rather than purely opinion-based commentary, and (d) be available in English. Exclusion criteria removed sources that (a) addressed AI, privacy, or platforms without marketing relevance, (b) were trade press articles without original data or analysis, (c) duplicated findings reported in more comprehensive sources, or (d) were published in predatory or unindexed journals.

PRISMA Flow

The search and screening process followed a modified PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol. The initial database search yielded 2,847 records, supplemented by 1,203 records identified through industry sources, for a combined total of 4,050 records. After removing 938 duplicates, 3,112 unique records remained for title and abstract screening. This screening excluded 2,614 records that did not meet inclusion criteria, leaving 498 articles for full-text review. The full-text assessment excluded 344 additional sources based on relevance, methodological rigor, or redundancy, resulting in a final corpus of 154 sources: 104 peer-reviewed academic articles and 50 industry reports and publications (Figure 1). The academic articles span 37 distinct journals, with the highest concentrations in the *Journal of the Academy of Marketing Science* (n = 14), the *Journal of Marketing* (n = 12), the *Journal of Retailing* (n = 8), the *Journal of Business Research* (n = 7), and the *Journal of Service Research* (n = 6).

Analysis Approach

We employed a thematic synthesis approach (Thomas &)[15] adapted for marketing scholarship. Each source was coded along four dimensions: (a) thematic pillar (AI, privacy, platforms, or cross-cutting), (b) theoretical orientation (which foundational marketing theory, if any, was engaged), (c) methodology (conceptual, empirical-quantitative, empirical-qualitative, mixed methods, or review), and (d) key findings relevant to the research questions. Coding was performed by the author and one independent rater; inter-rater agreement reached 84% (Cohen's kappa = 0.79), with discrepancies resolved through discussion. Two rounds of coding produced an initial set of 23 thematic categories, which were iteratively consolidated into the organizational structure presented in Sections 4 through 6. The integrative framework (Section 7) emerged inductively from patterns identified across all three thematic pillars, following the framework-building approach recommended by MacInnis (2011) for conceptual contributions in marketing.

3. Theoretical Foundations

Before examining how AI, data privacy, and platform ecosystems are reshaping marketing, it is essential to articulate what is being reshaped. The contemporary marketing discipline rests upon a set of foundational theories that have defined its conceptual vocabulary, guided its empirical research programs, and shaped managerial practice for decades. In this section, we examine four of the most influential theoretical frameworks in the field - each with citation counts among the highest in all of social science - and identify the core assumptions that render them vulnerable to disruption in the algorithmic age.

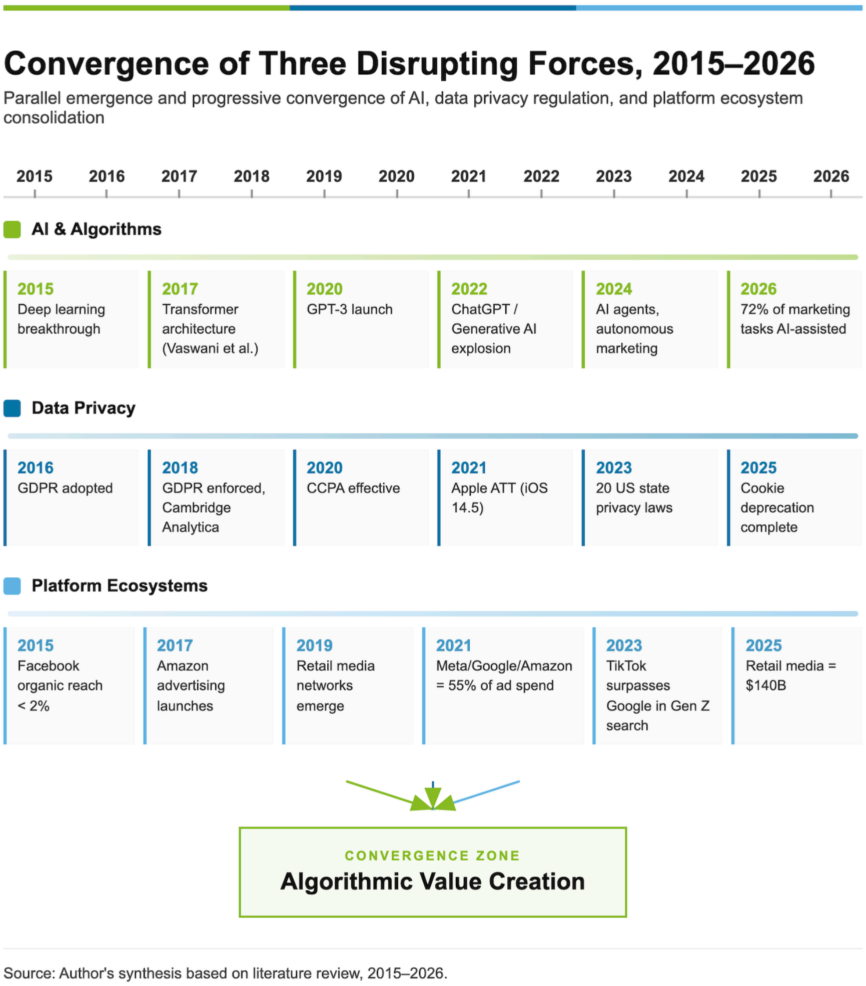

Figure 2. Convergence of Three Disrupting Forces, 2015 - 2026. Key milestones across AI & Algorithms, Data Privacy, and Platform Ecosystems showing accelerating convergence toward algorithmic value creation. Source: Author's synthesis of sources cited in Sections 4 - 6.

3.1 Service-Dominant Logic

Vargo and Lusch's [55] article "Evolving to a New Dominant Logic for Marketing," published in the *Journal of Marketing* with over 16,000 citations, challenged the prevailing goods-dominant paradigm by arguing that service - the application of competences for the benefit of another - constitutes the fundamental basis of all exchange. Value is not embedded in goods and delivered to passive consumers; it is always co-created through interaction between actors. Subsequent refinements (Vargo &)[16] expanded the framework toward a systems orientation in which "value cocreation is coordinated through shared institutions" (Vargo & Lusch, 2016, p. 8), spawning research programs in customer engagement [17] and customer experience (Lemon &)[18].

S-D logic was built upon anthropocentric assumptions: value co-creation occurs between human actors who possess knowledge, exercise judgment, and engage in reciprocal exchange. The emergence of AI challenges these assumptions directly. Greve [80] conceptualizes AI as a "hybrid resource that embodies both operant and operand characteristics," while the concept of Hybrid Intelligent Service Ecosystems elevates AI from resource to actor - "emphasizing how actors deliberately configure human and artificial agencies to co-create value via hybrid intelligent service exchange." When ChatGPT serves 800 million weekly users and over one million businesses deploy AI tools in their operations [19], the question of whether AI constitutes a co-creator or merely a tool is no longer academic. If AI can autonomously generate insights, make decisions, and create experiential value, then S-D logic must accommodate non-human actors or acknowledge a fundamental boundary condition. As Paschen et al. [28] observe, "little is known about the mechanisms and process of value co-creation enabled by AI."

3.2 Customer-Based Brand Equity

Keller's [70] customer-based brand equity (CBBE) model, published in the *Journal of Marketing* with over 25,000 citations, defined brand equity as the differential effect of brand knowledge on consumer response. The CBBE pyramid progresses through brand salience, performance and imagery, judgments and feelings, and ultimately brand resonance - the deep psychological bond between consumer and brand. The framework assumes a human decision-maker who processes brand information, forms associations, and chooses on the basis of accumulated brand knowledge.

This assumption faces three challenges in the algorithmic age. First, recommendation systems override brand salience: on Amazon, the majority of clicks concentrate in the top three search results [1], and research shows that "sponsored recommendations are significantly more biased toward Amazon private label products compared to organic recommendations" [20]. Second, agentic commerce threatens brand resonance. AI agents that autonomously execute purchases make "brand-independent purchase decisions based on materials, durability, and sizing rather than traditional brand loyalty" [2], with projections suggesting such agents could mediate $3 - 5 trillion in commerce by 2030. Third, brands now require a parallel form of equity within algorithmic systems: they must maintain sufficient standing for algorithms to surface them when users ask product questions, or risk algorithmic invisibility. This suggests the need for what might be termed *algorithm-based brand equity* - the standing of a brand within recommendation architectures and large language models that mediate consumer access to products.

3.3 Commitment-Trust Theory

Morgan and Hunt's [36] commitment-trust theory, published in the *Journal of Marketing* with over 22,000 citations, established trust and commitment as the central mediating variables in relationship marketing. Trust was defined as confidence in a partner's reliability and integrity; commitment reflected a desire to maintain a valued relationship. The theory demonstrated that these constructs mediate the effects of relationship benefits, shared values, and communication on cooperative outcomes. The framework was designed for relationships in which both parties possess intentionality, emotional capacity, and moral judgment.

AI-mediated interactions complicate this model. Consumers form parasocial relationships with chatbots that produce measurable "effects on CRM-related outcomes (behavioral intention, satisfaction, and trust) through competent brand personality" (Youn &)[21]. Yet trust in AI operates asymmetrically: "expectations in algorithmic advice are relatively even higher than in a human advisor," and these expectations are "more violated than towards a human, even though advice accuracy is identical" [22]. Huang and Rust's [71] "feeling economy" framework identifies three levels of AI intelligence - mechanical, thinking, and feeling - and argues that "as AI is becoming more able to think, human intelligence is deemphasizing thinking in favor of feeling." If AI can simulate reliability and empathy but cannot genuinely experience commitment, the theoretical foundations of relationship marketing require respecification for contexts in which one "partner" is an artificial agent.

3.4 The Customer Satisfaction Paradigm

The customer satisfaction paradigm, anchored by Oliver's [46] four-stage loyalty model (cognitive, affective, conative, action) and Szymanski and Henard's [47] meta-analysis (5,000+ citations), established that satisfaction arises from the disconfirmation of expectations and serves as the primary antecedent of loyalty. Algorithmic mediation disrupts each stage. At the cognitive level, AI-driven personalization shapes the formation of expectations: when recommendation engines curate choices and present selectively favorable information, the expectations against which performance is judged are themselves algorithmically constructed. AI chatbots achieve satisfaction scores of 92% [23], with implementations improving CSAT from 78% to 97% [24] - yet these metrics may reflect efficient resolution rather than the deep evaluative process Oliver theorized. At the conative and action stages, subscription auto-renewal, algorithmic nudges, and switching friction introduce structural determinants of repeat behavior that operate independently of satisfaction. When 50% of subscription churn is caused by payment failures rather than dissatisfaction [25], and 47% of consumers report feeling overwhelmed by subscription commitments [26], the satisfaction-loyalty link operates within a fundamentally different behavioral context than the one Oliver [46] and Szymanski and Henard [47] theorized.

These four theoretical pillars - value co-creation, brand equity, relational trust, and customer satisfaction - collectively define how marketing scholars understand the creation, communication, and delivery of value (Figure 2 illustrates the convergence timeline of the three forces disrupting these theories). Each was developed in an era when marketers communicated with consumers, consumers evaluated brands, and exchange relationships were mediated by human judgment. The following sections examine, in turn, how AI and algorithmic technologies (Section 4), data privacy regulation (Section 5), and platform ecosystems (Section 6) are disrupting these assumptions, before Section 7 proposes an integrative framework that reconceptualizes the foundations for the algorithmic age.

4. AI and Algorithmic Marketing

The integration of artificial intelligence into marketing practice represents what many scholars consider the most consequential transformation since the advent of digital media itself. Davenport et al. [6] characterize AI as a multidimensional force capable of augmenting - rather than replacing - human marketing managers across intelligence levels, task types, and embodiment forms. This section synthesizes the rapidly evolving literature on AI in marketing, tracing its trajectory from taxonomic frameworks through the generative AI revolution, personalization at scale, and the emerging authenticity paradox that complicates adoption.

4.1 The AI Marketing Taxonomy

The foundational framework for understanding AI's role in marketing was established by Huang and Rust [5], who proposed a three-stage model distinguishing *mechanical AI* (automation of repetitive tasks), *thinking AI* (data-driven analytical decisions), and *feeling AI* (emotion recognition and empathetic interaction). This taxonomy maps AI capabilities onto marketing functions across research, segmentation-targeting-positioning, and tactical execution stages, offering a structured lens through which practitioners can assess where AI creates value and where human intelligence remains indispensable. In subsequent work, Huang and Rust [89] extended this framework to articulate a collaborative model in which lower-level AI augments higher-level human intelligence, with human marketers progressively migrating to tasks requiring creativity, empathy, and strategic judgment as AI automates routine cognitive labor. Their later contribution on "the caring machine" (Huang &)[27] pushed the frontier further, proposing how feeling AI might be operationalized for customer care - a domain traditionally resistant to automation.

The empirical reality, however, reveals a significant gap between theoretical potential and organizational execution. McKinsey's *State of AI in 2025* report found that while 88% of organizations regularly use AI in at least one business function, only 6% qualify as "high performers" who have redesigned workflows and scaled AI deployment across the enterprise [2]. Nearly two-thirds of organizations have not begun scaling AI beyond pilot programs, and only 39% attribute any measurable EBIT impact to their AI investments. This pattern - near-universal adoption coupled with marginal value capture - suggests that competitive advantage accrues not from whether a firm deploys AI, but from how deeply it integrates AI into organizational processes and decision-making architectures. The gap between adoption rates and realized value represents a critical challenge for service-dominant logic: if AI is to function as a co-creative operant resource [28](Huang &)[5], organizations must develop the institutional arrangements - what Vargo and Lusch [16] term "shared institutions" - that enable human-AI value co-creation at the systemic level.

4.2 The Generative AI Revolution

The release of ChatGPT in November 2022 catalyzed a phase transition in AI marketing, shifting the dominant model from analytical and predictive applications toward content generation, creative production, and conversational interaction. Peres et al. [7] argue that generative AI will reshape customer interactions, content delivery across text, image, and video modalities, and product research and development, with particular implications for small firms that can now access capabilities previously reserved for enterprises with substantial technology budgets.

The scale of generative AI's penetration into marketing content is unprecedented. As of November 2024, AI-generated content accounted for 50.3% of newly published web articles, briefly surpassing human-authored content for the first time (Graphite, cited in eWeek, 2024). An Ahrefs study of 900,000 web pages found that 74% of new pages contain at least some AI-generated elements [29]. Europol-affiliated researchers project that AI-generated content may constitute 90% of internet content by 2026 (OODA Loop, citing Schick, 2024). This content saturation raises a theoretical question that Keller's [70] CBBE model did not anticipate: when the majority of brand communications are machine-generated, the "differential effect of brand knowledge on consumer response" may depend less on what resides in consumer memory and more on whether AI-produced brand messages are distinguishable from competitors' AI-produced messages at all.

Platform adoption data corroborates these trends at the enterprise level. OpenAI reported over one million business clients by November 2025, with ChatGPT serving 800 million weekly active users [19]. Meta disclosed that more than four million advertisers use its generative AI creative tools, producing over 15 million AI-enhanced advertisements per month (Meta, 2026). The Wharton School and GBK Collective (2025) found that 74 - 75% of enterprises report positive ROI from AI deployment.

Yet the most consequential finding across multiple studies concerns the hybrid model - the combination of AI generation with human editorial oversight. SmythOS (2025) reports that content produced through AI-human collaboration achieves 4.1 times better performance than purely AI-generated content, a finding consistent with the 73% of marketers who employ a hybrid approach. NP Digital's analysis of 744 articles found that human-written content attracted 5.44 times more organic traffic than pure AI output [30], while AI content without human oversight scored approximately 40% lower on Google's E-E-A-T (Experience, Expertise, Authoritativeness, Trustworthiness) quality signals [31]. These findings substantiate Davenport et al.'s (2020) theoretical proposition that AI is most effective as an augmentation technology rather than a replacement, and they align with Reisenbichler et al.'s (2022) experimental evidence from SEO content marketing demonstrating the continued indispensability of the human editorial function. In the language of Huang and Rust's [5] taxonomy, the hybrid model represents a stable equilibrium between thinking AI and human feeling intelligence - one in which algorithmic efficiency and human authenticity jointly produce value that neither can generate alone.

4.3 AI Personalization and Recommendations

Algorithmic personalization has become the primary mechanism through which AI creates measurable marketing value. Rafieian and Yoganarasimhan [77] provide a comprehensive synthesis of developments at the intersection of AI-driven personalization, targeting, and recommendation systems, documenting how machine learning architectures have progressively supplanted rule-based approaches. McKinsey's research quantifies the core finding: companies that have mastered hyper-personalization grow approximately 40% faster than their competitors [2], with AI-driven personalization yielding revenue uplifts of 5 - 15% and marketing ROI improvements of 10 - 30% [2].

The most compelling evidence of personalization's economic significance comes from platform-level data. Amazon's recommendation engine accounts for 35% of the company's total sales revenue [1], while Netflix reports that 75 - 80% of viewing activity originates from algorithmic recommendations rather than active user search [32][33]. These figures extend the theoretical work of Chung et al. [90] on adaptive personalization using social network data, and they carry a significant implication for the four foundational theories examined in Section 3: when recommendation algorithms mediate the majority of consumer-product interactions on the world's largest commercial platforms, the classical assumption that consumers autonomously seek, evaluate, and select brands - the assumption underpinning CBBE, satisfaction theory, and commitment-trust alike - requires substantial qualification.

AI-driven customer service represents another domain of significant value creation. AI chatbot interactions average $0.18 per interaction compared to $4.32 for human agents - a 24-fold cost advantage [24]. Beyond cost reduction, AI-powered customer service systems demonstrate substantial quality improvements: first response times decrease by 74%, and customer satisfaction scores improve from 78% to 97% following AI integration [24][23]. These metrics present a challenge for Oliver's [46] satisfaction paradigm: if algorithmically mediated service interactions consistently produce higher satisfaction scores than human interactions, the theoretical construct may need to distinguish between efficient resolution (what algorithms optimize) and the deeper evaluative judgment (what Oliver theorized) that gives satisfaction its predictive power for long-term loyalty.

4.4 The Authenticity Paradox

The rapid proliferation of AI-generated marketing content has surfaced a fundamental tension that Puntoni et al. [91] anticipated in their experiential framework of consumer-AI interaction: the paradox between efficiency gains and consumer demand for authentic human connection. Empirical evidence increasingly suggests that consumers exhibit a systematic negative reaction to content they perceive as AI-generated. Bynder's [86] consumer study found that 52% of consumers disengage from content when they suspect AI involvement, and 62% report being less likely to engage with AI-generated social media content. Yet the same study reveals a paradox within the paradox: when consumers are unaware of AI authorship, 56% actually prefer AI-generated articles, suggesting that the quality of AI content may be adequate but that the mere label of artificial origin triggers a heuristic rejection response.

This pattern extends to customer service interactions, where 79% of American consumers express a preference for human agents [34], and 93% hold a "strong preference" for human customer service [35] - despite evidence that AI chatbot satisfaction rates reach 80 - 92% [23]. Luo et al. [92] documented this phenomenon experimentally: undisclosed chatbots perform as effectively as proficient human workers, but disclosure of chatbot identity reduces purchase rates by 79.7%, as customers perceive disclosed AI agents as less knowledgeable and empathetic. The authenticity paradox thus reveals a boundary condition for commitment-trust theory (Morgan &)[36]: trust formation in AI-mediated relationships depends not on the objective reliability of the partner - a criterion the original theory emphasized - but on the consumer's perception of whether the partner is human or artificial.

The virtual influencer phenomenon crystallizes this authenticity tension. Virtual influencers achieve engagement rates approximately three times higher than human influencers, yet 46% of consumers report discomfort with brands using AI influencers, and only 23% express comfort with the practice (Amra & Elma, 2025). Research published in February 2025 warns that AI influencer marketing may pose a direct risk to brand trust (Phys.org, 2025).

Accenture's [93] Technology Vision survey introduces an additional dimension: 80% of executives worry that large language models will produce a homogenization of brand voice, as firms using identical AI platforms risk converging on indistinguishable marketing communications. This concern suggests that the authenticity paradox operates not only at the individual consumer level but at the brand-strategic level, where differentiation - the core objective of marketing - is threatened by the very tools designed to enhance marketing efficiency. For Keller's [70] CBBE model, homogenization of AI-generated brand content represents a structural threat to the "differential effect" that defines brand equity: if algorithms produce converging brand messages, the distinctiveness upon which equity depends is eroded at its source.

The resolution of this paradox appears to lie in transparency and hybrid approaches. SmythOS (2025) finds that AI disclosure increases ad trustworthiness by 73% and company trust by 96%, suggesting that consumer resistance is directed not at AI per se but at perceived deception about AI use. Hermann and Puntoni [94] propose the ASSURANCE framework - encompassing principles of Autonomy, Security, Sustainability, Representativeness, Accountability, Nonbiasedness, Crediting, and Empowerment - as a governance architecture for ethical generative AI deployment in marketing. Their framework offers a pathway through the paradox by positioning transparency and human oversight not as constraints on AI efficiency but as necessary conditions for sustainable AI-driven marketing value creation.

5. Data Privacy and the New Marketing Contract

The relationship between data collection and marketing effectiveness has undergone a fundamental restructuring since 2018, driven by an interlocking set of regulatory interventions, platform policy changes, and shifting consumer expectations. What was once a largely unregulated regime of behavioral tracking and third-party data exchange has evolved into a complex regulatory environment in which privacy compliance functions as both a constraint on marketing practice and, for strategically adaptive firms, a source of competitive advantage. This section examines the regulatory environment, the seismic impact of Apple's App Tracking Transparency framework, the persistent privacy paradox in consumer behavior, and the emerging post-cookie marketing infrastructure.

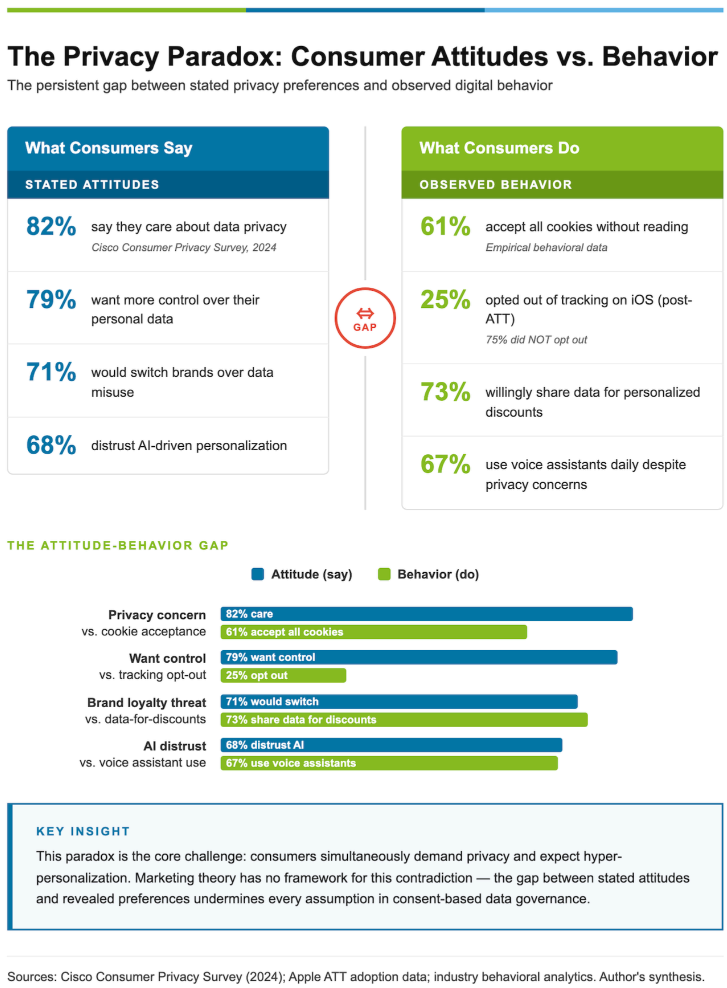

Figure 3. The Privacy Paradox: Consumer Attitudes vs. Behavior. Despite 82% of consumers reporting concern about data privacy, 61% accept all cookies without reading, illustrating the attitude - behavior gap. Sources: Cisco Consumer Privacy Survey (2024); Apple ATT adoption data; IAB (2025); industry behavioral analytics.

5.1 The Regulatory Tsunami

The General Data Protection Regulation (GDPR), which took effect in May 2018, established the regulatory template for data privacy enforcement globally. Through August 2025, European data protection authorities have issued over 2,800 enforcement actions totaling more than EUR 5.9 billion in cumulative fines (CMS Law, 2025; DLA Piper, 2025). The concentration of enforcement is revealing (Figure 4): eight of the ten largest penalties have been imposed on American technology companies, with Ireland - the European headquarters for most Silicon Valley firms - issuing EUR 3.5 billion in fines, four times the total of any other jurisdiction [37][38]. This enforcement pattern illustrates a structural asymmetry in which privacy regulation disproportionately targets the same platform corporations whose data infrastructure underpins algorithmic marketing (Section 6).

Academic research has documented the economic consequences of GDPR with increasing precision. Goldberg et al. [72] analyzed data from 1,084 firms using Adobe Analytics and found that GDPR reduced EU website page views and revenue by approximately 12%, with e-commerce revenue declining by 13.3%. Johnson et al. [73] demonstrated that GDPR caused a 15% reduction in web technology vendor usage and a 17% increase in market concentration, with larger vendors - particularly Google - gaining disproportionate market share. Peukert et al. [95] corroborated these concentration effects across 110,000 websites over 18 months, finding that websites substantially reduced third-party interactions post-GDPR while Google's tracking market share increased even as competitors declined. These findings collectively establish a theoretical paradox central to this review: privacy regulation, while protective of consumer interests, inadvertently strengthens incumbent platforms by raising compliance costs that function as barriers to entry for smaller competitors (Goldfarb &)[39]. The result is a concentration effect that reinforces the very platform power that Sections 6.2 and 6.3 document.

The compliance cost burden is substantial - Fortune 500 companies spent an average of $16 million on GDPR compliance, while mid-sized firms invested approximately $3 million (IAPP)[40] - yet European advertising expenditures have grown each year since GDPR's enactment, with double-digit growth in four of six years (Digiday, 2023), suggesting that the regulation's effects have been redistributive rather than uniformly contractionary. This redistribution is itself theoretically significant: privacy regulation has not reduced the volume of

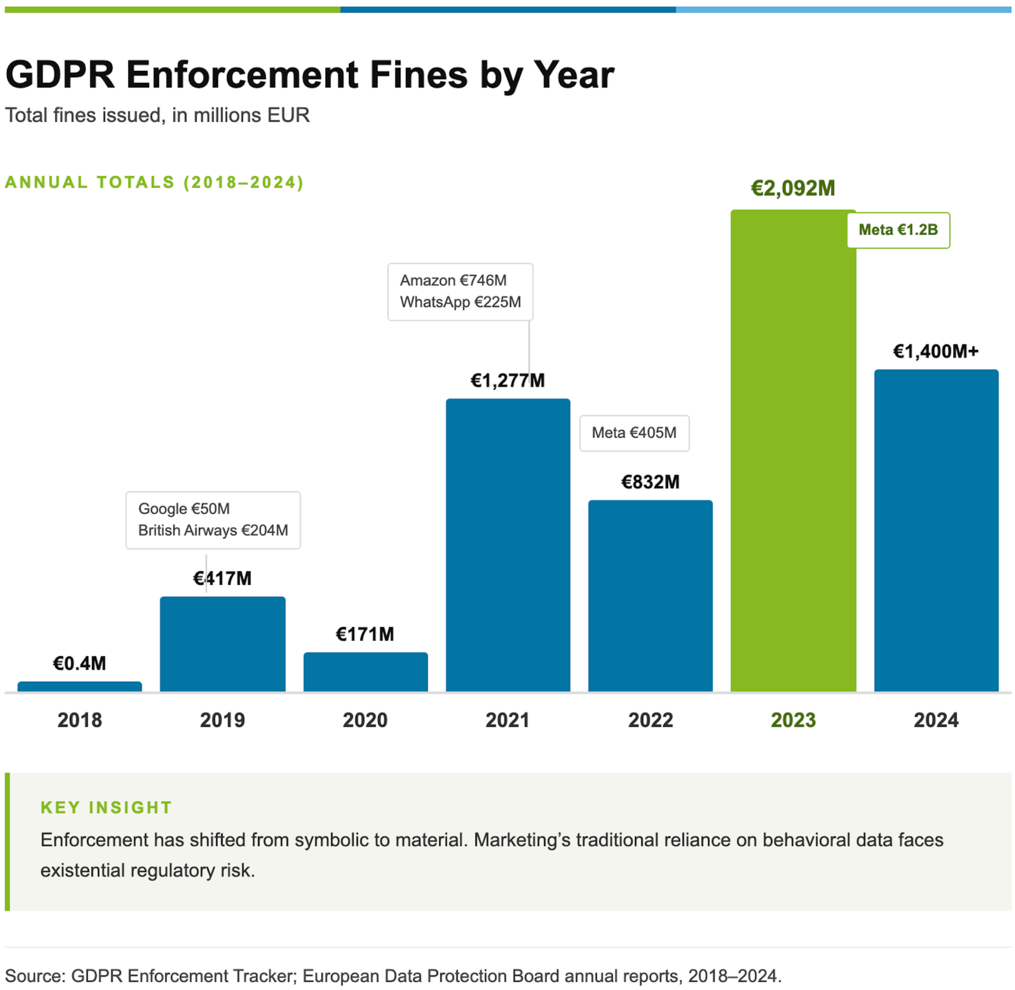

Figure 4. GDPR Enforcement Fines by Year, 2018 - 2024. Total fines escalated from EUR 0.4M in 2018 to EUR 2,092M in 2023, with Meta receiving the largest single penalty (EUR 1.2B). Source: CMS Law GDPR Enforcement Tracker; European Data Protection Board annual reports.

5.3 The Privacy Paradox

Consumer attitudes toward data privacy exhibit a well-documented inconsistency that Acquisti et al. [96] characterize as the "fundamental consumer desire for privacy alongside the prohibitive difficulty of achieving it through individual action." Survey data consistently reveals high levels of expressed privacy concern: 86% of consumers state that they care about data privacy, 82% are "extremely concerned" about data collection practices, and 79% express worry about how their data is used [41][42][43]. In the European context, 50 - 65% of users reject cookies when presented with a compliant banner offering a clearly visible "Reject All" option [44][45].

Yet consumer behavior in market contexts tells a different story. The Interactive Advertising Bureau's (2025) consumer survey found that 82% of consumers consider personalized advertisements helpful for product discovery, 80% value a free internet supported by advertising, and only 2% express specific concern about the use of their data for personalized advertising purposes. This 2% figure stands in stark contrast to the 86% who claim to "care about privacy," revealing an enormous gap between stated attitudes and specific behavioral objections. Bleier et al. [10] offer a theoretical explanation through the lens of *contextual integrity*: privacy concerns are triggered not by data collection per se but when data practices violate the norms of the informational context in which they occur. Consumers accept - and indeed prefer - personalization within contexts where they perceive value exchange as fair, such as product recommendations during active shopping, while rejecting identical practices in contexts perceived as surveillance, such as cross-site behavioral tracking. The privacy paradox, read through Bleier et al.'s framework, is thus less a failure of consumer rationality than an expression of norm-sensitive evaluation - a finding that challenges satisfaction models [46](Szymanski &)[47] premised on stable, context-independent preference structures.

Generational differences add further complexity to the privacy calculus. Gen Z consumers display approximately twice the willingness to share data for AI services compared to Baby Boomers, with 41% of Gen Z prioritizing convenience over privacy versus 29% of Boomers [48][49]. The generational divergence extends to trust structures: younger consumers place greater trust in social media platforms, while Boomers trust government institutions (71% versus Gen Z's low trust) and remain deeply skeptical of social media (4% trust) [50]. These patterns suggest that the privacy paradox may be at least partially a cohort effect, with digital-native generations exhibiting a qualitatively different cost-benefit calculus around data exchange - one that existing theories of trust and satisfaction, built on assumptions of generational stability, have not yet incorporated.

Aguirre et al. [78] established a critical boundary condition for the privacy paradox through a landmark field study on Facebook combined with three controlled experiments: personalization based on *covertly* collected data sharply reduces click-through rates when consumers become aware of the collection mechanism, while identical personalization based on *transparently* disclosed data collection enhances engagement. Martin and Murphy [97] elaborate this dynamic through their data privacy-marketing nexus model, demonstrating that perceived vulnerability from data collection mediates consumer trust and willingness to engage. Figure 3 visualizes this attitude - behavior gap across multiple domains. The implication is that the privacy paradox is less a paradox than a rational conditional response: consumers accept data exchange when they perceive transparency, control, and fair value, and reject it when they perceive opacity, coercion, or exploitation. This conditionality aligns with Morgan and Hunt's [36] original insight that trust depends on integrity - but extends it by showing that in algorithmic contexts, integrity must be demonstrated not only by the relational partner but by the entire data infrastructure through which the relationship is mediated.

5.4 The Post-Cookie Landscape

The anticipated deprecation of third-party cookies in Google Chrome - which would have constituted the most consequential structural change in digital advertising targeting since the introduction of cookies themselves - was abandoned in one of the industry's most significant strategic reversals. After four years of announcements, delays, and partial implementations (2020 - 2024), Google officially confirmed in April 2025 that it would not remove third-party cookies from Chrome and would not introduce a separate consent prompt for cookie tracking [51][44]. By October 2025, Google retired a substantial portion of its Privacy Sandbox APIs, effectively terminating the browser-level privacy solution narrative that had dominated digital advertising strategy discussions since 2020 (Axios, 2025).

Despite Chrome's reversal, the industry's strategic trajectory toward first-party data architectures has proven durable and self-reinforcing. McKinsey's research demonstrates that businesses effectively using first-party data achieve a 15% revenue increase while simultaneously reducing marketing expenditure by 20% [52]. Forrester's [87] analysis found that first-party data strategies improve customer acquisition costs (83% of implementing firms), customer satisfaction (78%), and overall ROI (72%). This convergence on first-party data represents a structural realignment whose theoretical significance extends beyond targeting methodology: it shifts the locus of marketing intelligence from intermediary networks (ad-tech firms brokering behavioral data) to firms with direct customer relationships, thereby reconstituting the informational foundations upon which personalization, brand building, and relationship management operate.

The most structurally significant development in the post-cookie environment is the explosive growth of retail media networks, which function as privacy-compliant advertising ecosystems built on retailers' first-party purchase data. These networks monetize the closed-loop connection between advertising exposure and verified purchase transactions - data that does not require cross-site tracking, cookie-based identification, or user consent beyond the existing customer relationship. The Spiegel Research Center at Northwestern's Medill School describes retail media as the most significant advertising ecosystem development since programmatic buying [53]. We examine these networks in detail in Section 6.2.

The transition from a third-party data regime to a first-party data regime thus represents not merely a technical adjustment in targeting methodology but a fundamental redistribution of power within the digital advertising ecosystem - from ad-tech intermediaries who brokered behavioral data toward platforms and retailers who own direct customer relationships and transactional data. This power redistribution challenges service-dominant logic's emphasis on value co-creation through "shared institutions" (Vargo &)[16]: the institutions governing data exchange are not shared equally among ecosystem participants, but are structured to favor those actors who control first-party data infrastructure.

6. Platform Ecosystems and Value Networks

Digital platform ecosystems have become the dominant organizational form through which marketing value is created, distributed, and captured in the algorithmic age. Rietveld and Schilling [13], in their systematic review of 333 articles spanning management, information systems, economics, and marketing, identify platform competition as one of the most active yet theoretically fragmented domains in business research. The theoretical fragmentation is itself revealing: it suggests that existing frameworks - developed for firm-to-consumer and firm-to-firm relationships - cannot fully account for the multi-sided, algorithmically governed market structures that platforms represent. This section examines four interconnected dimensions of platform-mediated marketing: the creator economy, retail media networks, algorithmic gatekeeping, and the subscription economy.

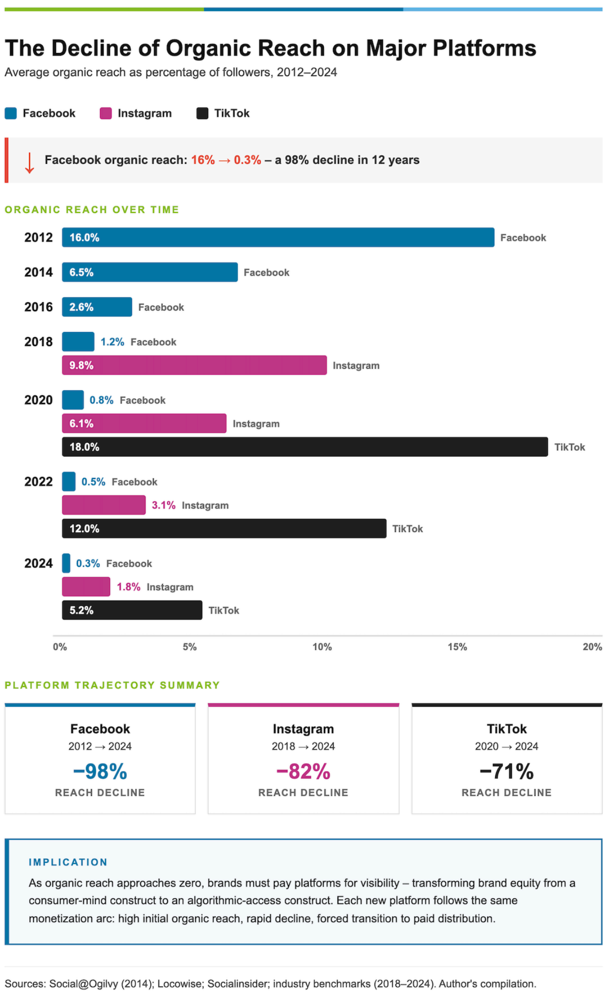

Figure 5. The Decline of Organic Reach on Major Platforms, 2012 - 2024. Facebook organic reach fell from 16% to 0.3% (a 98% decline), forcing brands to pay for algorithmic visibility. Sources: Social &Ogilvy (2014); Locowise; Socialinsider; Marketing Scoop (2024); industry benchmarks.

6.1 The Creator Economy

The creator economy has emerged as a structurally significant intermediary between brands and consumers, reshaping the traditional advertising model by inserting individual content producers as primary conduits of marketing communication. Goldman Sachs (2025) projects that the total addressable market of the creator economy will approximately double from $250 billion in 2024 to $480 billion by 2027, with growth to 107 million professionally active creators by 2030 (Goldman Sachs, 2025)[54]. This rapid expansion reflects the creator economy's role as a new institutional arrangement for value co-creation - one in which S-D logic's "actors applying operant resources for mutual benefit" (Vargo &)[55] now includes millions of independent content producers operating within platform-governed ecosystems.

Beichert et al. [98], in an empirical study published in the *Journal of Marketing*, found that nano-influencers (those with small followerships) outperform high-followership influencers by an order of magnitude on ROI, with engagement mediating the inverse relationship between audience size and per-dollar returns. This finding is consistent with broader industry data showing that micro-influencers generate two to three times higher engagement rates than macro-influencers, which explains why 44% of brands now prefer nano-influencers for partnership campaigns [56][4]. The nano-influencer advantage carries theoretical implications for commitment-trust theory: the higher engagement and ROI associated with smaller creators suggest that trust in marketing communication operates through perceived intimacy and authenticity rather than scale - a relational dynamic that Morgan and Hunt [36] would recognize as integrity-based trust, but one that operates through platform-mediated parasocial relationships rather than the direct exchange partnerships they theorized.

However, the creator economy exhibits extreme income inequality that challenges the democratization narrative frequently associated with platform-mediated work. CreatorIQ's (2025) compensation analysis reveals that the top 1% of creators received 21% of total advertising payment volume in 2025 (up from 15% in 2023), while the top 10% captured 62% of all payments (up from 53% in 2023). These concentration trends are accelerating, not stabilizing. A significant gender pay gap persists: male creators earn nearly double their female counterparts ($69,922 versus $37,065 annually), despite women constituting approximately 70% of the influencer market [57]. High-earning creators differentiate themselves through revenue diversification, maintaining seven or more income streams compared to just two for lower-earning creators [57]. Libai et al. [75] provide a value-chain framework for influencer marketing that maps these dynamics across firms, influencers, followers, and platforms, identifying value creation and capture mechanisms at each node. The concentration of value capture among a thin upper stratum of creators mirrors the platform concentration documented in Section 6.3 - suggesting that algorithmic ecosystems produce winner-take-most dynamics not only among platforms but among the actors who operate within them.

6.2 Retail Media Networks

Retail media networks represent the most consequential structural development in digital advertising since the rise of social media advertising in the early 2010s. Built on retailers' first-party purchase data, these networks offer advertisers the ability to target consumers at or near the point of purchase, with closed-loop measurement linking advertising exposure directly to verified transactions.

Market concentration in retail media is extreme and theoretically significant. Amazon Ads commanded 79.7% of the U.S. retail media market in 2025 (eMarketer, 2025), with Walmart Connect, the second-largest player, generating $6.4 billion in revenue [26]. Together, Amazon and Walmart absorb more than 84% of retail media advertising budgets in the United States (eMarketer, 2025). This duopolistic structure operationalizes the platform economics analyzed by Zhu and Liu [79], who documented Amazon's strategic pattern of entering successful product categories - a dynamic that retail media extends from product competition to advertising infrastructure competition. The result is a market architecture in which the retailer simultaneously serves as the distribution channel, the advertising platform, and the provider of measurement data - a concentration of functions that challenges the separability assumptions implicit in traditional marketing channel theory.

The competitive advantage of retail media derives from first-party transactional data that becomes more valuable as privacy regulations constrain alternative targeting mechanisms. Consumer packaged goods (CPG) brands deploying targeted in-store digital media through retail networks observe sales lifts of 15 - 35% for promoted products (NIQ, 2024)[58]. As the Spiegel Research Center (2024) notes, these networks are evolving toward "Retail Media 3.0," extending beyond on-site product search into social media and connected television, creating an integrated closed-loop system powered by first-party purchase data. This evolution positions retail media at the AI x Privacy intersection zone identified in Section 7.3: the networks resolve the personalization paradox by operating within a data environment where consent is embedded in the existing customer-retailer relationship, bypassing the third-party tracking infrastructure that ATT and GDPR have constrained.

6.3 Algorithmic Gatekeeping

Platform algorithms function as gatekeepers that mediate the visibility of marketing communications, exerting a form of structural power that Appel et al. [99] identified as a defining feature of social media's future trajectory. The empirical evidence demonstrates a sustained and accelerating erosion of organic brand reach across major platforms. Facebook's average organic reach for brand pages has declined from approximately 16% in 2012 to 1.2 - 1.95% in 2024 - 2025, with pages exceeding 100,000 followers achieving only 0.7% average reach [59][60]. TikTok business accounts experienced a 30 - 45% decline in organic reach during 2025 compared to 2024, while personal creator accounts remained stable [61] - a differentiation consistent with platform incentive structures that encourage paid promotion for commercial content. Figure 5 charts this systematic erosion of organic reach across Facebook, Instagram, and TikTok. This systematic suppression of organic brand reach represents a direct challenge to Keller's [70] CBBE framework: if brand salience - the foundation of the equity pyramid - is algorithmically gated, then the "power of a brand" resides not only in consumer minds but in the algorithmic architectures that determine whether consumers encounter the brand at all.

These algorithmic dynamics create structural dependency. Alphabet, Amazon, and Meta collectively capture approximately 55% of global advertising expenditure (excluding China), a share that rises to 72% of U.S. digital ad spending in 2025 [4](WARC, 2025). Within marketplace platforms, algorithmic gatekeeping operates even more directly: Amazon's Buy Box algorithm controls over 80% of sales on the platform [62], functioning as a de facto pricing and visibility mechanism whose criteria determine which sellers access consumer demand.

The governance implications of algorithmic gatekeeping have attracted increasing academic attention. Lee and Musolff [76] demonstrate that platform search algorithms shape market outcomes by creating asymmetric advantages for featured sellers. Zhang et al. [75] show that transitions from neutral to non-neutral recommendation algorithms increase price dispersion among merchants while simultaneously decreasing price competition intensity - a finding that suggests algorithmic curation may serve platform interests at the expense of both competitive markets and consumer welfare. Calvano et al. [100], in a landmark *American Economic Review* study, demonstrated that independent pricing algorithms spontaneously learn collusive strategies in simulated markets, reaching prices above Nash equilibrium without explicit coordination - raising fundamental questions about the applicability of traditional antitrust frameworks to algorithm-mediated markets. Assad et al. [101] provided real-world corroboration from the German retail gasoline market, documenting that algorithmic pricing increases price levels and margins in practice, not merely in simulation. Taken together, these findings suggest that algorithmic gatekeeping produces market outcomes that neither classical competition theory nor existing marketing frameworks adequately predict: algorithmic systems can coordinate pricing without collusion, suppress brand visibility without overt censorship, and reshape competitive dynamics through opaque optimization functions.

Platform algorithms are also becoming increasingly sophisticated in their content evaluation capabilities. YouTube's 2025 algorithm employs large language models (Gemini) for deep video analysis, evaluating not only engagement metrics but content substance, context, and emotional tone [63][64]. Instagram's 2025 algorithm prioritizes "sends per reach" (direct message shares) as the most critical distribution driver, favoring original content from smaller creators over aggregated reposts [65][32]. These developments extend Chen et al.'s (2022) analysis of platform governance as meta-organizational design, in which algorithmic mediation functions simultaneously as quality control, competitive regulation, and revenue optimization.

6.4 The Subscription Economy

The subscription economy represents an alternative value capture model that complements advertising-based platform economics. Subscription models offer firms predictable recurring revenue, direct customer relationships, and first-party behavioral data. However, the maturation of subscription markets has surfaced systemic challenges that threaten the model's sustainability and that illuminate the theoretical limits of the satisfaction-loyalty relationship.

Subscription fatigue has become a measurable constraint on growth. Approximately 47% of U.S. consumers report feeling overwhelmed by the number of subscription services available, and over 50% indicate willingness to cancel if prices increase without commensurate value addition [26][66]. The fatigue phenomenon is most acute in streaming video, where annual churn rates reached an all-time high of 44% in Q4 2024 [67]. Monthly churn across streaming services has escalated from 2% in 2019 to 5.5% by early 2025, reflecting a structural shift from growth-phase subscriber acquisition to maturity-phase retention competition [67].

The economics of churn reveal an underappreciated dimension that is theoretically consequential for the satisfaction paradigm: involuntary churn - cancellations triggered by failed card payments, expired credit cards, and declined transactions - accounts for approximately 50% of total subscription churn [25]. This finding disrupts the satisfaction-loyalty link at its core. Oliver's [46] model and Szymanski and Henard's [47] meta-analysis both position satisfaction as the primary antecedent of loyalty and its absence as the primary driver of defection. Yet when half of all churn is involuntary - a product of payment infrastructure failures rather than consumer evaluation - the model's explanatory scope is narrower than previously assumed. Satisfaction may be necessary for retention, but it is evidently not sufficient to prevent it when structural factors intervene.

Industry responses include "pause subscription" features, which reduce cancellations by 18% [25]; bundling strategies, which reduce churn by 34% [68]; and family plans, which increase retention by 52% [26]. These tactics - none of which operate through the satisfaction mechanism - further illustrate that subscription retention is determined by structural and architectural factors as much as by the evaluative psychological process that Oliver theorized.

These dynamics reflect the broader theoretical tension identified by Verhoef et al. [102] between the three stages of digital transformation - digitization, digitalization, and genuine digital transformation. Subscription models that merely digitize existing value propositions (putting content behind a paywall) face commoditization pressures, while those that achieve genuine transformation (using subscriber data to create personalized experiences, as Netflix and Spotify demonstrate) build structural competitive advantages that resist the fatigue cycle. The subscription economy thus serves as a natural experiment in the conditions under which

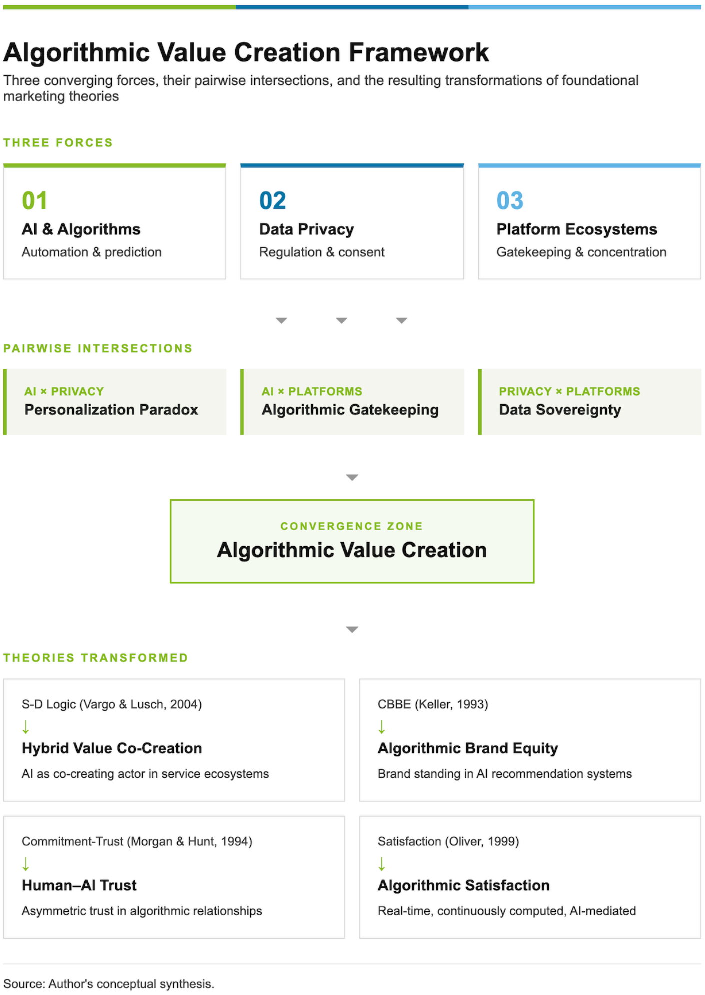

Figure 6. Algorithmic Value Creation Framework (AVCF). Three converging forces (AI & Algorithms, Data Privacy, and Platform Ecosystems) generate three intersection zones that jointly disrupt four foundational marketing theories. Source: Author's framework.

7.1 Toward an Integrative Model

Existing marketing theories were developed in an era when firms communicated with consumers directly, data collection was episodic and survey-based, and market competition was structured around product categories rather than platform architectures. Service-dominant logic (Vargo &)[69] provides an elegant account of value co-creation but does not yet specify the role of autonomous algorithmic agents. Customer-based brand equity [70] assumes human cognition as the locus of brand knowledge, yet an increasing share of purchase decisions is mediated - or entirely executed - by recommendation algorithms. Commitment-trust theory (Morgan &)[36] was designed for relationships between human actors, not for the parasocial bonds consumers form with AI chatbots (Huang &)[71].

Each of these theories captures a piece of the contemporary marketing puzzle, but none addresses the systemic interdependencies that define marketing practice in the mid-2020s. When a platform's recommendation algorithm (Axis 3) selects which brand a consumer sees, that decision depends on data the platform has collected (constrained by Axis 2) and processed through machine learning models (powered by Axis 1). A theory that examines only one of these axes in isolation will produce incomplete, and potentially misleading, explanations of how value is created, distributed, and captured. What is needed is a meta-framework - a conceptual architecture that integrates the three forces and reveals their joint effects on marketing theory.

The AVCF responds to MacInnis's (2011) call for conceptual contributions that perform the dual function of *relating* (connecting disparate phenomena through common theoretical threads) and *debating* (challenging whether existing theories can accommodate structural transformation). It is also consistent with Palmatier et al.'s (2018) criteria for impactful review articles: the framework organizes a fragmented literature, provides a visual integrating structure, and identifies specific research gaps.

7.2 The Three Axes

The AVCF is organized around three orthogonal axes, each representing a macro-force reshaping marketing:

Axis 1: AI and Algorithms. This axis captures the progression from mechanical AI (automating repetitive tasks), through thinking AI (processing data for decisions), to feeling AI (analyzing emotions and interpersonal interactions), as specified by Huang and Rust [5]. The recent emergence of generative AI - large language models, image synthesis, and autonomous agents - adds a fourth stage that transcends the original taxonomy. GenAI does not merely automate, analyze, or empathize; it *creates* marketing content, generates product descriptions, writes advertising copy, and, through agentic commerce, makes purchasing decisions on behalf of consumers [7]. McKinsey (2025) projects that AI agents could mediate $3 - 5 trillion of global consumer commerce by 2030, effectively inserting an algorithmic intermediary into the value chain at a scale without historical precedent.

Axis 2: Data Privacy and Regulation. The regulatory environment has shifted from an era of permissive data collection to one of structured consent. The General Data Protection Regulation (GDPR, 2018) reduced EU website page views and revenue by approximately 12% [72] and increased market concentration by 17% [73]. The California Consumer Privacy Act (CCPA, 2020), the EU AI Act (2024), and Apple's App Tracking Transparency policy (2021) have further constrained the data ecosystem. Cookie deprecation, the decline of third-party tracking, and the rise of first-party data strategies [74] are creating a new consent architecture in which data availability is no longer a given but a negotiated outcome.

Axis 3: Platform Ecosystems. Platforms have evolved from distribution channels to market architectures that govern visibility, pricing, and consumer-brand interaction. Retail media networks - in which retailers sell advertising on their own platforms - reached $60 billion in 2024 and are projected to exceed $72 billion in 2025 [53]. Amazon and Walmart control approximately 80% of this spend. The creator economy, valued at over $250 billion, has produced a new class of marketing intermediaries whose algorithmic reach often exceeds that of the brands they promote [75]. Platform algorithms - governing search ranking, content recommendation, and ad placement - function as gatekeepers that determine which brands reach which consumers, and under what conditions (Lee &) [76](Rietveld &)[13].

7.3 The Intersection Zones

The AVCF's primary theoretical contribution lies in identifying three intersection zones where pairs of axes interact to produce emergent phenomena that no single-axis theory can explain.

Intersection 1: AI x Privacy = The Personalization Paradox. More sophisticated AI requires more granular data, yet privacy regulation increasingly restricts data availability. This creates a structural tension: the very data that would make AI-driven marketing most effective is the data that consumers and regulators most want to protect. Aguirre et al. [78] demonstrated that covert data collection undermines the benefits of personalization, with click-through rates dropping sharply when consumers discover unauthorized data use. Bleier et al. [10] showed that privacy concerns are triggered when data practices violate contextual norms - norms that AI systems are particularly prone to transgressing because they aggregate data across contexts. The personalization paradox is not merely a practical trade-off; it is a theoretical contradiction at the heart of algorithmic marketing. A comprehensive review confirms that personalized advertising is generally more effective than generic advertising, but that the indirect effect via perceived relevance is moderated by perceived intrusiveness (Rafieian &)[77][78]. The question for theory is whether personalization and privacy can be reconciled, or whether they represent a permanent dilemma that constrains the scope of algorithmic value creation.

Intersection 2: AI x Platforms = Algorithmic Gatekeeping. Platform algorithms determine which brands are visible to consumers, and AI systems increasingly optimize these algorithms for platform profit rather than consumer welfare or brand equity. Research documents that "sponsored recommendations are significantly more biased toward Amazon private label products compared to organic recommendations" and that Amazon's algorithm includes "contribution profit" as a variable, systematically favoring its own higher-margin products (Zhu &)[79]. Two-thirds of product clicks come from the first page of search results, with clicks disproportionately concentrated in the top-ranked positions (Zhu &)[79]. When AI agents make purchases autonomously, they rely on algorithmic signals rather than brand loyalty, rendering traditional brand-building strategies insufficient. The concept of *algorithmic gatekeeping* captures a new power dynamic: platforms use AI to control consumer access to brands, creating an asymmetry that existing marketing theories - which assume relatively free consumer access to brand information - do not address.

Intersection 3: Privacy x Platforms = Data Sovereignty. The third intersection concerns the question of who owns consumer data: the platform that collects it, the brand that uses it, or the consumer who generates it. GDPR and similar regulations assert consumer data sovereignty, but platform architectures often make it impossible for consumers (or brands) to exercise meaningful control. Johnson et al. [73] found that GDPR increased market concentration because large platforms with existing data infrastructure (especially Google) gained competitive advantage from compliance costs that disproportionately burdened smaller actors. Peukert et al. [95] documented that websites substantially reduced third-party interactions post-GDPR, effectively ceding more data control to dominant platforms. The result is a paradox of data sovereignty: regulations designed to empower consumers have, in practice, concentrated data power in fewer hands.

7.4 Transformed Theoretical Constructs

The AVCF enables a systematic re-specification of foundational marketing theories for the algorithmic age:

Service-Dominant Logic becomes Algorithmic Value Co-creation. In S-D Logic, value is co-created through interaction among human actors who apply operant resources (knowledge, skills) for mutual benefit (Vargo &)[69]. In the AVCF, AI is reconceptualized as a hybrid resource that "embodies both operant and operand characteristics" [80]. The concept of Hybrid Intelligent Service Ecosystems (HISE) extends S-D Logic by "emphasizing how actors deliberately configure human and artificial agencies to co-create value via hybrid intelligent service exchange." Value co-creation, in this reframing, is no longer exclusively anthropocentric; it occurs across human-AI-platform networks in which algorithmic agents actively shape - and are shaped by - the co-creation process.

Brand Equity becomes Algorithmic Brand Equity. Keller's [70] CBBE model posits that brand power resides in consumer minds. In the algorithmic age, brand equity must also reside in algorithmic systems. Generative AI and large language models have transformed brand salience: brands must become strong enough for algorithms to surface them when users ask product questions; otherwise they risk algorithmic invisibility. Algorithmic brand equity thus describes a brand's visibility, favorability, and retrievability within AI recommendation systems, search algorithms, and autonomous purchasing agents - a construct that parallels but is distinct from consumer-based brand equity.

Commitment-Trust Theory becomes Human-AI Trust. Morgan and Hunt's [36] theory defines trust as "a belief in the reliability and integrity of a partner." Extending this to human-AI relationships reveals an asymmetric trust dynamic: "expectations in algorithmic advice are relatively even higher than in a human advisor, as erring as a human trait is accepted" [22]. AI must outperform humans to earn equivalent trust, yet trust recovery after AI failure is more difficult than after human failure. The "feeling economy" thesis (Huang &)[71] suggests that as AI handles mechanical and thinking tasks, the uniquely human contribution shifts to emotional intelligence - the last frontier before full algorithmic substitution.

Customer Satisfaction becomes Real-time Algorithmic Satisfaction. Traditional satisfaction measurement relies on post-hoc surveys administered at discrete intervals (Szymanski &)[47]. In algorithmically mediated environments, satisfaction signals are continuous: click-through rates, dwell time, return behavior, review sentiment, and app ratings provide real-time feedback that algorithms process to adjust marketing actions instantaneously. Satisfaction is no longer a psychological state measured retrospectively; it is a behavioral signal captured, computed, and acted upon algorithmically.

7.5 Algorithmic Brand Equity: Definition, Dimensions, and Measurement

The preceding analysis has established that brand equity must now reside in both consumer minds and algorithmic systems. Section 3.2 identified the challenge that Keller's [70] customer-based brand equity (CBBE) model faces in algorithmic environments; Section 7.4 proposed that "brand equity becomes algorithmic brand equity" as one of the AVCF's transformed constructs; and the research agenda (RQ4) called for new measurement scales. Yet the construct itself has not been formally defined, its dimensions have not been specified, and its relationship to CBBE has not been systematically articulated. This subsection addresses these gaps by proposing a formal operationalization of Algorithmic Brand Equity (ABE) as a theoretical construct and measurement domain (Figure 7).

Formal Definition. Algorithmic Brand Equity (ABE) is defined as *the differential standing of a brand within algorithmic recommendation, search, and decision architectures that determines its visibility, consideration probability, and selection likelihood independent of direct consumer cognition.* Where Keller (1993, p. 2) defined CBBE as "the differential effect of brand knowledge on consumer response to the marketing of the brand," ABE captures the differential effect of a brand's representation within algorithmic systems on that brand's market outcomes. The distinction is foundational: CBBE resides in human minds - in the associative networks, affective responses, and behavioral dispositions that consumers develop through experience and communication. ABE resides in computational systems - in the training data, ranking algorithms, recommendation architectures, and large language model parameters that increasingly mediate consumer access to brands. Both forms of equity are necessary for competitive advantage in the algorithmic age; neither alone is sufficient. A brand with strong CBBE but weak ABE will be recognized and preferred by consumers who encounter it, but may never be surfaced by the algorithms that govern discovery. A brand with strong ABE but weak CBBE will appear prominently in algorithmic outputs but fail to convert visibility into the deep psychological bonds that sustain long-term loyalty.

Why ABE Is Needed Now. The urgency of formalizing ABE derives from the accelerating displacement of human cognition by algorithmic mediation in the purchase process. Five empirical developments converge to make ABE a first-order theoretical and practical concern. First, AI agents are projected to mediate $3 - 5 trillion of global consumer commerce by 2030 [2], making autonomous, brand-independent purchasing decisions based on functional attributes rather than brand associations. In such transactions, CBBE is structurally irrelevant - the human consumer never evaluates or selects the brand; the algorithm does. Second, on Amazon - the world's dominant product discovery platform -

two-thirds of product clicks originate from the first page of algorithmic search results, with clicks heavily concentrated in the top-ranked positions (Zhu &)[79]. For the majority of consumer goods, algorithmic rank position is a stronger determinant of purchase probability than brand awareness. Third, generative AI platforms have become the primary product research tool for 25% of consumers [81], creating an entirely new information architecture in which brands must be represented within LLM training data and retrieval-augmented generation systems to be considered at all. Fourth, Google AI Overviews now appear in over 50% of search queries [4], supplanting traditional organic results with algorithmically synthesized answers that may include, exclude, or reframe brand information without the brand's knowledge or consent. Fifth, research documents that sponsored recommendations on major platforms are "significantly more biased toward Amazon private label products compared to organic recommendations" (Zhu &) [79], revealing that algorithmic systems do not neutrally transmit brand equity but actively reshape competitive standing through platform-advantaged ranking.

These developments collectively establish that the algorithmic layer between brand and consumer is no longer a transparent conduit but an active mediator with its own logic, incentives, and biases. A construct that captures a brand's standing within this mediating layer - distinct from its standing within the consumer's mind - is therefore theoretically indispensable.

The Four Dimensions of ABE. Drawing on the AVCF's three-axis structure and the existing literature on algorithmic gatekeeping (Section 6.3), recommendation systems (Section 4.3), and agentic commerce (Section 8.2), this review proposes four constituent dimensions of ABE, ordered from exposure to behavioral outcome.

Dimension 1: Algorithmic Visibility. Algorithmic visibility is defined as the frequency and prominence with which a brand appears in AI-generated recommendations, search results, and conversational AI responses. Visibility is the ABE analog of Keller's [70] brand salience - the foundational layer upon which all subsequent equity dimensions depend. A brand that is algorithmically invisible cannot be algorithmically retrieved, favorably represented, or selected. Visibility is determined by a brand's presence and ranking across multiple algorithmic touchpoints: search engine results pages, platform recommendation feeds, AI Overview summaries, chatbot responses, and agentic commerce catalogs. Observable indicators include share-of-recommendations within a product category, rank position stability across algorithmic updates, and presence or absence in AI-generated "best of" lists and summary responses. Critically, algorithmic visibility is platform-specific and temporally volatile: a brand may achieve high visibility on Amazon's recommendation algorithm while being entirely absent from ChatGPT's product suggestions, and a single algorithmic update can redistribute visibility overnight - a fragility that has no parallel in CBBE, where brand awareness changes gradually through accumulated consumer experience.

Dimension 2: Algorithmic Retrievability. Algorithmic retrievability is defined as the probability that an AI system retrieves and presents a brand when a relevant category query is made. Retrievability is conceptually distinct from visibility: visibility measures prominence given that the brand appears; retrievability measures the prior probability of appearance itself. A brand may have high conditional visibility (ranked first when it appears) but low retrievability (surfaced in only 30% of relevant queries). This dimension is particularly salient for large language models and generative AI systems, where the brand's representation in training data, the architecture of retrieval-augmented generation pipelines, and the stochastic nature of text generation all influence whether a brand is mentioned in response to a consumer query. Observable indicators include category retrieval rate across platforms (the percentage of relevant queries in which the brand is mentioned), mention frequency in LLM-generated responses to category-level prompts, and inclusion rate in algorithmically curated comparison sets. Retrievability captures the structural prerequisite of algorithmic consideration - the brand's capacity to pass through what might be termed the "algorithmic consideration gate."

Dimension 3: Algorithmic Favorability. Algorithmic favorability is defined as the valence and quality of a brand's representation within algorithmic outputs. An algorithm may retrieve a brand but represent it unfavorably - through negative sentiment aggregation, unflattering comparative positioning, or selective emphasis on adverse reviews. Favorability is the ABE analog of Keller's [70] brand judgments and brand feelings: the evaluative dimension that determines whether algorithmic exposure translates into positive or negative brand impressions. Observable indicators include sentiment analysis of AI-generated brand mentions, comparative positioning against competitors in recommendation outputs (e.g., whether a brand appears as a "budget alternative" or a "premium choice"), the ratio of positive to negative review content surfaced by recommendation algorithms, and the framing of brand information in AI Overview summaries and chatbot responses. Favorability is shaped by the aggregation logic of algorithmic systems, which synthesize signals from reviews, ratings, media coverage, social media sentiment, and structured product data. Brands with high visibility and retrievability but low favorability face a particularly insidious problem: the algorithm ensures they are seen, but the representation it constructs undermines consumer conversion.

Dimension 4: Algorithmic Selection Probability. Algorithmic selection probability is defined as the likelihood that an AI agent or AI-assisted decision process selects a brand for purchase or recommendation to a human decision-maker. This is the ultimate behavioral outcome dimension of ABE - the analog of Keller's [70] brand resonance, which represents the deepest level of consumer-brand connection. In CBBE, resonance is measured through behavioral loyalty, attitudinal attachment, sense of community, and active engagement. In ABE, the equivalent is the conversion from algorithmic representation to algorithmic action: the AI agent's decision to place the brand in a consumer's cart, the recommendation algorithm's decision to position the brand as the default option, or the procurement system's decision to select the brand in automated B2B purchasing. Observable indicators include conversion rate from AI recommendation to purchase, agentic purchase share (the percentage of brand sales initiated by autonomous AI agents), selection rate in automated procurement systems, and default-option frequency in AI-curated choice sets. As agentic commerce scales toward the $3 - 5 trillion range projected by McKinsey (2025), algorithmic selection probability may become the single most consequential metric for brand performance - the point at which a brand's standing in computational systems directly determines its commercial viability.

The CBBE - ABE Relationship: Complementary, Not Substitutive. ABE and CBBE are theoretically complementary constructs, not competing alternatives. Their relationship is characterized by mutual influence, partial independence, and the possibility of significant divergence.

CBBE influences ABE through several mechanisms. Brands with strong consumer awareness generate higher search volumes, more reviews, greater social media discussion, and more media coverage - all of which feed the data inputs that algorithmic systems use to determine visibility, retrievability, and favorability. A brand with deep consumer resonance will, ceteris paribus, accumulate stronger algorithmic signals than a brand that consumers ignore. In this sense, CBBE creates a "data exhaust" that algorithms interpret as relevance signals, establishing a positive feedback loop from human cognition to algorithmic standing.

Conversely, ABE influences CBBE. Algorithmic visibility creates brand awareness: a consumer who repeatedly encounters a brand in search results, recommendation feeds, and AI-generated responses develops familiarity and, through mere exposure effects [82], potentially favorable attitudes. Algorithmic favorability shapes brand associations: the comparative framing in which an algorithm presents a brand influences how consumers perceive its positioning. In this direction, algorithmic standing functions as a new form of brand communication - one that the brand may not control and may not even be aware of.

Yet the two constructs can diverge substantially. A legacy brand with decades of consumer goodwill may possess strong CBBE while suffering weak ABE if its digital infrastructure is poorly optimized for algorithmic systems - if its product data is unstructured, its review volume is low relative to digital-native competitors, or its content is underrepresented in LLM training corpora. Conversely, Amazon private-label brands and algorithmically promoted newcomers may achieve high ABE through platform-advantaged ranking and optimized product data while possessing minimal CBBE - consumers may purchase these brands through algorithmic default without developing any meaningful brand associations. This divergence has strategic implications: firms must audit and invest in both forms of equity, recognizing that excellence in one domain does not guarantee standing in the other.

Toward Measurement: An ABE Indicator Framework. The operationalization of ABE requires measurement instruments that capture each dimension across the algorithmic environments in which brands compete. Table 1 proposes an initial indicator framework designed to guide empirical scale development following Churchill's [84] paradigm.

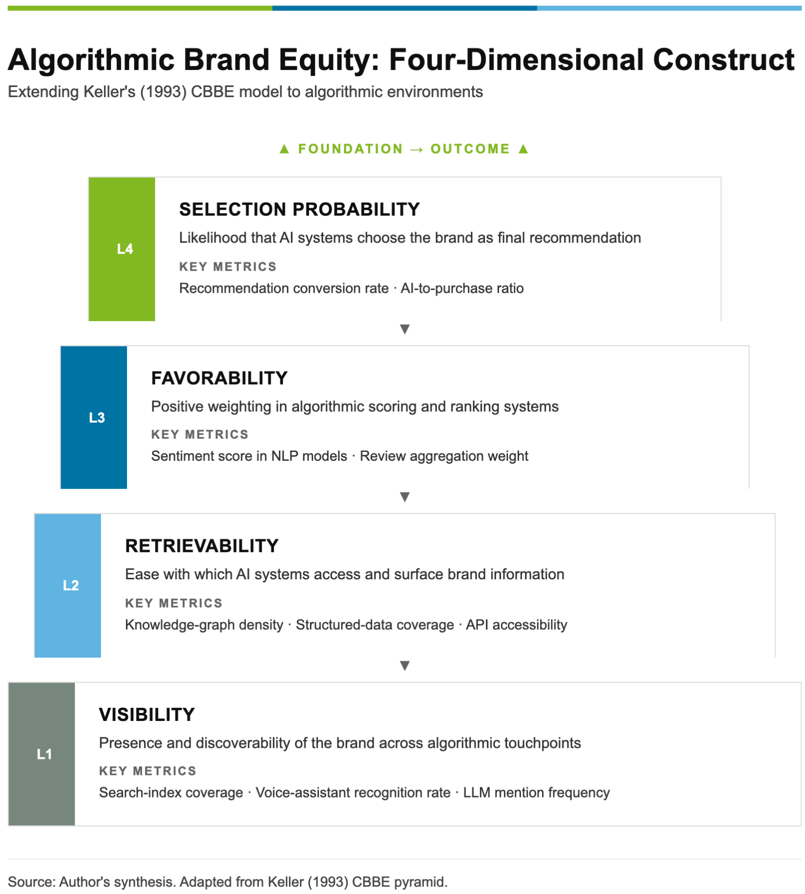

Figure 7. Algorithmic Brand Equity (ABE): Four-Dimensional Construct. Extending Keller's [70] CBBE pyramid to algorithmic environments, the ABE model comprises Visibility, Retrievability, Favorability, and Selection Probability. Source: Author's construct development.

Table 1. Algorithmic Brand Equity: Dimensions, Definitions, and Candidate Measures

ABE Dimension	Definition	Observable Indicators	Candidate Measures
Algorithmic Visibility	The frequency and prominence with which a brand appears in AI-generated recommendations, search results, and conversational AI responses	Share of recommendations; rank position; presence in AI Overviews and chatbot responses	Share-of-algorithmic-voice (% of category recommendations featuring the brand); mean rank position across platforms; AI Overview inclusion rate; cross-platform visibility index (weighted composite across search, social, e-commerce, and GenAI channels)
Algorithmic Retrievability	The probability that an AI system retrieves and presents the brand when a relevant category query is made	Category retrieval rate; LLM mention frequency; inclusion in comparison sets	Category retrieval rate (% of relevant queries returning the brand); LLM brand mention probability (across standardized category prompts); retrieval consistency score (variance in retrieval across query formulations and platforms)
Algorithmic Favorability	The valence and quality of brand representation within algorithmic outputs	Sentiment of AI-generated mentions; comparative positioning; review aggregation framing	Algorithmic sentiment index (mean sentiment of AI-generated brand references); competitive positioning score (brand's relative rank in evaluative outputs); review signal ratio (proportion of positive vs. negative signals surfaced by algorithms); framing valence in AI Overview summaries
Algorithmic Selection Probability	The likelihood that an AI agent or AI-assisted decision process selects the brand for purchase	Conversion from AI recommendations; agentic purchase share; default-option frequency	AI recommendation conversion rate; agentic purchase share (% of total sales from autonomous AI agents); default selection frequency (% of automated choice sets in which brand is the default); procurement algorithm win rate (B2B contexts)

Several methodological notes attend this measurement agenda. First, ABE measurement is inherently multi-platform: a brand's algorithmic standing on Amazon, Google, ChatGPT, TikTok Shop, and enterprise procurement systems may vary substantially, requiring either platform-specific measurement or a composite index with explicit weighting logic. Second, ABE is temporally dynamic in ways that CBBE is not - algorithmic updates, competitive bidding changes, and training data refreshes can shift ABE rapidly, necessitating continuous monitoring rather than periodic surveying. Third, the opacity of proprietary algorithms creates measurement challenges: brands cannot directly observe the ranking criteria or training data that determine their algorithmic standing, requiring inferential measurement through systematic query testing and output analysis. These challenges are significant but not insurmountable; they define the boundary conditions for the empirical program that RQ4 in the research agenda (Section 9) calls for.

The formalization of ABE as a four-dimensional construct - parallel to but distinct from CBBE - provides the conceptual architecture needed to study, measure, and manage brand equity in the algorithmic age. Just as Keller's [70] CBBE framework gave marketers a systematic language for understanding brand power in consumer minds, ABE offers a corresponding framework for understanding brand power in the computational systems that increasingly determine which brands consumers encounter, evaluate, and purchase. The marketing discipline's capacity to develop validated ABE measures will be a critical test of its ability to keep pace with the algorithmic transformation of commerce.

8. Theoretical Discussion

The Algorithmic Value Creation Framework described in Section 7 establishes the structural relationships among AI, privacy, and platforms. This section examines the deeper theoretical implications of these relationships for marketing as a discipline - its epistemological foundations, its ethical commitments, and its theoretical future.

8.1 The Epistemological Shift

Marketing scholarship has historically relied on theory-driven epistemology: researchers formulate hypotheses grounded in theoretical constructs, design studies to test them, and revise theory based on findings. This process - rooted in Popperian falsificationism and Kuhnian paradigm development - assumes that understanding precedes prediction. The algorithmic age inverts this relationship.

Chris Anderson (2008), then editor-in-chief of *Wired*, articulated the provocation most sharply: "Correlation supersedes causation, and science can advance even without coherent models, unified theories, or really any mechanistic explanation at all." In Anderson's view, massive datasets render theoretical models "fundamentally flawed and simplified," while statistical algorithms "find more accurate correlations based on almost infinite datasets." Applied to marketing, this thesis implies that we no longer need to *understand* why consumers behave as they do - we need only *predict* their next action.

The critical response has been substantial. Pasquale [103] identified the "black box problem": algorithms whose inner workings are opaque "cannot be contested, audited, or corrected." O'Neil [104] demonstrated that "mathematical models being used today are unregulated and uncontestable, even when they're wrong," functioning as "weapons of math destruction" that reinforce inequality under a veneer of objectivity. Floridi [105] offered the most nuanced synthesis, arguing that AI represents "a new form of agency" that "disrupts classical epistemological paradigms - empiricism, falsificationism, Kuhnian paradigm shifts, and social epistemology." Algorithms function as "new epistemic apparatuses that regulate knowledge production," raising questions about "how knowledge is produced, by which normative criteria it is legitimized, and who gains epistemic authority."

For marketing, the epistemological shift has concrete consequences. The transition from survey-based consumer knowledge (asking people what they want) to algorithmic knowledge (inferring what they want from behavioral data) fundamentally changes the relationship between marketer and consumer. The consumer becomes an object of prediction rather than a subject of understanding. Algorithmic marketing can optimize conversion rates without knowing *why* a particular creative resonates, *why* a consumer abandons a cart, or *why* a price point triggers purchase. The question is whether such optimization constitutes genuine marketing knowledge, or merely effective pattern-matching that lacks the explanatory depth required for theoretical progress.

This question is not academic in the pejorative sense. If marketing theory is to provide normative guidance - if it is to tell practitioners not just *what works* but *what they should do* - it requires causal understanding, not mere correlation. A marketing discipline that abandons explanation for prediction risks becoming, as critics of Anderson warned, "an activity more akin to stamp collecting."

8.2 Consumer Agency in the Algorithmic Age

Classical marketing theory assumes a consumer who exercises autonomous choice: evaluating alternatives, forming preferences, and making decisions based on personal criteria. Each layer of algorithmic mediation erodes this assumption.

Pariser [106] described "filter bubbles" - "digitally curated environments in which algorithms personalize a user's information feed based on previous behaviors" - while Sunstein [107] identified "echo chambers" in which "individuals predominantly engage with like-minded others." Though empirical evidence on the magnitude of these effects remains contested, the underlying mechanism is well-established: algorithmic personalization narrows the information set from which consumers make decisions.

The boundary between beneficial personalization and manipulation is increasingly difficult to locate. Thaler and Sunstein [108] defined a nudge as "any form of choice architecture that alters people's behavior in a predictable way without restricting options or significantly changing their economic incentives." Nudging is "paternalistic in that it tries to influence choices to make choosers better off by their own judgment, while being libertarian in ensuring people are free to opt out." But algorithmic personalization often removes the opt-out capacity entirely, or renders it so cognitively costly as to be effectively unavailable. Dark patterns - "deceptive UI/UX design techniques that direct users to perform certain actions without their awareness" (FTC, 2022) - exploit this asymmetry systematically, "disguising ads to look like independent content, making it difficult for consumers to cancel subscriptions, burying key terms or junk fees, and tricking consumers into sharing their data."

Research on algorithmic persuasion confirms that "most consumers are not fully aware of the role that algorithms play in advertising on social media, and thus algorithmic persuasion reflects hidden influence and/or manipulation." Matz et al. [109] demonstrated in field experiments with 3.5 million individuals that matching persuasive appeals to psychological profiles significantly alters behavior - a finding that raises profound questions about the ethical boundaries of targeting precision.

The most radical development is *agentic commerce*: AI agents that autonomously execute purchases on behalf of consumers. Current data indicate that 45% of consumers already use AI for shopping, and projections suggest AI agents could mediate $3 - 5 trillion of global consumer commerce by 2030 [2]. In agentic commerce, "customer AI agents will make brand-independent purchase decisions based on materials, durability, and sizing rather than traditional brand loyalty." The AI agent operates "autonomously once the user establishes parameters and permissions...executing the full purchase without requiring the human to click 'buy' themselves."

Research classifies algorithmic decision autonomy into three levels: *dictatorial substitute* (high autonomy), *co-assistant* (middle), and *pure performer* (low). At the dictatorial substitute level, the consumer has effectively delegated choice to an algorithm. The theoretical implications are significant: if the consumer does not make the brand choice, can brand loyalty exist in any meaningful sense? Does consumer satisfaction refer to the human's experience or the algorithm's optimization function? These questions challenge foundational constructs in marketing theory and demand new conceptual frameworks.

8.3 The Trust Asymmetry

Consumer trust in AI-mediated marketing is characterized by a structural asymmetry that existing trust theories do not fully address. Industry data reveal a 40-percentage-point trust gap: 93% of business leaders express confidence in AI-driven marketing, while only 53% of consumers share that confidence. This gap is not merely a communication failure; it reflects fundamentally different relationships to algorithmic systems.

Dietvorst et al. [22] documented *algorithm aversion*: "people lose confidence in algorithms more readily than they would in humans," even when algorithmic performance is objectively superior. This exists in tension with Logg et al.'s (2019) *algorithm appreciation*, whereby people prefer algorithmic advice on analytical tasks. The moderating factor is control: "participants were more trusting when they were able to have more control over the decision-making process." This suggests that the perception of agency - even if partially illusory - is more important for trust than the actual quality of algorithmic output.

A particularly revealing paradox emerges from consumer survey data: 79% of consumers express a preference for human customer service, yet 82% report positive attitudes toward personalized advertising - which is, by definition, algorithmically generated. The resolution lies in a distinction between *visible* and *invisible* AI. Luo et al. [92] found that undisclosed chatbots are as effective as proficient human workers, but disclosure of chatbot identity reduces purchase rates by 79.7%. Consumers reject AI they can see but embrace AI they cannot. This "visibility paradox" suggests that trust in AI-mediated marketing is not a function of AI capability but of AI salience: the more conspicuous the algorithmic mediation, the greater the consumer resistance.

The asymmetric trust dynamic has important theoretical implications. In Morgan and Hunt's [36] commitment-trust theory, trust is reciprocal and built through demonstrated reliability over time. In human-AI relationships, trust is unidirectional (the consumer must trust the algorithm, but the algorithm does not "trust" the consumer) and intolerant of error (AI must outperform humans to earn equivalent trust, and "based on expectation-disconfirmation theory, expectations towards the algorithm are more violated than towards a human, even though advice accuracy is identical"). This suggests that commitment-trust theory requires fundamental modification to accommodate the structural asymmetries of algorithmic relationships.

8.4 Surveillance Capitalism and Marketing Ethics

Shoshana Zuboff's [110] *The Age of Surveillance Capitalism* provides the most comprehensive critical framework for understanding the ethical foundations of algorithmic marketing. Zuboff argues that surveillance capitalism is "driven by a profit-making incentive" in which "vast wealth and power are accumulated in ominous new 'behavioral futures markets,' where predictions about our behavior are bought and sold." Behavioral data are "fabricated into prediction products that anticipate what you will do now, soon, and later." The system's "means of behavioral modification at scale erodes democracy from within because, without autonomy in action and in thought, we have little capacity for the moral judgment and critical thinking necessary for a democratic society."

Zuboff's central ethical indictment - "as industrial capitalism exploited nature, surveillance capitalism exploits human nature" - implicates marketing directly. The data infrastructure that powers personalized advertising, recommendation engines, and algorithmic targeting is the same infrastructure that enables surveillance capitalism's extraction of "behavioral surplus" - data beyond what is needed for service improvement, harvested for predictive purposes.

The privacy paradox complicates the ethical picture. Norberg et al. [9] documented the "dichotomy of information privacy attitude and actual information privacy behavior": consumers express concern about data handling but "voluntarily give away personal data." Zuboff's response is that "every survey of internet users has shown that once people become aware of surveillance capitalists' backstage practices, they reject them" - suggesting that the paradox reflects information asymmetry, not genuine consent.

For marketing theory, the ethical challenge is circular: personalization requires data; data collection enables surveillance; surveillance undermines autonomy; autonomy is the basis of genuine consumer choice; without genuine choice, marketing loses its theoretical foundation as a system of voluntary exchange. This circularity suggests that marketing cannot resolve the privacy problem through incremental adjustments (better consent forms, more transparent policies) but must confront the structural tension between

Theory Disruption Map

How three forces break four foundational marketing theories

DISRUPTION MATRIX

	AI & Algorithms	Data Privacy	Platform Ecosystems
S-D Logic Vargo & Lusch, 2004	Value co-creation assumes human actors; AI introduces non-human co-creators	Resource integration requires data access; privacy laws restrict it	Actor networks are platform-mediated; gatekeepers control interactions
CBBE Keller, 1993	Brand associations formed by algorithms, not just consumer experience	Personalized brand touchpoints require data that privacy laws restrict	Brand visibility depends on algorithmic ranking, not consumer recall
Commitment-Trust Morgan & Hunt, 1994	Trust calibration with non-human agents has no theoretical basis	Data breaches destroy trust asymmetrically and irreversibly	Platform dependency creates involuntary commitment
Satisfaction Oliver, 1999	Satisfaction is computed in real-time, not post-consumption	Satisfaction measurement requires tracking that users may block	Satisfaction is platform-mediated; reviews are algorithmically curated

Reading guide: Each cell identifies the specific theoretical assumption that the corresponding force disrupts. All twelve disruptions operate simultaneously, creating compound uncertainty for marketing theory and practice.

Source: Author's analysis based on literature review of foundational marketing theories.

Figure 8. Theory Disruption Map: How Three Forces Break Four Theories. Each cell identifies the specific theoretical assumption disrupted by the corresponding force, revealing twelve simultaneous disruption pathways. Source: Author's analysis based on literature reviewed in Sections 3 - 6.

AI and Value Creation (P1 - P3)

P1: As algorithmic mediation of purchase decisions increases, the explanatory power of consumer-based brand equity [70] for market share diminishes, while algorithmic brand equity - defined as a brand's visibility, favorability, and selection probability within AI recommendation systems - becomes an increasingly significant predictor.

Rationale: Evidence that the majority of Amazon clicks concentrate in the top search results (Zhu &)[79][1] and that AI purchasing agents make "brand-independent purchase decisions based on materials, durability, and sizing rather than traditional brand loyalty" [2] suggests that brand equity's locus is shifting from human cognition to algorithmic architectures. If this proposition holds, the Keller [70] CBBE pyramid requires a parallel construct - algorithm-based brand equity - that captures a brand's standing within recommendation engines, search algorithms, and autonomous purchasing agents. Validation would require developing an Algorithmic Brand Equity scale (following Churchill's 1979 paradigm) and demonstrating its incremental predictive validity for market share beyond traditional CBBE measures.

P2: In service ecosystems where AI agents perform both operant functions (generating insights, making decisions) and operand functions (executing instructions, processing data), value co-creation outcomes differ systematically from ecosystems mediated exclusively by human actors, exhibiting higher transactional efficiency but lower relational depth.

Rationale: Service-dominant logic holds that value is co-created through interaction among actors who apply operant resources for mutual benefit (Vargo &)[69]. Preliminary evidence from Greve (2025, conference paper) reconceptualizes AI as a "hybrid resource that embodies both operant and operand characteristics," and the Hybrid Intelligent Service Ecosystems framework positions AI as an active co-creator rather than a passive tool. Yet the evidence is ambiguous: AI chatbots achieve satisfaction scores of 92% [23], but consumers report that interactions with AI lack the relational quality they associate with human service encounters (Huang &)[71]. Testing this proposition would require comparative designs that hold service outcomes constant while varying the degree of AI mediation, measuring both efficiency metrics (resolution time, accuracy) and relational metrics (perceived care, emotional connection, commitment).

P3: As AI progresses from mechanical intelligence through thinking intelligence to feeling intelligence (Huang &)[5], the boundary between tasks that consumers prefer to delegate to AI and tasks they reserve for human interaction shifts progressively toward higher-order emotional and social domains, with this boundary moderated by individual differences in need for human connection and technology anxiety.

Rationale: Huang and Rust's [71] feeling economy framework predicts that AI will progressively substitute for human intelligence in marketing tasks, moving from routine automation to analytical decision-making to emotional engagement. Current evidence supports partial substitution: consumers accept AI for information retrieval and transaction processing but resist it for complaints requiring empathy, health consultations, and relationship-intensive services. The 67% of Fortune 500 companies deploying AI chatbots as primary service interfaces [23] are effectively testing this boundary in real time. A critical test would involve tracking consumer acceptance thresholds across service categories as AI emotional capabilities improve, identifying the "last frontier" beyond which consumers reject algorithmic substitution regardless of performance parity.

Privacy and Trust (P4 - P5)

P4: The privacy paradox - the gap between stated privacy concern and actual disclosure behavior - is not a stable individual trait but a context-dependent phenomenon that narrows when consumers receive transparent, real-time information about how their data will be used and what value they will receive in return.

Rationale: The persistence of the privacy paradox (86% of consumers express concern about data privacy, yet personalization driven by that data increases purchase intent by 80%) has been documented repeatedly but never adequately explained [9](Acquisti &)[8]. Aguirre et al. [78] demonstrated that covert data collection undermines the benefits of personalization, and Bleier et al. [10] showed that privacy concerns are triggered when data practices violate contextual norms. These findings suggest that the paradox reflects an information asymmetry rather than genuine consumer inconsistency. If transparency mechanisms can narrow the gap, then the privacy paradox is a design problem rather than a behavioral irrationality - with direct implications for how commitment-trust theory (Morgan &)[36] should be extended to data-sharing relationships. Experimental designs that manipulate the salience and specificity of data-use disclosures, while measuring both stated concern and revealed behavior, would provide a direct test.

P5: Privacy regulations that impose uniform compliance costs (e.g., GDPR, state-level US privacy laws) increase market concentration in digital advertising by disproportionately burdening smaller firms, thereby strengthening the data advantages of dominant platforms and reducing the competitive effectiveness of marketing by small and medium enterprises.

Rationale: Johnson et al. [73] found that GDPR increased market concentration by 17%, and Goldberg et al. [72] documented aggregate revenue declines of approximately 12% for EU websites. Peukert et al. [95] showed that websites substantially reduced third-party data interactions post-GDPR, effectively ceding more data control to dominant platforms with existing first-party data infrastructure. Apple's App Tracking Transparency framework, which prompted 80% of iOS users to opt out of cross-app tracking, cost Meta an estimated $10 - 13 billion annually but strengthened Apple's own advertising business. This evidence suggests a structural mechanism: privacy regulation reduces the total supply of behavioral data while concentrating the remaining supply among platforms large enough to collect it at scale through first-party relationships. Testing this proposition requires difference-in-differences analyses comparing marketing effectiveness metrics for SMEs versus large firms across jurisdictions with varying regulatory stringency, ideally exploiting the staggered adoption of US state privacy laws as natural experiments.

Platforms and Market Structure (P6 - P7)

P6: Platform recommendation algorithms function as market-making institutions that shape brand equity formation independently of, and sometimes in opposition to, consumer preferences, such that a brand's algorithmic visibility score predicts its sales trajectory more accurately than traditional awareness and consideration metrics.

Rationale: The evidence that Amazon's recommendation algorithm includes "contribution profit" as a ranking variable, systematically favoring higher-margin private-label products (Zhu &)[79], and that "sponsored recommendations are significantly more biased toward Amazon private label products compared to organic recommendations" [20], demonstrates that platform algorithms do not merely reflect consumer demand - they actively construct it. Retail media networks, which reached $60 billion in 2024 and are projected to exceed $72 billion in 2025 [53], have formalized this gatekeeping function by making brand visibility explicitly purchasable. If algorithmic visibility predicts sales above and beyond consumer-side brand equity, then the locus of brand strategy must shift from shaping consumer minds to optimizing algorithmic standing - a reorientation with profound implications for how firms allocate marketing resources. Quasi-experimental designs exploiting exogenous algorithm changes on major platforms, combined with brand-tracking surveys, would enable causal identification.

P7: In the creator economy, the relationship between creator audience size and brand partnership ROI follows an inverted-U pattern, with mid-tier creators outperforming both nano-influencers (who lack reach) and mega-influencers (who lack authenticity), and this pattern is amplified by platform algorithms that reward engagement rate over follower count.

Rationale: Beichert et al. [98] demonstrated that nano-influencers outperform high-followership creators on ROI by an order of magnitude, yet the creator economy exhibits extreme structural inequality, with the top 1% of creators capturing a disproportionate share of platform revenue. The Goldman Sachs (2025) estimate of a $480 billion total addressable market for the creator economy, combined with Libai et al.'s (2025) framework positioning creators as a new class of marketing intermediaries, suggests that brand-creator matching is becoming as consequential as media buying. Platform algorithms mediate this matching by determining which creator content reaches which audiences - and these algorithms increasingly favor engagement metrics (comments, shares, saves) over raw reach. An inverted-U relationship would imply that brands are systematically misallocating creator partnership budgets toward the extremes of the distribution, and that algorithmic amplification of engagement-optimized content provides a structural advantage to the mid-tier. Large-scale empirical analysis of brand partnership data across creator tiers, combined with algorithmic audit methods, would test both the functional form and the platform moderation effect.

Integrative Proposition (P8)

P8: The three forces identified in the Algorithmic Value Creation Framework - AI capability, privacy regulation, and platform market power - interact multiplicatively rather than additively, such that the combined effect of any two forces on marketing outcomes (brand equity, consumer trust, firm performance) cannot be predicted from their individual effects alone, and the direction of these interaction effects varies across institutional contexts (regulatory regime, platform architecture, cultural privacy norms).

Rationale: The AVCF's three intersection zones - the Personalization Paradox (AI x Privacy), Algorithmic Gatekeeping (AI x Platforms), and Data Sovereignty (Privacy x Platforms) - each describe emergent phenomena that arise only when two axes operate simultaneously. The personalization paradox illustrates this most clearly: more sophisticated AI requires more granular data, yet privacy regulation restricts data availability, creating a structural tension that neither the AI literature nor the privacy literature can explain in isolation. Similarly, the finding that GDPR increased market concentration [73] while simultaneously constraining the data inputs that platform algorithms require for effective recommendation suggests a non-linear dynamic in which regulation intended to limit platform power may, under certain conditions, amplify it. Cross-national comparative designs - exploiting variation in regulatory regimes (GDPR vs. CCPA vs. China's PIPL), platform architectures (Western app ecosystems vs. WeChat's super-app model), and cultural privacy norms [83] - would test both the multiplicative interaction hypothesis and its institutional contingencies.

Table 2. Master Mapping: From Foundational Theory to Algorithmic-Age

Reconceptualization

Foundational Theory	Core Assumption	Algorithmic Challenge	Revised Construct (AVCF)	Testable Implication
Service-Dominant Logic (Vargo &) [69]	Value is co-created through interaction among human actors who apply operant resources (knowledge, skills) for mutual benefit	AI agents perform both operant functions (generating insights, making autonomous decisions) and operand functions (executing instructions), blurring the boundary between resource and actor; ChatGPT serves 800 million weekly users and over one million businesses deploy AI tools [19]	**Algorithmic Value Co-creation:** Value co-creation occurs across human-AI-platform networks in which algorithmic agents actively shape, and are shaped by, the co-creation process; Hybrid Intelligent Service Ecosystems [80] reconceptualize AI as a hybrid resource-actor	P2: Hybrid ecosystems yield higher transactional efficiency but lower relational depth than human-only ecosystems; P3: The boundary of acceptable AI substitution shifts progressively toward emotional domains
Customer-Based Brand Equity [70]	Brand power resides in consumer minds; the differential effect of brand knowledge on consumer response drives market outcomes	Recommendation algorithms override brand salience (majority of clicks to top-ranked results); AI purchasing agents make brand-independent decisions [2]; brands must become strong enough for algorithms to surface them or risk algorithmic invisibility	**Algorithmic Brand Equity:** A brand's visibility, favorability, and selection probability within AI recommendation systems, search algorithms, and autonomous purchasing agents - a construct parallel to but distinct from consumer-based brand equity	P1: Algorithmic brand equity becomes an increasingly significant predictor of market share as algorithmic mediation increases; P6: Algorithmic visibility predicts sales more accurately than traditional awareness metrics
Commitment-Trust Theory (Morgan &)[36]	Trust is confidence in a partner's reliability and integrity; commitment reflects desire to maintain a valued relationship; both constructs assume intentionality and moral judgment in exchange partners	Consumers form parasocial relationships with AI chatbots; trust expectations for AI are higher than for humans, yet trust recovery after AI failure is more difficult [22]; 67% of Fortune 500 companies use AI chatbots as primary service interfaces	**Human-AI Trust:** An asymmetric trust dynamic in which AI must outperform humans to earn equivalent trust, trust violation by AI triggers stronger negative reactions than equivalent human failure, and the "feeling economy" (Huang &)[71] shifts the uniquely human contribution toward emotional intelligence	P3: Consumer delegation boundaries shift as AI emotional capability improves; P4: The privacy paradox narrows with transparent data-use disclosures, suggesting trust in data relationships is context-dependent rather than dispositional

Customer Satisfaction Paradigm [46] (Szymanski &) [47]	Satisfaction arises from disconfirmation of expectations, measured retrospectively through surveys; satisfaction is the primary antecedent of loyalty	AI-driven personalization algorithmically constructs the expectations against which performance is judged; satisfaction signals are now continuous (click-through, dwell time, return behavior) rather than episodic; structural lock-in (subscription auto-renewal, switching costs) decouples repeat behavior from satisfaction	**Real-time Algorithmic Satisfaction:** Satisfaction is reconceptualized as a continuous behavioral signal captured, computed, and acted upon algorithmically, rather than a discrete psychological state; the satisfaction-loyalty link is moderated by structural retention mechanisms that operate independently of evaluative judgment	P1: As algorithmic mediation increases, behavioral loyalty metrics diverge from attitudinal satisfaction measures; P8: The interaction of AI personalization (which inflates expectations) and platform switching costs (which suppress churn) produces satisfaction-loyalty dynamics not predictable from either force alone

Boundary Conditions and Limitations

These eight propositions are bounded by several conditions that future researchers should address explicitly. First, the propositions are grounded primarily in evidence from North American and European markets; their generalizability to institutional contexts with fundamentally different regulatory regimes (e.g., China's Personal Information Protection Law), platform architectures (e.g., the WeChat super-app model), and cultural orientations toward privacy and technology [83] remains an open empirical question. Second, the propositions assume a trajectory of increasing algorithmic mediation; regulatory interventions (such as the EU AI Act's prohibition of subliminal manipulation), technological disruptions (such as decentralized identity systems), or consumer backlash movements could alter this trajectory in ways that modify the predicted relationships. Third, the temporal dynamics of these propositions warrant attention: the shift from consumer-based to algorithmic brand equity (P1) and the progression of AI emotional capability (P3) are not instantaneous but unfold over years or decades, requiring longitudinal research designs that current cross-sectional methods cannot support. Fourth, several propositions involve constructs - algorithmic brand equity, human-AI trust, real-time algorithmic satisfaction - that lack validated measurement instruments; scale development following established paradigms [84][85] is a prerequisite for empirical testing. Finally, the integrative proposition (P8) posits multiplicative interactions among three macro-forces, each of which is itself evolving rapidly; testing such interactions demands research designs of considerable scale and complexity, ideally involving cross-national comparisons and multi-year observation windows. Despite these limitations, the propositions provide a structured, falsifiable foundation for the next decade of empirical inquiry into marketing theory in the algorithmic age.

10. Implications

The preceding analysis has mapped the algorithmic transformation of marketing across three interconnected domains - artificial intelligence, data privacy regulation, and platform ecosystems - and proposed the Algorithmic Value Creation Framework (AVCF) as an integrative theoretical architecture. This section draws out the implications of that analysis for marketing theory, managerial practice, and public policy.

10.1 Implications for Marketing Theory

The AVCF's central contribution is not the identification of AI, privacy, or platforms as important forces - that much is already well established - but the demonstration that these forces interact recursively to produce phenomena that no single theoretical tradition can explain in isolation. The personalization paradox (Intersection 1), algorithmic gatekeeping (Intersection 2), and the data sovereignty problem (Intersection 3) are each emergent properties of paired interactions among the framework's three axes. This structural interdependence has consequences for the four foundational theories examined in this review.

Service-dominant logic (Vargo &)[16] remains the most adaptable of the four frameworks, but its anthropocentric premises require substantive revision. The concept of value co-creation through interaction among human actors applying operant resources must now accommodate AI as a hybrid operant - operand resource - an entity that simultaneously applies knowledge (generating personalized content, optimizing pricing, mediating customer service) and is acted upon by other actors (trained on human data, constrained by platform architectures, regulated by privacy law). The theoretical question is not whether AI participates in value co-creation - the evidence that it does is overwhelming - but whether S-D Logic's axiom that "value is always uniquely and phenomenologically determined by the beneficiary" (Vargo & Lusch, 2016, p. 8) holds when the beneficiary's experience is shaped by algorithmic systems whose objectives may diverge from the beneficiary's own. Keller's [70] customer-based brand equity model faces perhaps the most fundamental challenge. If brand equity resides in consumer minds, what happens when algorithmic recommendation systems, AI search responses, and autonomous purchasing agents increasingly mediate the relationship between brand and consumer? The construct of algorithmic brand equity - a brand's visibility, favorability, and selection probability within machine decision architectures - does not replace Keller's framework so much as reveal its boundary condition: CBBE explains brand power when humans make decisions; algorithmic brand equity explains brand power when machines do. The two constructs will coexist for the foreseeable future, but the balance between them will shift as algorithmic mediation deepens. Morgan and Hunt's [36] commitment-trust theory, meanwhile, must contend with the asymmetric trust dynamics that characterize human-AI interaction. Algorithm aversion research [22] demonstrates that consumers hold algorithms to higher performance standards than human advisors and forgive algorithmic failures less readily. This asymmetry complicates the relational mechanisms that commitment-trust theory describes: trust-building in human-AI contexts is not merely a scaled version of interpersonal trust but a qualitatively different phenomenon requiring its own theoretical specification.

These challenges converge on a question raised in the theoretical discussion of Section 8: does the algorithmic transformation constitute a Kuhnian paradigm shift, or can existing theories absorb the accumulated anomalies through incremental extension? This review advocates for a third position - dialectical synthesis. The algorithmic transformation neither leaves marketing theory intact nor renders it obsolete. The normative commitment to value creation for all stakeholders is preserved, but the epistemological, ontological, and ethical assumptions underlying that commitment require fundamental updating. The four foundational theories retain explanatory power within their original domains of application, but each now possesses clearly identifiable boundary conditions beyond which new theoretical constructs - algorithmic brand equity, human-AI trust, hybrid intelligent service ecosystems, real-time algorithmic satisfaction - become necessary. The threshold for paradigm shift, we suggest, is empirical rather than definitional: when AI mediates more than 30% of consumer purchase decisions across major product categories, the accumulated anomalies will likely exceed the absorptive capacity of existing frameworks. Current trajectories suggest this threshold could be approached within the next three to five years, making the question not whether but when marketing theory will require comprehensive reconceptualization.

10.2 Implications for Managerial Practice

For marketing practitioners, the AVCF's recursive interaction logic carries a practical corollary: strategies that address AI, privacy, or platforms in isolation will systematically underperform those that manage the interdependencies among all three. An AI-driven personalization initiative that ignores privacy constraints will generate regulatory exposure and consumer backlash. A privacy-first data strategy that ignores platform architectures will forfeit the first-party data advantages that platforms exploit. A platform diversification effort that ignores algorithmic gatekeeping will misallocate resources across channels whose reach is determined by opaque algorithms. The managerial challenge is integrative, not modular.

Three principles distill the review's practical implications. First, the competitive advantage in algorithmic marketing accrues not to organizations that maximize AI deployment but to those that optimize the boundary between automated, augmented, and authenticated activities - or, more concisely, that deploy AI for scale while preserving humans for soul. The 4.1x performance advantage of hybrid AI-assisted content over pure AI-generated content [31], combined with the finding that 52% of consumers disengage from content they suspect is AI-generated [86], suggests that indiscriminate automation erodes the very brand authenticity it seeks to scale. Second, data strategy should be governed by the principle of earning rather than extracting consumer information - asking, not spying. The evidence consistently shows that consent-based, first-party data strategies produce superior commercial outcomes: 15% revenue increases, 20% cost reductions, and improvement across acquisition, satisfaction, and conversion metrics [2][87]. The privacy-performance tradeoff, long assumed to constrain marketers, is largely a false dichotomy. Third, platform algorithms provide discovery and reach, but enduring competitive advantage requires direct relationships that no algorithm can revoke - renting reach while owning relationships. When Facebook's organic reach for brand pages has collapsed to 1.2% [59], the distinction between followers and audience becomes critical. Email subscribers, app users, and community members represent owned channels; social media followers represent rented ones.

The 40-percentage-point gap between business confidence in AI (77% positive) and consumer acceptance (38% positive) documented in this review underscores the strategic risk of moving faster on AI deployment than consumer trust permits. The deeper tension underlying all three principles is the conflict between algorithmic efficiency and brand authenticity. Algorithms optimize for measurable outcomes - clicks, conversions, engagement metrics - but the qualities that build durable brand equity (trust, emotional resonance, perceived integrity) are precisely those most difficult to quantify and most easily sacrificed in pursuit of short-term optimization. The organizations that navigate this tension successfully will be those that treat algorithmic tools as means rather than ends, subordinating optimization to strategy rather than permitting optimization to become the strategy.

10.3 Implications for Public Policy

The algorithmic transformation of marketing raises regulatory questions that extend well beyond the data protection frameworks currently in force. The EU AI Act, whose full application in August 2026 will prohibit subliminal manipulation, exploitation of consumer vulnerabilities, and unconsented emotion recognition in marketing contexts, represents the most consequential regulatory intervention since GDPR. Its mandatory labeling requirements for AI-generated content - including synthetic influencer media, AI-manipulated product demonstrations, and voice-cloned advertisements - will impose transparency obligations across the marketing value chain. With maximum penalties reaching EUR 35 million or 7% of global annual revenue, and cumulative GDPR fines already exceeding EUR 5.9 billion (DLA Piper, 2025), the enforcement credibility of European regulators is established.

Yet a regulatory gap persists around algorithmic accountability in marketing. Platform recommendation algorithms that determine which brands consumers see, which products receive prominence, and which competitors are disadvantaged operate with minimal transparency or external oversight. The finding that Amazon's recommendation algorithm includes contribution profit as a variable, systematically favoring its own private-label products over competing brands (Zhu &)[79], illustrates a structural conflict of interest that existing competition law addresses only indirectly. Similarly, the concentration of 72% of U.S. digital advertising expenditure among three companies (Alphabet, Amazon, Meta) raises questions about whether current antitrust frameworks are adequate for markets in which competitive advantage derives not from superior products but from superior data and algorithmic infrastructure. Policymakers face a difficult calibration: regulation that is too restrictive will stifle innovation and disproportionately burden smaller firms (as GDPR's market-concentrating effects demonstrate), while regulation that is too permissive will allow algorithmic gatekeepers to entrench dominance at the expense of both consumer welfare and competitive markets. The evidence reviewed here suggests that the most productive regulatory focus is on algorithmic transparency - requiring platforms to disclose the criteria governing content ranking, ad placement, and recommendation systems - rather than on prescriptive rules that may quickly become obsolete in a rapidly evolving technological environment.

11. Limitations and Future Directions

11.1 Limitations

This review is subject to several limitations that condition the generalizability and durability of its findings. First, the temporal scope captures a period of exceptionally rapid change; findings that are current as of early 2026 may require revision as regulatory frameworks mature, technological capabilities evolve, and consumer attitudes shift. The EU AI Act's full enforcement, in particular, will generate empirical evidence about the effects of algorithmic regulation on marketing practice that this review can only anticipate.

Second, the industry data drawn from consulting firms and technology platforms carry inherent optimism biases. McKinsey, BCG, Gartner, and similar sources have institutional incentives to emphasize the transformative potential of AI and to present adoption rates in favorable terms. This review has attempted to mitigate such biases through triangulation across multiple sources and by privileging peer-reviewed evidence where available, but cannot entirely eliminate the risk that practitioner-oriented data overstate the pace or magnitude of change. More specifically, several statistics cited in Section 4 originate from commercial providers whose business models are directly tied to the outcomes they report - including Rebuy Engine (recommendation systems), SmythOS (AI content tools), and Hyperleap AI (chatbot solutions); readers should treat these figures as indicative pending peer-reviewed corroboration.

Third, the review focuses primarily on Western - specifically North American and European - markets and regulatory frameworks. The algorithmic transformation of marketing in Asian, African, and Latin American contexts may follow substantially different trajectories shaped by distinct regulatory regimes (e.g., China's Personal Information Protection Law, India's Digital Personal Data Protection Act), different platform architectures (e.g., WeChat's super-app model, which integrates social, commercial, and financial functions in ways without Western analogue), and different cultural norms surrounding privacy, data sharing, and trust in algorithmic systems. Gangwar et al. [83] demonstrated that AI adoption varies significantly across cultures, and the AVCF's three-axis structure may not capture the relevant forces in all contexts.

Fourth, the proposed Algorithmic Value Creation Framework requires empirical validation through primary research that this review, by design, does not provide. The framework's intersection zones, transformed theoretical constructs, and proposed boundary conditions are derived from synthesis of existing evidence, but their predictive validity and practical utility remain to be tested.

11.2 Boundary Conditions of the AVCF

The AVCF is designed to explain marketing dynamics in digitally mediated, consumer-facing markets - the contexts where AI, privacy regulation, and platform ecosystems exert their strongest combined influence. Its explanatory power is likely attenuated in several important domains. Business-to-business marketing, where purchase decisions involve extended buying centers, negotiated contracts, and relational governance structures that differ fundamentally from algorithmic consumer markets, may require a modified version of the framework that accounts for the distinct role of AI in sales enablement and account-based marketing rather than algorithmic recommendation. Low-digital-penetration markets, particularly in sub-Saharan Africa and parts of South and Southeast

Asia, present contexts where the framework's platform axis is less developed and where traditional marketing channels retain greater relevance. The assumption that algorithmic mediation is pervasive does not hold where internet penetration remains below 40% or where mobile-first ecosystems operate under bandwidth and infrastructure constraints that limit AI deployment. Luxury and prestige goods markets present a different boundary condition: in categories where scarcity, exclusivity, and human craftsmanship constitute the core value proposition, algorithmic optimization and platform-mediated distribution may actively undermine brand equity rather than enhance it. The luxury sector's deliberate resistance to marketplace platforms and algorithmic pricing (Kapferer &)[88] suggests that the AVCF's prescriptions do not apply uniformly across product categories.

These boundary conditions are not weaknesses of the framework but specifications of its domain of application. Future research should test the AVCF across these contexts to determine where its predictions hold, where they require modification, and where alternative frameworks are needed.

11.3 Directions for Future Research

The research agenda presented in Section 9 identifies eighteen specific research questions organized around the AVCF's three axes and their intersections. Three priorities deserve particular emphasis. First, empirical investigation of human-AI trust dynamics in marketing contexts - how trust forms, erodes, and recovers in relationships mediated by algorithmic systems - is essential for updating commitment-trust theory and for informing the design of AI-mediated customer experiences. Second, longitudinal research tracking the evolution of consumer decision autonomy under increasing algorithmic mediation is needed to assess whether the trajectory from recommendation to delegation to substitution is as linear as current evidence suggests, or whether consumer resistance and regulatory intervention produce a more complex pattern. Third, cross-national comparative research is urgently needed to test the generalizability of findings derived almost exclusively from North American and European contexts. The AVCF's integrative structure provides a common analytical language for such comparisons, but the empirical work remains to be done.

12. Conclusion

This systematic review has examined how three interconnected forces - artificial intelligence, data privacy regulation, and platform ecosystem dynamics - are collectively reshaping the theoretical foundations and practical operations of marketing. Across 154 sources encompassing peer-reviewed scholarship, industry research, and regulatory analysis, a coherent picture emerges: marketing is not undergoing incremental change within a stable paradigm but experiencing a structural transformation that challenges the discipline's foundational assumptions about value creation, brand equity, consumer agency, and relational trust.

The review's principal contribution is the Algorithmic Value Creation Framework, which maps the recursive interactions among AI, privacy, and platforms and traces their combined effects on four foundational marketing theories. The framework's key insight is that these forces are not independent parallel trends but deeply interdependent phenomena: AI's effectiveness depends on data access, which privacy regulation constrains, which platform ecosystems circumvent through first-party data advantages, which further concentrates market power, which necessitates more sophisticated AI to compete within concentrated platforms. This recursive loop means that no single force can be adequately understood - or strategically addressed - in isolation.

The framework challenges marketing scholarship to pursue what we have termed dialectical synthesis: preserving the normative commitment to stakeholder value creation while fundamentally updating the epistemological and ontological assumptions that underpin it. Keller's brand equity, Morgan and Hunt's commitment-trust theory, Vargo and Lusch's service-dominant logic, and Oliver's satisfaction paradigm each retain explanatory power within their original domains but each now possess clearly identifiable boundary conditions imposed by algorithmic mediation. The field's theoretical task is not to discard these frameworks but to specify where they apply, where they require extension, and where new constructs must take their place. This is, at bottom, a question of intellectual honesty: the theories that built the discipline remain valuable, but treating them as sufficient in the algorithmic age amounts to studying electricity with the vocabulary of steam.

For practitioners, the imperative is integrative strategy - managing AI deployment, data governance, and platform relationships not as separate functional initiatives but as interdependent dimensions of a coherent competitive posture. For policymakers, the imperative is algorithmic transparency - ensuring that the recommendation systems, ranking algorithms, and autonomous purchasing agents that increasingly mediate market exchange are subject to meaningful oversight.

Marketing was built on the premise that voluntary exchange between informed parties creates value for all participants. The algorithmic age does not invalidate that premise, but it demands that the discipline ask - with greater urgency than ever - who is informed, who is voluntary, and for whom value is being created.

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