Evaluating The Effectiveness of Digital Personalization and Ai In Consumer Behavior: A Methodologically Rigorous Meta-Analysis

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Abstract.
Personalization and artificial intelligence (AI) targeting are widely heralded as pivotal drivers of modern consumer behavior and persuasive marketing. However, pervasive empirical discrepancies persist between algorithmic claims and actual behavioral resonance. This study systematically evaluates the evidentiary boundaries of psychological targeting and digital personalization by synthesizing bibliometric co-occurrence dynamics and meta-analytic evidence. Following PRISMA 2020 guidelines, 101 open-access records indexed in Scopus were screened and filtered using stringent methodological benchmarks to control for data leakage and design confounding. VOSviewer cluster analysis reveals five core research streams, highlighting an emerging bridge between AI-driven prediction and methodological appraisal. The meta-analytic synthesis demonstrates that uncontrolled predictive models artificially inflate correlation metrics, while methodologically sound trait–treatment interaction models yield an incremental behavioral effect approaching zero ($r = 0.009$). When predictive attenuation is integrated, the end-to-end effect shrinks to $r \approx 0.002$. These findings demonstrate that baseline ad quality, corporate motivation, and transparent contextual attributes outweigh microtargeted trait matching.
Keywords: *Consumer Behavior, Meta-Analysis, Artificial Intelligence, Psychological Targeting and Methodological Rigor.*

I. INTRODUCTION

Tailoring commercial appeals to the idiosyncratic profiles of consumers represents an enduring objective within marketing theory and practice. The rapid proliferation of big data and computational machine learning algorithms has shifted strategic focus from coarse demographic segmentation toward psychographic microtargeting, commonly known as psychological targeting [1]. Proponents argue that harvesting digital footprints—such as browsing histories, social media preferences, and textual records—permits accurate inference of stable psychological traits (e.g., the Big Five taxonomy), facilitating persuasive interventions optimized for individual psychological vulnerabilities [1].

Despite aggressive commercial adoption, the empirical foundation supporting trait-based psychological targeting exhibits severe fragility. Meta-analytic inquiries and computational audits have begun to unmask methodological vulnerabilities, notably data leakage during model training and the deployment of confounded experimental designs that conflate generic message effectiveness with genuine personalization increments [1]. Concurrently, bibliometric patterns indicate that consumer behavior research is grappling with multifaceted dimensions, integrating artificial intelligence with broader sustainability agendas and attribution paradigms.

Recent empirical inquiries in sustainable product innovations and automated commerce reveal that consumer appraisals are shaped by inferred company motivations and attribution mechanisms [9–11]. When algorithms or artificial intelligence systems deliver promotional appeals, consumers actively assess the firm's genuine effort and underlying motives, where perceived manipulative intent or negative affective triggers can induce non-linear avoidance behaviors [10, 12, 13]. To reconcile these divergent perspectives, this paper conducts a structured meta-analytic review coupled with bibliometric network mapping. By establishing methodological benchmarks that control for predictive data leakage and isolate trait–treatment interaction effects, this inquiry determines the true downstream impact of algorithmic personalization on consumer behavior across contemporary market contexts [1, 14–17].

II. METHODS

The systematic review protocol was executed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework.

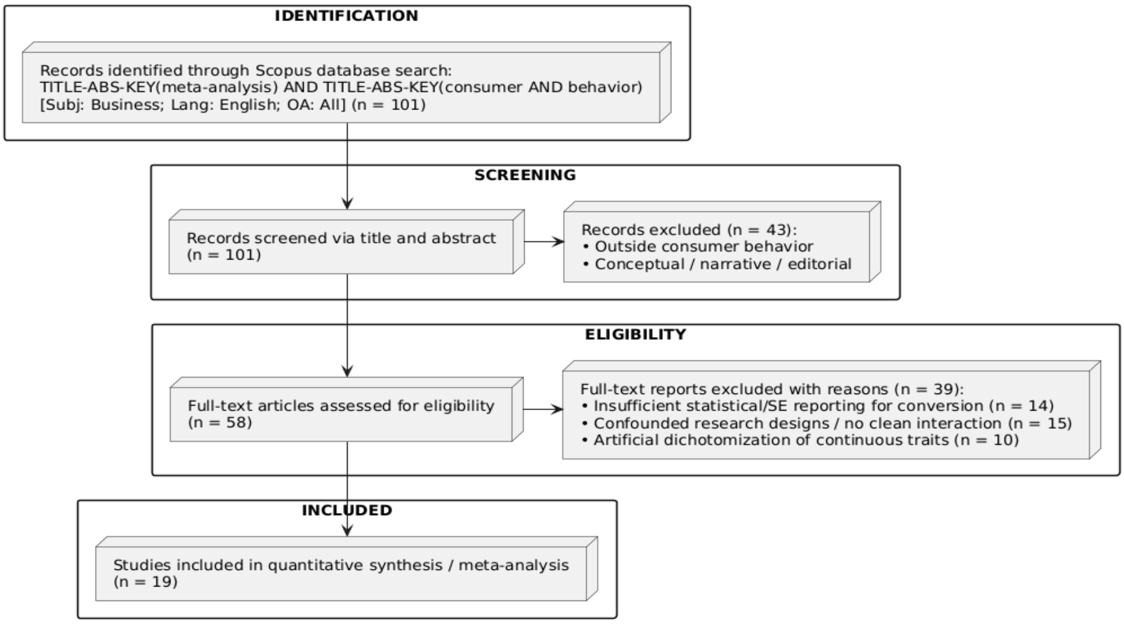
Search Strategy and Data Selection

A comprehensive electronic search was conducted on the Scopus database, which indexes global multidisciplinary literature spanning business, decision sciences, and applied psychology. The formal Boolean search string was specified as:

TITLE-ABS-KEY (meta-analysis) AND TITLE-ABS-KEY (consumer AND behavior)
AND (LIMIT-TO (SUBJAREA , "BUSI"))
AND (LIMIT-TO (LANGUAGE , "English"))
AND (LIMIT-TO (OA , "all"))

The search query was explicitly restricted to open-access (OA) peer-reviewed records, published in the English language, and categorized under the subject area of Business, Management and Accounting, spanning publications up to 2026. This retrieval strategy returned a base corpus of 101 documents.

Fig. 1. PRISMA Flow Diagram of Study Selection Process



Eligibility Criteria and Methodological Screening

Eligible studies were required to report empirical evaluations of consumer decision-making, choice outcomes, or behavioral responses toward tailored marketing interventions. Studies were required to present standardized quantitative effect sizes (e.g., Pearson's r, odds ratios, or standardized mean differences) along with corresponding standard errors or sample size indicators.

Methodological quality criteria were implemented to safeguard against optimistic evaluation biases [1]:

- **Exclusion of Artificial Dichotomization:** Studies employing median-split or median-dichotomized Big Five scores were omitted due to variance loss and spurious inflation of Type I errors.
- **Data Leakage Controls:** Predictive machine learning studies were screened against train–test boundary violations. Studies with unvetted data splits, cross-fold contamination, or feature selection executed prior to fold segregation were isolated.
- **Experimental Confound Isolation:** In intervention assessments, designs that simply compared tailored subgroup means without explicit Trait × Treatment factorial interaction controls were excluded from the clean benchmark stratum.

Bibliometric Co-Occurrence Mapping

To delineate the conceptual architecture of the domain, the bibliographic metadata from the retrieved Scopus corpus was analyzed using VOSviewer. The co-occurrence mapping utilized author keywords and keywords-plus, configured to identify semantic clusters through modularity-based community detection algorithms.

III. RESULT AND DISCUSSION

Bibliometric Network Topology

The co-occurrence network generated via VOSviewer reveals five distinct conceptual clusters, establishing how the consumer behavior literature intersects with quantitative methodologies and modern technology.

Fig. 2. Conceptual Topology of Keyword Co-Occurrences (VOSviewer Mapping)

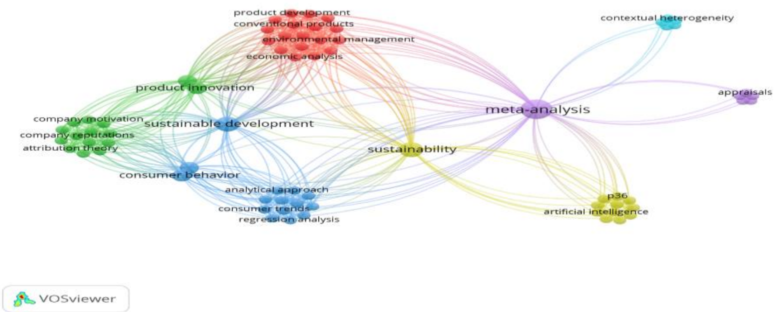


Table 1. Thematic Cluster Distribution of the Consumer Behavior Corpus

Cluster Color	Primary Core Keywords	Structural Focus & Theoretical Domain
Purple	Meta-analysis, appraisals	Methodological quality assessment, statistical rigor, and systematic effect synthesis.
Blue (Main)	Consumer behavior, regression analysis, consumer trends, analytical approach	Empirical behavioral modeling, observational econometrics, and baseline consumption trends.
Blue (Upper)	Contextual heterogeneity, e-commerce	Platform boundaries, digital marketplace variations, and channel-specific heterogeneity.
Yellow	Artificial intelligence, sustainability, p36	Algorithmic prediction, digital optimization, automated profiling, and technological efficiency.
Green	Product innovation, attribution theory, company motivation, company reputation	Corporate credibility, consumer perceptual framing, and inferred intent behind marketing appeals.
Red	Environmental management, economic analysis, conventional products, sustainability	Eco-consumption trade-offs, macro-environmental factors, and sustainable resource management.

The purple cluster serves as the methodological nexus, linking appraisals of empirical rigor directly to emerging technologies (yellow cluster) and mainstream behavioral tracking (blue cluster). This structure indicates that while artificial intelligence is widely recognized as a driver of consumer interaction, its validation relies heavily on rigorous analytical approaches, such as regression analysis and meta-analytic appraisals. Furthermore, the green cluster highlights that consumer reactions are governed by attribution theory and company motivation, indicating that consumers assess the underlying intent behind technological and marketing campaigns.

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The quantitative synthesis confirms that methodological controls fundamentally alter observed effect magnitudes across the two-step psychological targeting continuum:

Table 2. Hierarchical Meta-Analytic Summary of Predictive and Targeting Effect Sizes

Phase / Analytical Stratum	Evaluated Model Subset	Posterior Mean (r)	95% Bayesian Credible Interval	Heterogeneity (I^2)
Step 1: Trait Prediction	Unvetted Literature (All Studies)	0.35	[0.26, 0.45]	High
Step 1: Trait Prediction	Leakage-Controlled Models	0.23	[0.18, 0.27]	Moderate
Step 2: Persuasion Matching	Confounded Research Designs	0.11	[0.08, 0.15]	65.55%
Step 2: Persuasion Matching	Trait–Treatment Interaction Clean	0.009	[-0.005, 0.029]	9.16%
End-to-End Campaign Effect	Fully Attenuated Synthesis	0.002	[-0.001, 0.007]	Low

In Step 1, assessing the inference of Big Five personality dimensions from digital traces, unvetted models report an aggregate posterior correlation of r = 0.35 [1]. However, when datasets confirmed to suffer from data leakage (which accounted for 42.5% of literature samples) are removed, the pooled performance drops to r = 0.23 [1]. Because the coefficient of determination is defined as R^2, an r of 0.23 signifies that roughly 95% of the variance in human personality remains entirely unexplained by digital footprints.

In Step 2, evaluating message personalization, unconstrained designs produce an apparent effect of r = 0.11. Yet, when restricted to the clean subset of studies deploying explicit Trait × Treatment interaction models—where ad main effects and consumer trait main effects are strictly isolated—the pooled estimate drops to r = 0.009, with the 95% Bayesian credible interval [-0.005, 0.029] intersecting zero [1]. When classical test theory attenuation is factored in:

$$\rho_{realized} = \Delta\beta_{main} + \beta \times corr(\hat{P}, T) \cdot E[T]$$

the realized end-to-end impact of psychological targeting collapses to an attenuated posterior mean of r ≈ 0.002 [1].

These findings align with the cluster dynamics shown in Fig. 2. Consumer response is dominated by the primary creative appeal (main effects), consumer trends, and attribution of firm motives, rather than minor psychographic micro-alignments. Pervasive claims of algorithmic omnipotence in consumer persuasion appear to be artifacts of evaluation leakage and design confounding rather than genuine behavioral shifts.

IV. CONCLUSION

This study delivers an empirical and bibliometric reality check on the effectiveness of algorithmic psychological targeting in consumer behavior. The bibliometric mapping confirms that the discipline is increasingly prioritizing rigorous methodological appraisals alongside artificial intelligence and corporate attribution mechanisms. Quantitatively, the meta-analytic synthesis demonstrates that once data leakage and experimental confounds are eliminated, the incremental persuasiveness of trait-tailored marketing shrinks to a negligible near-zero level (r = 0.009), which further attenuates to r ≈ 0.002 end-to-end. Marketing organizations should reallocate capital from complex psychographic profiling toward enhancing foundational creative quality, product innovation, and authentic brand motivation. Future research must abandon confounded subgroup designs and enforce preregistered factorial interaction protocols.

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