

Reconfiguring marketing communication in the age of AI: a comparative case analysis of global brand transformations

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Abstract

Purpose – This research examines the impact of Artificial Intelligence (AI) on marketing communications strategies and processes, a gap within the empirical knowledge.

Design/methodology/approach – Using a multi-case study methodology based on three leading global companies: a beverage company that uses generative AI, a beauty distributor that uses conversational AI and an athletic apparel company that uses predictive AI, we explore the pervasive impact of AI.

Findings – Our framework reveals three overarching structural transformations: the dissolution of linear time barriers (real-time processing), the intensification of personalization (1:1 predictive analytics) and the offloading of strategic decisions to machines (machine learning). As part of our model development, we propose a new conceptual framework, the Adaptive Engagement Loop (AEL), which re-casts marketing communications as a perpetual, self-evolving process of five stages through AI.

Originality/value – This research serves as a theoretical intervention to transform AI from part of brand storytelling to a distributed brand storyteller, and from communication to collaboration, content to experience and segmentation to identity formation. From a managerial point of view, it provides direction to the responsible use of AI by proposing the setting of creative boundaries, investing in clear data models and user consent mechanisms and fostering cross-functional collaboration.

Keywords Artificial intelligence (AI), Marketing communication, Digital transformation, Adaptive engagement loop (AEL) model, Brand strategy, Digital brand identity, Comparative case study

Paper type Research article

1. Introduction

Artificial Intelligence (AI) is increasingly reshaping the marketing communication landscape, making this area significantly relevant to scholars and practitioners. The shift in the marketing function toward data-driven marketing has empowered marketers to develop personalized

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content at scale, automate customer engagements and perform real-time analysis of consumer behavior using AI tools (Chintalapati & Pandey, 2022; Mariani, Perez-Vega, & Wirtz, 2022; Verma, Sharma, Deb, & Maitra, 2021). Whilst Generative AI (GenAI) continues to develop, the capability of co-creating advertisements, visuals and narratives with them establishes a new standard in creative output and execution (De Bruyn, Viswanathan, Beh, Brock, & Von Wangenheim, 2020; Huang & Rust, 2018; Vidrih & Mayahi, 2023). Additionally, the trend toward incorporating chatbots, personalization engines and programmatic platforms in marketing communication attests the centrality of this capability to customer experience strategies (Hoyer, Kroschke, Schmitt, Kraume, & Shankar, 2020; Jain & Kumar, 2024). Therefore, examining the effect of AI on the communication process is crucial for marketing theory and practice in organizations.

The existing literature provides a rich understanding of the role of AI applications in predicting consumer behavior, automating campaigns and improving efficiency (Mariani *et al.*, 2022; Jain & Kumar, 2024; Kumar, Ashraf, & Nadeem, 2024). Reviews by Marti, Liu, Kour, Bilgihan, and Xu (2024), Chintalapati and Pandey (2022) and Mariani *et al.* (2022) developed theoretical models which pertain to how AI comes into contact with consumers and what are their reactions, while research on AI advertising has focused on the trust, personalization and effectiveness aspects (Chaisatitkul, Luangngamkhum, Noulpum, & Kerdvibulvech, 2024; Huh, Nelson, & Russell, 2023; Ford, Jain, Wadhwani, & Gupta, 2023; Wu & Jing Wen, 2021). The evolving role of AI in marketing over the past two decades has been mapped by Chintalapati and Pandey (2022), Kumar *et al.* (2022), Mariani *et al.* (2022) and Verma *et al.* (2021), though there remain concerns related to ethical governance, human–AI cooperation and trust dynamics (Liao & Sundar, 2022; Hermann & Puntoni, 2025; Kumar & Suthar, 2024; Vidrih & Mayahi, 2023). Recent GenAI research demonstrates design novelty in content and process, although mainly conceptual, with some adopting a survey instrument (Huang & Rust, 2018, 2021). Though there are very few empirical, comparative case-based studies researching how firms operationalize AI in marketing communication, and how they become concretely transformed.

This study seeks to provide insight into the impact of AI on the transformation of marketing communication, particularly with respect to capabilities, processes and governance across AI-enabled touchpoints. To do so, we employed a qualitative case study methodology to (1) follow the development of the AI-enabled marketing communication process, (2) establish the area of marketing communication (i.e. advertising production and consumer engagement management), that has been most impacted by AI, and the nature of the AI (generative, conversational and predictive) that contributed to this effect, and (3) outline the organizational boundary conditions (e.g. data protection/access, organizational governance capacity and platform dependency) that have shaped the successful implementation of AI for marketing communications. Our empirical focus on three large, digitally developed B2C companies and the examination of AI-enabled touchpoints rather than the complete scope of integrated marketing communications limits our ability to generalize findings broadly across other forms of marketing communications. Therefore, our contribution is best seen as an analytical generalization that companies are redefining their structures through the lens of AI, rather than testing the effects of consumer responses through all modes of interaction (Eisenhardt & Graebner, 2007; Yin, 2018).

By linking implementation procedures to communication effects, our work yields theoretical and practical contributions. In terms of theory, it contributes to the understanding of the technology–organization–environment framework by disentangling the internal communication process and the human–AI collaboration process. We offer a process model that ties AI affordance to changes in communication, people and output. From a practical perspective, the case studies' results advise managers how to responsibly and productively employ AI in the communication role, and contribute to articulation traps like AI-washing, algorithm aversion and trust in communication (Al Haddi, 2024; Sundar and Lee, 2022; Xie, Yu, Zhang, & Chen, 2022; Yalcin, Lim, Puntoni, & van Osselaer, 2022). As we wade through best practices and considerations of ethics, we're assisting companies in making the most of

the creative and efficiency potential inherent in AI while still being mindful of authenticity and trust – ones that will be top of mind for CMOs guiding AI transformational changes.

2. Literature review

2.1 Role of AI in marketing

There is a growing interest in AI in the contemporary marketing literature that has started to question the role of AI in customer engagement (Lemon & Verhoef, 2016), dynamic personalization (Wedel & Kannan, 2016) and marketing automation (Davenport, Guha, Grewal, & Bressgott, 2020). However, in most of the prior research, AI has been imagined predominantly as an operational technology, not as a constitutive system or a process of meaning-making in the context of brands and marketing communication. The brand co-creation (Ind & Coates, 2013), post-digital branding (Hackley & Rungpaka, 2020) and algorithmic consumer culture (Zuboff, 2023) theories indicate that AI brings different logics of authorship, discourse and interaction. This research adds to this emerging literature by offering empirical evidence from pioneering firms that have implemented different types of AI – generative, conversational and predictive – and exploring their marketing implications.

Recent research has recognized the role of AI co-creation of customer experience (CX), particularly in high-contact digital touchpoints (Hollebeek, Menidjel, Sarstedt, Jansson, & Urbanavicius, 2024; Huang & Rust, 2021). When AI systems are actors in the customer journey, they may also influence brand tone, responsiveness and even relational meaning (Grewal, Guha, Schweiger, Ludwig, & Wetzels, 2022; Rana, Gaur, Singh, Awan, & Rasheed, 2022). However, the existing body of literature typically simplifies the application of AI from its real-world nature, treating it either as a homogeneous capability or as a context-independent phenomenon (Arora, Bali, Aggarwal, Mangain, & Sharma, 2025). We know little about how distinct forms of AI – like large language models (LLMs), computer vision systems, quantum computing or reinforcement learning agents – generate specific communicative affordances and constraints in marketing teams and between brands and consumers.

The structural changes necessary to support AI-enabled conversations are also not given the attention they deserve. Despite being well theoretically grounded in dynamic capability theory (Teece, Pisano, & Shuen, 1997; Eisenhardt & Martin, 2000) and marketing ambidexterity frameworks (e.g. Cao, Sarkar, Ramesh, Mohan, & Park, 2024; Mishra, Bharti, Tiwari, & Pfajfar, 2024), we lack empirical insights into how firms re-arrange intrafirm processes, roles and governance in response to the integration of AI in brand message design. Increasing evidence shows that AI not only boosts speed or efficiency, but it also pushes traditional role boundaries, especially those of a creative and communicative nature (Mariani *et al.*, 2022; Davenport *et al.*, 2020). Nonetheless, we know relatively little about the conflicts and convergences that result from the collaboration of humans and AI in constructing brand stories.

Ethical and persuasive aspects of AI-mediated communication have also been relatively less studied and deserve finer attention. With brands delegating more communicative responsibilities to AI, concerns regarding brand trust, transparency and fear of algorithms abound (Liao & Sundar, 2022; Yalcin *et al.*, 2022). It is also known that consumers are sensitive to non-human cues of authorship, specifically when faced with emotional or cultural touchpoint content (Paschen, Pitt, & Kietzmann, 2020). But there is no strong theoretical framework to assess how trust and authenticity are being handled when AI is co-creating or is delivering brand content. This research gap is particularly important given the wide-scale adoption of generative AI in creative marketing disciplines.

The existing literature makes clear that AI is revolutionizing marketing communication with hyper-personalization (Rust, 2020), generative content creation (Davenport *et al.*, 2020) and autonomous journey orchestration (Lemon & Verhoef, 2016; Malthouse & Copulsky, 2023). Although research shows that AI can help optimize individual touchpoints such as programmatic ad targeting (Goldfarb & Tucker, 2011) or conversational agents (Grewal *et al.*,

2022), there remain gaps in understanding how firms combine these capabilities into coherent communication strategies. Also conspicuously missing are empirically tested models that connect the creative possibilities of generative AI (e.g. ChatGPT-generated campaign varieties) to organizational-level customer journey management (Huang & Rust, 2021).

Overall, while the marketing discipline has made progress in the acknowledgement of AI's strategic potential, more insights are needed to comprehensively understand the communication-specific, organizational and ethical ramifications of AI in specific use contexts. This study aims to fill these gaps by exploring how three multinational companies have used various types of AI in marketing communication, the types of transformation they experienced and the kind of impact they perceive on brand meaning, brand governance and on stakeholder trust.

2.2 Marketing communication frameworks and AI

Classic marketing communication theory has been rooted in effects-based and funnel-oriented models: AIDA, The Hierarchy of Effects, as well as derivative planning frameworks such as RACE (see Table 1). These models view communication as a progression from exposure to cognition, affect and ultimately behavior and provide managers with a parsimonious logic for campaign planning and evaluation. Despite the continued influence of these frameworks, they were created from a context of human-authored, episodic messaging campaigns and stable media environments, which is exactly the opposite of AI-driven communication systems.

At the same time, the hierarchy tradition is not monolithic. There are several alternative theories that have challenged the assumption of a universal cognition–affect–behavior sequence. These include reinforcement theory, affective primacy theory and low-attention learning theory. The Ehrenberg's (1974) Awareness–Trial–Reinforcement (ATR) model states that advertising maintains salience and reinforces prior experience of products and services to the consumer. This theory supports the view that algorithmic optimization for reminder advertising and recommender systems is effective in sustaining salience (Ehrenberg, 2000). Van Raaij's (1989) Primary Affective Reaction (PAR) model also emphasizes the idea that the rapid affective appraisal of an advertisement can occur before any form of conscious cognition of the advertisement. As algorithms personalize advertisements to the individual and optimize them for micro-responses in millisecond time frames, this theory becomes increasingly plausible. Heath's (2000) low-attention processing perspective also suggests that learning about brands can occur while consuming very little or no conscious attention, and this occurs most frequently through emotional cues (Heath & Nairn, 2005). Smith and Swinyard's integrated information response model provides a complementary theory of how message and source cues influence belief strength and attitude formation based on levels of involvement. Given the propensity of consumers to make assumptions regarding meaning from AI-generated or AI-disclosed content, this theory will be especially important in understanding how consumers process the content provided by AI systems (Smith & Swinyard, 1982; Grigsby, Michelsen, & Zamudio, 2025).

These models together illustrate how marketing communication effects can be heterogeneous, dependent upon specific contexts and often linear before the advent of AI. While current models provide insight into how consumers react to marketing communication stimuli, the models do not provide any insights as to how communication processes are changed when some of the tasks of sensing, developing content, identifying target audiences and refining the strategy are partially automated by machines. The generative capabilities of AI will allow for an increase in the scope and variety of creative work, while chatbots have merged the traditional boundaries between advertising and customer service functions, and predictive analytics tools are automating the sequencing, prioritizing and allocating budgets among different communication channels (Ma & Sun, 2020; Grewal et al., 2022). All of these new technologies are changing what is considered to be the marketing communication process of a company. In addition, many of the traditional theories assume that companies dictate their

Table 1. Theoretical contributions, limitations and AI-driven evolution of marketing communication models

Model	Theoretical contribution	Critical limitations	AI disruption impact
Shannon and Weaver (1949), Schramm (1954)	Linear transmission model establishing core elements (sender–message–channel–receiver) and introducing feedback/noise; foundation for later marketing communication models	Linear structure ignores psychosocial context; assumes unidirectional control, stable channels and limited interactivity; weak treatment of meaning co-construction, social context and nonconscious processing	AI not only enables real-time, algorithmically optimized feedback loops across channels (e.g. chatbot response tracking) but also introduces machine agency (LLMs and recommenders) and opaque mediation that the model does not theorize
AIDA (Lewis, 1899)	Pragmatic sales funnel (Attention → Interest → Desire → Action); useful for planning persuasive sequences and performance metrics	Overly linear and sales-centric; under-specifies post-purchase learning, social influence, brand equity and multi-touch journeys	AI compresses or reorders stages via predictive intent scoring, dynamic creative and agentic journeys (e.g. dynamic product recommendations); AIDA lacks mechanisms for adaptive orchestration and governance
Hierarchy of effects (Lavidge & Steiner, 1961)	Links attitudinal stages (Cognition → Affect → Conation) to long-term brand-building and measurement of intermediate effects	Assumes stable attitude formation and slow-moving measurement; limited ability to model implicit affect, habit and real-time feedback	AI shifts measurement from surveys to behavioral + sentiment signals and enables continuous optimization; the model lacks constructs for algorithmic learning and privacy/ethics constraints
RACE (Chaffey & Ellis-Chadwick, 2019)	Closed-loop digital planning optimization (Reach → Act → Convert → Engage)	Tactical focus, lacks brand-building mechanism and strategy integration; risks channel silos; limited guidance on governance/ethics	AI strengthens targeting, personalization, and experimentation at scale but also risks filter bubbles and manipulation; RACE needs explicit guardrails for responsible automation
Customer-Based Brand Equity - CBBE (Keller, 1993, 2001)	Explains how brand knowledge structures into building brand equity: Brand identity → meaning → responses → relationships (resonance); bridges communications to long-term brand assets	Resource-intensive; requires consistent cross-channel alignment; less explicit on platform dynamics, co-creation and fluid identity signals; assumes relative stability of brand meaning and firm stewardship	AI multiplies touchpoints and personalized brand expressions, challenging coherence; requires integrating machine-mediated authorship, synthetic content provenance and trust management
Awareness–Trial–Reinforcement (ATR) (Ehrenberg, 1974)	Advertising primarily builds salience and reinforces buying habits; emphasizes penetration, availability and repetition over persuasion, especially for frequently bought goods	Under-specifies strong persuasion contexts (high-involvement, high-risk categories) and overlooks cultural/identity meaning-making	AI can automate frequency/reach optimization and personalize reinforcement triggers, but ATR does not address hyper-personalized creative variants, attribution complexity or algorithmic bias effects

(continued)

Table 1. Continued

Model	Theoretical contribution	Critical limitations	AI disruption impact
Primary affective reaction model (Van Raaij, 1989)	Proposes an initial, often subconscious affective “gatekeeper” response during scanning that determines whether deeper processing follows; integrates emotion into early-stage attention	Conceptual and difficult to operationalize; limited treatment of sustained engagement, interactive media and downstream learning across touchpoints	AI-driven attention optimization (feeds, recommender systems) amplifies pre-attentive affective filtering; the model lacks an account of algorithmic curation and transparency effects on trust
Low-attention processing model (Heath, 2000)	Advertising can build implicit memory and emotional associations under low attention; brand effects accrue without active recall	Debates about measurement and boundary conditions; less suited to interactive, dialogic environments where consumers co-produce content	AI increases low-attention exposures (always-on, micro-content) and can personalize emotional cues; model needs extension to agent interfaces (chatbots/assistants) and synthetic media disclosure
Integrated information response model (Smith & Swinyard, 1982)	Integrates hierarchy-of-effects and low-involvement learning: advertising forms tentative beliefs that are strengthened/validated through trial and experience; emphasizes belief strength and sequencing	Assumes relatively discrete “ad → experience” sequencing; limited account of network effects, social proof and continuous algorithmic experimentation	AI blurs ad/experience boundaries (conversational commerce, generative service encounters) and continuously tests messages; model needs constructs for real-time experimentation, personalization externalities and governance

marketing communications through a predetermined, standard set of marketing communications routines. However, these assumptions rarely occur today.

We observe that researchers studying AI in marketing have recently started to acknowledge these tensions. Their empirical evidence shows that AI could make communication more personal, speed up experimentation and make decisions better. However, it also raises concerns about a lack of transparency, bias, authenticity and consumer trust ([Puntoni, Reczek, Giesler, & Botti, 2021](#); [Hermann & Puntoni, 2025](#)). A lot of this work is still focused on tools like chatbots, recommendation engines and generative content, instead of providing a unified process theory of AI-enabled communication. As a result, AI is often seen as a tool shaping the traditional marketing communication funnel stages rather than a tool that completely reconfigures the way the marketing communication process unfolds, from creative workflows to feedback loops and governance structures.

The gap identified above is particularly relevant and significant, since AI-supported communication is becoming increasingly continuous rather than episodic, adaptable rather than scripted and mediated by platforms (as opposed to firms). The outcomes of communication emerge from the interactions of human communicators who are involved as strategy and creative thinkers, from machine learning models, platform algorithms, training data and from consumer responses. Therefore, it is not just whether AI can increase the effectiveness of an organization’s communication efforts that needs to be theorized, but also how organizations reconfigure their marketing communications so that execution and learning can happen in near-real-time and at scale. In summary, existing frameworks of marketing communications have provided valuable insights to help explain consumer response processes. However, they have been less effective in helping to understand how organizations restructure their communication work when sensing, creating content,

providing personalized information and optimizing communication are increasingly supported by AI systems. As a result, there exists a need for a process-oriented framework that explores AI-enabled marketing communications. We will do this inductively by conducting comparative analyses of several organizations that have successfully implemented AI-supported marketing communications in the sections below.

3. Methodology

3.1 Research design

A comparative qualitative research design based on multiple case study methodology was used in this research to investigate how AI refashions marketing communication (Yin, 2018; Eisenhardt, 1989). Case studies are particularly suitable for investigating contemporary phenomena in real-world organizational contexts where the boundaries between the phenomenon and context are blurred (Yin, 2018). Such a design consequently allows for an in-depth exploration of emerging strategies, supporting mechanisms and the dynamic stakeholder interaction in the face of AI-driven transformation. Given the novelty and complexity of AI applications in marketing communication, a case-based approach allows for theory elaboration and contextualized insight (Beverland & Lindgreen, 2010).

This research adopts a multi-case design using replication logic to understand convergences as well as divergences across organizations (Eisenhardt & Graebner, 2007). Each case is treated both as an individual analytical unit and as part of a more general cross-case understanding of the implementation trajectory and communication outcomes. A processual approach was used to investigate how AI technologies become part of communication functions, how work practices change and how human–AI interaction influences strategic decision-making (Langley, 1999).

3.2 Case selection

Purposeful sampling was used to identify information-rich cases that reflect meaningful variation in AI application and marketing strategy. Three firms were selected based on the following criteria:

- (1) demonstrable and active use of advanced AI technologies in marketing communication;
- (2) recognized leadership within their respective industries; and
- (3) diversity in the sectoral context and AI typology to allow for comparative analysis.

The selected cases are (see a longer case description in [Appendix 1](#)):

- (1) Case A: A multinational beverage corporation employing generative AI for automated content creation, campaign ideation and real-time brand storytelling across digital channels.
- (2) Case B: A global beauty retailer using conversational AI (chatbots) and computer vision (for skin analysis) to enhance customer engagement and integrate service delivery across online and offline touchpoints.
- (3) Case C: A high-growth athletic apparel innovator deploying predictive analytics and recommendation engines to deliver hyper-personalized brand communication and optimize real-time customer interaction.

Anonymity was preserved to encourage disclosure and ensure organizational confidentiality. Our research focuses empirically on the communication touchpoints that are enabled by AI (i.e. generative production of work, conversational service interfaces, predictive personalization etc.). Therefore, we do not attempt to describe all of the integrated

marketing communication (IMC) activity across all media channels. Instead, we use the case studies to explain reconfiguration mechanisms for IMC under AI in those types of organizations that are the most likely to be in a state of digital maturity and have a brand-led B2C business model.

3.3 Data collection and analysis

Data were collected from multiple sources to enhance construct validity through triangulation (Gioia, Corley, & Hamilton, 2013; Yin, 2018). Sources included:

- (1) Main sources: internal strategy presentations, AI implementation roadmaps, training manuals and communication workflow documents.
- (2) Publicly available materials: press releases, corporate reports, investor briefings and campaign materials for the period 2021–2024.
- (3) Industry analyses: third-party reports from consultancies (e.g. McKinsey and Deloitte) and AI vendors involved in implementation.
- (4) Expert interviews: semi-structured interviews with 9 key informants (3 per organization), including marketing managers, data scientists and communication leads. Interviews lasted between 60 and 90 minutes and were recorded, transcribed and coded.

The interview guide was structured similarly across all case studies as follows: (1) the timeline and problem that led an organization to adopt AI; (2) how it affected its processes for developing content creatively, executing media plans and measuring performance; (3) the way human and AI resources divided responsibilities including which roles, what review processes were employed and which escalation mechanisms were put in place; (4) the data sources, privacy and consent practices that were utilized to personalize user experiences; and (5) potential risks associated with adopting AI (including bias, hallucinations, brand voice drift and regulatory risk). To avoid the risk of informants providing post-hoc rationales for their decisions, they were asked to detail two recent campaigns or customer journeys that had been executed using AI and detail each tool used and the key decision points where either an AI tool or a marketer made a decision, which allowed for both process tracing and comparative analysis across cases (Langley, 1999). A case protocol guided data collection to ensure consistency across sites, and an audit trail was maintained to track sources and researcher decisions.

The analysis focused on three leading global brands, each representing distinct AI modalities (generative, conversational and predictive) and operating across different sectors (beverage, beauty and apparel). We conducted thematic coding (Braun & Clarke, 2006) and cross-case synthesis (Miles, Huberman, & Saldaña, 2014) to identify patterns in AI implementation, strategic adaptation and stakeholder responses.

Thematic coding was conducted in two phases. First, open coding was applied to extract salient concepts related to AI adoption, organizational processes and marketing strategy adaptation. Second, axial coding was used to categorize themes around three analytical anchors: implementation dynamics, strategic adaptation with impact on marketing communication processes and stakeholder response, including implementation challenges. This process enabled both within-case depth and cross-case comparability (Gioia *et al.*, 2013). NVivo software supported the data organization and pattern identification across transcripts, internal documents and observational field notes.

In order to increase the reliability of our research design, we developed a structured codebook that was revised in an iterative process by comparing the patterns across and within cases. A second coder examined a portion of the data independently using the standard codebook for qualitative analysis, and if there were any discrepancies, they were resolved through discussion and redefinition of codes as per the recommended best practices for

qualitative reliability (Gioia *et al.*, 2013). In addition to the methods described above, we evaluated theoretical saturation at the mechanism level (e.g. “guardrails,” “real-time orchestration” and “automating prioritization”) as opposed to the surface theme level. Theoretical saturation was concluded when evidence was added that repeatedly illustrated already determined mechanisms without identifying new properties or boundary conditions (Eisenhardt, 1989; Langley, 1999). Finally, we documented a transparent line of evidence from original text materials (raw data; i.e. transcripts and other documents), to first-order concepts, second-order themes and then to aggregate dimensions to ensure that the empirical basis of the model was supported (Yin, 2018).

Cross-case synthesis allowed us to identify both convergent and divergent trends about the adoption of AI technologies in marketing practices. This form of analysis was not just comparative in nature but also cumulative – enabling us to generate new theoretical understandings of the solidifying role of AI as a mediating mechanism within brand-communication processes. Consistent with Eisenhardt (1989) case analysis guidelines, case-level insights were progressively compared and contrasted to develop generalizable themes and maintain depth of interpretation. In addition, within-case analysis produced narrative depth on the trajectory of AI implementation in the firms and its influence on marketing communication practices. This dual strategy – within-case depth and cross-case breadth – allowed for the discovery of recurring themes, unique contingencies and emergent causal mechanisms across cases (Eisenhardt & Graebner, 2007). Through ongoing engagement with data and existing literature, it allowed the development of theory and analytical generalization to ensure empirical validity and theoretical relevance.

Multiple strategies were used to enhance research rigor (Lincoln & Guba, 1985):

- (1) Credibility: triangulation of sources, member checks with interviewees and expert review of findings ensured interpretive accuracy.
- (2) Transferability: rich contextual descriptions allow readers to assess relevance across organizational settings.
- (3) Dependability and confirmability: a case protocol, coding reliability checks and reflexive memos ensured analytic transparency and minimized researcher bias.
- (4) Ethics: all case study participants provided consent for anonymized use of their interviews, with an opt-out option in the event of a potential disclosure, while identifiable details (e.g. company size and exact revenue) were generalized to prevent deductive disclosure.

4. Case study findings and thematic insights

4.1 Overview of case contexts and brand characteristics

4.1.1 Case A: multinational beverage corporation. A world-leading provider of beverages, for more than a century renowned for emotive branding and mass advertising, embarked on a journey of transformation by infusing creative AI into its commercial communication. Hitherto relying on ubiquitous messaging to cut through high-profile, landmarked campaigns, the company had adapted to make room for AI when it came to creative production. Working with leading AI companies and consultancies, the company used large language models (LLMs) and image generation systems to enable scalable content creation, localized storytelling and consumer co-creation. It was a move that was inspired not only to stay culturally relevant but also to increase content output for the worldwide market. Adopting AI empowered the brand to interact with its consumers, not only as passive message receivers but as co-writers of the brand story. Although the firm encountered skepticism within the creative teams and concerns about diluting the brand with generic content outputs, these challenges were addressed through clearly defined protocols for human–AI collaborations, such as

human-led curation of AI tracks and establishing internal ethical guidelines. The case provides an example of a wider theoretical shift from centralized message control toward distributed, algorithmically mediated brand authorship and opens the door to a discussion of tensions and opportunities present in post-digital marketing ecospheres.

4.1.2 Case B: global beauty retailer. A top omnichannel beauty retailer known for its innovation in customer experience and personalized marketing has revolutionized how it communicates with customers since introducing conversational AI technology. Traditionally, it has been a curator of expert beauty tips and luxury products, while it has recently transitioned toward an experience-centric model by integrating chatbot systems, augmented reality (AR) interfaces, and facial recognition tools into its customer-facing platforms. They enable users to virtually try on products in real-time, receive personalized product recommendations and engage with responsive customer service agents, and in doing so, turn classic transactional touchpoints into immersive micro-engagements. The retailer's use of AI was rooted in a customer-focused approach and emphasized utility, empowerment and easy integration with services. But the company's push into AI-driven personalization also raised other ethical and operational issues, particularly in the areas of privacy and bias in the AI that drives the facial recognition feature. These were alleviated by adopting open data governance practices and retraining AI models on more comprehensive datasets. The process of strategically repositioning AI throughout its communication touchpoints has not only enabled the company to increase the perceived quality of service and brand intimacy but also to develop tenable strategic and theoretical justification for the roles that AI can play in emotional engagement, operational economy and identity-based marketing.

4.1.3 Case C: sportswear and footwear pioneer. A fitness lifestyle brand known around the world for performance, innovation and standing at the intersection of cultures has reimaged marketing communications and customer engagement using predictive AI technology. Leveraging a direct-to-consumer (DTC) model, the company engaged sophisticated data analytics tools and machine learning models to power hyper-personal messaging, drive product recommendations that were optimized based on individual preferences and deliver real-time nudges via custom mobile apps. This shift is part of a larger strategic repositioning, one driven by platform-led ecosystem creation (as opposed to product-focused storytelling), in which marketing communication is more and more personalized and situationally relevant. The goal of their AI strategy is to capture and analyze user behavior at all times in order to drive adaptive content flows and dynamic customer segmentation. The logic behind being able to drive exemplary consumer engagement and brand loyalty is sound, but the approach brought raised a number of concerns, not least with the risk of over-personalization (cognitive fatigue), as well as tensions with long-standing restrictions from traditional retail partners that see data exclusivity and eternal brand access at a premium. Algorithms have been diversified and selective agreements to share data have been reached to address these concerns. This is an example of AI and lifestyle branding coming together, where predictive technologies allow marketing communication to stretch into a consumer's daily life, strengthening brand salience and loyalty through the lens of the digitized consumer journey.

4.2 Evolution of AI implementation across the three global brand cases

A precise timeline of the AI implementations, drawing from significant internal milestones associated with each case and important global AI innovations, demonstrates to be converging, as shown in [Table 2](#). The timeline ranges from 2017 to 2025 and highlights major events and milestones with respect to technology and communication strategies and marketing communication transformation at these firms. We can see that the beverage brand (case A) transformed along with the creativity level of AI. Their milestones were not so far from the arrival of generative multimodal AI (DALL·E, GPT-4). A multinational beauty retailer (case B) harmonized with the development of conversational and AR AI, with real business impacts being sped up by digital engagement as a result of COVID-19. Athletic apparel brand (case C)

Table 2. Marketing transformation through AI timeline across the three global brand cases

Year	Global AI innovations	A. Beverage brand	B. Beauty retailer	C. Athletic apparel brand
2017	Transformer architecture is introduced (Vaswani et al., 2017) – foundational for NLP breakthroughs	–	–	AI is considered for a personalization pilot in a mobile app
2018	BERT by Google revolutionizes natural language understanding	–	Initial exploration of chatbot interfaces	Initial use of AI for app recommendations
2019	GPT-2 is released (OpenAI), the first commercial-level text generation models	–	Beta-testing conversational commerce with NLP engines	AI-enhanced segmentation models are tested for e-commerce
2020	AI in image generation (GANs) becomes widely usable; global shift to digital post-COVID	Brand starts exploring generative visuals for culture-driven content	COVID-19 pandemic drives chatbot adoption for online skin consultations	Fitness behavior data fuels hyper-personalization project
2021	DALL·E and CLIP emerge; diffusion models advance multimodal content	Pilot with DALL·E-like tools for creative marketing campaigns	Full-scale launch of AI chatbot across major markets	Predictive offer engine integrated into mobile notifications
2022	ChatGPT (GPT-3.5) launches; consumer-level conversational AI goes mainstream	Global user prompt marketing campaign with AI-generated visuals	Conversational AI handles more than 40% of digital queries	Predictive personalization drives over 30% of push interactions
2023	GPT-4 and Midjourney improve creative and reasoning abilities; GenAI goes viral	Expanded use of GenAI for seasonal marketing campaigns and co-creation contests emerges	Integration of GenAI into the AR try-on and makeup tutorial system	Launch of real-time AI content adaptation platform
2024	Diffusion models for video, multimodal GPTs and real-time personalization APIs are mature	An internal AI lab is created to support multi-brand activation	An ethical AI framework is launched; facial bias detection algorithms are developed	An AI-led marketing campaign is tested and optimized in less than a 24-hour cycle
2025	Agentic AI and multimodal consumer interfaces (visual, gesture and speech) mature	Brand personality is modeled in LLM for dynamic creative briefs	Conversational agents are trained on brand tone for 1:1 AI sales	Real-time “adaptive storytelling” engine is going live in all DTC apps

Note(s): NLP = natural language processing, GAN = generative adversarial network, LLM = large language model, DTC = direct-to-consumer, AR = augmented reality, GenAI = generative artificial intelligence, API = application programming interface

was an early adopter of predictive AI, whose strategy was always heavily influenced by mobility behavior and a direct-to-consumer approach and real-time optimization.

4.3 Comparative analysis of AI's impact on marketing communication

The deployment of generative AI in the marketing strategy of a *multinational beverage corporation* has revealed significant good and bad effects there. On the bright side, all of

these AI-driven tools made consumer interaction that much more engaging and effective with interactive and user-generated content campaigns, which increased observable engagement behaviors (e.g. content submissions, interaction depth and sharing of campaign artifacts) and strengthened the perceived relevance of the brand's storytelling among digitally active segments. What's more, the new system offered a way to roll out thousands of creative variants quickly and affordably, speeding up the content creation process and giving the drink brand the agility it needed to serve up content that was on trend. More importantly, AI allowed a global-local nexus by personalizing the core brand message per local cultural context, enhancing relevance across international markets. The reaction was generally very favorable among consumers, especially younger consumers, because of the novelty and co-creation aspect. Marketing agencies had a mixed reaction, as some creatives feared their skills would be replaced by AI. Investors were optimistic about the AI application in beverage marketing communication mainly because of cost-effectiveness and innovative image. But those benefits came with serious downsides. Foremost were questions about the authenticity, as heavy reliance on AI-generated content sparked debate over the diminishing role of human creativity and emotional depth in brand storytelling. In addition, leveraging generative AI created legal uncertainties regarding intellectual property and the potential for bias to become coded in marketing messages. These are the tensions that bring to the fore the importance of a balanced and ethically guided approach to the use of AI in brand communication strategies.

A *global beauty retailer's* use of AI is associated with improvements in customer-journey performance metrics (e.g. reduced service latency, higher assisted-conversion rates and increased product discovery within AI-mediated journeys), while also introducing heightened governance demands due to biometric and sensitive preference data. On the upside, AI-enabled programs allowed for hyper-personalized communication, with emails and app interfaces changing dynamically according to individual user preferences instantly. This customization led to more product discovery and removed friction from the customer journey, which in turn led to higher conversion rates – chatbot-enabled interactions clocked out 11% higher than static web pages, for example. Younger generations like Generation Z and Millennials embraced these changes in AI functionality particularly well, loving the idea of interactive and on-demand engagement. Employees were also responding favorably, learning and gaining capabilities such as customer relationship management and analytics tools. But the retailer's growing dependence on AI caused problems. A number of users reported that responses from chatbots lacked warmth and tone, suggesting that there is a trade-off between efficiency and emotional connection. More fundamentally, the reliance on facial and skin tone data for personalization is intertwined with major privacy concerns around the ethical collection and treatment of biometric data. These are the issues that led privacy advocates to draw attention to the importance of accountable and transparent data governance, with AI increasingly infiltrating beauty retailing.

The strategic adoption of AI by an *athletic apparel and footwear brand* has produced a range of performance and perceptual outcomes, reflecting both the promise and complexity of data-driven personalization in the (apparel) retail sector. On the positive side, AI-driven personalization drove impressive customer retention, as consumers who engaged with personalized content were more active and more often buying within the brand's digital ecosystem. The ability to forecast demand also resulted in well-managed inventory, thereby avoiding overstock and understock situations across sales channels. These advancements assisted brand loyalty, as people felt like they were heard and cared for through personalized marketing communication – notably in the fitness-focused consumer segments. This strategy of specialization had, however, its drawbacks. Excessive dependence on algorithmic forecasts sometimes resulted in lost opportunities, especially in minority or new customer segments. Furthermore, the narrowing effect of over-personalization – commonly referred to as a “filter bubble” – limited consumer exposure to the brand's other product categories. The reaction from stakeholders was mixed: consumers largely enjoyed the new experience, but many retail

partners disliked the brand’s deepening focus on the direct-to-consumer channel, which contradicted traditional wholesale relationships. Still, investors cheered, seeing the financial upside of higher margins and more detailed customer insight. This dual result underscores the need for AI strategies that optimize the trade-off between personalization and inclusion, and innovation and ecosystem equity. See [Table 3](#) for a summary.

Table 3. Cross-case comparison of AI impact in marketing communication

<i>Aspect/factor</i>	A. Beverage brand	B. Beauty retailer	C. Athletic apparel brand
<i>Marketing communication focus</i>	Generative AI, storytelling, personalization	Conversational AI, chatbot-driven consumer experience	Predictive messaging, app-based personalization
<i>Personalization depth</i>	Medium: visual, language, thematic	High: skin tone, preferences	Very high: interests, fitness, behavior
<i>Marketing strategy</i>	Creative co-creation, global to local content	Data-driven consumer experience and conversion focus	Hyper-personalization, lifetime value
<i>Brand identity and strategy</i>	Heritage + innovation (AI enhances brand legacy)	Empowerment + utility (AI as a service tool)	Performance + innovation (AI reflects brand’s tech-forward edge)
<i>Brand positioning evolution</i>	From mass storytelling to dynamic co-creation	From expert brand to personal beauty guide	From gear supplier to digital coach
<i>Communication process</i>	AI-enabled content production → human curation → multichannel delivery	Customer query → chatbot interaction → personalized consumer journey	Behavior tracking → predictive analytics → dynamic content delivery
<i>Consumer role in communication</i>	Co-creator and content generator	Participant in a guided dialogue	Tracked user and feedback provider
<i>Consumer engagement</i>	AI-enabled user participation in marketing campaigns	AI-driven consumer interaction evolution through 1:1 dialogue through chatbots, virtual try-ons	AI-driven training, coaching, product curation
<i>Organizational change</i>	Creative retraining, AI onboarding	CRM and frontline staff AI integration	Advanced data engineering teams deployed
<i>Speed to the market</i>	Increased dramatically via AI	Improved with an AI-assisted consumer experience	Real-time targeting and rapid content refresh
<i>Human-AI balance</i>	Human curation of AI content	Human handoff for chatbot interactions	AI handles analysis, humans refine strategy
<i>Key challenge</i>	Risk of brand dilution via generic AI content	Privacy and bias in facial recognition	Over-personalization and channel conflict
<i>Solution strategy</i>	Human-AI co-creation, content validation pipelines	Inclusive data training, human bot hybrid consumer experience	Diverse algorithms, customer data platform investment, retail diplomacy
<i>Outcome</i>	Scalable creative content with global appeal	Frictionless and fun product discovery	Boosted loyalty, app retention, targeted promotions
<i>Long-term strategic value</i>	Brand differentiation, cultural resonance	Customer intimacy, loyalty loop	Strategic resilience via owned ecosystem
<i>Practical implication</i>	Shift to platform-brand thinking: generative brand assets	Integration of service and communication into the consumer experience	Behavior-based brand-building and real-time marketing

4.4 Transforming the marketing communication process

Across all cases, AI reshaped marketing communications from one-way communication to a responsive, interactive and co-constructed experience. Generative AI allowed customers to join in message creation, conversational AI wove marketing into the service delivery, and predictive AI turned behaviors into triggers for communication. To address this impact of AI in the marketing communication process, we present an original and dynamic model for AI-enabled marketing communication – the Adaptive Engagement Loop (AEL) model (see Figure 1).

The AEL was developed through an iterative abductive process between cross-case identified marketing communications reconfigurations and existing marketing communications theories. In terms of empirics, we identified three repeating marketing communications reconfiguration mechanisms: (1) real-time sensing and orchestration (i.e. ongoing and rapid feedback incorporation and version deployment); (2) personalization at scale (i.e. automated tailoring of content, product/service recommendations and interaction flow); and (3) governance supported decision-making by machines (i.e. algorithmic prioritizing of the next best action and budget allocation). These mechanisms were then transformed into a 5-stage process of AI-enabled marketing communications (data, engagement, conversion decisioning, relationship deepening and governance), as opposed to a sequential effect on consumers. To further support transparency, Table 4 links each stage of the AEL to its empirical indicators and provides representative evidence for each of the three case studies, creating a chain of evidence from the practice observations to the proposed theoretical framework (Yin, 2018; Gioia et al., 2013).

The AEL presents an integrative model that combines the strengths of established frameworks (i.e. the digital funnel efficiency of RACE, the action-oriented sequencing of AIDA and the brand equity focus of the Hierarchy of Effects) and together compensates for flaws associated with AI-based dynamism. At its essence, the AEL model reframes marketing communications as a continuous, self-learning process built on five integrated stages: (1) Data-enabled reach and salience, (2) Dynamic engagement, (3) Predictive conversion, (4) Co-creation-enabled relationship deepening and (5) Ethical optimization. Unlike static models, the AEL system is a closed-loop process, where AI systematically improves each stage

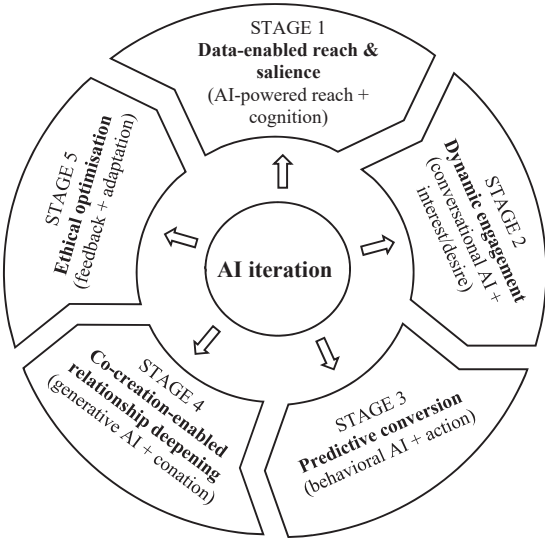


Figure 1. AI-transformed marketing communication model – the adaptive engagement loop (AEL)

Table 4. Empirical grounding of the AEL model: stage definitions, indicators and cross-case evidence

AEL stage	Stage definition	Empirical indicators observed across cases	Cross-case examples	Quotes from the interviews
<i>Stage 1: Data-enabled reach and salience</i>	Organizational practices that use AI to allocate attention and optimize exposure sequencing across platforms – not creating awareness from zero, but dynamically managing reach, frequency and contextual relevance	Real-time audience modeling; platform-driven reach optimization; rapid testing; automated creative versioning for micro-contexts; localization of global assets	<i>Case A:</i> rapid creative variant production and localization; reduced time-to-market and improved relevance through scalable adaptation. <i>Case B:</i> dynamic email/app interfaces adapting to preferences. <i>Case C:</i> DTC/app ecosystem enabling continuous behavioral sensing and personalized nudges	“We used AI to localize the ad content by finding alternatives of our iconic advertising context and stayed relevant in every market we serve without starting the ad production from scratch” (CASE A) “With the help of our platform’s AI, we identified beauty audiences at scale that we would never find manually, thereby expanding reach beyond existing consumer segments” (CASE B) “The AI integrated in our systems helps us determine which segments are getting popular and which less, while helping us communicate to athletes and build a relationship with them at the exact time when they are searching for items and comparing it” (CASE C)
<i>Stage 2: Dynamic engagement</i>	AI-mediated interaction design that turns touchpoints into adaptive dialogues and service-like experiences; engagement emerges from responsiveness, tone control, and context-sensitive interaction flows	Conversational flows; adaptive tone; service–communication integration; sentiment detection and routing; escalation to humans; multimodal assistance (e.g. AR try-on guidance)	<i>Case A:</i> interactive UGC/campaign participation enabled by GenAI. <i>Case B:</i> GPT-4–powered chatbot interactions; tone adaptation via sentiment analysis; AR/vision-enabled guidance; reported engagement lift (e.g. “11% higher” interactions vs static pages)	“Our creative ads used to be static and we treated it as a movie creation, while now with the AI we treat creative as a living system and learn with the audience when they engage with our ads in real time” (CASE A) “AI is actually changing the total experience for our consumers, as it adapts the communication tone and choices based on the AI-assessed mood of the consumer, making the experience sound much more like they were talking to a real beauty advisor” (CASE B) “We continuously refresh the ad creative based on what AI tells us that our potential consumers actually watched” (CASE C)

(continued)

Table 4. Continued

AEL stage	Stage definition	Empirical indicators observed across cases	Cross-case examples	Quotes from the interviews
Stage 3: Predictive conversion	Machine-supported prioritization of “next best actions” that determines when, how, and whether to intervene with offers, content or pushed data – integrating propensity, timing and sequencing	Next-best-action models; offer timing optimization; churn propensity triggers; automated variant allocation; dynamic CTA; automated budget shifts; conversion path tailoring	Case B: conversion gains within AI-mediated journeys. Case C: predictive AI embedded into app-based push; continuous segmentation; concerns about over-personalization/ cognitive fatigue and partner tensions	“The AI is used to predict, based on viewing behavior data, which story version of the ad would resonate best with our target audiences” (CASE A) “For the consumer journey to be felt like a consultation, the predictive ability of AI to shift the communication tone, for instance, from inspiration to problem solving, is critical” (CASE B) “The AI model helps us to figure out when is the best time to engage with the athletes, which is critical, as in case we act too soon, we may lose trust” (CASE C)
Stage 4: Co-creation-enabled relationship deepening	AI-supported mechanisms that lower the cost of identity-relevant participation and community contribution, expanding loyalty beyond repeat purchase to include advocacy, co-creation, and engagement behaviors	Co-created assets; remixing and sharing; community participation; identity-relevant customization; UGC participation; engagement beyond purchase; sustained interaction loops	Case A: GenAI-enabled consumer co-creation/remixed packaging and UGC uptake; concerns about authenticity and brand voice drift. Case C: lifestyle ecosystem and daily-life integration via app pushes and personalization	“We invited each single one of our consumers to co-create ads with the help of AI and share them, which gave everybody a personal feel, while still keeping our brand’s iconography intact” (CASE A) “We want the community to help shape the brand’s beauty conversation by letting consumers build their looks and share them, thereby influencing what we feature in our marketing communication” (CASE B) “We want athletes to tell and shape the story of our products and brand itself – our ultimate goal is to turn the personalization into participation” (CASE C)

(continued)

Table 4. Continued

AEL stage	Stage definition	Empirical indicators observed across cases	Cross-case examples	Quotes from the interviews
Stage 5: Ethical optimization	Embedded oversight that defines acceptable AI behavior and ensures accountability (i.e. creative guardrails, disclosure, audits, and escalation protocols) is treated as a constitutive stage rather than an add-on	Guardrails and style constraints; human-in-the-loop review; disclosure policies; bias/quality audits; privacy/consent controls; compliance monitoring; incident response	<i>Case A:</i> protocols to prevent dilution and generic outputs; internal ethical guidelines. <i>Case B:</i> bias audits for AR try-on; performance improvements after mitigation (e.g. darker skin tone issues; “27% uplift”). <i>Case C:</i> algorithmic diversity strategies and partner data constraints	“Establishing AI governance is critical for mitigating brand-safety risk, as otherwise speed could quickly become a risk to our brand’s reputation” (CASE A) “Responsible use of AI in beauty means ensuring privacy and conducting constant performance checks. For instance, when we identified performance gaps between skin tones, we stopped the rollout until it was fixed” (CASE B) “AI should never compromise an athlete’s trust, thus we are very strict when it comes to transparency and what data we use and share” (CASE C)

through real-time iteration based on omnichannel feedback, allowing for super-personalization, algorithmic adaptability and collaborative brand–consumer interactions.

Stage 1 (Data-enabled reach and salience) is an example of this shift to, and it combines the “Reach” of RACE with “Cognition” from Hierarchy effects through generative AI to scale up local content (e.g. localizing relevant global campaigns to regional cultural complexities) and through predictive AI to help find an audience (e.g. modeling via Meta’s algorithms). This shifts marketing from mass broadcasting to algorithmically coordinating an audience, and reducing CPM (i.e. Cost per Mille) costs. Here, “reach & salience” does not imply that AI single-handedly creates brand awareness for established brands; rather, it captures how AI systems optimize attention allocation, contextual relevance and exposure sequencing in platforms and channels, functions that become even more important for emerging brands with limited budgets and weaker prior familiarity. Stage 2 (Dynamic engagement) uses conversational AI and sentiment analysis to turn one-way interactions into emotionally intelligent conversations; for example, a beauty retailer that is rolling out GPT-4 powered chatbots that are able to adapt the messaging tonality based on the emotional sentiment (more than 50% sentiment improvement according to the case B). Most importantly, Stage 3 (Predictive conversion) extends beyond AIDA’s linear “Action” by using behavioral AI to even select next-best actions – e.g. dynamic pricing or individual consumer level-triggered discounts – to accelerate the checkout velocity.

The AEL’s innovation is most visible in Stage 4 (co-creation-enabled relationship deepening), where generative AI systems expand consumers’ opportunities to participate in brand meaning-making through remixing, customization and community sharing. In this case, AI lowers the cost of identity-relevant participation, a driver of engagement behaviors and relational value in contemporary brand ecosystems (Merz, He, & Vargo, 2009; Harmeling, Moffett, Arnold, & Carlson, 2017). In this stage, loyalty is treated as a multidimensional outcome that includes repeat purchase and non-transactional engagement (advocacy, co-creation and community participation), which AI can amplify when governed by clear brand

voice constraints and responsible disclosure practices (Puntoni *et al.*, 2021; Hermann & Puntoni, 2025).

Lastly, Stage 5 (Ethical optimization) includes governance mechanisms (e.g. IBM Watson bias audits) to see AI deliver on its promises operationally for rapid feedback integration and to avoid marketing communication that will damage our brand trust (e.g. a global beauty retailer (case B) used Watson to audit its AI in AR try-on. They found it was not very effective for darker skin tones – mitigation led to greater inclusivity and 27% uplift in engagement). Combining these stages into a non-linear, real-time adaptive system, the AEL fills important gaps in the previous models of marketing communication by overcoming AIDA's transactional myopia, the Hierarchy of effects' measurement lag and RACE's narrow scope of tactics.

The theoretical contribution of the AEL is two-fold: it is informed by a combination of performance and ethics, and it crosses the academia-practitioner divide by merging performance and ethics in the AEL. For academics, it formalizes the contribution of AI to marketing theory by introducing constructs like algorithmic brand co-creation and closed-loop ethical calibration. For the professionals, it provides a road map about scaling personalization and still being true to the brand – a pain point glaring in the case of a beverage multinational's potential brand dilution. Cross-industry validations of the AI governance framework could also be validated in other industries, in particular, regulated ones, where the importance of ethical AI governance is high. As AI evolves, the iterative nature of the AEL means it will always be a living framework ready for emergent technologies such as agentic AI and quantum machine learning. This places the AEL not merely as a model, but as a meta-framework for the AI-augmented marketing era. Altogether, a synthesized AEL theoretical model bridged the gaps in extant marketing communication models by incorporating (as in our cases) generative AI for co-creation, conversational AI for dynamic engagement and predictive AI for real-time conversion – all within an ethically calibrated framework.

5. Discussion and conclusions

5.1 Theoretical implications

Our research contributes to the marketing theory by understanding AI no longer solely as a means of enhancing efficiency but also as a sociotechnological mediation tool that is involved in creating, testing and disseminating brand meanings. Consequently, we have used the term “distributed authorship” to describe how meanings are created in the context of AI-enabled marketing communication, as opposed to suggesting that AI alone “authors” meaning. With AI-enabled marketing communications, meanings emerge from the interaction of the human strategists and creatives who develop campaigns, the algorithms and training data on platforms where messages are communicated, and feedback from consumers, which creates a paradigmatic shift from the traditional campaign-centric broadcasting model to a continuous orchestration of messaging across multiple touchpoints (Lemon & Verhoef, 2016; Ma & Sun, 2020; Puntoni *et al.*, 2021). What we observe changing in the three case studies are not the intentions of the AI as a purposeful author of meaning, but the way in which the organizations divide tasks: generative AI systems expand both the number of possible options for messages, and they increase the rate at which those options can be developed and communicated; conversational AI systems redefine the boundaries of services and communications; and predictive systems automatically prioritize time, and schedule message delivery. The AEL framework illustrates these mechanisms, while providing a structure to explore the ethical design conditions necessary to create distributed authorship that is both legitimate and trustworthy (Grigsby *et al.*, 2025; Hermann & Puntoni, 2025).

For decades, traditional marketing theories have characterized brand communication as a narrative constructed by firms and distributed to passive audiences (Holt, 2002; Keller, 2003). Yet, the findings of this study are challenging that view, as it becomes evident that AI technologies are responding to the real-time in which AI technologies are, quite literally,

remixing, personalizing and even producing branded content in real time. Thus, AI affords more subtle “orchestration” of content, context and consumer engagement; that is, brand meaning is not fixed but co-evolve on-line (Wedel & Kannan, 2016; Rust, 2020).

By taking machine learning outputs as strategic inputs, the case organizations have moved from static message dispensers to modular identity orchestrators, with AI-generated artifacts (e.g. images, interactions and predictions) reacting in a contextual yield from micro-moments. This confirms theoretical evolution from mass communication models to hyper-personalized brand conversation (Lemon & Verhoef, 2016; Ma & Sun, 2020).

This study repositions the brand from a source of narrative to a resource that helps make meaning, in support of newer brand co-creation theories (Ind & Coates, 2013; Merz *et al.*, 2009). The introduction of AI as a third actor in the brand–consumer relationship changes the dynamic of the traditional dyad since brands now become curators of algorithmically produced, consumer-responsive content.

At the same time, Case A (a multinational beverage brand) provided an example of how generative AI broadens brand authorship to incorporate the consumer and the machine, and audiences as creative actors. Case B (global beauty retailer) highlighted the shift from “the 4P’s” to “experience as communication” where conversational AI redefines product discovery as service experiences, which is in line with recent calls for experience-based brand ecosystems (Voorhees *et al.*, 2017). Case C (athletic apparel brand) disrupts the traditional linear funnel model, introducing AI-powered predictive personalization loops as a new architecture of continuous engagement (Libai *et al.*, 2020).

These findings point to several foundational theoretical shifts:

- (1) *From communication to co-authorship*: brands are no longer sole narrators but facilitate multi-agent meaning-making, including machine agency.
- (2) *From content to experience*: AI has the effect of blurring what we used to identify as branded communication and branding in service experiences, embedding branding in real-time touchpoints (Bolton *et al.*, 2018).
- (3) *From segmentation to identity shaping*: Utilization of AI-powered personalization is not simply about content targeting per se but about curating identity storylines which shape brand-related meaning (Hollebeek & Macky, 2019).

These shifts suggest an evolution in customer experience management (CX), where AI is crucial to emotional, behavioral and cognitive branded touchpoints (Harmeling *et al.*, 2017; Ameen, Tarhini, Reppel, & Anand, 2021; Peruchini, da Silva, & Teixeira, 2024). Consequently, we developed AEL model, a key theoretical contribution of this study, that unites the strengths of existing marketing communications models and AI implications as described above. The model is theoretically grounded, but calls for empirical testing. For instance, the model demands deeper enquiry into how algorithmic outputs mediate authenticity, trust and emotional engagement – core aspects of brand equity theory (Christodoulides and De Chernatony, 2010).

The deployment of AI within brand meaning systems raises fresh organizational imperatives like the control of AI outputs, human–machine collaboration orientations, and the integration of creative and engineering dimensions. Consequently, this study calls for cross-functional agility in marketing organizations (Day, 2011; Wirtz & Stock-Homburg, 2025), a prerequisite for a successful AI adoption in marketing communication. Case firms adopted different strategies to manage the paradox of personalization versus consistency, including content guardrails (Case A), inclusive design principles (Case B) and algorithmic diversity strategies (Case C). Combined, these changes reshape core concepts in marketing strategy, branding, perceptions and communication, and ultimately provide a foundation for inquiry into machine-augmented brand ecosystems.

5.2 Managerial implications

This study provides several strategic takeaways for marketing managers when deciding on the use of AI in brand communication. As AI embeds deeper in customer touchpoints, marketing managers will need to refigure traditional campaign workflows, team structures and data governance models. The results from the three cases suggest that the adoption of AI is not merely a technical agenda and means to an end – AI adoption is strategic and cross-functional in terms of content creation, CX and in terms of ethics.

AI permits brand-level targeted personalization at scale, but hyper-optimization at an algorithmic level can result in the loss of brand cohesion and consistent brand identity (Lemon & Verhoef, 2016; Odionu, Bristol-Alagbariya, & Okon, 2024). Brands must set “creative guardrails” which protect a brand voice, but still offer diversity across consumer segments. *Case A* shows how the brand as a platform for co-creating content (not a monologic broadcaster) will resonate with long-term equity and personalization. Marketing managers should treat AI as a supplementary – rather than a substituting – factor to creative strategy, and implement internal reviews that integrate the outputs of automation with human judgment (Haenlein & Kaplan, 2019). This maintains brand essence amid AI-fueled, channel-based hyper-targeted content.

As AI increasingly requires real-time behavioral data, consumer trust becomes a strategic asset. *Case B* highlights the need and value in investing in transparent data architectures and user-consent frameworks for ethical AI implementation (Martin & Murphy, 2017; Bleier, Goldfarb, & Tucker, 2020). Companies must also formalize the adoption of data governance policies that help to address algorithmic biases and drive inclusivity, in particular when sensitive areas such as beauty, health or finance are involved. Practical steps include having ethical review boards for algorithmic systems, bias audits of training data and CX audits to evaluate fairness across demographics (Bolton *et al.*, 2018). As we blur the lines even further between personalization and experience delivery, customer-centric data ethics will become the single most important area of differentiation and resilience.

The power of AI to produce immediately actionable insights and content will require organizational speed and agility. *Case C* demonstrates that the maximum value of AI tools comes not in isolated silos such as AdTech or CRM, but as part of an integrated marketing ecosystem which includes creative solutions, analytics, customer success, brand strategy, etc. This complements the view by earlier scholars (e.g. Lee & Joshi, 2007; Ojika *et al.*, 2021; Ahmad, Boit, & Aakula, 2023; Wirtz, Hofmeister, Chew, & Ding, 2023) that successful AI implementation necessitates revisiting old-fashioned departmental boundaries and embracing cross-functional collaboration models. Firms need to invest in hybrid teams of data scientists, brand strategists, experience designers and other new emerging virtual roles (Vuchkovski, Zalaznik, Mitrega, & Pfajfar, 2023). In addition, marketing stacks need to move toward omnichannel orchestration, where AI-enabled touchpoints (e.g. apps, stores and social media) provide frictionless and contextually relevant brand experiences (Verhoef, Kannan, & Inman, 2015). To sum up the above discussion, corporate adoption of the AI-driven approach to marketing communication should involve the building (or acquiring from external sources) of a new set of (dynamic) capabilities, governance norms and interpretive (marketing) context. Success is not only a matter of technical competence, but also of cultural preparation, ethical vision and strategic imagination.

Beyond firm performance, we look at the potential broader social implications of using AI in marketing communication, as it has the ability to create new, large-scale cultural narratives and information environments. In addition to the risk of misinformation that could occur by lowering the marginal cost of creating different forms of persuasive messages with generative AI and AI targeting systems, there is a possibility of a more subtle loss of brand meaning while being persuaded by highly personalized communications created by synthetic media and optimized by systems that are nearly impossible to audit. This is raising concerns about authenticity, accountability and autonomy as consumers interact with adaptive systems that provide them with brand touchpoints. The level of trust that exists between a consumer and a

brand, as well as its marketing communication systems, will depend upon the degree to which they disclose their use of these systems, the contestability of such systems and the levels of governance that limit the potential for manipulation and bias (Puntoni *et al.*, 2021; Hermann & Puntoni, 2025). The regulatory trajectory regarding the development and implementation of AI, particularly in marketing communication, has already raised similar concerns. The European Union's (EU) proposed AI Act includes transparency and accountability standards that will likely significantly influence how companies document the use of models, manage risks associated with those models and communicate to stakeholders when AI was used in marketing communication processes (European Parliament, 2025). Therefore, AI in marketing communication should be considered as a publicly accountable legitimacy issue rather than just an internal compliance task.

5.3 Research limitations and future research

This study offers theoretical and managerial implications on how AI is transforming marketing communication through viewing its function not only as a tool for optimization, but also as a co-creator of brand meaning. Although the multi-case nature of our approach allowed for a rich understanding of AI-driven transformations in three global consumer brands, it also introduces several limitations warranting future scholarly attention.

First, the study focused on a small number of cases (only three in consumer-centric industries, such as beverages, cosmetics and athletic apparel) in advanced economies. These brands are examples of successful AI adoption in marketing communication, but do not necessarily represent the range of organizational contexts, particularly in developing economies or when considering B2B organizations, service businesses, etc. Hence, future studies should cover cross-industry and cross-regional studies, in order to test the generalizability and boundary conditions (Rust, 2020; Akaka & Vargo, 2014) of the AEL model formulated here. Second, our work offers a snapshot of AI adoptive behavior and communicative outcomes, the view of brand dynamics at one point in time (i.e. even if cases span across a period of time, data are collected at a point in time). But the impact of AI is cumulative and evolving – its long-term consequences for consumer–brand relationships, brand equity, even identity consistency have not been given as much attention. In the future, longitudinal research methods are encouraged to examine reciprocal development between AI capabilities and consumer expectations (Chandy, Johar, Moorman, & Roberts, 2021; Lemon & Verhoef, 2016). This may have involved ethnographic research in terms of internal observation of brand groups, or monitoring of consumer perceptions for an extended period of time.

Third, the results highlight the socio-technical and creative frictions/contradictions between human curation and algorithmic orchestration. However, our study primarily considers marketing leaders' and firms' perspectives. Future studies could employ multi-stakeholder methodologies (e.g. consumer ethnography and behavioral experiments) to unravel how users co-interpret and co-create the meaning with AI-fueled brand content (Huang & Rust, 2021; Campbell, Inman, Kirmani, & Price, 2020). Fourth, although the paper offers an emergent conceptual model based on qualitative data, further exploration should attempt to test and develop the proposed framework quantitatively. Researchers could work to provide measures for AI-based personalization, modular brand identity and algorithmic trustworthiness and their impact on consumer-based brand equity and model it (Gao *et al.*, 2023; Schmitt, 2012).

Lastly, future research may investigate the ethical implications of such generative and conversational AI technologies, and their fairness, transparency and digital identity manipulation, while both are nascent. Such work is needed to inform responsible governance and regulation by which value co-creation for all is maximized (Ooi *et al.*, 2025; Puntoni *et al.*, 2021). By exploring these territories, marketing academics could begin to chart a path toward understanding how AI isn't just changing the way we communicate, but transforming the nature of what it means to be a brand in a post-human, algorithmically mediated marketplace.

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