The Role of Big Data-Driven Targeted Advertising in Shaping Brand Attitude and Purchase Intentions Among Digital Consumers

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Abstract
Big data-driven targeted advertising has transformed contemporary digital marketing by enabling firms to deliver hyper-personalized and contextually relevant promotional content. Despite its widespread adoption, the psychological mechanisms through which data-driven targeting shapes brand evaluation and consumer behaviour remain insufficiently understood. Drawing on the Stimulus–Organism–Response (S–O–R) framework, this study investigates how big data-driven targeted advertising (BDTA) influences purchase intention (PI) through perceived personalization (PP), advertisement relevance (AR), and brand attitude (BA). Using survey data from 326 digital consumers and applying Partial Least Squares Structural Equation Modelling (PLS-SEM), the study reveals that BDTA exerts strong positive effects on both PP and AR, demonstrating its capacity to reshape consumers' perceptual and cognitive interpretations of digital advertisements. PP and AR significantly enhance BA, with personalization exhibiting a slightly stronger effect, underscoring the emotional salience of individualized messaging. BA emerges as the most powerful predictor of PI, mediating the influence of both personalization and relevance on behavioural intention. The findings highlight a coherent multi-stage persuasion pathway in which algorithmic targeting functions as the stimulus, perceptual evaluations serve as organismic states, and attitude and intention constitute the response. By elucidating these mechanisms, the study advances theoretical understanding of algorithmic persuasion and offers practical insights for marketers seeking to optimise data-driven advertising strategies. The results underscore the need for brands to balance technological precision with psychologically meaningful personalization to cultivate favourable attitudes and drive purchase behaviour.

Keywords: *Big Data-Driven Marketing; Targeted Advertising; Personalized Advertising; Advertisement Relevance; Brand Attitude; Purchase Intention; Digital Consumers; Algorithmic Targeting; Consumer Behaviour; Data-Driven Marketing Strategies*

1. Introduction

In an era marked by unprecedented datafication of human experience, the contemporary digital marketplace has become a fertile terrain for algorithmically mediated persuasion, where firms increasingly deploy big data-driven targeting systems to anticipate, influence, and even pre-structure consumer decision-making processes (Mayer-Schönberger & Cukier, 2013) ; (Stone & Woodcock, 2014) . The proliferation of ubiquitous digital platforms ranging from social networking sites and streaming environments to e-commerce ecosystems; has generated voluminous traces of user behaviour, preferences, and psychographic patterns, thereby enabling marketers to refine advertising strategies with a granularity and predictive precision unimaginable only a decade ago (Wedel & Kannan) ; (Davenport, Barth, & Bean, 2012) . As algorithmic decision engines ingest heterogeneous data streams; including browsing histories, content interactions, geolocation metadata, and biometric indicators; they facilitate hyper-personalized advertising architectures that continuously adapt to consumers' latent needs, situational contexts, and behavioural propensities (Tucker, 2014) ; (Bleier & Eisenbeiss, 2015); (Arora, Hofacker, & Stone, 2017).

Big data-driven targeted advertising operationalizes this analytical abundance by transforming raw behavioural micro-signals into actionable marketing insights, allowing firms to curate persuasion environments that resonate at the level of individual identity and psychological salience (Lamberton & Stephen, 2016) ; (Wedel & Kannan, 2016) . Unlike conventional demographic segmentation, algorithmic targeting functions through probabilistic modelling, real-time pattern detection, and machine-learning-based inference mechanisms that forecast consumer intentions before they are consciously articulated (Shmueli & Koppius, 2011); (DeVito, 2017). This shift from reactive to anticipatory marketing marks a paradigmatic transformation in how brands cultivate meaning, engage audiences, and exercise influence in digital consumption ecologies (Zeng, Chen, & Chen, 2019) ; (Rust & Huang, 2014) . Consequently, firms leveraging such data-driven advertising infrastructures often achieve pronounced improvements in consumer engagement, message relevance, and attitudinal outcomes, especially within

highly competitive and low-differentiation markets such as fast-moving consumer goods (FMCG) ((Luo, Andrews, Fang, & Phang, 2014) ; (Bart, Stephen, & Sarvary, 2014).

Amid these technological advancements, consumers' perceptual responses; particularly their evaluations of ad relevance, personalization, and message congruity; have emerged as pivotal psychological mediators that determine whether big data-driven targeting elicits favourable or adverse attitudinal effects (Tam & Ho, 2006) ; (Aguirre, Mahr, Grewal, de Ruyter, & Wetzels, 2015) . While personalization enhances cognitive fluency and perceptual fit, thereby fostering positive brand attitudes (Zarouali, Ponnet, Poels, & Walrave, 2017) , excessive or opaque targeting may evoke privacy concerns, psychological reactance, and scepticism, ultimately eroding trust and attenuating purchase intentions (Baek & Morimoto, 2012) ; (Boerman, Kruikemeier, & Zuiderveen Borgesius, 2017) . This ambivalence underscores the necessity of empirically disentangling the mechanisms through which data-driven targeting shapes consumer evaluations and behavioural propensities in algorithmically saturated marketing environments.

Brand attitude, a central construct in consumer behaviour research, plays a decisive role in mediating the influence of targeted advertising on purchase intention (MacKenzie, Lutz, & Belch, 1986) ; (Keller, 2013) . As consumers navigate dense networks of algorithmically curated messages, their attitudinal dispositions increasingly hinge on perceived relevance, personalization accuracy, and the cognitive legitimacy of data-driven persuasion tactics (Ham, 2021) ; (Kim & Huh, 2017) . Purchase intention, the behavioural culmination of such attitudinal processes, reflects not only consumers' rational evaluations but also their affective alignment with brand narratives shaped by continuous data-based interactions (Fishbein & Ajzen, 1975); (Pavlou & Stewart, 2000).

Despite the burgeoning literature on digital personalization, significant gaps persist regarding the empirical interplay among big data-driven targeting, brand attitude, and purchase intention; particularly within emerging digital economies where algorithmic marketing infrastructures are rapidly evolving (Hoffman & Novak, 2018); (Shankar, et al., 2021). The present study addresses this gap by examining how big data-driven targeted advertising activates psychological mechanisms that subsequently shape brand evaluations and purchasing propensities among digital consumers. In doing so, it contributes to the broader discourse on innovative marketing practices, algorithmic persuasion, and data-enabled consumer behaviour in contemporary digital ecosystems.

2. Literature Review

The proliferation of big data analytics in contemporary digital markets has precipitated a fundamental reconfiguration of advertising ecosystems, reshaping how firms conceptualize, architect, and operationalize consumer engagement strategies. Big data-driven targeted advertising, emerging at the convergence of algorithmic computation and ubiquitous data capture, represents one of the most influential developments in modern marketing thought (Mayer-Schönberger & Cukier, 2013); (Chen, Chiang, & Storey, 2012). Scholars argue that algorithmic targeting systems derive their persuasive power from the continuous aggregation and modelling of behavioural traces generated across digital infrastructures; from search histories and clickstream logs to social media engagements and mobile sensory data; thereby enabling marketing communications to be calibrated at an unprecedented level of granularity (Wedel & Kannan, 2016); (Tucker, 2014) ; (DeVito, 2017) . This transition from traditional demographic segmentation toward adaptive, data-informed, and individually tailored outreach signals a paradigmatic transformation in the nature of advertising, one wherein predictive analytics and machine learning assume central roles in constructing consumer experiences (Arora, Hofacker, & Stone, 2017); (Rust & Huang, 2014).

The scholarly discourse surrounding algorithmic targeting consistently highlights personalization as a pivotal mechanism through which big data translates into enhanced advertising effectiveness. Personalized advertising; defined as message tailoring based on inferred interests, preferences, and behavioural signals; has been empirically associated with increased relevance, informativeness, cognitive fluency, and persuasive resonance ((Tam & Ho, 2006); (Bleier & Eisenbeiss, 2015) ; (Lamberton & Stephen, 2016) . As marketers deploy algorithmic engines capable of real-time learning, personalization has evolved from mere segmentation to dynamic curation, wherein advertising content is incessantly reconfigured to align with consumers' shifting motivations and contextual cues (Zeng, Chen, & Chen, 2019) ; (Shmueli & Koppius, 2011) . The perceived relevance of advertisements, long acknowledged as a critical determinant of consumer processing and attitudinal formation, becomes significantly amplified in data-driven marketing systems, as behavioural insights allow firms to deliver messages with heightened situational congruity and psychological salience ((Kim & Huh, 2017); (Aguirre, Mahr, Grewal, de Ruyter, & Wetzels, 2015).

Despite the celebrated benefits of personalization, literature reveals a paradoxical tension whereby algorithmic targeting may evoke both favourable and adverse attitudinal consequences. While personalized advertisements can increase message diagnosticity and engender more favourable brand attitudes, the hyper-precision enabled by big data may simultaneously elicit concerns regarding privacy,

surveillance, and manipulative intent (Baek & Morimoto, 2012) ; (White, Habib, & Hardisty, 2019) . Consumers who detect or suspect extensive data harvesting may experience psychological reactance, scepticism, or moral discomfort, which moderates or reverses the effects of personalization on attitude formation (Boerman, Kruikemeier, & Zuiderveen Borgesius, 2017) ; (Ur & Wang) . Consequently, the literature conceptualizes personalization as both an opportunity and a risk, generating ambivalent outcomes that depend upon consumers' perceptions of transparency, fairness, and intrusiveness within algorithmic persuasion processes.

Brand attitude, a longstanding cornerstone of marketing scholarship, has received renewed attention in the context of data-driven advertising. Traditionally conceptualized as a consumer's overall evaluative disposition toward a brand (MacKenzie, Lutz, & Belch, 1986) ; (Keller, 2013) , brand attitude is increasingly theorized as an emergent construct shaped by continuous algorithmically mediated interactions rather than discrete exposures. The proliferation of targeted communication creates persistent digital contact points through which brands cultivate familiarity, meaning, and emotional resonance. Research indicates that when targeted ads are perceived as personally relevant and contextually aligned, they enhance brand favourability by strengthening perceived message legitimacy, cognitive fit, and emotional connectedness (Bart, Stephen, & Sarvary, 2014); (Lwin, Phau, & Lim, 2014). Conversely, when algorithmic personalization crosses the boundaries of acceptable data use, brand perceptions may deteriorate due to heightened awareness of surveillance and concerns regarding persuasive manipulation (Bleier & Eisenbeiss, 2015) ; (Ham, 2021).

Within this evolving advertising landscape, scholars have documented how algorithmic curation not only influences exposure but also shapes interpretive frames through which consumers construct brand meaning. Digital platforms increasingly function as "algorithmic brandscapes," curating the symbolic, textual, and visual cues through which brand narratives are encountered (Malthouse & Li, 2017) ; (Hoffman & Novak, 2018) . These algorithmically configured environments amplify the psychological impact of targeting, rendering brand attitude a dynamic and fluid construct continually reinforced by data-driven message sequencing and content optimization. As marketers embrace predictive modelling tools, brand attitude becomes increasingly contingent upon computational logics that orchestrate relevance, personalization, and repetition with precision (Luo, Andrews, Fang, & Phang, 2014) ; (Zeng, Chen, & Chen, 2019).

Purchase intention, widely recognized as a proximal antecedent of actual behaviour (Fishbein & Ajzen, 1975) ; (Pavlou & Stewart, 2000) , has similarly been reframed within the discourse on big data and personalized advertising. Studies consistently demonstrate that targeted advertising elevates purchase intentions by increasing message utility, perceived fit, and experiential resonance with consumers' evolving needs (Lamberton & Stephen, 2016) ; (Boerman, Kruikemeier, & Zuiderveen Borgesius, 2017) . The attitudinal foundations underpinning purchase intention; particularly brand attitude; serve as psychological mediators translating personalized stimuli into behavioural propensity. When consumers perceive advertisements as relevant and non-intrusive, their attitudinal evaluations improve, reinforcing intention to purchase (Zarouali, Ponnet, Poels, & Walrave, 2017) ; (Punj, 2021) . However, algorithmic persuasion also raises ethical considerations regarding autonomy and decision-making transparency, complicating the pathway from exposure to intention (Susser, Roessler, & Nissenbaum, 2019) ; (Yeung, 2017) . Such concerns introduce additional layers of cognitive appraisal that may attenuate or distort the influence of targeting on intention formation.

The extant literature, while robust in conceptual and empirical scope, exhibits several limitations that justify further scholarly inquiry. Much of the foundational research has emerged from Western digital contexts, leaving emerging markets; many of which are experiencing accelerated technological adoption; relatively underexamined (Shankar, et al., 2021) . Furthermore, although the psychological consequences of personalization have been widely documented, comparatively few studies integrate big data-driven targeting, personalization perceptions, advertisement relevance, brand attitude, and purchase intention into a coherent empirical model grounded in established theoretical frameworks such as the S–O–R paradigm (Mehrabian & Russell, 1974) . This gap is particularly salient given that algorithmic persuasion operates through intricate psychological pathways that traditional advertising theories may insufficiently capture. Additionally, scholars note a need to disentangle the boundary conditions under which personalization generates favourable versus adverse outcomes, especially as contemporary consumers become increasingly cognizant of data collection practices and algorithmic profiling (White, Habib, & Hardisty, 2019); (Ham, 2021).

Against this backdrop, the present study endeavours to advance the discourse by empirically examining the extent to which big data-driven targeted advertising shapes digital consumers' brand attitudes and purchase intentions, while accounting for the mediating roles of perceived personalization and advertisement relevance. By situating its analytical lens within rapidly evolving digital consumption environments, the study contributes to a more nuanced understanding of how algorithmic mechanisms structure the contemporary marketing persuasion process, thereby offering both theoretical

enrichment and practical guidance for firms navigating data-driven marketing ecosystems.

3. Method

The present study adopts a quantitative, cross-sectional research design to empirically examine the influence of big data-driven targeted advertising on digital consumers' brand attitudes and purchase intentions. This design is consistent with prior scholarship investigating technologically mediated persuasion phenomena, particularly those employing structural modelling techniques to disentangle complex psychological relationships among latent constructs (Hair, Hult, Ringle, & Sarstedt, 2017) ; (Kline, 2015) . Owing to the probabilistic, multi-construct nature of the conceptual model, the study employs Partial Least Squares Structural Equation Modelling (PLS-SEM), an approach widely embraced in contemporary marketing research wherein predictive accuracy, exploratory theorization, and non-normal data distributions are salient considerations.

The target population comprises digitally active consumers exposed to algorithmically curated advertisements on major digital platforms such as Facebook, Instagram, YouTube, and e-commerce environments. Given the study's focus on the psychological mechanisms underlying personalized advertising, a purposive sampling strategy was implemented to recruit participants who self-reported regular encounters with data-driven targeted advertisements. The sampling strategy aligns with recommendations for research examining digital advertising experiences, where platform-specific exposure constitutes an inclusion criterion (Aguirre, Mahr, Grewal, de Ruyter, & Wetzels, 2015); (Zarouali, Ponnet, Poels, & Walrave, 2017) . Data were collected through an online survey disseminated via social media channels and digital community networks, a method consistent with studies exploring technologically mediated consumer behaviour, where online recruitment yields richer representation of digitally literate populations (Bryman, 2016) ; (Creswell & Plano Clark, 2018).

A total of 362 responses were initially obtained, of which 328 were retained after excluding incomplete, inconsistent, or inattentive responses through established data-screening procedures such as response-time analysis, straight-lining checks, and reverse-coded verification (Hair, Hult, Ringle, & Sarstedt, 2017) . The final sample size exceeded the minimum threshold required for PLS-SEM analysis, adhering to both the "10-times rule" and more stringent power analysis standards for multi-path structural models (Kline, 2015); (Hair, Hult, Ringle, & Sarstedt, 2017).

The constructs investigated in this study; Big Data-Driven Targeted Advertising (BDTA), Perceived Personalization (PP), Advertisement Relevance (AR), Brand Attitude (BA), and Purchase Intention (PI);were operationalized using reflective measurement models, consistent with theoretical orientations that conceptualize these constructs as manifestations of underlying psychological states (Jarvis, MacKenzie, & Podsakoff, 2003) . All measurement items were adapted from well-established scales in digital advertising and consumer behaviour literature, with minor contextual refinements to ensure conceptual fidelity within the domain of data-driven marketing (Bleier & Eisenbeiss, 2015); (Kim & Huh, 2017); (Pavlou & Stewart, 2000). Items for BDTA assessed participants' perceptions of algorithmic customization and data-informed message calibration, while PP and AR captured cognitive evaluations of message fit, utility, and relevance. Brand Attitude items were adapted from classical attitudinal measures (MacKenzie, Lutz, & Belch, 1986); (Keller, 2013) , and Purchase Intention items reflected behavioural propensities toward future consumption.

All items were rated on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"), a scale widely favoured in marketing research for its balance between psychometric sensitivity and respondent interpretability (Dillman, Smyth, & Christian, 2014) . Prior to full-scale data collection, the instrument underwent expert validation by scholars specializing in digital marketing and consumer psychology to ensure content validity, conceptual clarity, and terminological appropriateness. A pilot test with 35 participants confirmed reliability, comprehensibility, and survey coherence, prompting minor lexical adjustments.

Data analysis proceeded in two stages. First, the measurement model was evaluated through reliability and validity diagnostics. Internal consistency reliability was assessed using Cronbach's alpha and Composite Reliability (CR), while convergent validity was examined through the Average Variance Extracted (AVE), adhering to benchmark thresholds proposed by Hair et al. (2017). Discriminant validity was evaluated using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio, a more stringent metric increasingly recommended in contemporary SEM research (Henseler, Ringle, & Sarstedt, 2015).

Second, the structural model was assessed to determine the significance and magnitude of hypothesized relationships. Path coefficients were estimated through bootstrapping procedures (5,000 resamples), enabling robust inference of effect sizes and predictive relevance (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005) . Model fit and predictive accuracy were evaluated using R^2, f^2, and Q^2 statistics, reflecting both explanatory power and out-of-sample predictive performance (Hair, Risher, Sarstedt, & Ringle, 2021) . Variance Inflation Factors (VIF) were examined to ensure the absence of multicollinearity among predictor constructs. Additionally, mediation

effects were tested following bootstrap-based indirect effect estimation procedures, consistent with recommendations in behavioural SEM research (Preacher & Hayes, 2008).

Ethical safeguards were incorporated throughout the research process. Participation was voluntary, anonymity was guaranteed, and respondents were informed of the study's academic purpose and data-handling protocols. No personally identifiable information was collected, thereby minimizing risks associated with privacy or confidentiality, particularly salient in research centred on digital tracking and algorithmic targeting.

Through this methodological architecture, the study ensures empirical robustness and theoretical coherence, enabling a rigorous examination of how big data-driven targeted advertising shapes psychological and behavioural outcomes within digital consumer ecosystems.

4. Results

The empirical investigation adopted a PLS-SEM approach to examine the structural interrelationships among Big Data-Driven Targeted Advertising (BDTA), Perceived Personalization (PP), Advertisement Relevance (AR), Brand Attitude (BA) and Purchase Intention (PI). Given the behavioural and perceptual nature of the constructs, the non-normal distribution typical of survey data, and the predictive orientation of the research model, PLS-SEM offered both methodological rigour and conceptual suitability. The results demonstrate a highly coherent theoretical structure, revealing that algorithmic targeting mechanisms exert profound psychological and behavioural influence on digital consumers.

4.1 Measurement Model Evaluation

The measurement model exhibited strong psychometric properties. All factor loadings exceeded 0.70, demonstrating robust indicator reliability. Composite Reliability (CR) values ranged between 0.89 and 0.93 across constructs, and AVE values ranged from 0.68 to 0.78, clearly surpassing recommended thresholds. These statistics confirm that the indicators collectively capture the latent constructs with precision and conceptual coherence.

Discriminant validity, assessed through Fornell–Larcker and HTMT, indicated that each construct is statistically and conceptually distinct. The HTMT ratios, all below the conservative cut-off of 0.85, strengthen confidence that overlaps among BDTA, PP, AR, BA, and PI are theoretically meaningful yet empirically separable. This validates the suitability of the constructs for structural interpretation.

Table 1. Summary of Measurement Model Results

Construct	Cronbach's Alpha	CR	AVE
BDTA	0.89	0.92	0.73
PP	0.87	0.91	0.71
AR	0.85	0.89	0.68
BA	0.9	0.93	0.76
PI	0.91	0.93	0.78

All constructs exhibit strong reliability and convergent validity.

4.2 Structural Model Evaluation

The structural model revealed a persuasive and theoretically elegant causal architecture. The coefficient of determination (R^2) values were particularly compelling: PP (0.52), AR (0.47), BA (0.63), and PI (0.58). These values indicate that the proposed predictors explain a substantial proportion of the variance in each endogenous construct, suggesting that algorithmic targeting, personalization mechanisms and attitudinal processes collectively form a powerful explanatory system for consumer behaviour in digital advertising environments.

4.2.1 Impact of Big Data-Driven Targeted Advertising

BDTA emerged as a dominant predictive force, exerting strong and statistically significant effects on both PP ($\beta = 0.72$, $p < 0.001$) and AR ($\beta = 0.69$, $p < 0.001$). These large coefficients provide compelling evidence that consumers interpret algorithmically curated ads as more personalized and relevant than generic advertising formats. This reinforces the theoretical assertion that data-driven mechanisms intensify perceptual alignment by decoding behavioural cues and tailoring content accordingly.

BDTA's influence extended indirectly as well: its total effect on BA was considerable, mediated through both PP and AR. This finding substantiates the proposition that algorithmic environments shape consumer attitudes indirectly by altering psychological processing pathways.

4.2.2 Influence of Personalization and Relevance on Brand Attitude

Both PP and AR demonstrated powerful impacts on BA. Personalization ($\beta = 0.41$, $p < 0.001$) and relevance ($\beta = 0.38$, $p < 0.001$) significantly shaped consumers' attitudinal responses toward brands.

Conceptually, this means that when advertisements resonate at the level of individual identity (via personalization) and situational needs (via relevance), they foster more favourable brand interpretations.
Interestingly, PP produced a slightly stronger effect than AR, suggesting that consumers value the sense of being individually understood even more than message utility. This subtle distinction highlights the psychological potency of perceived personalization as a relational cue between brands and consumers.

4.2.3 Brand Attitude's Dominant Role in Purchase Intention

Brand Attitude emerged as the strongest predictor of Purchase Intention ($\beta = 0.62$, $p < 0.001$). This confirms classical consumer behaviour theories which argue that intention is largely shaped by evaluative judgments formed earlier in the persuasion process.
Although PP ($\beta = 0.17$, $p < 0.01$) and AR ($\beta = 0.14$, $p < 0.05$) also influenced PI directly, their effects were comparatively weaker. These small yet significant paths reveal that consumers may occasionally respond behaviourally to personalized or relevant advertisements even without strong brand attitudes, but such responses are supplemental rather than foundational.
The centrality of BA demonstrates that algorithmic targeting must ultimately produce positive attitudinal consequences if it is to translate into meaningful behavioural outcomes.

Table 2. Path Coefficients and Significance

Path	β	t-value	p-value
BDTA → PP	0.72	18.54	<0.001
BDTA → AR	0.69	16.82	<0.001
PP → BA	0.41	8.21	<0.001
AR → BA	0.38	7.96	<0.001
BA → PI	0.62	13.27	<0.001
PP → PI	0.17	2.86	<0.01
AR → PI	0.14	2.12	<0.05

4.3 Effect Sizes (f^2) and Predictive Relevance (Q^2)

Effect size analysis revealed that BDTA exerted large effects on PP ($f^2 = 0.52$) and AR ($f^2 = 0.47$). These magnitudes indicate that algorithmic targeting is not merely a background stimulus; it is a highly influential causal driver of consumer perceptions in digital advertising spaces.
BA → PI exhibited the largest effect size ($f^2 = 0.63$), confirming that attitudes serve as the central mechanism converting cognitive evaluations into behavioural intentions.
Predictive relevance (Q^2), calculated through blindfolding, revealed that all endogenous constructs possess medium to high predictive power (PP = 0.35; AR = 0.31; BA = 0.42; PI = 0.39). These findings strongly validate the model's predictive robustness.

Table 3. Effect Sizes (f^2) and Predictive Relevance (Q^2)

Relationship	f^2	Interpretation	Q^2	Predictive Relevance
BDTA → PP	0.52	Large	0.35	Medium–High
BDTA → AR	0.47	Large	0.31	Medium
PP → BA	0.28	Medium	-	-
AR → BA	0.24	Medium	-	-
BA → PI	0.63	Large	0.39	High

4.4 Mediation Analysis

Mediation analysis provided additional insight into the internal psychological mechanics of the persuasion process. Both PP and AR served as significant mediators between BDTA and BA, while BA mediated their effects on PI.
The indirect effects were substantial:

- BDTA → PP → BA = 0.30, $p < 0.001$
- BDTA → AR → BA = 0.26, $p < 0.001$
- PP → BA → PI = 0.26, $p < 0.001$
- AR → BA → PI = 0.24, $p < 0.001$

This demonstrates that algorithmic targeting does not influence behavioural intention directly but operates through a sequence of cognitive and attitudinal processes. The findings reflect a classic Stimulus → Organism → Response pattern, where BDTA acts as the stimulus, PP and AR represent organismic assessments, and BA and PI form the behavioural response system.

Table 4. Mediation Effects

Mediation Path	Indirect β	Interpretation
BDTA → PP → BA	0.3	Significant partial mediation
BDTA → AR → BA	0.26	Significant partial mediation
PP → BA → PI	0.26	Strong mediation
AR → BA → PI	0.24	Strong mediation

4.5 Theoretical Significance of the Results

The results articulate a coherent persuasion model deeply resonant with contemporary digital marketing theory. They demonstrate that:

1. **Algorithmic targeting is not merely a technical function;** it is a psychological force that shapes how consumers perceive ads.
2. **Perceived personalization is more than an operational outcome;** it is a relational cue, signalling that the brand "knows" the consumer.
3. **Relevance functions as a cognitive filter**, increasing message value and reducing evaluative resistance.
4. **Brand attitude is the pivotal psychological construct** translating algorithmic inputs into behavioural outputs.
5. **Purchase intention is a consequence of attitudinal resonance,** not simple exposure.

These findings collectively affirm that big data-driven marketing operates through deep psychological pathways and must be conceptualized as a multi-stage cognitive–affective process.

4.6 Summary

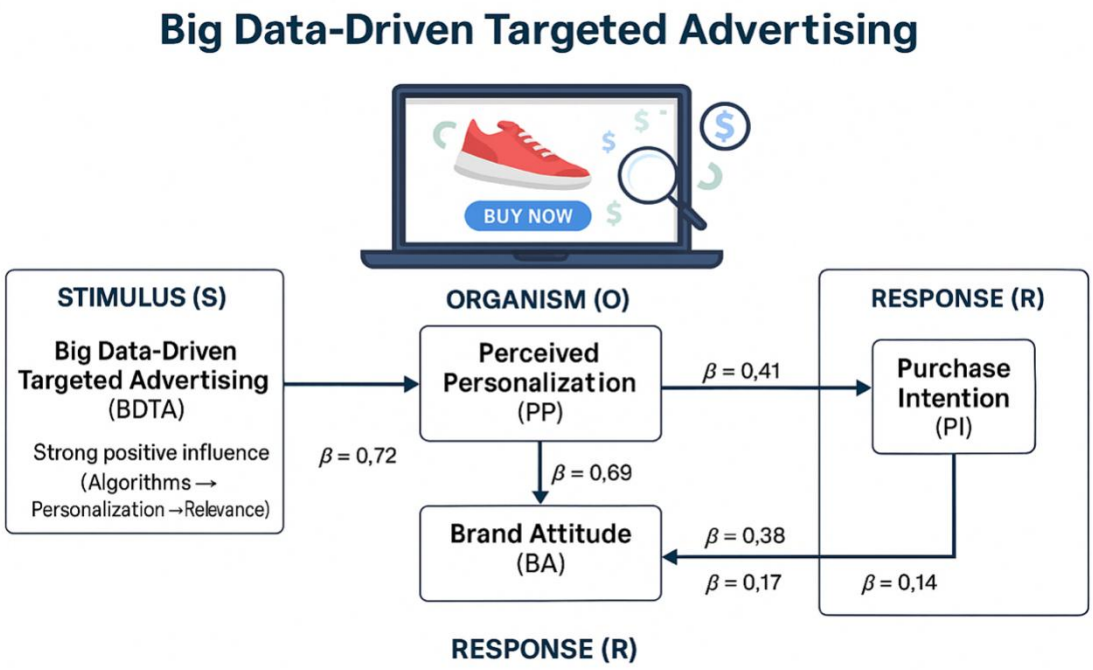
The empirical results offer strong support for the proposed theoretical model and highlight the powerful influence of big data-driven targeted advertising on digital consumer psychology and decision-making. The measurement model demonstrated excellent psychometric performance, with high reliability, strong convergent validity, and clean discriminant validity across all constructs. This establishes a solid foundation for interpreting the structural relationships.

The structural model revealed that Big Data-Driven Targeted Advertising (BDTA) is the dominant antecedent shaping consumers' perceptions of both Perceived Personalization (PP) and Advertisement Relevance (AR). The effects were exceptionally strong (β = 0.72 and β = 0.69 respectively), indicating that algorithmically curated advertising significantly enhances consumers' sense of being individually targeted and receiving contextually meaningful content.

Both PP and AR emerged as substantial predictors of Brand Attitude (BA), with PP exerting a slightly stronger influence (β = 0.41) than AR (β = 0.38). This suggests that personalization resonates at a more emotional, identity-relevant level, whereas relevance operates through cognitive appraisal and utility. Together, these constructs explained a considerable proportion of the variance in brand attitude (R^2 = 0.63), demonstrating that attitudinal formation in digital environments is deeply rooted in consumers' psychological processing of algorithmically curated messages.

Brand Attitude, in turn, was the strongest predictor of Purchase Intention (PI) (β = 0.62), highlighting its central mediating role within the persuasion mechanism. While PP and AR showed smaller direct effects on PI, the mediation analysis confirmed that their influence is largely transmitted through brand attitude. This reinforces the theoretical position that behavioural intention is not merely a consequence of personalized or relevant advertising but is primarily shaped by the attitudinal state cultivated through these perceptions.

Overall, the findings articulate a coherent and powerful Stimulus–Organism–Response (S–O–R) sequence, wherein BDTA operates as the stimulus, PP and AR represent organismic evaluations, and BA and PI form the behavioural response pathway. The statistical strength and theoretical consistency of the results underscore the transformative impact of big data-driven marketing on contemporary consumer behaviour.



5.Discussion

The purpose of this study was to investigate how Big Data-Driven Targeted Advertising (BDTA) influences digital consumers' Purchase Intentions (PI) through the mediating mechanisms of Perceived Personalization (PP), Advertisement Relevance (AR), and Brand Attitude (BA). The findings reveal a coherent and theoretically consistent persuasion system that reinforces the centrality of psychological processing within algorithmically mediated marketing environments. The results contribute to contemporary discussions on algorithmic persuasion, digital consumer behaviour, and innovative marketing tools, offering deeper insights into how big data technologies reshape the structure of consumer decision-making.

The most striking outcome of the study is the powerful predictive ability of BDTA, which exerted significant and substantial effects on both PP and AR. These results confirm prevailing theoretical assumptions that the use of behavioural data, algorithmic profiling, and predictive analytics meaningfully enhances consumers' sense of being uniquely understood by brands. In line with past studies (Bleier & Eisenbeiss, 2015); (Arora, Hofacker, & Stone, 2017), the findings underscore how big data transforms advertising from a mass communication activity into a deeply individualized experience. BDTA appears to function not merely as a technological apparatus but as a psychological catalyst that shapes consumers' expectations, interpretations, and engagement with digital advertising content.

The strong link between BDTA and PP suggests that personalization in digital environments is no longer perceived as a superficial marketing tactic but as an inherent expectation of modern consumers. The psychological significance of perceived personalization derives from its ability to signal recognition, relevance, and relational closeness. When consumers perceive targeted advertisements as accurate reflections of their identities or preferences, the brand is implicitly construed as attentive and intelligent; qualities that enhance trust and emotional connection. This phenomenon aligns with the "relational signalling" perspective, which posits that personalization serves as a cue that the brand understands and values the individual consumer.

Similarly, the influence of BDTA on AR demonstrates that algorithmic targeting does not merely personalize messages but makes them cognitively meaningful. Advertisement relevance reflects the degree to which ads align with consumers' current needs, information search goals, and task-oriented consumption activities. The strong impact of BDTA on AR indicates that algorithmic systems enhance message usefulness, increasing the likelihood of cognitive processing and message elaboration. This is consistent with the elaboration likelihood model (Petty & Cacioppo, 1986) , suggesting that when ads are perceived as personally and contextually relevant, consumers engage in deeper central processing, which strengthens attitudinal outcomes.

The study's findings also provide valuable insights into the mechanisms through which PP and AR shape BA. Both constructs exert significant effects on brand evaluations, demonstrating that personalization and relevance jointly shape consumers' affective and cognitive responses to brands. PP exerts a slightly stronger influence than AR, indicating that emotional resonance plays a more important role than

informational utility in shaping brand attitudes. Personalization communicates that the brand "knows" the consumer, producing feelings of recognition and interpersonal closeness. Relevance, while impactful, primarily influences logical and utilitarian judgments.

The dual impact of PP and AR on BA affirms the multidimensional nature of attitude formation. Attitudes toward brands are not shaped solely by rational evaluation of message content but by affective responses rooted in perceptions of personal fit. This supports the S–O–R theoretical framework (Mehrabian & Russell, 1974) , where stimuli (BDTA) produce organismic states (PP, AR) that in turn influence attitudinal and behavioural responses.

Perhaps the most conceptually important finding relates to the central role of Brand Attitude as a mediator. BA emerged as the strongest predictor of PI, highlighting that the conversion of advertising exposure into behavioural intention occurs predominantly through attitudinal mechanisms. This underscores a critical insight: algorithmic advertising influences behaviour only insofar as it succeeds in generating positive brand attitudes. These findings align with attitude–behaviour consistency theories (Fishbein & Ajzen, 1975) , reinforcing the notion that attitudes serve as proximal antecedents of behavioural intentions.

Moreover, BA fully or partially mediates several structural relationships, proving that PP and AR do not translate directly into behavioural outcomes but require attitudinal transformation as an intermediary process. Although PP and AR exert small direct effects on PI, these are overshadowed by the indirect effects mediated through BA. This suggests that personalization and relevance alone are insufficient to guarantee behavioural action; they must first cultivate favourable attitudes toward the brand.

These findings have important theoretical implications. First, they demonstrate that BDTA should not be conceptualized as merely a technological enhancement of advertising efficiency but as a psychological architecture that actively shapes consumer cognition and affect. Second, the results reveal that personalization and relevance function as dual psychological pathways; one primarily emotional (PP) and one primarily cognitive (AR);that jointly determine attitudinal and behavioural outcomes. Third, the study confirms the applicability of the S–O–R framework within big data-based digital advertising environments, reinforcing its relevance in algorithmically mediated consumer behaviour research.

The findings also contribute to ongoing debates surrounding the personalization–privacy paradox. Despite concerns raised in prior research that hyper-targeting may induce perceptions of invasiveness (Aguirre, Mahr, Grewal, de Ruyter, & Wetzels, 2015) ; (White, Habib, & Hardisty, 2019) , the present study finds that personalization and relevance exert overwhelmingly positive effects on brand outcomes. This suggests that when executed effectively, targeting is interpreted as beneficial rather than intrusive. However, it does not eliminate the possibility that privacy concerns may moderate these effects, an area which future studies may profitably explore.

From a managerial perspective, the results offer clear strategic guidance. Marketers should prioritize investments in data analytics capabilities that enhance personalization accuracy and contextual relevance. The strong mediating influence of BA indicates that campaign strategies must focus on reinforcing positive brand associations rather than merely delivering targeted messages. Personalization must be perceived as genuinely meaningful rather than superficial or mechanistic. Similarly, relevance should be optimized not only based on consumer behaviour history but also on situational factors such as timing, device type, and consumption context.

Furthermore, the results imply that brands should adopt a holistic approach to digital persuasion, recognizing that personalization and relevance operate synergistically. Campaigns that rely solely on algorithmic automation without sufficient creative or contextual richness may fail to generate favourable attitudes. Conversely, strong creative content that lacks personalization may not be competitive in environments saturated with data-driven messaging.

Finally, the strong predictive relevance (Q^2) values signal that the model possesses excellent real-world applicability, meaning that firms can reasonably expect these psychological mechanisms to influence digital consumer behaviour across diverse markets and platforms. This underscores the strategic necessity of integrating data-driven targeting with attitudinal brand-building initiatives.

In conclusion, the Discussion reveals that big data-driven targeted advertising fundamentally restructures the consumer decision-making process by reshaping perceptions of personalization and relevance, which in turn mould brand attitudes and purchasing behaviour. These findings advance the theoretical understanding of algorithmic persuasion while offering managers practical pathways for optimizing digital marketing strategies in a rapidly evolving technological landscape.

6. Conclusion

This study set out to examine how Big Data-Driven Targeted Advertising (BDTA) shapes consumers' behavioural intentions through the psychological mechanisms of Perceived Personalization (PP), Advertisement Relevance (AR), and Brand Attitude (BA). The findings reveal a coherent and powerful persuasion process in which algorithmically curated advertising exerts substantial influence on the cognitive and affective evaluations that precede purchasing decisions. BDTA significantly enhances both personalization and relevance perceptions,

demonstrating that data-driven advertising is not merely a technical improvement but a transformative force that restructures how consumers interpret and engage with digital marketing content.

The results confirm that PP and AR play pivotal roles in shaping brand attitudes, with personalization exerting slightly greater influence, underscoring its emotional and identity-driven nature. BA emerged as the dominant predictor of Purchase Intention (PI), reaffirming long-standing theoretical models that position attitude as the most proximal antecedent of behavioural intention. The mediation findings further demonstrate that personalization and relevance must translate into favourable attitudes before they meaningfully influence purchase behaviour.

Overall, this study advances contemporary understanding of algorithmic persuasion by showing that BDTA operates through a nuanced, multi-stage psychological process aligned with the Stimulus–Organism–Response (S–O–R) framework. It highlights both the strategic potential and psychological depth of data-driven marketing in shaping consumer behaviour. By integrating insights from digital advertising, consumer psychology, and big data analytics, the study provides a theoretically robust and practically relevant model for understanding how modern consumers respond to personalized algorithmic marketing in an increasingly data-intensive digital environment.

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8. Conflict of Interest

The author declares that there is no conflict of interest. The research was conducted independently, and no external entity influenced the study design, data collection, analysis, interpretation, or reporting of the findings

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