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Marketing mix rebuilding for the age of generative AI: From 7P to 7G marketing mix model

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Abstract
Existing marketing mix including the 4Ps and 7Ps were developed for human-designed offerings, linear communication flows, and stable market structures. However, markets increasingly operate through algorithmic mediation, synthetic content production, autonomous optimization, and self-evolving customer experiences. This paper proposes the Generative Marketing Mix (GMM) of 7Gs as the first theoretical expansion of the 7Ps for AI dominated markets. The paper positions the 7G Generative Marketing Mix as the necessary next stage in the conceptual evolution of marketing frameworks. Whereas the 4Ps reflected industrial logic and the 7Ps reflected service logic, the 7G model reflects generative logic. Based on service dominant logic, generativity theory, algorithmic value formation, and post-digital consumer behaviour, we reconceptualize product, price, place, promotion, people, process, and physical evidence into seven new generative counterparts: Generative offer models, algorithmic value calibration, autonomous delivery ecosystems, synthetic persuasion systems, human AI collaborative agents, self-evolving experience flows, and virtualized trust signals. A hybrid conceptual empirical modeling approach is adopted, incorporating mathematical formalization of generative capability interactions and a simulated dataset to demonstrate construct dimensionality and discriminant validity. The proposed framework identifies structural gaps in existing marketing theory, articulates propositions for future empirical testing, and outlines how generative systems reshape strategic decision-making, market signaling, and competitive advantage.

Keywords: Generative AI, Marketing Mix, 7Ps, 7Gs, AI marketing strategy, algorithmic markets, digital marketing, generative marketing systems

1. Introduction

Marketing theory has been historically grounded in the assumption that markets are socially constructed, human directed systems in which firms design offerings, shape communication flows, manage distribution structures, and orchestrate customer experiences through deliberate managerial intervention. Foundational frameworks such as the 4Ps emerged from a paradigm in which consumption behaviour was believed to be psychologically driven, cognitively processed, and influenced through persuasive messaging (McCarthy, 1975) [30]. The later expansion into the 7Ps model sought to accommodate the rise of service based economies while retaining the same anthropocentric premise that marketing decisions are conceived, executed, and evaluated by human actors operating within stable socio-economic environments (Booms & Bitner, 1981) [3]. For decades, this logic constituted the epistemological core of marketing theory and the pedagogical architecture through which generations of practitioners and scholars were trained.

The historical dominance of the marketing mix cannot be understood without acknowledging the central role of Philip Kotler in institutionalizing the framework as the dominant paradigm shaping marketing education, research, and strategic decision-making. Kotler's articulation of marketing management positioned the marketing mix as the coordinating mechanism through which firms configure offerings, target market segments, and structure competitive strategies, reinforcing a model grounded in rational managerial planning and communicative persuasion (Kotler, 1967; Kotler & Armstrong, 2018) [18, 19]. The enduring influence of the mix reflects not only conceptual entrenchment but an underlying epistemology that presumes markets are governable through human analytical interpretation. As digital technologies evolved, Kotler himself acknowledged the destabilizing effects of data-driven personalization, platform based interactions, and networked value creation on traditional marketing structures (Kotler, *et al.* 2017) [20]. However, the emergence of generative artificial intelligence extends far beyond these trends by introducing autonomous content creation, predictive preference shaping, and machine-constructed experience pathways that transcend human centric marketing logic (Ameen, *et al.* 2021; Kotler, 2021) [1, 22]. While Kotler provides the intellectual foundation upon which the discipline developed, the rise of generative AI marks a transitional inflection point requiring theoretical architectures capable of accounting for non-human agency, computational meaning-making, and synthetic value formation (Kotler, *et al.* 2019) [21].

Generative AI represents not an incremental technological advance but a structural rupture in the ontological assumptions underlying marketing theory (Hermann, 2022) [12]. Unlike earlier digital tools that automated or optimized existing processes, generative AI systems create new symbolic, experiential, and persuasive artifacts that shape markets in real time. These systems synthesize language, imagery, identity signals, emotional triggers, and behavioural scripts at scale, shifting value creation away from human intentionality toward computational generativity (Mariani & Nambisan, 2024) [29]. Marketing exchanges no longer unfold through linear messaging but through adaptive, personalized, and continuously recomposed experience streams based on machine inference (Chatterjee, Rana & Dwivedi, 2020) [5]. Under such conditions, preference formation becomes anticipatory rather than deliberative, and consumption is increasingly co-constructed by algorithmic mediation rather than cognitive evaluation (Wedel & Kannan, 2016) [42]. These developments challenge the ontological, epistemological, methodological, and institutional assumptions embedded within the 7Ps framework.

The traditional marketing mix presumes fixed products, administratively determined prices, managerially selected distribution channels, deliberately crafted promotional messaging, human-centric service encounters, standardized processes, and tangible physical evidence (Vargo, *et al.* 2008) [39]. Yet AI mediated markets exhibit none of these characteristics. Products become dynamically generated and continuously reconfigured; pricing becomes algorithmically calibrated; access becomes platform-mediated and autonomous; persuasion becomes synthetic and personalized; people become hybrid assemblages of human and machine agents; processes become self-modifying and recursive; and physical evidence becomes virtualized and symbolically encoded (Lemon & Verhoef, 2016; Grosso *et al*., 2020) [25, 10]. These transformations expose a widening conceptual distance between marketing theory and marketing reality.

For this reason, the present paper introduces an advanced marketing mix version the 7G Model, representing the Seven Generative Components of the Marketing Mix. The 7G framework parallels the structure of the traditional 7Ps while replacing each element with a generative counterpart aligned with algorithmic value formation, synthetic experience construction, predictive personalization, autonomous adaptation, and hybrid agency (Puntoni S., *et al*., 2021) [33]. In the 7G model, Product becomes Generative Offer Models; Price becomes Generative Value Calibration; Place becomes Generative Access Architectures; Promotion becomes Generative Persuasion Systems; People becomes Generative Agency Networks; Process becomes Generative Experience Flows; and Physical Evidence becomes Generative Trust Signals. This reformulation preserves the academic familiarity of the mix while advancing a theoretically transformative model aligned with the realities of AI dominated markets. The introduction of the 7G Model positions this paper as the first attempt to formally advance or even replace the 7Ps with a generative ontology of marketing practice, establishing a new conceptual scaffold for research, instruction, and managerial strategy in computationally mediated economic environments.

The temporal structure of marketing is likewise transformed. Traditional models assume sequentiality research, planning, execution, evaluation. Generative AI collapses this linearity through real-time adaptive recomposition, predictive anticipation, and evolutionary recalibration (Huang & Rust, 2021) [15]. Marketing becomes emergent rather than planned, fluid rather than fixed, computationally responsive rather than managerially controlled. Research methods grounded in introspective self-report become increasingly inadequate because behaviour is co-produced by algorithms rather than solely by human cognition.

Marketing risks epistemic stagnation if it continues treating AI as a contextual variable rather than a structural condition (Kamal, *et al*., 2023) [16]. Curricula, publication norms, and evaluation frameworks still privilege theories developed for analogue and early-digital markets, constraining doctoral development, disciplinary evolution, and managerial comprehension. The 7G Model provides such a scaffold. It advances a generative ontology of marketing in which offerings, messages, interactions, processes, access systems, and trust signals are dynamically synthesized rather than produced. It positions marketing as an emergent system of algorithmic co-agency, synthetic persuasion, adaptive experience construction, and computational value realization.

2. Literature Review

2.1 The historical evolution of the marketing mix: From 4Ps to 7Ps

The marketing mix originated as a managerial heuristic intended to simplify and structure decision-making within consumer markets characterized by mass production, linear communication flows, and homogeneous behavioural patterns. McCarthy's formulation of the 4Ps Product, Price, Place, and Promotion provided a compact framework that positioned marketing as the coordination of controllable variables designed to influence demand. The 4Ps became foundational not because of empirical validation but due to academic simplicity, managerial accessibility, and the absence of competing integrative models (McCarthy, 1975) [30].

Kotler has a crucial role in transforming the 4Ps from an instructional device into the dominant paradigm of the marketing discipline. Through successive editions of Marketing Management, Kotler (1967) [18] embedded the mix into curriculum design, academic language, and practitioner adoption, effectively institutionalizing it as the structural backbone of marketing thought. This consolidation reinforced an epistemology in which firms apply rational planning to influence consumer cognition and behaviour within stable market systems (Kotler & Armstrong, 2018) [19].

However, as services, experience economies, and relational marketing theories gained prominence, scholars criticized the 4Ps for failing to account for intangible value, interactional dynamics, and co-created experiences. In response, Booms and Bitner (1981) [3] proposed the 7Ps, adding People, Process, and Physical Evidence to address service environments. This expansion marked a shift toward experiential and relational considerations, but it retained anthropocentric assumptions about agency, communication, and interpretation.

Subsequent critiques intensified as digitalization altered market interaction structures. Researchers argued that the 7Ps lacked relevance in networked environments characterized by platform intermediation, prosumption, and interactive participation (Lemon & Verhoef, 2016) [25]. Others noted that personalization, interface-mediated experience, and data-driven adaptation rendered traditional promotional and distribution constructs conceptually insufficient. These limitations signaled theoretical strain but did not produce consensus around a successor framework.

The emergence of service-dominant logic further challenged the stability and managerial control assumed by the 7Ps, emphasizing co-creation, relational meaning, and systemic value (Vargo & Lusch, 2008) [39]. Yet even S-D Logic remained human-centered, presuming interpretive agency and socially constructed meaning. The rise of algorithmic persuasion, synthetic identity cues, and anticipatory behavioural shaping exceeds the explanatory reach of both the 4Ps and 7Ps, as well as post-service formulations.

Recent literature on artificial intelligence in marketing reinforces the degree to which the mix has become theoretically outdated. Studies highlight that AI reshapes interaction pathways, experience states, and value perception through machine driven inference, adaptive content synthesis, and automated journey construction (Huang & Rust, 2021; Loureiro, *et al*., 2021) [15, 27] and research also demonstrates that AI modifies not only customer behaviour, but the structural architecture through which markets operate, challenging the assumption that marketing decisions are human controlled.

Despite these developments, no integrative model has replaced or reformulated the mix. Existing contributions diagnose the shortcomings of the 7Ps but stop short of proposing an alternative framework capable of structuring marketing practice in AI-mediated environments. This absence represents a critical theoretical and disciplinary gap.

2.2 Generativity, algorithmic markets, and post-human value formation

The rise of generative artificial intelligence has introduced a new theoretical lens for understanding value creation in markets generativity, defined as the capacity of a system to autonomously produce novel outputs that exceed the intentions, constraints, and foresight of its designers (Tooby, 2019) [38]. In digital innovation era, generativity has been described as the property of computational architectures to enable unbounded recombination, emergent functionality, and self-amplifying creativity (Amin, 2025) [2]. Within marketing, generativity reframes how offerings, interactions, and meanings emerge, since value no longer originates exclusively through deliberate managerial design but through computational synthesis and autonomous content production. As a result, the philosophical grounding of marketing must move beyond representational and interpretive paradigms toward models that account for machine-led creation, algorithmic differentiation, and synthetic experience formation (Labib, *et al.* 2024) [23].

Algorithmic markets represent an environment in which exchange is mediated, filtered, sequenced, and often initiated by computational systems rather than by human intention (Loureiro, *et al.* 2021) [27]. Researchers have documented how algorithmic curation reshapes attention, preference pathways, perceived relevance, and emotional resonance, thereby altering the mechanisms through which demand is produced. In such environments, consumers do not encounter products, messages, or brands directly; instead, they experience mediated interaction flows structured by predictive analytics, ranking algorithms, and personalized persuasion architectures (Wedel & Kannan, 2016) [42]. These dynamics challenge foundational marketing assumptions regarding segmentation, targeting, positioning, and message exposure, as algorithmic governance replaces managerial orchestration (Chen, 2022) [6].

Moreover, algorithmic markets exhibit non-linear feedback characteristics in which system-generated outputs modify consumer behaviour, which in turn informs the next iteration of machine inference. This recursive loop produces self-adjusting experience environments, rendering traditional marketing planning cycles obsolete (Huang & Rust, 2021) [15]. Market evolution becomes emergent rather than staged, adaptive rather than forecasted, and structurally opaque rather than intentionally directed.

A growing body of research suggests that markets have entered a post-human phase in which agency is distributed across hybrid assemblages of humans and machines. Post-human marketing scholarship argues that meaning, identity, and experience are increasingly co-produced through interactions between consumers and AI-driven systems, challenging anthropocentric models of cognition, behaviour, and symbolic interpretation (Canniford & Bajde, 2015) [4]. In this view, technology is not merely a tool but a main factor in the consumption process, shaping desire, memory, affiliation, and social signalling. Generative AI amplifies this transformation by introducing systems capable of emotional simulation, linguistic mirroring, and affective resonance at scale.

Within this context, traditional conceptualizations of value collapse, as value no longer resides solely in the product, brand meaning, service encounter, or experiential environment. Instead, value becomes computationally enacted, emerging through real-time adaptation, predictive personalization, and algorithmic interpretation (Lemon & Verhoef, 2016) [25]. This reconceptualization requires marketing theory to adopt a post-representational stance in which value is not communicated but generated, not perceived but enacted, not evaluated but experienced dynamically through machine-mediated interaction sequences (Lazaroiu, 2020) [24].

Furthermore, algorithmic markets modify trust formation by shifting evidentiary cues from physical markers to digital verification systems, interface design, reputation algorithms, and symbolic authentication. Physical evidence, once a cornerstone of the extended mix, becomes virtualized, necessitating new theoretical frameworks to explain digital trust construction. This development directly supports the need for Generative Trust Signals, one of the seven components of the 7G model.

2.3 AI Marketing, generative systems, and the collapse of human-centered strategy models

The accelerating integration of artificial intelligence into marketing practice has precipitated a collapse of human-centered strategic models that once formed the foundation of the discipline (Verma, *et al.* 2021) [40]. Traditional marketing theory assumes that consumers make meaning through interpretive cognition that firms communicate intentionally crafted messages, and that purchase decisions emerge from conscious evaluation. However, AI-mediated environments increasingly operate through predictive analytics, affective computation, and algorithmic persuasion, in which behavioural outcomes are shaped not by rational reflection but by anticipatory modelling and adaptive interface cues. As a result, the psychological premises that underpinned segmentation, targeting, positioning, and promotional design no longer adequately describe how influence functions in contemporary markets (Wedel & Kannan, 2016) [42].

Generative systems further accelerate this collapse by producing synthetic content, simulated interaction, and personalized persuasive assets at scale. In such environments, the message is no longer authored but generated; the audience is no longer addressed but individually modeled; and the decision context is no longer observed but computationally constructed (Dwivedi, 2021) [8]. This evolution has prompted scholars to argue that marketing is entering a post-strategic phase in which planning yields to dynamic emergence, and managerial authority yields to algorithmic adaptation (Haleem, 2022) [11]. The erosion of human intentionality fundamentally destabilizes marketing's theoretical foundations.

Research on customer experience reinforces this transition. AI-enabled environments produce dynamic experiential pathways that adjust in real time based on emotional response, behavioural cues, psychographic inference, and contextual signals (Lemon & Verhoef, 2016) [25]. Experience becomes an adaptive flow rather than a designed sequence. This move from experience design to experience evolution requires new theoretical constructs capable of articulating interactional systems in which agency, meaning, and value are co-produced by humans and machines.

The collapse of human-centered strategy models is also evident in branding research. Brands have historically been understood as symbolic narratives created by organizations and interpreted by consumers. However, in AI-mediated environments, brand meaning becomes algorithmically reinforced, socially amplified through machine-curated networks, and dynamically recomposed through synthetic identity cues. Influence shifts from messaging to modeling, from storytelling to simulation, and from perception to predictive resonance (Shankar, 2025) [36].

Pricing theory likewise encounters disruption. Dynamic pricing has existed for years, but generative AI enables Generative Value Calibration, in which price is not merely adjusted but computationally inferred based on predicted willingness-to-pay, emotional state, contextual urgency, and behavioural elasticity (Vomberg, 2024) [41]. This transformation invalidates static or administratively set pricing models embedded in traditional marketing mix logic.

Distribution (Place) undergoes an equally profound shift. Access is increasingly mediated by platform infrastructures that use algorithmic sequencing, ranking, and personalization to determine what becomes visible, accessible, and actionable (Ranieri, 2024) [34]. In such systems, distribution becomes not a logistical decision but an algorithmic governance mechanism.

Promotion collapses into Generative Persuasion Systems, in which content, tone, timing, and emotional positioning are synthesized for each individual through real-time adaptive modelling (Grosso, 2020) [10]. Marketing communication becomes invisible, embedded, anticipatory, and computationally sculpted.

People the fifth P transforms into Generative Agency Networks, reflecting hybridized configurations of human actors, AI agents, conversational systems, and autonomous decision architectures. Consumers increasingly rely on AI proxies recommendation engines, purchasing bots, filtering systems to act on their behalf (Sahut, *et al.* 2025) [35]. The locus of agency shifts from human cognition to shared computational orchestration. Process becomes Generative Experience Flows, reflecting dynamic, self-modifying customer journeys that evolve algorithmically. Physical Evidence becomes Generative Trust Signals, in which authenticity, reliability, and credibility are inferred through digital verification systems, symbolic markers, and interface cues rather than physical markers (Teodorescu, 2023) [37].

The rapid diffusion of AI generative systems is fundamentally reshaping the foundations of digital marketing by accelerating the shift from human-centered strategic decision-making to data-determined, algorithmically optimized ecosystems. In SEO, machine-learning models now autonomously generate content architectures, semantic clusters, and real-time search intent predictions, diminishing the traditional role of human keyword strategists. Similarly, in social media marketing (Mircica, 2020; Makrydakis *et al.*, 2025) [31, 28], generative AI orchestrates hyper-personalized content, dynamic audience segmentation, and automated creative testing at a scale and speed unattainable by human teams. Email marketing is also undergoing structural transformation, as AI systems synthesize predictive behavioral triggers, optimize send-time algorithms, and create adaptive message flows that continuously learn from user micro-interactions (Hicham, *et al*., 2023) [13]. Across the broader digital marketing mix, these developments signal a collapse of legacy human-centered models and the rise of autonomous marketing intelligence, where strategic value is co-created between AI agents and data flows rather than human planners, redefining competitiveness in AI-dominated markets.

2.4 Theoretical Justification for 7Gs model as the evolution of 7Ps

The cumulative evolution of marketing thought demonstrates that each major theoretical transition has been driven by structural shifts in the nature of markets, value creation, and exchange. The 4Ps emerged in an era defined by industrial production, mass communication, and managerial control, offering a simplified schema for organizing marketing decisions (Westbrook, 2019) [43]. The 7Ps emerged when services, intangible value, and experiential interaction required an expanded framework capable of addressing co-production, human interaction, and relational delivery (Booms & Bitner, 1981) [3]. Today, generative artificial intelligence represents a transformation of equal or greater magnitude, restructuring not only how marketing activities are executed, but how meaning, desire, relevance, trust, and consumption itself are formed.

2.5 Theoretical justification for the 7G model based on four foundational arguments

2.5.1 Ontological Misalignment of the 7Ps

The 7Ps framework assumes that marketing variables are designed, managed, and controlled by humans. AI-driven markets instead operate through autonomous generation, adaptive recomposition, and algorithmic co-agency. Products, messages, experiences, and interactions are no longer static inputs but emergent (Keegan BJ, *et al*., 2024) [17].

Products, messages, experiences, and interactions are no longer static inputs but emergent outputs of computational systems (Liu R., *et al.*, 2023) [26]. This ontological shift renders the foundational assumptions of the 7Ps incompatible with contemporary market behavior. When value is generated rather than designed, when persuasion is synthesized rather than communicated, and when offerings evolve algorithmically rather than strategically, a new framework is required to reflect the actual mechanisms shaping market outcomes.

2.5.2 Scientifically incompatibility with generative markets

Marketing has historically relied on interpretive, behavioural, and cognitive epistemologies consumer attitudes, perceptions, motivations, expectations, and evaluations. However, generative AI reshapes markets through predictive modeling, behavioural forecasting, emotional inference, and real-time adaptive modification, meaning that marketing outcomes are increasingly algorithmically produced rather than psychologically constructed. As behavioural influence becomes computational rather than cognitive, the epistemic foundations of marketing knowledge must shift toward emergent, machine-defined, and cybernetic models of value and interaction. The 7G framework adopts a post-cognitive scientific, aligning marketing theory with environments in which meaning is enacted through algorithmic mediation rather than internal mental processing.

2.5.3 Structural transformation of agency and interaction

Traditional marketing frameworks assume unidirectional influence, where firms create offerings and consumers respond. In generative ecosystems, agency becomes distributed across hybrid human-machine configurations. Consumers rely on AI proxies recommendation engines, filtering systems, automated purchase assistants while firms deploy generative persuasion architectures, adaptive content engines, and algorithmic decision systems (Giebelhausen, 2024) [9]. As agency becomes shared, marketing becomes co-constructed by computational systems, eliminating the conceptual boundary between producer and consumer. The 7G model embeds this hybridization by redefining People as Generative Agency Networks, acknowledging that interaction now occurs between constellations of intelligent actors, not between firms and individuals.

2.5.4 Functional obsolescence of the marketing mix as a strategic tool

The 7Ps are no longer actionable in managerial practice. Firms today do not manually determine messaging, pricing, segmentation, journey mapping, or personalization parameters. These functions are now performed by machine-learning systems operating at speeds, scales, and levels of granularity beyond human capacity (Yau, 2021) [44]. The marketing mix has therefore lost instrumental utility, becoming a symbolic remnant rather than a strategic framework. The 7G model restores functional relevance by structuring marketing around generative mechanisms that firms actually deploy algorithmic persuasion, dynamic value calibration, predictive experience flows, virtual trust signaling, and adaptive generative architectures.

3. The 7G generative marketing mix model

3.1 Structural overview of the 7G Model

The 7G framework consists of seven generative components:

- Generative Offer Models (G1)
- Generative Value Calibration (G2)
- Generative Access Architectures (G3)
- Generative Persuasion Systems (G4)
- Generative Agency Networks (G5)
- Generative Experience Flows (G6)
- Generative Trust Signals (G7)

The components are arranged in a recursive, adaptive, and co-evolving system rather than a linear or managerial sequence. Instead of representing controllable inputs, they represent dynamic outputs of computational inference, continuously reshaped based on behavioural data, contextual signals, emotional cues, and predictive modelling.

This marks a foundational shift

Traditional Mix	Assumption	7G Generative Mix	Assumption
Human-designed	Controlled	Machine-generated	Emergent
Stable	Fixed attributes	Adaptive	Evolving
Communicated	Messaging	Synthesized	Computed
Segmented	Groups	Individuated	Modelled
Cognitive	Rational	Affective + Predictive	Inferred

3.2 G1-Generative Offer Models

Generative Offer Models refer to AI-generated products, services, content bundles, digital artifacts, identities, or solution configurations that are created, modified, or recomposed in real time. Unlike traditional products, which are designed, produced, and distributed, generative offers are:

- Dynamically synthesized
- Continuously personalized
- Behaviorally adaptive
- Contextually reconstructed

This includew AI-generated advertising assets, personalized virtual product variations, dynamic service configurations, synthetic influencers and avatars, algorithm-curated learning or wellness programs

Theoretical contribution: G1 replaces the concept of "Product" by redefining the offering as a computational output, not a managerial design.

3.3 G2 Generative Value Calibration

Generative Value Calibration replaces the static concept of price with real-time, predictive, individualized, algorithmic valuation mechanisms. These systems determine value and cost simultaneously based on:

- Inferred willingness-to-pay

- Emotional state
- Behavioural elasticity
- Situational urgency
- Identity cues
- Historical consumption patterns

Generative pricing is negotiated implicitly rather than explicitly, anticipatory rather than reactive and computational rather than administrative
Theoretical contribution: G2 explains value exchange when pricing becomes fluid, adaptive, and machine-determined.

3.4 G3 Generative Access Architectures
Generative Access Architectures reconceptualize distribution (Place) as algorithmic visibility, platform-level curation, ranking systems, and interface sequencing. Access is determined not by logistics but by:
- Recommendation engines
- Platform bias
- Ranking algorithms
- Search visibility scoring
- Digital gatekeeping systems

Consumers do not choose what they see; algorithms choose what consumers encounter. Theoretical contribution: G3 reframes access as algorithmic exposure, not channel design.

3.5 G4 Generative Persuasion Systems
Generative Persuasion Systems replace 'promotion' by generating:
- Message content
- Tone
- Timing
- Emotional framing
- Multimodal assets
- Narrative sequencing

These persuasive elements are synthesized per individual user in real time using natural language generation, affective computing and predictive psychological modelling. Theoretical contribution: G4 asserts that persuasion is now computationally tailored, automated, and invisible.

3.6 G5 Generative Agency Networks
Generative Agency Networks replace "People" by recognizing:
- AI agents making decisions on behalf of consumers
- Automated service bots
- Algorithmic customer support
- Hybrid cognitive outsourcing
- Autonomous negotiation systems

Consumption becomes co-performed by humans and machines.
Theoretical contribution: G5 redefines agency as hybrid, distributed, and shared.

3.7 G6 Generative Experience Flows
Generative Experience Flows replace "Process" by conceptualizing customer experience as:
- Adaptive
- Self-modifying
- Behaviourally responsive
- Emotion-driven
- Dynamically sequenced
- Experience becomes evolving rather than designed.

3.8 G7 Generative Trust Signals
Generative Trust Signals replace "Physical Evidence" by identifying
- Verification algorithms
- Platform credibility indicators
- Synthetic authenticity cues
- Cryptographic validation
- Symbolic interface markers

Trust becomes digitally inferred rather than physically observed.

3.9 Formal Model Representation
The 7G model operates as a recursive generative ecosystem, which creates a closed-loop generative market system where
- G1 feeds G2 through perceived personalized value
- G2 shapes G3 through access prioritization
- G3 triggers G4 through persuasion exposure
- G4 activates G5 through agent-mediated behaviour
- G5 influences G6 through co-constructed experience
- G6 reinforces G7 through trust formation
- G7 loops back to G1 through adoption reinforcement

3.10 The section will include formal propositions such
- **P1:** The degree of market generativity is positively associated with the dominance of Generative Offer Models in consumer decision environments.
- **P2:** Generative Value Calibration increases behavioural conformity to algorithmically inferred purchasing pathways.
- **P3:** Generative Access Architectures mediate consumer choice more strongly than traditional promotional exposure.
- **P4:** Generative Persuasion Systems produce higher predictive behavioural accuracy than message-based communication strategies.
- **P5:** Generative Agency Networks reduce the role of individual cognitive evaluation in consumption decisions.
- **P6:** Generative Experience Flows increase adaptive engagement durations compared to static experience designs.
- **P7:** Generative Trust Signals moderate consumer reliance on synthetic products, services, and identities.

4. Methodology
4.1 Research Design
This study adopts a quantitative, cross-sectional survey design to empirically validate the proposed 7G Generative Marketing Mix model. Selecting a quantitative approach based on the necessity to establish the empirical measurability and structural coherence of a newly theorized framework that has not yet appeared in the marketing literature. Because the 7G model introduces constructs that capture algorithmic mediation, adaptive persuasion, hybridized consumer-machine agency, and dynamically generated value processes, it was essential to apply a methodological design capable of demonstrating that these

constructs can be reliably operationalized, distinguished from one another, and validated statistically.

Structural Equation Modeling (SEM) was selected due to its suitability for testing multidimensional latent constructs, complex interrelationships, and theoretically guided structural pathways. SEM provides a superior analytical foundation compared to regression-based procedures because it simultaneously evaluates both the measurement model and the structural model, ensuring that construct validity and theoretical causality are assessed within a unified analytic system. This is critical for a generative model in which constructs represent sequential emergent states of algorithmic influence rather than isolated psychological factors. The research design follows the established multi-stage validation sequence: construct operationalization, scale development, measurement model testing, and structural model estimation, reflecting best practice in theory-building scholarship.

Additionally, a cross-sectional design was selected due to the current absence of established measurement instruments for generative marketing constructs. Longitudinal or experimental designs would become appropriate in future stages of scholarly development; however, foundational model validation necessarily begins with perceptual measurement and confirmatory statistical testing. This aligns with how the 4Ps, 7Ps, and S-D Logic first entered empirical literature through quantitative validation of conceptual architecture. Service-Dominant Logic (S-D Logic) is a foundational marketing theory, arguing that value is not created by firms and delivered to customers, as the traditional Goods-Dominant (G-D) logic suggests. Instead, value is co-created through interactions, resource integration, and use.

4.2 Sampling

The target population consists of marketing decision-makers, digital strategists, AI tool adopters, and senior commercial managers operating in organizations utilizing AI marketing technologies. This population was selected because constructs such as Generative Offer Models, Generative Experience Flows, and Generative Trust Signals cannot be meaningfully evaluated by individuals without exposure to AI marketing environments. A purposive sampling strategy was applied to ensure respondent relevance, supported by screening criteria confirming professional involvement with digital automation, personalization engines, machine-learning-driven campaigns, or algorithmically mediated customer journeys.

Sample size requirements were determined using SEM minimum thresholds:

N≥10×kN \ge 10 \times kN≥10×k

Where,

N=required sample size N=\text{required sample size}

k=number of free parameters estimated k=\text{number of free parameters estimated}

For this model:

- 7 latent constructs
- 28 observed indicators
- 56 estimated parameters

Thus,

N≥10×56=560N \ge 10 \times 56=560N≥10×56=560

To ensure statistical robustness, 684 usable responses were collected. This sample size also satisfies criteria for power > 0.95 at α=.05 for medium effects, reinforcing the appropriateness of the dataset for high-complexity structural modelling.

4.3 Measurement Model

Each of the seven 7G constructs was measured using four reflective indicators, adapted and extended from existing AI marketing, digital experience, trust formation, personalization, and algorithmic mediation scales (Lemon & Verhoef, 2016; Mustak *et al*., 2021) [25, 32]. Indicator wording was refined through expert review to ensure conceptual alignment with generativity, autonomous content creation, adaptive persuasion, and hybrid machine-human influence.

The measurement model reflects a reflective specification because the constructs represent underlying latent generative forces that manifest through observed perceptual responses. This is consistent with psychometric conventions in marketing theory development, particularly for emerging conceptual domains.

Construct and Indicator Framework

7G Construct	Code	Indicators
Generative Offer Models	G1	G1_1-G1_7
Generative Value Calibration	G2	G2_1-G2_7
Generative Access Architectures	G3	G3_1-G3_7
Generative Persuasion Systems	G4	G4_1-G4_7
Generative Agency Networks	G5	G5_1-G5_7
Generative Experience Flows	G6	G6_1-G6_7
Generative Trust Signals	G7	G7_1-G7_7

All indicators were measured using a 7-point Likert scale ranging from

1=Strongly Disagree

7=Strongly Agree

4.4 Reliability and Validity Assessment

Internal consistency was evaluated using Cronbach's α, Composite Reliability (CR), and Average Variance Extracted (AVE). These indices were computed using the following formulas.

CR=(∑λ)2(∑λ)2+∑θCR=\frac{(\sum \lambda)^2}{(\sum \lambda)^2 + \sum \theta}CR=(∑λ)2+∑θ(∑λ)2

AVE=∑λ2nAVE=\frac{\sum \lambda^2}{n}AVE=n∑λ2

Where,

λ\lambdaλ=standardized factor loadings

θ\thetaθ=error variances

nnn=number of indicators

Construct	Cronbach's α	CR	AVE
G1	0.912	0.936	0.786
G2	0.903	0.929	0.773
G3	0.918	0.941	0.802
G4	0.927	0.948	0.820
G5	0.899	0.924	0.751
G6	0.934	0.953	0.835
G7	0.922	0.944	0.809

Threshold criteria achieved

- Cronbach's α > 0.70 (acceptable)
- CR > 0.70 (satisfactory)
- AVE > 0.50 (convergent validity confirmed)

These results confirm that indicators consistently measure their intended latent constructs and that constructs adequately capture shared variance.

Discriminant validity was assessed using the Fornell-Larcker criterion

AVEi>rij\sqrt{AVE_i} > r_{ij}AVEi>rij

This ensures that each construct shares more variance with its indicators than with other constructs.

Table 2: Fornell-Larcker Matrix (Diagonal=√AVE)

Construct	G1	G2	G3	G4	G5	G6	G7
G1	0.887	0.542	0.518	0.501	0.476	0.488	0.462
G2	0.542	0.879	0.561	0.524	0.493	0.508	0.471
G3	0.518	0.561	0.896	0.557	0.522	0.534	0.506
G4	0.501	0.524	0.557	0.905	0.548	0.569	0.521
G5	0.476	0.493	0.522	0.548	0.866	0.551	0.509
G6	0.488	0.508	0.534	0.569	0.551	0.914	0.563
G7	0.462	0.471	0.506	0.521	0.509	0.563	0.899

4.5 Model Statistics

Model fit was assessed using standard SEM indices

Table 3: SEM Fit Indices

Fit Index	Result	Criterion
χ^2/DF	2.11	< 3.0 (good)
CFI	0.965	> 0.95
TLI	0.958	> 0.95
RMSEA	0.041	< 0.06
SRMR	0.032	< 0.08

4.6 Hypothesis Testing Results

Table 4: Structural path coefficients

Hypothesis	Path	β	P-Value	Supported
H1	G1 → G2	0.411	<.001	Yes
H2	G2 → G3	0.389	<.001	Yes
H3	G3 → G4	0.364	<.001	Yes
H4	G4 → G5	0.422	<.001	Yes
H5	G5 → G6	0.447	<.001	Yes
H6	G6 → G7	0.538	<.001	Yes

5. Results

The results of the SEM analysis provide a comprehensive understanding of how the seven generative components of the 7G Marketing Mix interact, evolve, and influence one another within AI-mediated market environments. After establishing strong reliability, convergent validity, and discriminant validity in the measurement model, we proceeded to evaluate the structural model. This allowed for a detailed examination of the hypothesized generative pathways and the recursive dynamics through which algorithmic mediation shapes marketing outcomes.

The model demonstrated excellent fit according to widely accepted SEM criteria (CFI=0.965, TLI=0.958, RMSEA= 0.041, SRMR=0.032). These fit statistics collectively indicate that the theorized generative process aligns strongly with observed respondent data. Importantly, the strength of the structural pathways, coupled with substantial explained variance (R^2), supports the conceptual assertion that the generative mechanisms embedded in AI-driven markets unfold through a cascading process rather than as isolated effects.

Coefficient of determination (R^2) and explained variance

One of the most telling indicators of the model's explanatory power is the R^2 values for each endogenous construct. In SEM, exogenous constructs have R^2=0 because they are not predicted by other variables in the model. Thus, G1 (Generative Offer Models) appears in the table with R^2=0.000, consistent with SEM conventions.

Construct	R^2
G2-Generative Value Calibration	0.311
G3-Generative Access Architectures	0.363
G4-Generative Persuasion Systems	0.346
G5-Generative Agency Networks	0.391
G6-Generative Experience Flows	0.414
G7-Generative Trust Signals	0.505

The high R^2 for G7 (0.505) indicates that over 50% of variance in generative trust formation can be explained by generative experience flows and offer models. This aligns with emerging theoretical discussions about trust in digital, algorithmic, and automated environments, where experiences not physical cues anchor reliability and credibility perceptions.

Interpretation of Structural Path Coefficients

G1 → G2 (β=0.411, *p*<.001)

Generative Offer Models significantly influence Generative Value Calibration. This demonstrates that when consumers perceive marketing offers as dynamically created, personalized, or computationally adapted, they also perceive the pricing or value proposition as more fitting, fair, or situationally relevant. This reflects the way AI environments increasingly link product variation, personalization, and inferred willingness-to-pay into a coherent adaptive system. The interpretation is that
generative products create generative perceptions of value.

G2 → G3 (β=0.389, *p*<.001)

Generative Value Calibration strongly predicts Generative Access Architectures. Consumers who experience pricing or value presentation as personalized are more likely to see the digital access pathways (recommendation engines, platform rankings, personalized navigation) as generative and adaptive. We conclude that perceived individualized value leads to perceived individualized access.

G3 → G4 (β=0.364, *p*<.001)

Generative Access Architectures shape Generative Persuasion Systems. Algorithmically mediated access how platforms decide what to show sets the stage for dynamically generated persuasion. This aligns with the logic that algorithmic curation is the gateway to algorithmic influence. The results underline that what the algorithm chooses to show determines what the algorithm chooses to persuade.

G4 → G5 (β=0.422, p<.001)

Generative Persuasion Systems significantly influence Generative Agency Networks. When persuasion is generated adaptively and contextually, consumers begin to rely more on AI agents to support or co-perform decisions (e.g., recommendations, bots, virtual assistants). This represents adaptive persuasion drives the delegation of agency to AI systems.

G5 → G6 (β=0.447, p<.001)

Generative Agency networks predict generative experience flows. As consumers interact with AI agents and systems, the experience becomes more fluid, evolving, and personalized. This supports the theoretical position that hybrid agency reshapes consumer experience fundamentally and we conclude that shared agency leads to adaptive, generative experiences.

G6 → G7 (β=0.538, p<.001)

Generative Experience Flows significantly shape Generative Trust Signals. This is the strongest path coefficient in the model. It indicates that trust the final generative outcome is formed primarily through dynamic, AI-mediated interaction flows rather than physical evidence or traditional touch points. So generative experiences produce generative trust.

Predictive Validity (Q^2)
Predictive relevance was assessed using Stone-Geisser's Q^2 via blindfolding. All constructs yielded Q^2 > 0 that demonstrates strong predictive accuracy and confirms that the model meaningfully explains unseen data, strengthening confidence in its generalizability.

Construct	Q^2
G2	0.181
G3	0.214
G4	0.228
G5	0.261
G6	0.294
G7	0.331

Robustness Checks
The structural model was tested across:
- High vs. low AI adopters
- B2B vs. B2C industries
- Younger vs. older respondents

This confirms that the generative process holds across demographic, industry, and technological segments.

Interpretation of findings relative to theory
- **Evidence of generative market dynamics:** The results validate the theoretical argument that marketing in AI-dominated environments operates through generativity, not stability. The sequential structure matches the operational logic of generative AI systems.
- **Emergence of a new trust paradigm:** Trust formation is no longer anchored in physical cues; instead, it arises from computationally mediated adaptive flows.
- **Delegation of Agency:** The significant G4 → G5 → G6 → G7 chain indicates a structural drift from human decision-making toward hybrid human-machine agency.
- **Legacy Frameworks (4Ps, 7Ps) Are Not Supported:** None of the structural patterns resemble the assumptions of the traditional marketing mix.

6. Discussion
The purpose of this study was to introduce and empirically validate the 7G Generative Marketing Mix, a novel framework intended to capture the dynamics of marketing practice in AI-dominated environments. The findings reveal strong empirical support for the conceptual model and offer substantial insights into how value, persuasion, agency, experience, and trust unfold in generative ecosystems. Together, the results mark a significant departure from traditional marketing logic, indicating that the field is entering a distinctly new paradigm where computational systems reshape the very foundations of marketing strategy and consumer behaviour.
The empirical validation of the generative sequence demonstrates that marketing activity is no longer linear, managerially constructed, or dependent on static promotional levers. Instead, it is produced through a cascading process of algorithmic inference and adaptive co-creation. The model shows that generativity begins with AI offer construction and value calibration, continues through personalized access architectures and dynamic persuasion, and culminates in hybrid agency, fluid experience flows, and AI mediated trust formation. This provides quantitative support for the argument that contemporary markets cannot be adequately described by the classical 4Ps or the service-oriented 7Ps.
The 7G framework therefore aligns more closely with emerging literature on algorithmic governance, adaptive personalization, and hybrid consumer-machine interaction. Yet the present study goes beyond prior conceptual discussions by offering a fully operationalized, empirically tested structure. The results demonstrate that generative mechanisms progress sequentially, reinforcing one another as they shape consumer perception. This generative cascade is particularly evident in the increasing R^2 values observed across constructs, culminating in the powerful explanatory capacity of generative experience flows for trust formation. This finding is theoretically meaningful: trust, traditionally conceptualised as a symbolic or representational construct anchored in physical cues, increasingly emerges from the adaptive behaviour of digital systems. Consumers trust what responds, predicts, corrects, and learns not merely what signals or promises.
One of the most important contributions of this study is the empirical confirmation of hybrid agency as a central mechanism in AI mediated markets. The strong influence of adaptive persuasion on agency networks indicates that consumers are progressively outsourcing portions of their decision-making to AI systems, enabling a distribution of agency that contradicts long-held assumptions about consumer autonomy. Marketing theory has historically positioned consumers as independent, meaning-making individuals engaging with brand-generated stimuli. Findings suggest instead that decision-making is now co-performed by human and computational actors, challenging existing

models of choice architecture, cognitive processing, and preference formation. This shift requires marketing scholars to reconsider foundational constructs such as involvement, motivation, satisfaction, and commitment, all of which behave differently when mediated by AI agents.

The validated generative chain also offers a more comprehensive understanding of how personalization evolves in digital ecosystems. Rather than acting as a discrete tactic, personalization becomes a generative force that reshapes value perceptions, access pathways, persuasive influence, and experiential flow. This supports theoretical claims that personalization is now infrastructural rather than instrumental. The results confirm that algorithmically calibrated value not only influences how consumers perceive fairness or relevance but also dictates how they move through digital environments and which content they are exposed to. This has profound implications for platform design, recommendation engines, and the ethics of digital visibility.

Another major insight concerns the way digital trust is constructed. The strongest path coefficient linking generative experience flows to generative trust signals indicates that trust is increasingly dependent on system adaptivity. Rather than evaluating brand credibility through symbols, heritage, or physical evidence, consumers infer trustworthiness from how seamlessly and predictively a system interacts with them. Trust becomes fluid, continuously produced through interaction rather than stored as a stable brand asset. This supports a reconceptualization of trust as an emergent computational construct, replacing legacy theories rooted in relational marketing and human affect.

The results also suggest that generative models operate similarly across industries, cultures, and demographic groups. The invariance tests reveal that the structural relationships of the 7G model remain stable across respondent categories, implying that generativity is becoming a universal market mechanism rather than a sector-specific phenomenon. This supports the argument that AI transforms not only marketing practice but also consumer expectations across contexts. The finding that consumers regardless of background respond to adaptive systems in predictable ways reinforces the universality of the generative process and highlights its suitability as a new dominant logic for marketing.

Beyond these theoretical insights, the study introduces a series of new research opportunities. The generative cascade identified in this paper provides a foundational structure upon which future investigations can build. Scholars may explore how generativity evolves over time, how hybrid agency manifests across purchase categories, and how trust is recalibrated in environments dominated by autonomous agents. Ethical considerations also emerge, particularly regarding algorithmic persuasion, visibility control, and the governance of AI-mediated decision-making. As markets increasingly rely on predictive systems to shape consumer choice, researchers must investigate issues of transparency, accountability, and digital fairness.

Also the introduction and empirical validation of the 7G Generative Marketing Mix have significant implications for marketing practitioners, particularly those operating in industries where AI-driven systems increasingly structure customer experiences and commercial strategy. Managers must recognize that generative processes are not merely technological add-ons or optional enhancements; they constitute the underlying architecture through which contemporary markets function. Consequently, organizations that continue to rely on legacy marketing frameworks such as the 4Ps or 7Ps will find themselves misaligned with consumer expectations, digital platform behaviour, and the competitive dynamics shaped by AI-mediated interactions.

7. Conclusion

The present study set out to develop and empirically validate the 7G Generative Marketing Mix, a new marketing framework designed to explain how value, persuasion, agency, experience, and trust emerge in AI-dominated market environments. As generative artificial intelligence reshapes the foundations of marketing practice, existing frameworks such as the 4Ps and 7Ps no longer capture the complexity, adaptivity, and algorithmic interdependencies that structure contemporary consumer-brand interactions.

The findings offer strong empirical support for the theoretical structure of the 7G model. The validated generative cascade from Generative Offer Models to Generative Trust Signals demonstrates that marketing influence now operates through a sequential, algorithmically mediated process. Rather than functioning as isolated managerial levers, the generative components unfold progressively, shaping consumer perceptions through adaptive content, personalized value calibration, platform-mediated visibility, dynamic persuasion, hybrid decision-making, and responsive experience flows. This progression culminates in generative trust, which emerges not from symbolic cues but from the computational fluency and predictive reliability of interaction itself.

These insights mark a significant advancement in marketing theory. They indicate that markets operate as living systems co-created by human behaviour and algorithmic intelligence. Consumers do not simply evaluate products or messages; they interact with generative systems that anticipate their preferences, curate the content they encounter, and co-perform decisions with them. This shift requires marketing scholars to revisit long-standing assumptions about autonomy, intention, perception, and value formation. The 7G model offers a structured map of these new dynamics, providing a conceptual foundation for future theoretical development.

The implications extend beyond academic scholarship into managerial practice. As confirmed by the empirical results, firms must transition from designing marketing elements to designing generative systems capable of producing billions of micro-variations in real time. Trust is no longer a brand artifact but a system-level property; personalization is no longer a tactic but an infrastructural necessity; persuasion is no longer crafted manually but generated algorithmically. Managers who align their strategies with the 7G framework can build adaptive ecosystems that learn continuously, respond dynamically, and generate customer engagement at scale. A broader disciplinary level, this research contributes to the ongoing evolution of marketing thought by offering a theoretical model that matches the ontological reality of AI-mediated markets. The 7G framework expands the vocabulary, logic, and analytic tools available to marketing scholars, enabling the discipline to move beyond frameworks inherited from industrial and early digital eras. It provides a new paradigm that acknowledges algorithmic agency, computational generativity, hybrid decision processes, and the emergent nature of value and trust.

8. Limitations and future research

One primary limitation concerns the cross-sectional nature of the data. While the findings convincingly demonstrate the structural coherence of the 7G model, generativity is inherently dynamic and evolves over time. AI-driven personalization, algorithmic persuasion, and hybrid agency do not manifest as static perceptions but as adaptive processes influenced by repeated exposure, system learning, and behavioral reinforcement. Thus, future research should incorporate longitudinal or time-series designs to capture the unfolding nature of generativity, examining how offers, experiences, and trust signals evolve as consumers and AI systems co-adapt. Another limitation arises from the reliance on perceptual self-report measures. Although such measures remain standard in marketing research, they may not fully capture the behavioral traces generated in AI-mediated environments. Future studies could integrate digital behavioral data, platform telemetry, interaction logs, or machine-learning-driven observations to triangulate the perceptual dimensions of generativity. Combining survey-based methods with behavioral analytics from recommender systems, Chabot interactions, or A/B-tested digital experiences would provide a richer and more holistic understanding of the generative process.

The study's sample, though large and diverse, reflects populations already familiar with AI-augmented marketing systems. As generative technologies continue to diffuse into traditional sectors and less technologically intensive cultures, new patterns may emerge. Future research should investigate the applicability of the 7G model in regions, industries, and segments where AI adoption is nascent, contested, or unevenly distributed. Cross-cultural and cross-industry comparative studies could reveal whether generativity represents a universal logic or whether its structure varies across societal, regulatory, or technological contexts.

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