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INTEGRATION OF KNOWLEDGE FROM COMMERCIAL MARKETING INTO AI-AUGMENTED POLITICAL MARKETING: ANALYTICAL FRAMEWORK AND LITERATURE SYNTHESIS

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Abstract

This article synthesizes the literature on how techniques and capabilities developed in commercial marketing travel into AI-augmented political marketing. We group evidence into three channels of transfer—direct adoption (e.g., micro-segmentation, A/B testing, attribution modeling), adaptation under political constraints (compliance, transparency, content governance), and capability spillovers (data infrastructures and generative content pipelines). Using a scoping review across political communication, marketing, and information systems, we map: (1) the technical repertoire (targeting, recommendation, predictive modeling, generative systems), (2) organizational enablers (data governance, absorptive capacity, boundary-spanning teams), and (3) outcomes and risks (effectiveness, measurement validity, bias, and normative implications). We find consistent evidence for capability diffusion but methodologically heterogeneous findings on persuasive impact and causal attribution. We propose a typology of transfer mechanisms and a research agenda prioritizing external validity, auditability, and cross-jurisdictional comparisons. The contribution is integrative—bridging siloed strands—and programmatic, by outlining standards for transparency, reporting, and evaluation pertinent to AI-enhanced political campaigns.

Keywords: ***political marketing; artificial intelligence; knowledge transfer; micro-segmentation; generative models; campaign strategy; literature review.***

Introduction

Over the last decade, artificial intelligence (AI) has expanded the analytical and operational repertoire of commercial marketing—from predictive models and incrementality testing to generative systems for creative development and research assistance. Recent advances in generative AI widen the avenues of transfer to political marketing, accelerating the diffusion of technical repertoires and organizational routines from commerce into electoral and governmental contexts (Grewal et al., 2024). We proceed from the premise that these transfers are already observable yet undertheorized in comparative perspective, while their consequences for deliberative processes remain heterogeneous and difficult to measure. By “knowledge transfer” we refer to the movement, adaptation, or imitation of practices, technologies, and routines across organizational settings. Management research indicates that successful transfer depends on the absorptive capacity of recipient organizations—prior knowledge, learning routines, and data infrastructures—and on the social mechanisms that enable knowledge circulation (Cohen & Levinthal, 1990, Argote & Ingram, 2000).

Transposed to political marketing, this framework suggests that parties, campaigns, and public institutions can import commercial algorithmic capabilities (fine-grained segmentation, A/B testing, recommender systems, generative models), subject to resources, vendor/platform relationships, and normative constraints.

In parallel, political communication and technology-law scholarship documents the migration of tactics such as online microtargeting from commercial systems into campaigns, promising efficiency but raising risks for pluralism, transparency, and data protection (Zuiderveen Borgesius et al., 2018, Dobber, Ó Fathaigh & Zuiderveen Borgesius, 2019). The literature on computational propaganda further shows how automation and platform infrastructures can amplify strategic partisan communication, creating system-level effects that escape traditional campaign metrics (Woolley & Howard, 2018, Bradshaw & Howard, 2019). Any account of transfer must therefore foreground the governance of adopted technologies and the accountability of private intermediaries in political communication.

Technically, the AI-in-service perspective offers a useful lens to decompose transferable capabilities (mechanical/analytical/intuitive/empathetic) and to distinguish augmentation from automation—an analytically salient boundary for campaign design and for accountability in algorithmic decision-making (Huang & Rust, 2018). Complementarily, recent work on generative AI in marketing proposes implementation typologies (from generic to highly personalized inputs; varying degrees of human-in-the-loop) which translate into operational scenarios for political communication: message generation, creative prototyping, synthesis of field feedback, and simulation of audience reactions.

Two persistent gaps motivate this study. First, external validity: many claims about tactical effectiveness are context-bound and resist generalization across media systems and regulatory regimes. Second, causal measurement: attributing persuasive effects in hyper-personalized, platform-mediated environments remains methodologically challenging even in commerce; transfer into political domains heightens requirements for auditability and transparency. To address these issues, we conduct a scoping review spanning marketing, political communication, and information systems to (i) map technical repertoires, (ii) identify transfer mechanisms (direct adoption, constrained adaptation, capability spillovers), and (iii) outline a research agenda centered on transparency, causal evaluation, and cross-jurisdictional comparison.

Conceptual Framework: knowledge transfer, algorithmic affordances, and commercial vs. political differences:

1) Knowledge transfer — from capabilities to routines

In organization science, transfer denotes the movement and adaptation of practices across contexts, mediated by structures, ties, and learning processes. (Argote & Ingram, 2000) Successful transfer depends on absorptive capacity—the prior knowledge base, learning routines, and data infrastructures that enable recognizing, assimilating, and exploiting external knowledge (Cohen & Levinthal, 1990). In political campaigns and public institutions, absorptive capacity translates into data-governance processes, analytics literacy, and boundary-spanning roles (e.g., data strategists embedded with creative and field teams) able to absorb commercial heuristics and translate them into political operations. We treat the transfer object as a capability bundle: (a) analytical (predictive modeling, uplift estimation, multi-touch attribution), (b) operational (A/B testing pipelines, content operations, CRM integrations), and (c) creative/generative (prompting strategies, fine-tuning, human-in-the-loop review) (Grewal et al., 2024). These bundles are not plug-and-play; adoption hinges on routines that stabilize their use (e.g., weekly experimentation cadences, cross-functional stand-ups, model-risk practices). Codified, modular bundles (clear interfaces, schemas, testing protocols) travel better; tacit, context-dependent practices often degrade in performance when lifted from commerce. (Argote & Ingram, 2000, Cohen & Levinthal, 1990)

2) Spillovers and the ecology of diffusion

Beyond dyadic transfer, field-level spillovers diffuse capabilities via talent mobility, vendor ecosystems, and shared infrastructures (adtech stacks, SDKs, cloud ML services). Spillovers lower adoption costs by making advanced tooling accessible as managed services. While classic accounts emphasize productivity externalities (Griliches, 1992), in politics the spillovers concern capabilities and embedded assumptions (optimization targets, experimentation ethics, success metrics). These are amplified when platforms and agencies create “political” variants of commercial products (e.g., lookalikes or creative optimization tailored to civic topics). (Grewal et al., 2024)

3) Algorithmic affordances — constraints and possibilities

To specify what commercial technologies make possible in politics, we adopt affordances - action possibilities offered by an artifact to particular actors in context (Gibson, 1979, Hutchby, 2001) Affordances are relational: they depend on users’ competencies and institutional environments. We identify four families: targeting (segmentation and prioritization), generative (synthesis/personalization at scale), optimization (experimentation and budget allocation, often mediated by platform optimizers), and infrastructural (APIs, identity graphs, clean rooms enabling compliant data fusion and measurement). Affordances open efficiency gains (e.g., adaptive messaging in minority languages) but also constrain action by privileging what is measurable and optimizable—nudging actors toward platform-native proxies (engagement) over public-value metrics (Zuiderveen Borgesius et al., 2018. Dobber, Ó Fathaigh & Zuiderveen Borgesius, 2019, van Dijck, Poell & de Waal, 2018).

4) Commercial vs. political — why similar tools behave differently

(a) Objective functions differ (revenue vs. persuasion/legitimacy); (b) feedback cycles are continuous in commerce and punctuated in campaigns; (c) data governance and platform policies impose stricter constraints in politics; (d) externalities are systemic (e.g., polarization) rather than firm-level; (e) organizational capabilities vary widely. These differences threaten measurement validity when commercial attribution logics are transplanted into politics and motivate higher standards for auditability (Zuiderveen Borgesius et al., 2018. Dobber, Ó Fathaigh & Zuiderveen Borgesius, 2019, Woolley & Howard, 2018, Bradshaw & Howard, 2019, van Dijck, Poell & de Waal, 2018).

5) A three-part transfer typology

We distinguish between: (i) direct adoption (minimal adaptation of tools/workflows—e.g., creative A/B pipelines, copy variant generation) (Grewal et al., 2024, Huang & Rust, 2018); (ii) constrained adaptation (modifications to satisfy law/ethics/platform rules—e.g., cohort-level targeting, safety filters, transparency reporting) (Zuiderveen Borgesius et al., 2018, Dobber, Ó Fathaigh & Zuiderveen Borgesius, 2019, van Dijck, Poell & de Waal, 2018); (iii) capability spillovers (diffusion via vendors/talent that reshapes expectations even without direct transfer—e.g., demand for incrementality tests).

Methodology

Design and reporting

We conducted a scoping review to chart, classify, and synthesize how capabilities originating in commercial marketing are taken up in AI-augmented political marketing. Our review protocol follows the seminal framework proposed by Arksey & O'Malley and subsequent refinements by Levac et al., while reporting adheres to the PRISMA-ScR checklist; where relevant, we align the flow diagram with PRISMA 2020 terminology. To avoid formulaic phrasing, we describe below the concrete operationalization used in this study and cite the guidance at first mention. (Levac, Colquhoun & O'Brien, 2010, Tricco et al., 2018)

Review questions and scope

We address three questions: (RQ1) Which commercial capabilities (analytical, operational, creative/generative) are reported as transferring into AI-augmented political marketing? (RQ2) Through what mechanisms (direct adoption, constrained adaptation, spillovers), and under what organizational contingencies (e.g., absorptive capacity, governance) does transfer occur? (RQ3) What methodological, organizational, and normative consequences are associated with such transfers (e.g., measurement validity, auditability, implications for deliberation)? The corpus spans peer-reviewed articles and scholarly reports in marketing, political communication, information systems, and adjacent areas (e.g., law/technology) that explicitly analyze tactics, tools, or infrastructures relevant to commercial-to-political transfer.

Eligibility

We included records that (a) treat AI-related marketing capabilities or workflows (e.g., micro-segmentation, attribution, recommenders, generative pipelines); (b) examine political applications (campaigns, parties, public institutions) or theorize cross-domain transfer; and (c) provide at least minimal methodological transparency (data, methods, or conceptual scaffolding). We excluded purely technical ML papers without a marketing application, opinion pieces without methods, studies limited to non-AI persuasion lacking a transfer dimension, duplicates, and non-scholarly blog posts. Coverage: 2013–September 2025; languages: English and Romanian.

Sources and search strategy

Databases: Scopus; Web of Science Core Collection; Communication & Mass Media Complete; ACM Digital Library and IEEE Xplore (to capture IS/engineering work with marketing applications); and Google Scholar for academic gray literature. Queries combined three semantic blocks—domain, AI, techniques—using Boolean operators. Each search round was logged (date, database, query version, hit count) for traceability in line with scoping-review guidance (Arksey & O'Malley, 2005, Levac, Colquhoun & O'Brien, 2010). Example combinations: "political marketing" AND "generative AI" AND micro-segment*; "political communication" AND "machine learning" AND (attribution OR uplift OR recommender). Database-specific notes and synonyms are summarized in an appendix table.

Screening and selection.

We exported all records to a shared spreadsheet, removed duplicates, and screened titles/abstracts independently by two reviewers, followed by full-text assessment against the eligibility criteria. Disagreements were resolved by discussion or third-reviewer adjudication. Before full screening, we calibrated decisions on a 10% pilot; agreement statistics (percent agreement, Cohen's κ) are reported in an appendix. The study flow is presented in a PRISMA-style diagram adapted to scoping reviews as recommended by PRISMA-ScR and PRISMA 2020. (Arksey & O'Malley, 2005, Levac, Colquhoun & O'Brien, 2010, Tricco et al., 2018)

Data charting and synthesis

We iterated a charting template/codebook to capture: bibliographic details; disciplinary area; country/region and platform context; study type; AI capability (predictive modeling, uplift, attribution, recommenders, generative pipelines); transfer mechanism; organizational features (governance, proxies for absorptive capacity); outcomes/metrics (persuasion, mobilization, engagement) with validity checks; and normative considerations (transparency, data protection, fairness). Given heterogeneity, we used narrative/thematic synthesis structured along (1) capability bundles, (2) transfer mechanisms, and (3) governance/measurement implications. To reduce subjectivity, we complemented the narrative with descriptive bibliometric exploration (co-word/co-citation) to visualize clusters; thresholds and tooling are specified in online/appendix materials (Page et al., 2021).

Quality, sensitivity, and limitations

Consistent with scoping aims, we did not exclude on critical-appraisal grounds; instead, we recorded indicators of methodological transparency to contextualize claims—especially when commercial metrics are repurposed as political outcomes. We ran two pre-specified sensitivity checks: (a) time-window (2016–2025) to assess the impact of the generative-AI era; (b) discipline-stratified synthesis (marketing vs. political communication vs. information systems). We discuss limitations from cross-disciplinary terminology and platform-policy shifts over 2013–2025.

Conclusions

Our scoping review maps how analytical, operational, and generative capabilities from commercial marketing enter AI-augmented political marketing via direct adoption, constrained adaptation, and capability spillovers. Outcomes hinge on absorptive capacity and on how actors enact algorithmic affordances within legal and platform constraints. Diffusion of capabilities (micro-segmentation, experimentation, attribution, recommenders, generative pipelines) is the consistent pattern; persuasive and mobilization effects remain unevenly evidenced and highly context-dependent. We argue for moving from the question of whether commercial techniques appear in politics to how they are adapted and governed across jurisdictions, and we call for causally credible designs tailored to platform-mediated environments, alongside minimum disclosure standards (method notes, audit trails, repository-ready metadata) to make political uses of AI reviewable.

Implications for practice and policy

For campaign organizations and agencies: pre-specify incrementality tests for AI-mediated interventions and maintain an experiment register; treat attribution models as hypothesis-generating unless validated on political outcomes; invest in absorptive capacity (cross-functional teams, codified experimentation, model-risk basics); operationalize safeguards for generative AI (human review for sensitive topics, provenance/watermark checks where available, incident-response playbooks).

For policymakers, regulators, and platforms: require public ad libraries with method notes; establish disclosure standards for AI-mediated political communication and mandate retention of audit logs; encourage cohort-level or contextual optimization where individual microtargeting poses heightened risks; support comparable reporting templates and independent testing environments for causal evaluation.

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