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CONSUMER RESISTANCE TO AI ADVERTISING: INSIGHTS FROM BIBLIOMETRIC MAPPING AND SYSTEMATIC REVIEW

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ABSTRACT

The rapid diffusion of artificial intelligence (AI) in advertising has attracted increasing scholarly attention, largely centered on consumer acceptance, effectiveness, and personalization. However, emerging research suggests that AI-driven advertising can also provoke consumer resistance due to concerns over manipulation, surveillance, transparency, and ethical governance. This study offers a systematic and integrative overview of this literature by combining bibliometric mapping and systematic review methods applied to 1085 peer-reviewed journal articles indexed in Scopus. Bibliometric analysis identifies publication trends, influential journals and authors, core intellectual foundations, and major thematic clusters in AI advertising research. The systematic review complements these findings by synthesizing empirical evidence with a specific focus on resistance-oriented mechanisms. Results indicate that the field is dominated by acceptance-focused, performance-driven frameworks, while resistance-related constructs remain marginal and weakly theorized: within the advertising-relevant segment of the corpus, no resistance construct exceeds 4.4% of records, against 31.7% for optimisation-related terms, and psychological reactance appears in no author or index keyword field across the entire corpus.

Keywords: Artificial intelligence (AI) advertising, consumer resistance, bibliometric mapping, systematic review.

1. INTRODUCTION

The rapid integration of artificial intelligence (AI) into advertising has transformed contemporary marketing practices at an unprecedented pace [1]. AI-driven technologies now permeate the advertising value chain, enabling automated media buying, real-time targeting, content generation, and interactive consumer engagement [2]. Market evidence underscores the scale and momentum of this transformation. The AI in social media market alone is projected to reach USD 7.87 billion by 2029, expanding at a compound annual growth rate (CAGR) of 30.7%, driven by advances in personalized platform experiences, algorithmic targeting accuracy, sentiment analysis, conversational AI, and AI-enabled customer care [3]. These developments signal not only the growing economic significance of AI advertising but also its increasing embeddedness in consumers' everyday media environments [4].

Consistent with this expansion, academic research has documented numerous performance-related benefits of AI advertising, including higher conversion rates, enhanced consumer engagement, and improved relevance of personalized messages [5]-[8]. Consequently, much of the existing literature adopts an acceptance-oriented perspective, emphasizing constructs such as perceived usefulness, trust, anthropomorphism, and personalization effectiveness [9], [10]. Within this dominant framing, AI is largely portrayed as a value-enhancing tool that optimizes advertising efficiency and consumer experiences.

However, as AI systems become more autonomous, opaque, and data-intensive, a growing body of research points to a less optimistic dimension of AI advertising: consumer resistance. Recent studies highlight that AI-driven advertising can trigger skepticism, avoidance, psychological reactance, and ethical concerns, particularly when consumers perceive manipulation, surveillance, or loss of autonomy [11]-[13]. High-profile public backlash against AI-generated campaigns - criticized for inauthenticity or cultural misalignment - further illustrates rising ambivalence toward automated creative content [14], [15]. Paradoxically, mechanisms intended to enhance persuasion, such as transparency, anthropomorphism, and algorithmic optimization, may intensify resistance by activating persuasion knowledge and heightening perceptions of control loss [16].

Despite these emerging insights, scholarly understanding of consumer resistance to AI advertising remains fragmented. Most studies are embedded within acceptance-focused frameworks that implicitly treat resistance as a residual outcome rather than as a theoretically distinct and meaningful response [5], [17]. Moreover, the literature is dominated by short-term, individual-level analyses, offering limited insight into how resistance develops over time or is shaped by socio-cultural norms, institutional trust, and regulatory environments across markets [18], [19]. As a result, the intellectual structure of research on consumer opposition to AI advertising lacks coherence and integrative theorization.

To address these limitations, this study employs bibliometric mapping combined with a systematic review to analyze 1085 peer-reviewed journal articles indexed in Scopus. By adopting a field-level, data-driven perspective, the study seeks to clarify how AI advertising research has evolved, how consumer resistance has been conceptualized within it, and where critical gaps persist. Specifically, the study addresses the following research questions:

RQ1: What are the publication trends and theoretical underpinnings of AI advertising research?

RQ2: What prevailing and nascent themes define studies on consumer resistance to AI advertising, and what important gaps persist?

RQ3: What future research agendas can address these gaps and advance understanding of consumer resistance to AI-driven advertising?

By shifting analytical attention from acceptance-centered models toward resistance-oriented mechanisms, this study contributes to a more balanced and nuanced understanding of consumer–AI interactions in advertising. In doing so, it elucidates conceptual fragmentation within the literature and delineates critical directions for future research that incorporate ethical, cultural, and longitudinal perspectives on consumer resistance to AI advertising.

2. THEORETICAL BACKGROUND

2.1. Artificial Intelligence (AI) in marketing and advertising

Artificial intelligence (AI) refers to computer systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, perception, and decision-making [20].

In marketing and advertising contexts, AI encompasses a broad set of technologies, including machine learning, natural language processing, computer vision, and generative models, which enable automated data analysis, prediction, personalization, and content creation [21].

Within advertising, AI has transformed both strategic and operational processes [22]. AI-driven systems are now widely used for programmatic media buying, real-time bidding [23]; audience segmentation [24], dynamic creative optimization, chatbot-based brand communication [25]; virtual influencers [26], [27], and generative advertising content [28], [9], [29]. These applications allow advertisers to tailor messages at scale, optimize campaign performance in real time, and engage consumers across multiple touchpoints. Consequently, AI advertising has been predominantly framed as a value-enhancing innovation that improves efficiency, relevance, and effectiveness of persuasive communication.

2.2. Acceptance-Oriented perspectives in AI advertising research

The dominant theoretical perspectives in AI advertising research draw heavily on acceptance-oriented frameworks, including the Technology Acceptance Model (TAM), trust-based models, and anthropomorphism theory [30]. These frameworks emphasize perceived usefulness, ease of use, trustworthiness, and human-likeness as key drivers of positive consumer responses to AI systems [31]. In advertising settings, personalization enabled by AI is often assumed to increase message relevance and persuasion, thereby enhancing attitudes toward ads and brands [18], [32].

However, this literature implicitly assumes that increased automation, transparency, and personalization will uniformly lead to greater acceptance. Such assumptions overlook the possibility that these same mechanisms may activate consumer concerns related to privacy, autonomy, and ethical boundaries [9]. As AI systems become more opaque and data-intensive, consumers may not perceive AI advertising solely as helpful or convenient, but also as intrusive or manipulative [33], [34].

2.3. Conceptualizing consumer resistance in AI advertising contexts

Consumer resistance refers to consumers' deliberate or reactive opposition to marketing practices perceived as undesirable, manipulative, or threatening to personal autonomy [35], [36]. Resistance may manifest in various forms, including skepticism [37], avoidance [38], psychological reactance [39], negative word-of-mouth [40], or active rejection of persuasive attempts. Unlike simple dissatisfaction or low acceptance, resistance reflects a motivated response aimed at restoring perceived control or protecting personal values [41].

In the context of AI advertising, resistance has gained increasing scholarly attention. Research indicates that AI-driven personalization and automation may heighten perceptions of manipulation, surveillance, and loss of autonomy, particularly when consumers lack understanding of how algorithms operate or how their data are used [11]. Disclosure of AI usage, chatbot identity, or algorithmic decision-making has produced mixed effects, sometimes mitigating distrust but at other times intensifying resistance [42], [43].

Moreover, emerging forms of AI advertising - such as deepfakes, virtual influencers, and generative emotional appeals - raise new ethical concerns regarding authenticity, bias, and deception [14], [44]. These developments suggest that consumer resistance is not merely a byproduct of low acceptance but a distinct and theoretically meaningful phenomenon that warrants systematic investigation.

Taken together, existing research highlights a conceptual imbalance in AI advertising scholarship, with acceptance-oriented models dominating the field and resistance-oriented perspectives remaining underdeveloped and fragmented.

Accordingly, this study adopts a bibliometric and systematic review approach to map the intellectual structure of AI advertising research, identify how consumer resistance has been theorized across disciplines, and delineate critical gaps that inform future research agendas.

3. METHODOLOGY

3.1. Research design and data retrieval strategy

This study employs a mixed-methods approach that combines bibliometric analysis and systematic review to investigate the intellectual framework and research progression of AI advertising, specifically emphasizing customer opposition.

Bibliometric analysis facilitates extensive, objective mapping of publication trends, citation frameworks, and thematic connections, while the systematic review enhances these insights by offering qualitative interpretations of resistance-focused research trajectories. This integrated methodology is particularly effective for combining fragmented and interdisciplinary research fields [45], [46].

The data were obtained from the Scopus database, renowned for its extensive coverage of high-quality, peer-reviewed journals in marketing, advertising, psychology, and social sciences. Scopus is especially appropriate for bibliometric research owing to its systematic indexing, citation tracking, and compatibility with bibliometric tools [47].

To ensure systematic and replicable data collection, the following search query was employed:

(TITLE-ABS-KEY (advertising) OR TITLE-ABS-KEY (advertisement) OR TITLE-ABS-KEY (ad) AND TITLE-ABS-KEY (artificial AND intelligence) OR TITLE-ABS-KEY (ai) AND (LIMIT-TO (SUBJAREA, "SOCI") OR LIMIT-TO (SUBJAREA, "BUSI") OR LIMIT-TO (SUBJAREA, "DECI") OR LIMIT-TO (SUBJAREA, "ECON") OR LIMIT-TO (SUBJAREA, "ARTS") OR LIMIT-TO (SUBJAREA, "PSYC") OR LIMIT-TO (SUBJAREA, "MULT")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (PUBSTAGE, "final")) AND (LIMIT-TO (LANGUAGE, "English")).

Notably, resistance-related descriptors (e.g., resistance, reactance, skepticism, avoidance, privacy concern) were deliberately excluded from the retrieval string. A central claim of this study is that consumer resistance occupies a marginal position within AI advertising scholarship. Restricting retrieval to resistance-laden records would have amounted to selecting on the outcome of interest and would have made it structurally impossible to establish the relative weight of resistance against acceptance-oriented streams. The analytical logic adopted here is therefore one of negative evidence: resistance is assessed by its frequency and structural position across the field as a whole, not by the content of the subset of studies that already address it.

Because the retrieval string combines advertising and artificial intelligence descriptors through a high-recall Boolean union, the resulting corpus is deliberately inclusive and extends beyond advertising-specific scholarship. A post-retrieval composition analysis was therefore conducted to establish the analytical base for domain-level claims. Each record was classified as advertising-relevant if its title, abstract, or keyword fields contained at least one advertising or marketing descriptor (advertising, advertisement, marketing, brand, consumer, customer, promotion, campaign, purchase, shopper). Table 1 reports the resulting composition.

Two denominators are consistently utilized throughout this study. Field-specific bibliometric models (publication trends, co-citation networks, keyword co-occurrence charts) are introduced for the complete dataset (n = 1085), as these models illustrate the traits of the obtained intellectual domain and their constraints are analytically informative. All numerical claims concerning the relative importance of specific constructs in advertising research originate from the advertising-specific sample (n = 590), thereby avoiding the erroneous attribution of absent resistance constructions to the presence of non-advertising elements. Rather than retroactively excluding the non-advertising sector, the study retains and quantifies it, as its importance substantiates the persistent conceptual boundary between AI advertising research and the wider domain of AI academia (see Section 4.2.3).

Table 1. Composition of the retrieved corpus (n = 1085)

Corpus segment	n	% of corpus
Tier 1 corpus as retrieved from Scopus	1085	100.0
Advertising-relevant records (analytical base for domain-level claims) *– of which carry an advertising descriptor in the keyword field*	590 *355*	54.4 *32.7*
Records containing no advertising or marketing descriptor	495	45.6
Biomedical or clinical records (e.g., dementia diagnosis, neuroimaging) *– biomedical and simultaneously non-advertising*	182 *169*	16.8 *15.6*

Note: Classification was performed on the combined title, abstract, author keyword, and index keyword fields. Percentages are computed over the full retrieved corpus. Data retrieval date: 26 February 2026.

3.2. Systematic review procedure

Table 2. Systematic review procedure

Stage	Step	Description
Stage I: Planning ↓	Step 0: Establishing the rationale for the review	Identified the need for an integrative review of AI advertising scholarship, motivated by the rapid growth of the field and by the apparent absence of a consolidated account of how consumer responses other than acceptance have been conceptualised. Whether resistance is in fact marginal within the field was treated as an open empirical question to be tested, not as a premise.
	Step 1: Designing the review framework	Developed a review proposal defining the scope, objectives, and research questions, adopting a field-level analytical perspective in which consumer resistance functions as the interpretive lens rather than as a retrieval filter.
	Step 2: Formulating the review protocol	Established an ex ante protocol specifying database selection (Scopus), search string construction, subject-area and document-type criteria, language and publication-stage restrictions, and the analytical strategy, together with the rationale for each decision, to ensure transparency and replicability.
Stage II: Conducting ↓	Step 3: Executing the search and assembling the corpus *(n=1085)*	Executed the protocol on Scopus (retrieval date: 26 February 2026), exported full bibliographic records including abstracts, keywords, affiliations, and cited references, removed duplicate and incomplete entries, and standardised keyword variants (e.g., “AI” and “artificial intelligence”) to ensure consistency in co-occurrence analysis.
	Step 4: Delimiting the analytical base	Classified all 1,085 records by domain relevance through descriptor matching across title, abstract, and keyword fields, distinguishing advertising-relevant from non-advertising records. Rather than excluding the latter, this step establishes the two analytical denominators reported in Table 2 and fixes the evidentiary base for construct-level claims.
	Step 5: Appraising theoretical and	Identified the most frequently cited and thematically central studies within the advertising-relevant subset and appraised them through close reading, assessing the theoretical frameworks through which consumer responses are

	thematic centrality	conceptualised and the conceptual contribution each makes to resistance theorisation.
	Step 6: Extracting and managing data	Applied a structured extraction template to the appraised studies, recording theoretical framework, AI application type, research design, outcome variables, and the construct vocabulary used to denote consumer opposition, and organised the results in a coding matrix aligned with the construct categories reported in Table 5.
	Step 7: Synthesising evidence	Conducted a narrative synthesis across the extracted studies, triangulating interpretive findings against two independent quantitative sources: the co-citation and co-occurrence structures obtained from VOSviewer, and the construct-frequency distribution reported in Table 5.
Stage III: Reporting	Step 8: Presenting findings and deriving implications	Reported bibliometric structures and construct-frequency evidence in Section 4, and derived the interpretive research agenda in Section 5, identifying intellectual foundations, dominant and nascent themes, structural gaps, and future research directions concerning consumer resistance to AI advertising.

This study employed a systematic review methodology, comprising three primary stages: planning, conducting, and reporting and disseminating the review, to enhance the bibliometric analysis and provide conceptual depth. The methodology was derived from recognized systematic review frameworks in management and marketing research [48], [49], [50], as depicted in Table 1.

3.3. Bibliometric analysis techniques

A bibliometric study was performed utilizing VOSviewer, which is a prominent tool for mapping and visualizing scientific knowledge. Table 3 summarizes the bibliometric techniques applied, their analytical objectives, and the key parameters used.

Table 3. Overview of bibliometric analysis techniques and analytical conditions

Bibliometric technique	Analytical objective	Unit of analysis	Thresholds/ parameters	Key references
Performance analysis ↓	Identify publication trends, influential journals, prolific authors, and highly cited articles	Articles, journals, authors	Annual publication counts; total citations; h-index	[45], [46]
Co-citation analysis ↓	Reveal intellectual foundations and core theoretical streams in AI advertising research	Cited references	Minimum citation threshold for inclusion; network normalization	[51], [52]
Keyword co-occurrence analysis ↓	Identify dominant and emerging research themes	Author keywords and Keywords Plus	Minimum occurrence threshold; association strength normalization	[53], [47]
Overlay visualization	Examine temporal evolution of research themes and shifts in thematic focus	Keywords	Average publication year; color gradient mapping	[52], [46]

A performance analysis was initially performed to assess the growth trajectory of AI advertising research, emphasizing significant publishing periods, prominent journals, and influential scientists. Co-citation analysis was then utilized to reveal the intellectual underpinnings and theoretical frameworks influencing the field. Keyword co-occurrence analysis was conducted to elucidate theme structure, focusing specifically on resistance-related concepts including manipulation, privacy, ethics, disclosure, and psychological reactance. Ultimately, overlay visualization was utilized to examine the temporal evolution of study themes, facilitating the recognition of transitions from acceptance-oriented viewpoints to growing resistance-focused investigations.

4. RESULTS

4.1. Publication trends and intellectual foundations of AI advertising research (RQ1)

4.1.1. Publication trends of AI advertising research

Figure 1 presents a comprehensive overview of publication trends and intellectual foundations in AI advertising research, combining data from 1085 Scopus-indexed journal articles and employing bibliometric mapping via VOSviewer. The six subfigures collectively illustrate the temporal evolution (1a), disciplinary foundation (1b), geographical distribution (1c), collaborative framework (1d), subject-area composition (1e), and thematic progression of the field (1f). Figure 1 demonstrates the evolution of AI advertising research from a peripheral, technology-focused subject to a swiftly growing, multidisciplinary field increasingly focused on advertising theory, consumer behavior, and human–AI interaction. This visual synthesis contextualizes consumer resistance research within the broader and unequal intellectual landscape of AI-driven advertising study, setting the stage for following investigations.

Figure 1a depicts the temporal evolution of scholarly output in AI advertising research. The results reveal a prolonged period of marginal academic activity prior to 2010, followed by a marked and sustained growth beginning around 2017. This inflection point coincides with rapid advancements in machine learning, the diffusion of platform-based advertising ecosystems, and the emergence of generative AI applications. The acceleration becomes particularly pronounced after 2020, signaling intensified scholarly attention to AI-driven personalization, automation, and associated ethical challenges within advertising contexts.

Figure 1b presents publication trends by source, demonstrating that AI advertising research is primarily disseminated through leading advertising and marketing journals, including Journal of Advertising and Journal of Interactive Marketing, alongside interdisciplinary outlets. This pattern underscores the field's intellectual positioning at the intersection of advertising theory, consumer behavior, and digital technology research, rather than being confined to computer science or engineering domains alone.

Geographically, Figure 1c shows that research output is dominated by the United States, followed by the United Kingdom and China, with emerging contributions from Europe and Asia. This distribution reflects both the concentration of digital advertising markets and the institutional capacity for AI-related research. The international collaboration network (Figure 1d) reveals dense cross-country linkages, indicating a globally interconnected yet institutionally concentrated intellectual structure underpinning the development of AI advertising scholarship. Subject area analysis (Figure 1e) further confirms the multidisciplinary foundations of AI advertising research, spanning business and management, social sciences, computer science, psychology, and decision sciences.

The overlay map (Figure 1f) illustrates a distinct trajectory of AI research in advertising and associated domains. Initial keywords (blue–light green, 2016–2019) emphasize artificial intelligence, big data, decision-making, neural networks, and optimization. This era regarded

AI chiefly as a tool for decision-making and optimization, highlighting its performance and data processing abilities. Subsequently, following keywords (yellow, post-2020) progressively transition towards advertising, social media, influencer marketing, consumer trust, attitudes, and chatbots. This transition signifies the increasing focus on human-AI interaction in persuasive communication, emphasizing consumer emotional responses, perceptions, and beliefs as essential elements.

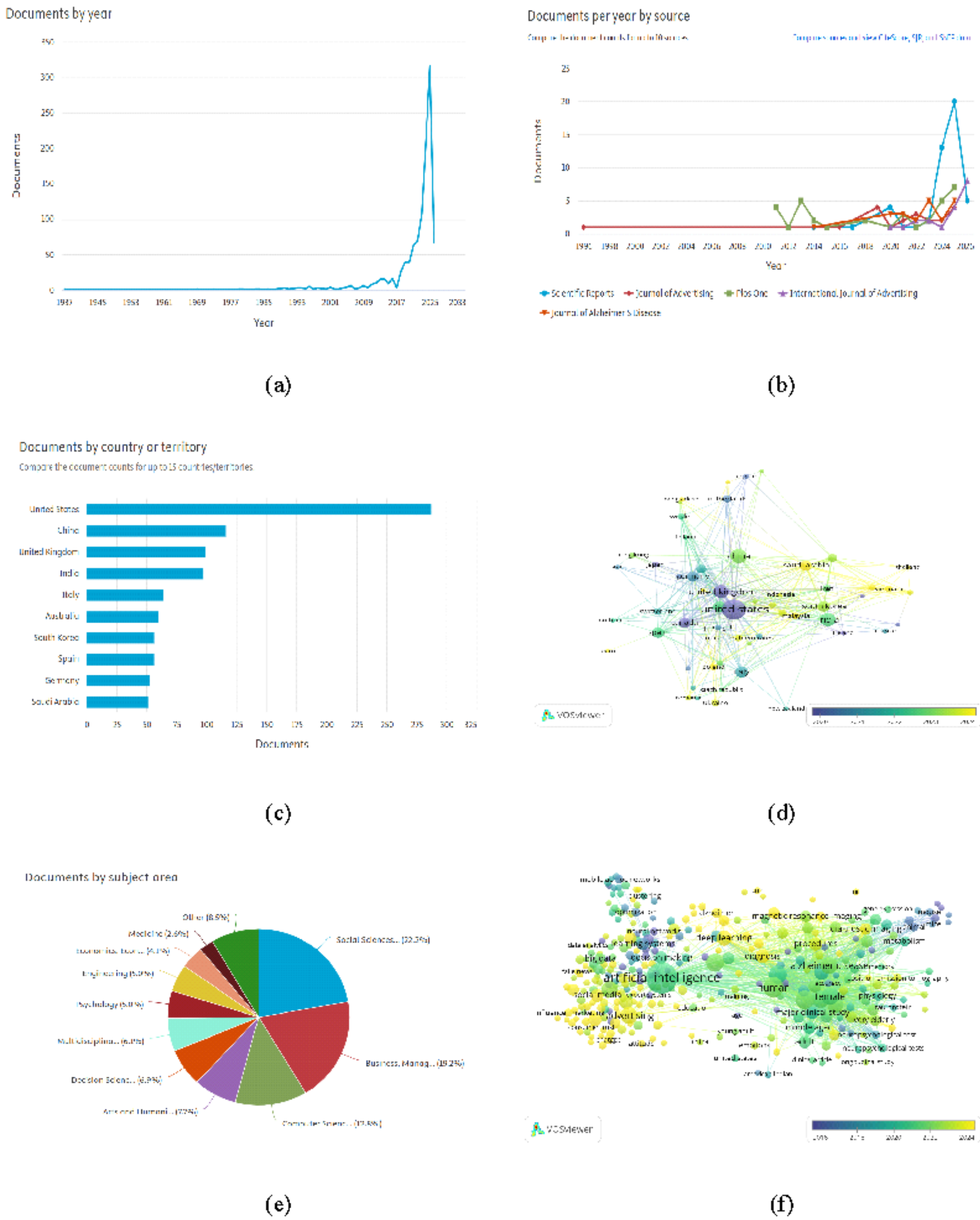

Figure 1. Publication trends, disciplinary distribution, and international collaboration patterns in AI advertising research (*Source: own research*)

4.1.2. Intellectual foundations of AI advertising research

The publication trends and disciplinary dispersion illustrated in Figure 1 establish a crucial contextual basis for understanding the theoretical framework of the discipline. The swift proliferation and interdisciplinary broadening of AI advertising research indicate not just a heightened volume but also a diversification of concepts. A co-citation analysis was performed to reveal the intellectual roots of this evolution, identifying the theoretical core and predominant information streams influencing the area.

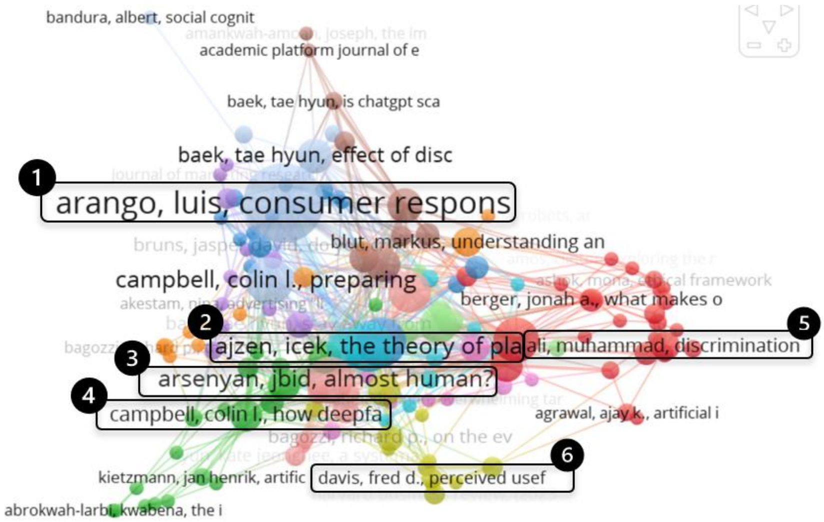

Figure 2. Author co-citation network of AI advertising research (*Source: own research*)

Author co-citation analysis reveals six distinct yet interrelated theoretical clusters that collectively constitute the intellectual foundations of AI advertising research (Figure 2). These clusters reflect how the field has evolved from classical persuasion theories toward emerging concerns related to human–AI interaction, governance, and consumer resistance.

Table 4. Intellectual foundations of AI advertising research: Author co-citation clusters

Cluster	Core theoretical foundation	Key representative scholars	Implications for consumer resistance to AI advertising
(1) Consumer response & persuasion	Advertising persuasion theory; consumer response models	Arango et al. [54]	Resistance is largely implicit; negative responses are treated as reduced effectiveness rather than active opposition
(2) Planned behavior & intentional models	Theory of Planned Behavior (TPB)	Ajzen [55]	Frames resistance as low intention or unfavorable attitudes, under-theorizing affective and moral resistance
(3) Anthropomorphism & perceived humanness	Social cognition; Human–AI interaction; Anthropomorphism theory	Arsenyan & Mirowska [56]	Highlights ambivalence: anthropomorphism may increase engagement while simultaneously provoking discomfort and resistance

Cluster	Core theoretical foundation	Key representative scholars	Implications for consumer resistance to AI advertising
(4) Disclosure, transparency & persuasion knowledge	Persuasion Knowledge Model (PKM); Advertising ethics	Friestad & Wright [57]	Positions resistance as an activated cognitive defense against perceived manipulation and hidden persuasion
(5) Ethics, bias & algorithmic governance	Algorithmic ethics; fairness and discrimination theory	Ali et al. [58]	Frames resistance as a rational response to perceived injustice, surveillance, and loss of autonomy
(6) Technology acceptance & perceived usefulness	Technology Acceptance Model (TAM)	Davis [59]	Reinforces acceptance-oriented logic; resistance is conceptualized as adoption failure rather than meaningful opposition

The co-citation clusters indicate that AI advertising research is fundamentally grounded in frameworks of persuasion, planned behavior, and technology acceptance, which predominantly interpret customer responses through acceptance-focused and performance-oriented perspectives. Perspectives on resistance - focusing on ethics, disclosure, anthropomorphism, and algorithmic governance - are notably fragmented and marginal, highlighting the necessity for cohesive theoretical frameworks that explicitly regard consumer resistance as a primary, independent reaction to AI-driven advertising. The subsequent section (RQ2) analyzes keyword co-occurrence and thematic evolution to discern dominant and emerging research themes, along with significant gaps that hinder theoretical progress in comprehending consumer opposition to AI-driven advertising.

4.2. Prevailing and nascent themes in consumer resistance to AI advertising (RQ2)

The integrated network (Figure 3) and density (Figure 4) visualizations offer complementary perspectives on the theme framework of AI advertising research and its ramifications for consumer resistance. The network image displays separate yet interconnected topic clusters, whereas the density map emphasizes regions of intellectual concentration and relative disregard.

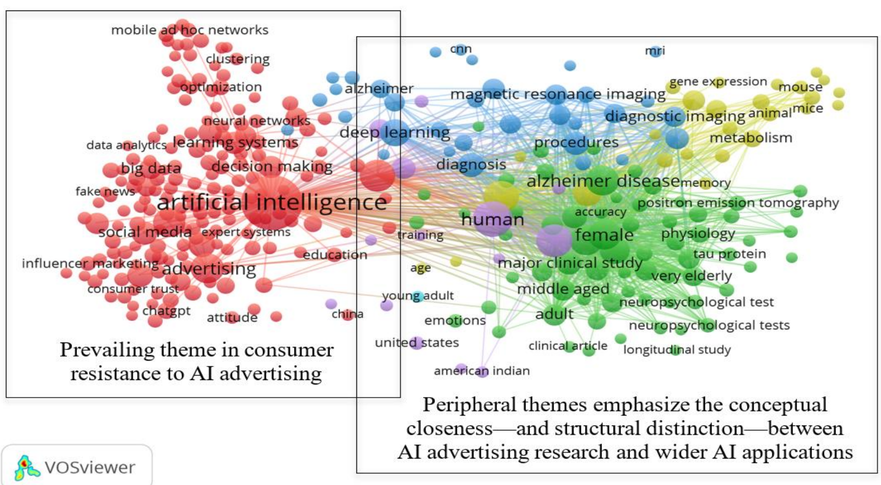

Figure 3. Keyword co-occurrence network of AI advertising research (*Source: own research*)

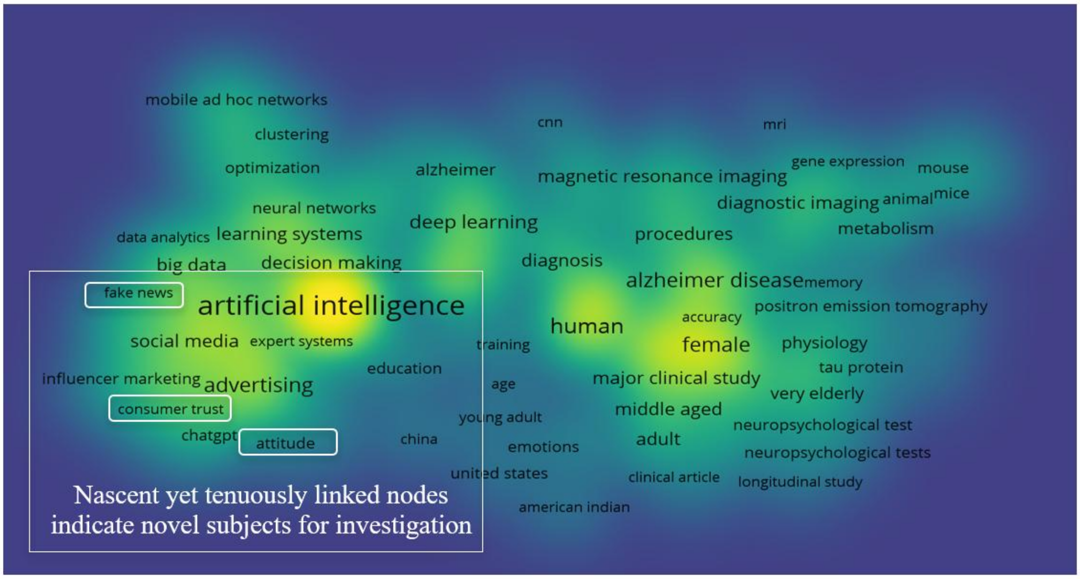

Figure 4. Density visualization of keyword co-occurrence in AI advertising research (*Source: own research*)

4.2.1. Prevailing theme in consumer resistance to AI advertising

Examining the red advertising-related clusters in the keyword co-occurrence map uncovers a research landscape characterized by a management and performance-driven paradigm, wherein customer resistance is inadequately hypothesized. The primary cluster focuses on AI-driven advertising optimization, including terms such as *artificial intelligence, advertising, social media, big data, optimization*, and *decision-making*. This cluster illustrates a dominant instrumental perspective on AI as a tool for enhancing targeting precision, personalization efficacy, and campaign effectiveness. In this context, *decision-making* is generally regarded as a functional precursor to performance outcomes, rather than as a contentious notion influenced by feelings of manipulation, surveillance, or diminished agency. Consequently, resistance-related behaviors are often implicitly categorized as performance risks instead of being analyzed as theoretically separate phenomena.

This imbalance is measurable instead of solely perceptual. Table 5 presents the occurrence of resistance-related and acceptance-oriented constructs throughout the text. In the advertising-related subset (n = 590), no resistance construct surpasses 4.41% of entries, while terms associated with optimization and efficiency constitute 31.69%, and personalization accounts for 17.80%, indicating an approximate sevenfold disparity between the predominant resistance construct and the leading performance construct. The disparity in author-assigned keywords is even more pronounced: merely 26 out of 1085 records (2.40%) include a resistance descriptor, the phrase "consumer resistance" is mentioned once, and "psychological reactance", arguably the pivotal concept of resistance theory, is absent from both author and index keyword fields throughout the corpus. Opposition in AI advertising academia is therefore not just insufficiently theorized; to a significant extent, it remains unacknowledged.

Table 5. Frequency of resistance-related versus acceptance-oriented constructs

Construct	Keyword field n (% of 1,085)	Title, abstract, keyword n (% of 1,085)	Advertising subset n (% of 590)
PANEL A. RESISTANCE-RELATED CONSTRUCTS			
Consumer resistance	1 (0.09)	2 (0.18)	1 (0.17)
Psychological reactance	0 (0.00)	1 (0.09)	1 (0.17)
Skepticism	3 (0.28)	11 (1.01)	7 (1.19)
Ad avoidance/rejection	1 (0.09)	2 (0.18)	2 (0.34)
Algorithm/AI aversion	3 (0.28)	4 (0.37)	4 (0.68)
Distrust/mistrust	0 (0.00)	3 (0.28)	3 (0.51)
Privacy concern (consumer-referent)	8 (0.74)	28 (2.58)	**26 (4.41)**
Perceived manipulation	2 (0.18)	6 (0.55)	6 (1.02)
Perceived surveillance	2 (0.18)	5 (0.46)	5 (0.85)
Autonomy threat loss of control	4 (0.37)	8 (0.74)	8 (1.36)
Intrusiveness/creepiness	1 (0.09)	5 (0.46)	4 (0.68)
Persuasion knowledge	3 (0.28)	6 (0.55)	6 (1.02)
Any resistance construct	**26 (2.40)**	**69 (6.36)**	**61 (10.34)**
PANEL B. ACCEPTANCE-ORIENTED CONSTRUCTS			
Artificial intelligence	691 (63.69)	1,075 (99.08)	588 (99.66)
Advertising	251 (23.13)	560 (51.61)	560 (94.92)
Optimisation/efficiency/effectiveness	68 (6.27)	301 (27.74)	**187 (31.69)**
Machine learning / deep learning	173 (15.94)	234 (21.57)	97 (16.44)
Personalisation	44 (4.06)	127 (11.71)	105 (17.80)
Engagement	23 (2.12)	100 (9.22)	87 (14.75)
Attitude	26 (2.40)	88 (8.11)	**77 (13.05)**
Technology acceptance/adoption	25 (2.30)	102 (9.40)	75 (12.71)
Purchase intention	9 (0.83)	35 (3.23)	35 (5.93)
Consumer trust	7 (0.65)	24 (2.21)	**24 (4.07)**

Note: Ambiguous terms were disambiguated by requiring co-occurrence with a consumer-referent term (consumer, customer, user, audience, shopper, individual). Of 76 records mentioning privacy, only 23 refer to consumer privacy concern rather than technical data privacy; of 18 mentioning surveillance, only 4 refer to perceived consumer surveillance rather than military or public-health surveillance; of 31 mentioning manipulation, only 6 refer to perceived persuasive manipulation rather than political or image manipulation. Counts are article-level and not mutually exclusive.

4.2.2. Nascent theme in consumer resistance to AI advertising

Encircling the primary cluster, several nascent yet weakly connected nodes - most notably *attitude*, *fake news*, and *consumer trust* - signal an emerging shift toward resistance-oriented concerns in AI advertising research. The growing prominence of *attitude* reflects increasing scholarly attention to consumers' evaluative and affective responses to AI-generated advertising, particularly when algorithmic persuasion is perceived as intrusive or opaque [32]. Simultaneously, the linkage between AI advertising and *fake news* highlights escalating anxieties surrounding authenticity, credibility, and information manipulation, positioning AI not merely as a neutral optimization tool but as a potential catalyst for deception and persuasive excess [27], [57]. Within this context, *consumer trust* operates as a critical mediating construct, bridging technological deployment and consumer acceptance, while its fragility underscores conditions under which AI-enabled advertising may trigger skepticism, psychological reactance, and avoidance rather than engagement [14]. Despite their conceptual relevance to resistance theory, these themes remain marginal relative to the dominant performance- and efficiency-driven discourse in the field.

The numerical data shown in Table 5 elucidates this emerging transition. Consumer trust and attitude, albeit the most prominent resistance-related elements on the co-occurrence map, constitute merely 4.07% and 13.05% of the advertising-related subset respectively, and neither is posited as resistance in the studies that include them. The map's indication of a nascent shift is more accurately characterized as an expansive evaluation of acceptance research rather than the advent of a resistance framework.

4.2.3. Peripheral clusters and the unsettled boundary of AI advertising research

In addition to the primary advertising-focused cluster, many peripheral clusters arise that are not explicitly based on advertising concept. The deep learning cluster (blue) predominantly represents algorithmic and procedural research, providing technological foundations instead of insights into persuasion or consumer behavior. Similarly, the human-centered cluster (purple) emphasize system training and human-AI interaction without direct involvement in advertising results. The biological and diagnostic clusters (yellow and green) exemplify the transdisciplinary dissemination of artificial intelligence research across practical areas.

The extent of this peripheral portion constitutes a discovery rather than an artifact for validation. According to Table 1, 495 entries (45.6%) lack any advertising or marketing identifiers in all indexed fields, while 182 entries (16.8%) pertain to biomedical or therapeutic sectors. Two consequences ensue. Initially, all construct-level assertions in this research are derived from the advertising-specific subset, hence the paucity of resistance constructions noted in Table 5 cannot be ascribed to corpus dilution. Secondly, and more significantly, the substantial non-advertising remainder yielded by a domain-specific retrieval strategy suggests that the conceptual demarcation between AI advertising research and broader AI scholarship has not yet been established within the indexing frameworks utilized for retrieval and mapping in the field. This ambiguity of boundaries is significant for resistance studies specifically: concepts like privacy, surveillance, and manipulation are prevalent in AI literature but primarily possess technical, political, or clinical interpretations, with only a minor portion relating to consumer-oriented contexts. Defining clearer conceptual boundaries is therefore a prerequisite for, not merely a consequence of, a cohesive resistance research initiative in advertising.

5. DISCUSSION AND FUTURE RESEARCH AGENDA (RQ3)

5.1. Repositioning consumer resistance as a central theoretical construct

The co-citation framework (Table 4) identifies six theoretical clusters, none of which focus on resistance as a central idea. Instead, resistance appears in each cluster only as a byproduct of theories based on technology acceptance, persuasion, planned behavior, anthropomorphism, and algorithmic ethics. This structural interpretation is supported by the construct-frequency evidence, which also greatly improves it. Only 26 out of 1085 entries (2.40%) contain any description of resistance in their keyword fields, the term “psychological reactance” is not present in either the author or index keyword fields, and the phrase "consumer resistance" appears only once. No resistance construct exceeds 4.41% of the data in the advertising-related subset. These patterns imply that resistance is not only understudied but also poorly categorized: the field does not have a uniform vocabulary for writers to acknowledge their contributions as addressing consumer protest. Rather than being viewed as a separate reaction with its own origins and behavioral patterns, resistance is evaluated in a derivative way, defined as lower efficacy, weak will to adapt, or negative disposition. Instead than focusing solely on the residue of acceptance, future research should consider resistance as a primary construct. There are three more stages that follow. First, resistance-focused theory should be freely incorporated, using persuasion knowledge [60], [16] and perceived autonomy threat [12], [39] to explain why customers resist AI-mediated persuasion instead of just rejecting it. Second, since cognitive defense, affective reactance, and behavioral avoidance are not conceptually or experimentally interchangeable, resistance should be described as a complex construct. Thirdly, the field requires verified metrics: without instruments that distinguish between minimal acceptance and resistance, the above-mentioned derivative theorization would persist regardless of theoretical intent.

5.2. Examining AI advertising affordances that trigger resistance mechanisms

Table 5 measures the asymmetry that results from organizing the keyword co-occurrence structure around a management and optimization paradigm. Terms related to efficiency and optimization appear in 31.69% of the advertising-relevant subset, while terms related to personalization appear in 17.80%, compared to 4.41% for consumer privacy concerns and 1.02% for perceived manipulation. Thus, affordances are examined on a large scale, although they are mostly used as performance levers. Research on personalization, generative content, anthropomorphism, and disclosure is lacking, but what is lacking is research that addresses these same affordances as potential sources of resistance. When mechanisms intended to improve persuasion activate persuasion knowledge or ethical concern, they may, paradoxically, increase skepticism and reactance [9], [34], [16]; the field currently lacks the research necessary to identify the circumstances under which each consequence occurs. Therefore, affordances should be modeled as two-edged in future study. Priority questions include how algorithmic personalization transitions from perceived relevance to perceived surveillance; whether disclosing AI-generated content reduces or increases mistrust, considering the conflicting effects documented thus far [28], [43]; and how anthropomorphism simultaneously boosts engagement and encourages attributions of ulterior motive [56], [16]. Since perceived deceit and authenticity loss are fundamental rather than incidental properties of these formats, generative applications like deepfake advertising and virtual influencers are particularly instructive test cases [14], [26], [27], [57].

5.3. Contextualising resistance across time, cultures, and regulatory regimes

Although the overlay visualization (Figure 1f) shows a thematic transition from optimization-centered keywords (2016–2019) to trust, attitude, and human–AI interaction (post-2020), the supporting data is essentially unchanged. Longitudinal or temporal designs are found in 1.36% of records and cross-cultural or cross-national designs in 1.69% of the advertising-relevant subset, compared to 19.15% for experimental designs and 13.22% for cross-sectional surveys. 0.34% of descriptions of technological opposition include institutional trust, a crucial mediator. The geographic concentration shown in Figure 1c exacerbates the issue: evidence is primarily drawn from the United States, the United Kingdom, and China. Regulatory and governance descriptors are more visible at 12.88%, but they cluster in work on AI governance generally rather than on consumer response. Theory is limited in a particular way by this arrangement. Since what is considered intrusive is measured against current regulatory protection and cultural norms of privacy and autonomy, resistance is plausibly cumulative—the result of repeated exposure, growing privacy fatigue, and changing normative expectations—and plausibly dependent on institutional context. Both claims cannot be decided by a literature that is virtually exclusively made up of single-exposure studies in a small number of markets. Thus, resistance research should be expanded along three contextual axes in future studies. To ascertain if resistance increases, habituates, or oscillates with repeated exposure to AI-mediated advertising, temporal longitudinal and diary-based designs are required. Cross-national comparisons should examine whether the affordance-resistance connections found in Section 5.2 are culturally variable or immutable, especially between nations with different institutional trust and privacy norms. The EU AI Act, sectoral disclosure standards, and lighter-touch environments are examples of divergent regulatory regimes that provide a natural experiment for determining the impact of required AI disclosure on consumer response. Since regulatory and cultural framing is precisely what separates consumer-referent resistance from the technical and political senses in which terms like privacy, surveillance, and manipulation otherwise circulate in AI scholarship, addressing these axes would also address the conceptual boundary problem described in Section 4.2.3.

6. CONCLUSION

This study aimed to thoroughly analyze the intellectual framework of research on consumer resistance to AI advertising by combining bibliometric mapping with a systematic review of 1,085 peer-reviewed papers indexed in Scopus. The findings indicate a domain that has swiftly evolved with the proliferation of AI-driven advertising technology yet remains conceptually uneven. Bibliometric analysis indicates that AI advertising research is primarily characterized by acceptance-focused, performance-oriented frameworks that prioritize optimization, personalization, and managerial efficiency, whereas resistance-related constructs remain marginal and poorly integrated within the intellectual framework.

Co-citation and keyword co-occurrence analyses, corroborated by construct-frequency evidence, indicate that resistance-oriented concerns such as consumer trust, fake news, and attitude are emerging but lack theoretical cohesion, and that the vocabulary of resistance is largely absent from the terms by which authors themselves label their work. This fragmentation is exacerbated by the dominance of short-term, individual-level studies and the insufficient incorporation of socio-cultural, institutional, and longitudinal views.

This study provides a significant reorientation of AI advertising research by shifting the analytical focus from acceptance to opposition. It elucidates the structural deficiencies in current scholarship and delineates a prospective research agenda that underscores resistance as a multifaceted, dynamic, and contextually situated phenomena. Future research that incorporates resistance-oriented philosophy, investigates particular AI affordances, and employs longitudinal and cross-cultural methodologies will be crucial for developing a more equitable and consumer-focused comprehension of AI advertising. These discoveries enhance advertising theory and have significant implications for ethical governance and responsible AI implementation in modern marketing practices.

This study, despite its merits, has several drawbacks that must be recognized. The bibliometric study is only based on the Scopus database, which, while extensive, may not encompass all pertinent publications, especially those indexed in alternative databases like Web of Science or growing regional sources. The inclusion criteria were limited to English-language journal papers, potentially omitting crucial insights from non-English academia and alternative publication formats. The dataset's cross-sectional character restricts the capacity to document the latest advancements in this swiftly changing domain. These constraints suggest that future research may benefit from multi-database strategies, broader inclusion criteria, and retrieval designs that impose tighter domain precision than the high-recall strategy adopted here. We also note that construct frequency, as measured through indexed descriptors, captures the explicit vocabulary of a field rather than the full substance of its arguments; a study may engage resistance phenomena without labelling them as such, and complementary full-text or qualitative coding approaches would refine the estimates reported in Table 5.

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