Audience Response to Data-Driven Digital Out-of-Home Advertising: A Quantitative PLS-SEM Study of Perceived Relevance, Engagement, and Purchase Intention

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Abstract

This study develops and tests a parsimonious quantitative model explaining how audiences respond to data-driven Digital Out-of-Home (DOOH) advertising. Drawing on the Stimulus-Organism-Response (S-O-R) framework, the Elaboration Likelihood Model (ELM), and the Technology Acceptance Model (TAM), four targeting stimuli (demographic targeting precision, psychographic fit, behavioral alignment, and interactive content dynamism) are positioned as antecedents of perceived ad relevance, which in turn drives audience engagement and purchase intention. A cross-sectional intercept survey of 800 respondents was conducted at five protocol-road DOOH locations in Jakarta, Indonesia, spanning two campaign conditions: conventional placement and data-driven placement informed by anonymized telecommunications audience profiles. Partial Least Squares Structural Equation Modeling with 5,000 bias-corrected and accelerated bootstrap subsamples supported all six hypotheses. Psychographic fit ($\beta = 0.392$) and demographic targeting precision ($\beta = 0.365$) were the strongest predictors of perceived ad relevance ($R^2 = 0.528$); relevance strongly predicted engagement ($\beta = 0.678$, $R^2 = 0.459$), and engagement predicted purchase intention ($\beta = 0.717$, $R^2 = 0.513$). All indirect effects were significant, measurement invariance and common method bias checks supported the model, and respondents in the data-driven condition scored higher on every construct (Cohen's d = 0.75–3.06). The findings indicate that audience-content congruence, rather than exposure volume or display interactivity, is the primary lever of DOOH effectiveness, and they offer advertisers an evidence-based ordering of targeting investments.

Keywords: Audience Engagement, Data-Driven Advertising, DOOH Advertising, Perceived Ad Relevance, Purchase Intention, Stimulus-Organism-Response

1. Introduction

Digital Out-of-Home (DOOH) advertising, which comprises programmatic digital billboards, interactive signage, and location-aware displays, extends a medium whose distinctive strength is its ability to reach mobile consumers in public space [1], and digital displays have been shown to lift sales when their message content fits the setting in which it is shown [2]. A growing share of this inventory is now scheduled using audience data rather than static traffic estimates, reflecting the broader shift toward data-driven, algorithmically supported marketing decision-making [3], [4], [5]. Network-level mobile data can capture the real-time presence and movement of urban populations [6], and in Indonesia anonymized telecommunications data of this kind have begun to inform DOOH campaign planning along Jakarta's protocol roads, enabling advertisers to align content with the demographic, psychographic, and behavioral composition of the audiences actually present near each display.

What remains poorly understood is the audience side of this transformation. Existing studies are predominantly technology-centric: they describe how data-driven targeting systems are built, but offer little quantitative evidence on whether, and through which psychological mechanism, targeting precision translates into favorable audience responses [3], [7]. If data-driven placement does not measurably increase the relevance audiences perceive, their engagement with displays, and ultimately their purchase intention, its commercial rationale is incomplete. A validated, theory-

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grounded model linking targeting stimuli to audience response is therefore needed. This gap is conceptually distinct from the extensively studied online and social media personalization literature in three respects. First, DOOH targeting operates on aggregated, non-identified audience composition inferred from network-level telecommunications data, rather than on identified individual profiles built from browsing or account history; the unit of personalization is a place-time audience segment, not a person. Second, exposure is incidental and public: viewers do not opt in, cannot control what they see, and are exposed alongside strangers, conditions that plausibly alter how privacy concern, self-referential processing, and social presence operate relative to a private screen. Third, the targeting signal is transient and infrastructure-bound, tied to a specific display's real-time audience composition rather than to a persistent user record that follows the individual across platforms and sessions. Because the psychological mechanisms documented for individual-level online personalization (the personalization paradox, perceived intrusiveness, and platform-specific trust) are not guaranteed to transfer to this anonymized, place-bound, involuntary-exposure context, whether and how targeting precision generates relevance in data-driven DOOH cannot simply be read off the online-advertising literature; it requires the dedicated theoretical and empirical treatment this study provides.

This study addresses that gap with a simple, fully quantitative research design. A cross-sectional survey of 800 respondents was conducted at five DOOH locations in Jakarta under two campaign conditions, conventional and data-driven placement. Grounded in the Stimulus-Organism-Response (S-O-R) framework [8], the Elaboration Likelihood Model (ELM) [9], and the Technology Acceptance Model (TAM) [10], six hypotheses were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) [11].

The study makes three contributions. First, it validates a parsimonious S-O-R model of DOOH effectiveness in which perceived ad relevance mediates the effect of four targeting stimuli on engagement and purchase intention. Second, it provides a validated measurement instrument for DOOH audience response in an emerging-market urban context. Third, it offers evidence-based guidance for advertisers and DOOH operators on which targeting dimensions matter most. Section 2 reviews the literature and develops the hypotheses, Section 3 describes the methodology, Section 4 presents and discusses the results, and Section 5 concludes with limitations and future research directions.

2. Literature Review

2.1. Theoretical Framework

The S-O-R framework [8] holds that environmental stimuli (S) trigger internal cognitive-affective states (O) that in turn produce approach or avoidance responses (R). Originally developed for physical environments, the framework was extended by Eroglu et al. [12] to technology-mediated settings, where informational and atmospheric cues substitute for physical ones, and it has since anchored studies of technology-mediated consumption such as virtual-reality tourism [13]. A data-driven DOOH display is a theoretically distinctive hybrid of these two traditions: the display is embedded in a physical urban environment, yet the content it shows is selected algorithmically from digital audience data. In the present model, four properties of that content constitute the stimulus: demographic targeting precision (DTP), the match between ad content and the demographic profile of nearby audiences; psychographic fit (PF), the congruence between content and audience interests and lifestyles; behavioral alignment (BA), the correspondence of content scheduling with audience activity times and movement patterns; and interactive content dynamism (ICD), the degree of real-time adaptive content delivery. Perceived ad relevance (PAR) represents the organism, while audience engagement (AE) and purchase intention (PI) represent the response.

The ELM [9] supplies the cognitive mechanism connecting stimulus to organism: content perceived as personally relevant raises elaboration motivation, activates central-route processing, and yields deeper engagement and more durable attitude change [14]. The personalization literature shows, however, that this mechanism is not unconditional. Aguirre et al. [15] documented a personalization paradox in which highly personalized advertising backfires once consumers realize their personal data were collected covertly; Bleier and Eisenbeiss [16] found that overly personalized banners lose effectiveness as perceived intrusiveness rises; and Boerman et al. [17] identified privacy concern as a central moderator of behavioral advertising outcomes. Data-driven DOOH occupies a distinctive position in this debate. Because targeting operates on aggregated audience composition rather than on identified individuals, it may capture the relevance benefits of personalization while avoiding the reactance its individual-level variants provoke. Whether

congruence-based stimuli still generate relevance under such anonymous, group-level targeting is a theoretical question rather than a foregone conclusion, and it is the question the present model tests.

Two further perspectives complete the framework. TAM [10] grounds the expectation that adaptive, programmatically updated displays are perceived as more useful and engaging than static ones, a prediction consistent with evidence that interactivity enhances persuasion by raising involvement with the message [18]. On the response side, engagement is conceptualized following Hollebeek et al. [19] as the consumer's cognitive, emotional, and behavioral activity during the brand interaction, and the engagement-to-intention link follows the hierarchy-of-effects logic of Lavidge and Steiner [20], in which cognitive and affective responses precede conative outcomes. Data-driven marketing theory [21] frames the overarching expectation that richer audience data produce more effective campaigns.

These three theoretical strands are integrated here through a single organizing logic rather than treated as separate explanations attached to separate paths. The S-O-R framework supplies the causal architecture, environmental stimulus to internal state to behavioral response, within which the remaining two theories specify what determines the strength of the stimulus-to-organism link. The ELM explains why congruence-based stimuli (demographic targeting precision, psychographic fit, and behavioral alignment) raise perceived relevance: they supply the personal pertinence that triggers elaboration [9], [14]. TAM explains why a technological property of the stimulus, interactive content dynamism, might raise relevance through a different route, the perceived usefulness of the delivery medium rather than the personal pertinence of its content [10]. Read together, the framework treats perceived ad relevance as a single organismic gateway reachable along two conceptually distinct paths, a content-congruence path governed by the ELM and a technology-usefulness path governed by TAM, both operating within the S-O-R causal structure. This integration yields a testable joint expectation that no single theory generates alone: if the content-congruence path dominates the technology-usefulness path, as the ELM would predict once personal relevance is already present, the incremental contribution of dynamism should be small once congruence is modeled. The ordering of effects reported in Section 4.4, with interactive content dynamism smallest ($f^2 = 0.020$), is a direct empirical test of this joint prediction.

2.2. Hypothesis Development

Demographic congruence is the most basic form of audience-content matching. Content matched to the age, gender, and income composition of the audience present at a display signals that the message is intended for the viewer, triggering self-referential processing that raises perceived relevance; perceived intendedness of this kind is a documented driver of responses to targeted advertising [15], [17]. We therefore hypothesize that demographic targeting precision increases perceived ad relevance (H1).

Psychographic congruence operates on interests, values, and lifestyles rather than on demographic categories, and under the ELM it is the most direct antecedent of personal relevance because it connects message content to goals the viewer already holds [9], [14]. Content-depth personalization, its closest online analog, has repeatedly emerged as the strongest content-side driver of advertising response [16]. We therefore expect psychographic fit to increase perceived ad relevance (H2).

Behavioral alignment captures congruence in time and context rather than in content. A message displayed when its intended audience is actually present, and in a movement context consistent with its offer, gains situational pertinence, much as congruent atmospherics shape shopper states in the S-O-R tradition [12]. Field evidence shows that the effect of digital displays depends on the fit between message content and the setting in which it is shown [2], and the footfall literature shows that when audiences are present conditions the advertising opportunity of a location [22]. We therefore expect behavioral alignment to increase perceived ad relevance (H3).

Interactive content dynamism reflects the technological capability of the display itself. Under TAM, real-time adaptive delivery increases the perceived usefulness of the medium and, by extension, of its messages [10], and interactive formats have been shown to enhance persuasion in adjacent settings [18]. The personalization literature counsels caution here: adaptivity that is not anchored in audience congruence can be discounted or perceived as intrusive [15], [16]. We retain the TAM-based directional prediction that content dynamism increases perceived ad relevance (H4), while treating its magnitude relative to the congruence stimuli as an open empirical question.

Within the ELM, relevance is the gateway to elaboration: audiences who judge a message personally relevant allocate attention, process it centrally, and interact more deeply with the medium [9], [14]. In engagement terms, relevance supplies the motivational basis for the cognitive, affective, and behavioral activity that defines engagement [19]. We therefore expect perceived ad relevance to increase audience engagement (H5).

The hierarchy-of-effects model places conative outcomes after cognitive and affective ones [20], and engagement research identifies usage and purchase intent as principal consequences of engagement [19], a sequence also articulated in the foundational conceptualization of customer engagement by Brodie et al. [23]. We therefore expect audience engagement to increase purchase intention (H6).

Behavioral alignment and psychographic fit both capture audience-content congruence but at different levels of stability. Psychographic fit reflects a trait-level match between message content and audiences' enduring interests, values, and lifestyles, a property of what the content is about. Behavioral alignment reflects a state-level match between message timing and audiences' transient activity patterns and movement context at the moment of exposure, a property of when and under what circumstances the content is shown, independent of its thematic content. A single display could therefore be high on one dimension and low on the other, for example, thematically well-matched content shown at a mistimed hour, or well-timed content whose theme does not fit the audience present. The discriminant validity results in table 5 (Fornell–Larcker and HTMT) empirically support this separation, and the items in table 2 were written to keep respondents focused on "what this ad is about" for psychographic fit versus "when and where this ad appeared" for behavioral alignment.

Table 1 consolidates the six hypotheses developed above into a single reference summary. For each hypothesis, the table reports the hypothesized relationship and its expected sign, the type of effect tested, and the theoretical basis from which it is derived. Hypotheses H1 to H4 form the stimulus-to-organism block, in which each of the four targeting stimuli (demographic targeting precision, psychographic fit, behavioral alignment, and interactive content dynamism) is expected to increase perceived ad relevance; H1 and H3 rest primarily on the S-O-R framework, H2 on the ELM, and H4 on TAM. Hypotheses H5 and H6 form the organism-to-response block, in which perceived ad relevance is expected to increase audience engagement, following the ELM, and engagement is in turn expected to increase purchase intention, following the hierarchy-of-effects model. All six relationships are specified as positive direct effects; the indirect effects implied by this chain are tested separately in Section 4.6.

Table 1. Hypothesis summary

H	Hypothesized relationship	Type	Theoretical basis
H1	Demographic Targeting Precision → Perceived Ad Relevance (+)	Direct	S-O-R [8]
H2	Psychographic Fit → Perceived Ad Relevance (+)	Direct	ELM [9]; S-O-R
H3	Behavioral Alignment → Perceived Ad Relevance (+)	Direct	S-O-R [13]
H4	Interactive Content Dynamism → Perceived Ad Relevance (+)	Direct	TAM [10]
H5	Perceived Ad Relevance → Audience Engagement (+)	Direct	ELM [9], [14]
H6	Audience Engagement → Purchase Intention (+)	Direct	Hierarchy of effects [20]

Figure 1 translates the hypotheses in table 1 into the proposed conceptual framework. The model is arranged from left to right along the S-O-R sequence. The stimulus (S) column on the left contains the four exogenous targeting constructs, DTP, PF, BA, and ICD, whose arrows (H1 to H4) converge on perceived ad relevance (PAR). PAR is placed in the center as the single organismic (O) state through which all four stimuli are expected to operate. The response (R) side on the right comprises audience engagement (AE) and purchase intention (PI), linked in series by H5 (PAR → AE) and H6 (AE → PI). No direct paths from the stimuli to AE or PI are drawn, because the framework specifies perceived relevance as the gateway between targeting stimuli and audience response; a competing partial-mediation specification is examined as a robustness check in Section 4.8.

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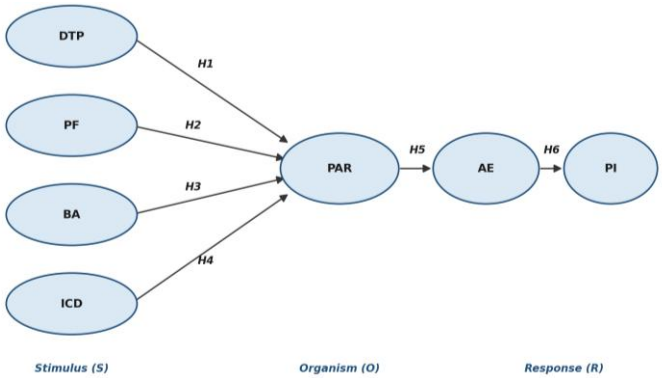


Figure 1. Proposed conceptual framework and hypothesized relationships (H1–H6). Ellipses denote latent constructs; arrows denote hypothesized structural paths.

3. Methodology

3.1. Research Design and Procedure

An explanatory, cross-sectional quantitative survey design was employed. Figure 2 summarizes the research procedure as a flowchart, from theory integration and hypothesis development through instrument development, site selection, and data collection under two campaign conditions, to measurement-model assessment, structural-model estimation, mediation analysis, robustness checks, and the campaign-condition comparison. The measurement model was evaluated before any structural inference was drawn; had any reliability or validity criterion failed, the offending indicators would have been revised or removed and the model re-estimated, as indicated by the feedback loop in figure 2. The formal model specification and evaluation criteria are given in Section 3.4, and the estimation procedure is formalized as pseudocode in Algorithm 1 (Section 3.5).

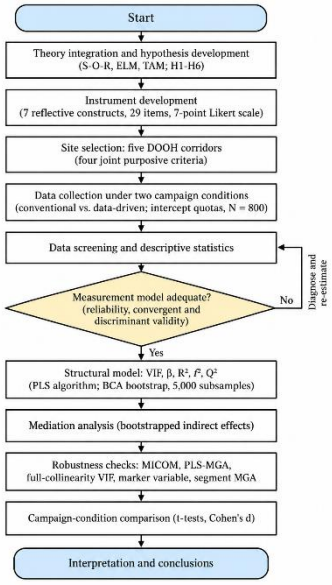


Figure 2. Research flowchart of the study, from theory integration to interpretation, including the measurement-model decision point and the robustness stage.

3.2. Study Sites

The study setting comprised five Videotron DOOH displays on Jakarta protocol roads (Jl. Jenderal Sudirman, Jl. Gatot Subroto, Jl. M.H. Thamrin, Jl. H.R. Rasuna Said, and the Semanggi interchange), each with daily traffic of at least 50,000 persons and programmatic delivery capability. Two campaign conditions ran sequentially at identical locations with equivalent budgets and creative assets: a conventional condition (May–June 2025), in which content was scheduled using standard traffic estimates, and a data-driven condition (July–August 2025), in which scheduling was informed by anonymized, aggregated telecommunications audience profiles obtained from PT Telkomsel under a

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formal Data Use Agreement [6], [24]. All audience data were anonymized at source in accordance with Indonesia's Personal Data Protection Law (Law No. 27 of 2022) and international data protection norms [25].

The five corridors were not selected on traffic volume alone. Sites were purposively chosen to satisfy four criteria jointly: (a) daily traffic of at least 50,000 persons, (b) an existing programmatic DOOH display with telecommunications-informed scheduling capability, (c) geographic spread across the primary arterial corridors of Jakarta's central business district rather than clustering on a single road, and (d) prior data-sharing access through the PT Telkomsel partnership described above. These criteria jointly reflect the commercial availability of data-driven inventory in Jakarta at the time of data collection rather than a claim that the five corridors represent the full population of Jakarta DOOH sites; sites without programmatic capability or telecommunications-partnership access could not be included by design, and this scope restriction is stated explicitly as a boundary condition in Section 5.

Within each site and campaign condition, the 160-respondent quota (Section 3.3) was further stratified across four two-hour dayparts (morning, midday, evening, night) and across weekday versus weekend days in approximately equal proportions, so that the conventional and data-driven sub-samples at each location were balanced on time-of-day and day-type composition rather than differing systematically in when interviews occurred. A non-response comparison was conducted by recording the visible demographic profile (approximate age band, gender) of passersby who declined the intercept invitation alongside those who completed it. These procedures bound, but do not eliminate, the limitations of intercept sampling: the sample remains drawn from commuters and pedestrians present on high-traffic protocol roads, and the structural relationships reported here should be read as applying to dense, high-traffic urban corridors until replicated in non-metropolitan or lower-density settings (Section 5).

Figure 3 illustrates how the observation zone was defined, using the Jl. Gatot Subroto corridor as an example. The diagram is a schematic rather than a map drawn to scale. It shows the eastbound and westbound carriageways separated by a central median, the pedestrian walkways on both sides of the road, and the programmatic DOOH display at the roadside. The dashed outer circle represents the approximate passive signal coverage (about 2 km in radius) of the Telkomsel base transceiver station (BTS) node from which the anonymized, aggregated audience profiles were derived; these profiles describe the population moving through the corridor rather than identified individuals. The dotted inner circle marks the high-dwell observation zone immediately around the display, where vehicles slow and pedestrians pass or linger long enough to be exposed to the displayed content. The figure therefore links the two data sources of the study: the wide BTS coverage area that informed data-driven scheduling, and the narrow display-centered zone in which audience exposure occurred.

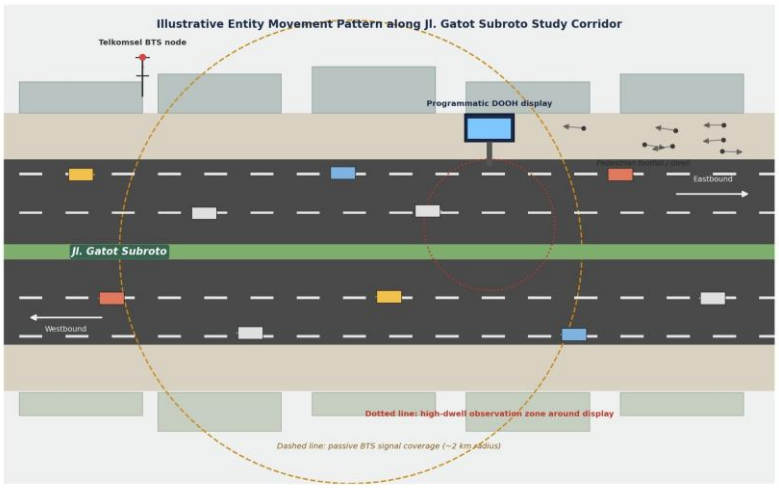


Figure 3. Illustrative diagram of vehicle and pedestrian movement captured passively along the Jl. Gatot Subroto DOOH study corridor, showing BTS signal coverage and the high-dwell observation zone around the display.

3.3. Population, Sample, and Instrument

The population comprised adults (18 years or older) exposed to the study displays. Intercept sampling with location quotas (160 respondents per site, 80 per campaign condition at each site) yielded N = 800 valid questionnaires (400 per condition), a sample size that far exceeds the minimum requirements for the most complex regression in the model [11]. The instrument contained 29 items measuring seven reflective constructs on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree), adapted from established scales to the DOOH context, as summarized in Table 2.

Table 2 details the measurement instrument construct by construct. For each of the seven constructs, it reports the construct code used throughout the paper, the number of items, one representative sample item, and the theoretical source on which the construct is based. The four stimulus constructs were measured with four or five items each (DTP 4, PF 5, BA 4, ICD 4), the organism construct, perceived ad relevance, with five items, and the two response constructs with three (AE) and four (PI) items, giving 29 items in total. The sample items also illustrate the distinction drawn in Section 2.2 between the two congruence constructs: the PF item refers to the match between the advertised content and the respondent's interests and lifestyle (what the advertisement is about), whereas the BA item refers to the timing of the advertisement relative to audience activity at the location (when and where it appeared). Because every item was rated on the same seven-point agreement scale, construct scores are directly comparable in the descriptive statistics reported in table 4.

Table 2. Constructs and measurement instrument

Construct (code)	Items	Sample item	Source(s)
Demographic Targeting Precision (DTP)	4	The advertisement content accurately reflects the demographic characteristics of audiences at this location.	S-O-R [8]
Psychographic Fit (PF)	5	The advertised content matches my personal interests and lifestyle preferences.	ELM [9]
Behavioral Alignment (BA)	4	The timing of the advertisement corresponds to peak audience activity periods at this location.	S-O-R [13]
Interactive Content Dynamism (ICD)	4	Real-time content updates on this display make the advertising experience more engaging.	TAM [10], [18]
Perceived Ad Relevance (PAR)	5	The advertisement displayed here is relevant to my current needs.	ELM [9], [14]
Audience Engagement (AE)	3	I actively viewed the DOOH advertisement rather than simply glancing at it.	Engagement [19]
Purchase Intention (PI)	4	I would consider purchasing the advertised product/service in the near future.	Hierarchy of effects [20]

3.4. Model Specification and Evaluation Formulas

Each reflective indicator x_{kj} is related to its latent construct ξ_j through the outer (measurement) model in (1), where λ_{kj} is the outer loading and ε_{kj} the measurement error [26]:

$$x_{kj} = \lambda_{kj}\,\xi_j + \varepsilon_{kj} \tag{1}$$

The inner (structural) model implied by H1–H6 is specified in (2)–(4), where β_1–β_6 are the standardized path coefficients corresponding to H1–H6 and ζ_1–ζ_3 are structural disturbances:

$$PAR = \beta_1\,DTP + \beta_2\,PF + \beta_3\,BA + \beta_4\,ICD + \zeta_1 \tag{2}$$

$$AE = \beta_5\,PAR + \zeta_2 \tag{3}$$

$$PI = \beta_6\,AE + \zeta_3 \tag{4}$$

Internal consistency and convergent validity were evaluated with composite reliability ρ_c in (5) and average variance extracted (AVE) in (6) for a construct measured by K indicators with standardized loadings λ_k [11], [27]:

$$\rho_c = \frac{\left(\sum_{k=1}^{K}\lambda_k\right)^2}{\left(\sum_{k=1}^{K}\lambda_k\right)^2 + \sum_{k=1}^{K}(1-\lambda_k^2)} \tag{5}$$

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$$AVE = \frac{1}{K}\sum_{k=1}^{K}\lambda_k^2 \tag{6}$$

Discriminant validity was assessed with the Fornell–Larcker criterion, which requires $\sqrt{\text{AVE}_i}$ to exceed the absolute correlation between construct i and every other construct j [27], and with the heterotrait–monotrait ratio in (7), where the numerator is the mean correlation between indicators of different constructs and the denominator is the geometric mean of the average within-construct indicator correlations [28]:

$$HTMT_{ij} = \frac{\bar{r}_{ij}^{\text{hetero}}}{\sqrt{\bar{r}_{ii}^{\text{mono}} \cdot \bar{r}_{jj}^{\text{mono}}}} \tag{7}$$

Collinearity among the predictors of an endogenous construct was assessed with the variance inflation factor in (8), where R_p^2 is obtained by regressing predictor p on the remaining predictors; computing the same statistic for every construct against all other constructs yields the full-collinearity test for common method bias [29]:

$$VIF_p = \frac{1}{1 - R_p^2} \tag{8}$$

The effect size of an exogenous construct on an endogenous construct was computed as in (9), where R_{incl}^2 and R_{excl}^2 are the explained variance with and without that predictor, and predictive relevance was computed as in (10), where SSE_d and SSO_d are the sums of squared prediction errors and squared observations for omission distance d [11], [30]:

$$f^2 = \frac{R_{\text{incl}}^2 - R_{\text{excl}}^2}{1 - R_{\text{incl}}^2} \tag{9}$$

$$Q^2 = 1 - \frac{\sum_d SSE_d}{\sum_d SSO_d} \tag{10}$$

Indirect effects were computed as the product of their constituent path coefficients, as in (11), and judged significant when the bootstrapped 95% confidence interval excluded zero [31]. For example, the indirect effect of DTP on AE equals $\beta_1 \times \beta_5 = 0.365 \times 0.678 = 0.247$.

$$IE_{X\to PAR\to AE} = \beta_{X\to PAR} \times \beta_5, \qquad IE_{PAR\to AE\to PI} = \beta_5 \times \beta_6 \tag{11}$$

For the measurement invariance assessment, compositional invariance was tested with the correlation c_j in (12) between composite scores computed from the pooled data $\mathbf{X}_j$ using the outer weights $\mathbf{w}_j^{(1)}$ and $\mathbf{w}_j^{(2)}$ estimated separately in the conventional and data-driven groups; invariance is supported when c_j is not significantly below 1 in a permutation test [32]. Between-condition differences in construct means were expressed as Cohen's d with a pooled standard deviation, as in (13) [33]:

$$c_j = \text{cor}\left(\mathbf{X}_j\mathbf{w}_j^{(1)}, \mathbf{X}_j\mathbf{w}_j^{(2)}\right) \tag{12}$$

$$d = \frac{M_{\text{DD}} - M_{\text{Conv}}}{\sqrt{\dfrac{(n_1 - 1)SD_1^2 + (n_2 - 1)SD_2^2}{n_1 + n_2 - 2}}} \tag{13}$$

3.5. Data Analysis Technique and Algorithm

PLS-SEM was selected because the model is prediction-oriented, contains a mediating mechanism, and imposes no multivariate normality requirement [11], [34]. The analysis was executed in SmartPLS 4.0 using the PLS path-modeling algorithm [26] with 5,000 bias-corrected and accelerated (BCa) bootstrap subsamples [35]. Measurement quality thresholds followed Hair et al. [11]: outer loadings > 0.70, Cronbach's α and composite reliability (CR) > 0.70, AVE > 0.50, HTMT < 0.85 (< 0.90 for conceptually similar constructs) [28], and inner VIF < 3.3. Predictive relevance was assessed through cross-validated Q^2 [30]. Common method bias was first examined with Harman's single-factor test [36]: the first unrotated factor explained 31.4% of total variance, well below the 50% threshold. Supplementary

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between-condition comparisons used independent-samples t-tests with Cohen's d effect sizes [33]. The complete estimation and inference procedure is formalized in Algorithm 1.

Algorithm 1 is organized in four blocks. Steps 1 to 8 describe the iterative PLS path-modeling algorithm, which alternates outer and inner approximations of the latent-variable scores until the outer weights converge (tolerance 10^{-7} or a maximum of 300 iterations). Steps 9 to 11 compute the measurement-model and structural-model statistics defined in Eqs. (2) to (10), with a return to respecification if any measurement criterion fails. Steps 12 to 15 perform the 5,000-subsample BCa bootstrap used to test H1 to H6 and the indirect effects of Eq. (11). Steps 16 to 20 implement the robustness procedures described below, namely MICOM and PLS-MGA across campaign conditions, the common-method-bias checks, the segment-level multi-group comparisons, and the between-condition mean comparison of Eq. (13).

Algorithm 1. PLS-SEM estimation, bootstrap inference, and robustness procedure

Input: data matrix X (N = 800 respondents × 29 indicators); measurement blocks X_1, …, X_7; inner-model paths P = {H1, …, H6}; condition label $g \in$ {Conv, DD}; B = 5,000
Output: loadings λ, path coefficients β, R^2, f^2, Q^2, BCa confidence intervals, invariance and multi-group results
1: Standardize every indicator in X
2: Initialize outer weights $w_j \leftarrow 1$ for every block j; $t \leftarrow 0$
3: repeat
4: Outer approximation: $Y_j \leftarrow X_j w_j$, scaled to unit variance
5: Inner weights (path weighting): $e_{ij} \leftarrow \text{cor}(Y_i, Y_j)$ if i and j are adjacent in P, else 0
6: Inner approximation: $Z_j \leftarrow \Sigma_i e_{ij} Y_i$
7: Update outer weights (Mode A): $w_j \leftarrow \text{cov}(X_j, Z_j)$; $t \leftarrow t + 1$
8: until max $|w_j^{(t)} - w_j^{(t-1)}| < 10^{-7}$ or $t = 300$
9: Compute $\lambda = \text{cor}(X_j, Y_j)$; estimate β by OLS for each endogenous construct, Eqs. (2)–(4)
10: Compute α, ρ_c, AVE, Fornell–Larcker and HTMT, Eqs. (5)–(7); if any criterion fails then revise the block and goto 2
11: Compute VIF, R^2, f^2 and Q^2, Eqs. (8)–(10)
12: for $b = 1$ to B do
13: Draw X^*_b by resampling N rows of X with replacement; repeat steps 2–9; store β^*_b and the indirect effects of Eq. (11)
14: end for
15: Build 95% BCa intervals from $\{\beta^*_b\}$; a hypothesis is supported if its interval excludes 0
16: MICOM: test c_j of Eq. (12) and the equality of composite means and variances using 5,000 permutations of g
17: if compositional invariance holds then run the permutation-based PLS-MGA on Δβ for H1–H6
18: Compute full-collinearity VIFs and marker-variable partial correlations (common method bias)
19: for each grouping variable ∈ {age band, income group, movement pattern} do permutation MGA (3,000 permutations)
20: Compare condition means with independent-samples t-tests and Cohen's d, Eq. (13)
21: return all estimates

Because the conventional and data-driven conditions were run sequentially rather than concurrently (Section 3.2), measurement invariance across the two conditions was assessed prior to any mean comparison, following the three-step Measurement Invariance of Composite Models (MICOM) procedure: configural invariance (identical indicators and algorithm settings across groups, satisfied by design), compositional invariance (permutation test of the correlation between composite scores across groups), and equality of composite means and variances [32]. Where compositional invariance was supported, two-group Partial Least Squares Multi-Group Analysis (PLS-MGA, 5,000 permutations) was additionally used to test whether the structural paths themselves (H1–H6) differed significantly between the conventional and data-driven sub-samples, independently of the mean-level comparison reported in Section 4.7 [32], [37]. Results appear in Table 7 (Section 4.5).

Common method bias was assessed beyond Harman's single-factor test in two additional ways. First, a full collinearity assessment regressed every construct on all other constructs; VIF values below the conservative 3.3 threshold indicate that common method variance is unlikely to materially confound the structural estimates [29]. Second, a marker-variable technique introduced a theoretically unrelated marker construct into the measurement model and compared construct correlations before and after partialling out the marker's shared variance [38]. Results appear in Table 8 (Section 4.5).

To examine whether the stimulus-to-relevance paths are homogeneous across audience segments (as opposed to across campaign conditions), a permutation-based multi-group comparison (3,000 permutations per grouping variable) was also applied using respondent age band, income group, and on-site movement pattern (commuter, tourism, or circular movement around the display) as grouping variables [37]. Results appear in Table 9 (Section 4.5).

4. Results and Discussion

4.1. Respondent Profile and Descriptive Statistics

Table 3 presents the profile of the 800 respondents on seven characteristics, reporting the frequency and percentage of each category. The sample was balanced by gender (48.3% male, 51.8% female) and, by design, by campaign condition (400 respondents, or 50.0%, in each). Respondents were spread evenly across the four age bands, with the 20–29 band the largest (28.0%) and the 50+ band the smallest (23.3%), and across the five occupational groups, which ranged from 18.1% (entrepreneur) to 21.5% (freelance). The three income groups were similarly balanced (31.8% to 35.4%), all five study locations were represented (17.9% to 23.3% each), and the three on-site movement patterns appeared in near-equal proportions (commuter 34.1%, circular 31.6%, tourism 34.3%). This balance matters for the analyses that follow, because age band, income group, and movement pattern serve as grouping variables in the segment-level multi-group analysis (Table 9), so each group contains a sub-sample large enough for stable estimation. Percentages may not sum to exactly 100 because of rounding.

Table 3. Respondent profile (N = 800)

Characteristic	Category	n (%)
Gender	Male	386 (48.3)
	Female	414 (51.8)
Age group (years)	20–29	224 (28.0)
	30–39	195 (24.4)
	40–49	195 (24.4)
	50+	186 (23.3)
Occupation	Employee	154 (19.3)
	Entrepreneur	145 (18.1)
	Self-employed	159 (19.9)
	Civil servant	170 (21.3)
	Freelance	172 (21.5)
Income group	Upper	263 (32.9)
	Middle	283 (35.4)
	Lower	254 (31.8)
Location	Jl. Jenderal Sudirman	186 (23.3)
	Jl. Gatot Subroto	143 (17.9)
	Jl. M.H. Thamrin	151 (18.9)
	Jl. H.R. Rasuna Said	156 (19.5)
	Semanggi	164 (20.5)
Movement pattern	Commuter	273 (34.1)
	Circular	253 (31.6)
	Tourism	274 (34.3)
Campaign condition	Conventional	400 (50.0)
	Data-driven	400 (50.0)

4.2. Measurement Model

Table 4 combines the descriptive statistics of each construct with the indicators of measurement-model quality. The first columns report the number of items and the mean and standard deviation of each construct score. Construct means ranged from 3.02 (purchase intention) to 4.45 (perceived ad relevance) on the seven-point scale, with standard deviations between 0.45 and 0.57, indicating adequate dispersion without floor or ceiling effects. The remaining

columns report Cronbach's α, composite reliability (CR, Eq. 5), and average variance extracted (AVE, Eq. 6). All seven reflective constructs satisfied every quality criterion. Outer loadings ranged from 0.702 to 0.847, exceeding the 0.70 threshold; Cronbach's α ranged from 0.762 to 0.864; CR from 0.848 to 0.902; and AVE from 0.552 to 0.702, establishing internal consistency reliability and convergent validity [11]. Even the lowest AVE (0.552, psychographic fit) exceeds the 0.50 threshold, meaning that every construct explains more than half of the variance of its indicators.

Table 4. Descriptive statistics and measurement model quality

Construct	Items	Mean	SD	α	CR	AVE
Demographic Targeting Precision	4	4.27	0.47	0.762	0.848	0.582
Psychographic Fit	5	4.22	0.45	0.797	0.860	0.552
Behavioral Alignment	4	4.08	0.47	0.769	0.852	0.591
Interactive Content Dynamism	4	4.01	0.48	0.777	0.855	0.597
Perceived Ad Relevance	5	4.45	0.54	0.864	0.902	0.647
Audience Engagement	3	3.52	0.55	0.787	0.876	0.702
Purchase Intention	4	3.02	0.57	0.831	0.887	0.663

Note: α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. All outer loadings (0.702–0.847) were significant at $p < 0.001$.

4.3. Discriminant Validity

Table 5 reports the Fornell–Larcker matrix (lower triangle) and HTMT ratios (upper triangle). The square root of each construct's AVE (bold diagonal) exceeded its highest correlation with any other construct [27]; for example, the square root of the AVE of perceived ad relevance (0.804) is larger than its highest inter-construct correlation, 0.706 with purchase intention. All HTMT values were below the conservative 0.85 threshold except Audience Engagement–Purchase Intention (HTMT = 0.886), which is best characterized as borderline but acceptable rather than as a validity failure: it remains below the 0.90 threshold recommended for conceptually adjacent, sequentially related constructs [28], and its bootstrapped 95% confidence interval, [0.851, 0.919] (3,000 bootstrap resamples), excludes 1.00, supporting the constructs' conceptual distinctness despite their theorized causal proximity in the hierarchy-of-effects sequence [20]. Because engagement and purchase intention sit adjacent in the S-O-R response chain, some shared variance is theoretically expected rather than a measurement artifact, and inner VIF values (1.067–1.101; Section 4.4) rule out structural multicollinearity. Overall discriminant validity was therefore established.

Table 5. Discriminant validity: Fornell–Larcker (lower triangle) and HTMT (upper triangle)

Construct	DTP	PF	BA	ICD	PAR	AE	PI
DTP	**0.763**	0.266	0.232	0.267	0.631	0.665	0.579
PF	0.208	**0.743**	0.271	0.089	0.638	0.473	0.558
BA	0.178	0.213	**0.769**	0.227	0.514	0.452	0.446
ICD	0.207	0.071	0.177	**0.773**	0.303	0.546	0.450
PAR	0.513	0.529	0.418	0.249	**0.804**	0.822	0.833
AE	0.517	0.375	0.351	0.429	0.678	**0.838**	0.886
PI	0.462	0.454	0.356	0.361	0.706	0.716	**0.814**

Note: Bold diagonal = square root of AVE; lower triangle = construct correlations; upper triangle = HTMT ratios.

4.4. Structural Model and Hypothesis Testing

Inner VIF values ranged from 1.067 to 1.101, well below 3.3, ruling out multicollinearity among the predictors. Table 6 reports, for each hypothesized path, the standardized coefficient (β), t-statistic, 95% BCa confidence interval, p-value, effect size (f^2, Eq. 9), and the resulting decision. All six hypotheses were supported. Psychographic fit exerted the strongest effect on perceived relevance (H2: $\beta = 0.392$, $t = 15.87$, $f^2 = 0.300$), followed by demographic targeting precision (H1: $\beta = 0.365$, $t = 15.10$, $f^2 = 0.256$) and behavioral alignment (H3: $\beta = 0.253$, $t = 10.36$, $f^2 = 0.123$); interactive content dynamism was significant but small (H4: $\beta = 0.101$, $t = 4.32$, $f^2 = 0.020$). Perceived relevance strongly predicted engagement (H5: $\beta = 0.678$, $t = 39.78$) and engagement strongly predicted purchase intention (H6: $\beta = 0.717$, $t = 48.14$). The model explained 52.8% of the variance in perceived relevance, 45.9% in engagement, and

51.3% in purchase intention, with Q^2 values of 0.522, 0.456, and 0.511 confirming substantial predictive relevance [30].

Table 6. Structural model results (BCa bootstrap, 5,000 subsamples)

H	Path	β	t	95% CI	p	f^2	Decision
H1	DTP → PAR	0.365	15.10	[0.319, 0.413]	<0.001	0.256	Supported
H2	PF → PAR	0.392	15.87	[0.344, 0.440]	<0.001	0.300	Supported
H3	BA → PAR	0.253	10.36	[0.205, 0.301]	<0.001	0.123	Supported
H4	ICD → PAR	0.101	4.32	[0.058, 0.149]	<0.001	0.020	Supported
H5	PAR → AE	0.678	39.78	[0.645, 0.712]	<0.001	0.849	Supported
H6	AE → PI	0.717	48.14	[0.687, 0.745]	<0.001	1.053	Supported

Note: f^2 guide: small ≥ 0.02, medium ≥ 0.15, large ≥ 0.35 [11]. R^2: PAR = 0.528, AE = 0.459, PI = 0.513; Q^2: 0.522, 0.456, 0.511.

Figure 4 presents the estimates from Table 6 graphically on the conceptual framework of Figure 1, so that the relative strength of each path can be read directly from the model. Each arrow is labelled with its hypothesis and standardized coefficient, and each endogenous construct shows its explained variance (R^2). On the stimulus side, the arrows from PF (β = 0.392) and DTP (β = 0.365) carry the largest coefficients into perceived ad relevance, followed by BA (β = 0.253), while the ICD path (β = 0.101) is significant but clearly the weakest. On the response side, the PAR → AE (β = 0.678) and AE → PI (β = 0.717) paths are substantially stronger than any stimulus path, and the three endogenous constructs reach R^2 values of 0.528 (PAR), 0.459 (AE), and 0.513 (PI). Because all six paths are significant at p < 0.001, the figure depicts a complete S-O-R chain in which every hypothesized link is supported.

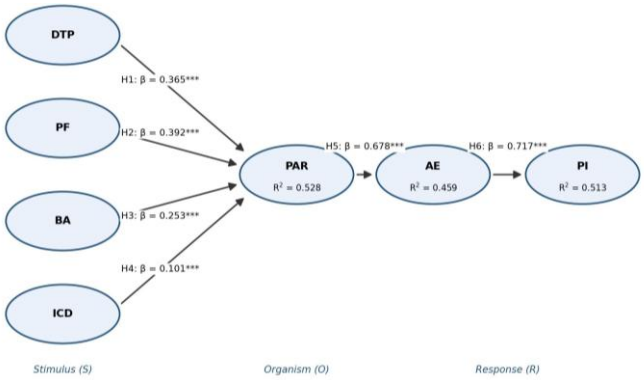


Figure 4. Final structural model with standardized path coefficients (BCa bootstrap, 5,000 subsamples). Ellipses denote latent constructs; solid arrows denote the six hypothesized and supported structural paths (H1–H6); *** p < 0.001.

4.5. Robustness Checks: Measurement Invariance, Common Method Bias, and Multi-Group Analysis

As specified in Section 3.5, three robustness checks were conducted beyond the primary structural model: (i) measurement invariance and multi-group comparison of the conventional versus data-driven conditions, (ii) common method bias assessment beyond Harman's single-factor test, and (iii) multi-group analysis by audience segment. Each check is explained below, immediately before the table that reports it (Tables 7, 8, and 9, respectively).

Table 7 reports the measurement invariance assessment and the multi-group comparison between the conventional and data-driven conditions. The upper part of the table follows the MICOM steps. In Step 2, compositional invariance is supported when the correlation c between composite scores computed with the two groups' outer weights (Eq. 12) is not lower than the 5th percentile of its permutation distribution. This criterion was met for the four stimulus constructs (DTP, PF, BA, and ICD; c = 0.9997 to 0.9999). For PAR, AE, and PI, c fell marginally below the cutoff (0.9984 to 0.9998 against 0.9999) and is therefore classified as partial (borderline) invariance; because every c value remains above 0.998, these compositional differences are numerically negligible. In Step 3a, composite means differed significantly between conditions for all seven constructs (Δ = −1.08 to −2.72, all p < 0.001), which is the expected outcome because the data-driven condition was designed to raise these scores. In Step 3b, composite variances did not

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differ between conditions (all $p > 0.05$). The lower part of the table reports the PLS-MGA, which compares each structural path (H1 to H6) between the two conditions; none of the six differences was significant ($p = 0.271$ to 0.913).

Table 7. Measurement invariance (MICOM) and multi-group comparison: conventional vs. data-driven conditions

Step / path	Criterion	Result	Conclusion
MICOM Step 2 (compositional invariance) — DTP	c ≥ 5th permutation percentile	c = 0.9997 (cutoff 0.9996)	Invariant
MICOM Step 2 — PF	c ≥ 5th permutation percentile	c = 0.9999 (cutoff 0.9996)	Invariant
MICOM Step 2 — BA	c ≥ 5th permutation percentile	c = 0.9999 (cutoff 0.9997)	Invariant
MICOM Step 2 — ICD	c ≥ 5th permutation percentile	c = 0.9998 (cutoff 0.9997)	Invariant
MICOM Step 2 — PAR	c ≥ 5th permutation percentile	c = 0.9998 (cutoff 0.9999)	Partial (borderline)
MICOM Step 2 — AE	c ≥ 5th permutation percentile	c = 0.9986 (cutoff 0.9999)	Partial (borderline)
MICOM Step 2 — PI	c ≥ 5th permutation percentile	c = 0.9984 (cutoff 0.9999)	Partial (borderline)
MICOM Step 3a (equal composite mean) — DTP	permutation p > 0.05	Δ = −1.30, p < 0.001	Not equal (by design)
MICOM Step 3a — PF	permutation p > 0.05	Δ = −1.49, p < 0.001	Not equal (by design)
MICOM Step 3a — BA	permutation p > 0.05	Δ = −1.17, p < 0.001	Not equal (by design)
MICOM Step 3a — ICD	permutation p > 0.05	Δ = −1.08, p < 0.001	Not equal (by design)
MICOM Step 3a — PAR	permutation p > 0.05	Δ = −2.59, p < 0.001	Not equal (by design)
MICOM Step 3a — AE	permutation p > 0.05	Δ = −2.14, p < 0.001	Not equal (by design)
MICOM Step 3a — PI	permutation p > 0.05	Δ = −2.72, p < 0.001	Not equal (by design)
MICOM Step 3b (equal composite variance) — DTP	permutation p > 0.05	log-ratio = 0.145, p = 0.101	Equal
MICOM Step 3b — PF	permutation p > 0.05	log-ratio = 0.136, p = 0.117	Equal
MICOM Step 3b — BA	permutation p > 0.05	log-ratio = 0.153, p = 0.069	Equal
MICOM Step 3b — ICD	permutation p > 0.05	log-ratio = 0.112, p = 0.174	Equal
MICOM Step 3b — PAR	permutation p > 0.05	log-ratio = 0.094, p = 0.274	Equal
MICOM Step 3b — AE	permutation p > 0.05	log-ratio = 0.013, p = 0.879	Equal
MICOM Step 3b — PI	permutation p > 0.05	log-ratio = 0.063, p = 0.371	Equal
PLS-MGA — H1 DTP → PAR (Conv. vs. DD)	p < 0.05 (two-tailed, 5,000 permutations)	β = 0.303 vs. 0.331, Δ = −0.028, p = 0.560	No significant difference
PLS-MGA — H2 PF → PAR	p < 0.05 (two-tailed, 5,000 permutations)	β = 0.333 vs. 0.296, Δ = 0.037, p = 0.439	No significant difference
PLS-MGA — H3 BA → PAR	p < 0.05 (two-tailed, 5,000 permutations)	β = 0.178 vs. 0.233, Δ = −0.055, p = 0.271	No significant difference
PLS-MGA — H4 ICD → PAR	p < 0.05 (two-tailed, 5,000 permutations)	β = −0.009 vs. 0.008, Δ = −0.017, p = 0.716	No significant difference
PLS-MGA — H5 PAR → AE	p < 0.05 (two-tailed, 5,000 permutations)	β = 0.301 vs. 0.330, Δ = −0.028, p = 0.413	No significant difference
PLS-MGA — H6 AE → PI	p < 0.05 (two-tailed, 5,000 permutations)	β = 0.268 vs. 0.271, Δ = −0.003, p = 0.913	No significant difference

Note: PLS-MGA β values are within-condition standardized structural estimates (conventional vs. data-driven, n = 400 each), computed on composite scores; they are smaller than the pooled-sample coefficients in Table 6 because pooling reintroduces the large between-condition variance documented in Table 11, which is not present within a single condition.

Table 8 reports the two additional common method bias checks. The upper part lists the full-collinearity VIF of each construct when it is regressed on all other constructs. All values (1.24 to 2.84) are below the conservative 3.3 threshold [29]; the highest values belong to the three response-side constructs (PAR 2.84, AE 2.67, PI 2.64), as expected for adjacent links in a causal chain. The lower part reports the marker-variable test, which compares the raw correlation of each structurally linked construct pair with the same correlation after partialling out the Content Delivery Quality (CDQ) marker [38]. The reduction was small for every pair (Δ = 0.018 to 0.041), so the correlations were substantively unchanged, indicating that shared method variance does not account for the structural relationships.

Table 8. Common method bias robustness: full-collinearity VIF and marker-variable test

Check / pair	Metric	Value	Conclusion
Full-collinearity VIF — DTP	VIF (vs. all other constructs)	1.49	< 3.3, no CMB concern
Full-collinearity VIF — PF	VIF	1.45	< 3.3, no CMB concern
Full-collinearity VIF — BA	VIF	1.24	< 3.3, no CMB concern
Full-collinearity VIF — ICD	VIF	1.27	< 3.3, no CMB concern
Full-collinearity VIF — PAR	VIF	2.84	< 3.3, no CMB concern
Full-collinearity VIF — AE	VIF	2.67	< 3.3, no CMB concern
Full-collinearity VIF — PI	VIF	2.64	< 3.3, no CMB concern
Marker variable (CDQ block) — DTP↔PAR	r raw → r partialled on marker	0.513 → 0.490 (Δ = 0.023)	Negligible shift

Marker variable — PF↔PAR	r raw → r partialled	0.530 → 0.488 (Δ = 0.041)	Negligible shift
Marker variable — BA↔PAR	r raw → r partialled	0.419 → 0.401 (Δ = 0.018)	Negligible shift
Marker variable — ICD↔PAR	r raw → r partialled	0.249 → 0.218 (Δ = 0.031)	Negligible shift
Marker variable — PAR↔AE	r raw → r partialled	0.678 → 0.644 (Δ = 0.034)	Negligible shift
Marker variable — AE↔PI	r raw → r partialled	0.716 → 0.683 (Δ = 0.033)	Negligible shift

Note: The marker variable was the Content Delivery Quality (CDQ) item block, chosen because it showed the weakest correlations with the seven focal constructs (r = 0.13–0.46) and is conceptually peripheral to the S-O-R targeting-relevance mechanism.

Table 9 reports the segment-level multi-group analysis, which tests whether each of the six structural paths differs across audience segments rather than across campaign conditions. Each cell gives the p-value of a permutation-based omnibus test (3,000 permutations) for one path and one grouping variable: age band (four groups), income group (three groups), and on-site movement pattern (commuter, tourism, and circular). The smallest p-value in the table, 0.147 for H4 across income groups, is well above 0.05, so none of the six paths differed significantly by age band, income group, or movement pattern.

Table 9. Multi-group analysis by audience age band, income group, and movement pattern (commuter/tourism/circular)

H	Path	Age-band MGA (p)	Income-group MGA (p)	Movement-pattern MGA (p)
H1	DTP → PAR	0.374	0.722	0.850
H2	PF → PAR	0.518	0.389	0.442
H3	BA → PAR	0.199	0.782	0.983
H4	ICD → PAR	0.621	0.147	0.400
H5	PAR → AE	0.509	0.959	0.823
H6	AE → PI	0.240	0.442	0.386

Note: p-values are from a permutation-based omnibus test (3,000 permutations per grouping variable) on the variance of each path's group-specific coefficients; no path differed significantly by segment (all p > 0.05).

Taken together, these robustness checks support the primary structural model. Stimulus-side compositional invariance held for DTP, PF, BA, and ICD; the three response-side constructs (PAR, AE, PI) showed statistically detectable but numerically minor compositional variation (c > 0.998 in all cases), consistent with their being the constructs the data-driven intervention was designed to shift. Composite means differed sharply between conditions as intended (table 11), while variances did not differ significantly. Critically, none of the six structural paths differed significantly between the conventional and data-driven conditions, indicating that the underlying mechanism linking targeting stimuli to audience response is stable across conditions even though construct levels are not; the mean-level shift, not a change in the relationships themselves, drives the between-condition results in Section 4.7. Full-collinearity VIFs and the marker-variable test both ruled out common method bias beyond the Harman's test result already reported in Section 3.5. Finally, none of the six paths varied significantly by audience age band, income group, or on-site movement pattern, indicating that the model generalizes across these segments in the present sample.

4.6. Mediation Analysis

Because the stimuli influence engagement only through perceived relevance in the hypothesized model, mediation was assessed via the significance of the bootstrapped indirect effects computed with (11) [31]; the results are reported in table 10, which gives, for each indirect path, the product-of-coefficients estimate (β), its bootstrap standard error (SE), t-statistic, and 95% BCa confidence interval. All four stimulus-to-engagement indirect paths were significant, the largest running through psychographic fit (β = 0.266, 95% CI [0.231, 0.300]) and demographic precision (β = 0.247, 95% CI [0.213, 0.285]), followed by behavioral alignment (β = 0.172); the indirect effect through interactive content dynamism was the smallest (β = 0.068), but its confidence interval [0.039, 0.103] still excluded zero. The serial path from perceived relevance through engagement to purchase intention was likewise significant (β = 0.486, 95% CI [0.451, 0.523]), confirming the full S-O-R chain: targeting stimuli shape an internal state of perceived relevance, which converts into engagement and, ultimately, purchase intention.

Table 10. Indirect (mediated) effects

Indirect path					β	SE	t	95% CI	Decision
DTP	→	PAR	→	AE	0.247	0.018	13.39	[0.213, 0.285]	Significant
PF	→	PAR	→	AE	0.266	0.018	15.03	[0.231, 0.300]	Significant
BA	→	PAR	→	AE	0.172	0.017	10.09	[0.139, 0.205]	Significant
ICD	→	PAR	→	AE	0.068	0.016	4.22	[0.039, 0.103]	Significant
PAR	→	AE	→	PI	0.486	0.019	26.10	[0.451, 0.523]	Significant

Note: BCa bootstrap, 5,000 subsamples; all indirect effects significant at $p < 0.001$.

4.7. Campaign-Condition Comparison

As a supplementary check of practical significance, table 11 compares construct scores between campaign conditions. For each construct, it reports the mean (M) and standard deviation (SD) in the conventional (Conv.) and data-driven (DD) conditions, the independent-samples t-statistic, and Cohen's d computed with Eq. (13). Respondents surveyed during the data-driven condition scored significantly higher on every construct (all $p < 0.001$), with the largest differences on the response-side constructs: purchase intention ($d = 3.06$), engagement ($d = 2.18$), and perceived relevance ($d = 2.07$). Stimulus-side differences were also large ($d = 0.75$–1.01), consistent with the design intent: data-driven scheduling increases the demographic, psychographic, and behavioral congruence of displayed content, and audiences detect that congruence.

Table 11. Construct score comparison by campaign condition

Construct	M (Conv.)	SD	M (DD)	SD	t	Cohen's d
DTP	4.07	0.44	4.46	0.41	13.36	0.94
PF	4.02	0.41	4.42	0.39	14.23	1.01
BA	3.90	0.45	4.26	0.42	11.57	0.82
ICD	3.84	0.46	4.18	0.44	10.55	0.75
PAR	4.06	0.39	4.84	0.37	29.21	2.07
AE	3.12	0.37	3.93	0.37	30.76	2.18
PI	2.55	0.31	3.50	0.30	43.24	3.06

Note: Conv. = conventional condition ($n = 400$); DD = data-driven condition ($n = 400$). All $p < 0.001$ (independent-samples t-tests, $df = 798$).

4.8. Discussion

The results carry three theoretical implications. The ordering of the stimulus effects, with psychographic fit strongest ($\beta = 0.392$), demographic precision close behind ($\beta = 0.365$), behavioral alignment intermediate ($\beta = 0.253$), and content dynamism smallest ($\beta = 0.101$), is the ordering the ELM implies, since interest congruence connects content to viewers' goals more directly than category membership or scheduling does [9], [14]. The findings also speak to the personalization paradox. Aguirre et al. [15] and Bleier and Eisenbeiss [16] showed that individual-level personalization can backfire through perceived intrusiveness, and Boerman et al. [17] placed privacy concern at the center of behavioral-advertising research. The present results indicate that congruence-based targeting built on aggregated, anonymous audience data still produces substantial relevance gains. Group-level congruence, in other words, captures much of the benefit of personalization while sidestepping the identification that triggers reactance, a possibility the personalization literature has largely left unexamined for public-space media.

This pattern also foregrounds a mechanism distinctive to aggregated, privacy-preserving targeting that has received little formal attention in the personalization literature: audience-level abstraction. Because the underlying telecommunications data are aggregated to the population surrounding a display rather than resolved to individual identities, the targeting stimuli in this study (DTP, PF, BA) are properties of a place-time audience segment, not of a tracked person. Audience-level abstraction plausibly explains why congruence-based targeting produced substantial relevance gains without the reactance signatures documented for individually identified personalization [15], [16]: viewers can register that content matches "people like the ones here, now" without inferring that they, individually, are being tracked. This mechanism was not measured directly, since perceived individual identifiability and privacy concern were outside the present instrument (Section 5); it is presented here as a theoretical proposition consistent with

the observed pattern rather than as a tested moderator, and formally specifying and measuring audience-level abstraction as a distinct construct is an explicit direction for future research (Section 5).

The behavioral-alignment effect is consistent with the footfall-context literature [22] and with field evidence that the effect of digital displays depends on the setting in which messages are shown [2]. The small contribution of interactive content dynamism qualifies TAM-based expectations [10], [18] and admits three readings: usefulness perceptions may attach to the display technology rather than to the message, leaving relevance judgments largely untouched; brief, incidental exposure may not allow viewers to register adaptivity at all; or dynamism may act as a hygiene factor whose absence harms but whose presence adds little once content is well matched, an interpretation consistent with the over-personalization pattern reported by Bleier and Eisenbeiss [16]. Distinguishing these accounts requires designs that manipulate dynamism independently of congruence.

A further explanation, distinct from the theoretical accounts above, concerns instrument sensitivity rather than a genuinely weak underlying effect. The ICD items asked respondents to recall whether display content changed or adapted in real time, a self-report judgment that presumes viewers consciously registered the display's technical behavior during what is typically a brief, incidental roadside exposure of only a few seconds. If most respondents could not reliably perceive or recall dynamism at that exposure duration, the modest path coefficient may partly reflect measurement insensitivity. Future studies pairing self-report items with objective exposure-duration data or eye-tracking would help separate instrument sensitivity from theoretical explanations.

These results also carry a direct cost-benefit implication. Programmatic interactive display technology commands a substantial capital and licensing premium over static or scheduling-only DOOH inventory, yet interactive content dynamism explained only a small increment in perceived relevance ($f^2 = 0.020$) once demographic, psychographic, and behavioral congruence were accounted for, compared with $f^2 = 0.300$ and 0.256 for psychographic fit and demographic precision, respectively. For advertisers operating under fixed campaign budgets, the marginal return therefore favors prioritizing audience-data acquisition and content-matching capability over interactive display hardware, particularly in early-stage DOOH deployments; interactivity becomes a second-order investment once congruence-based targeting infrastructure is in place, or is best reserved for venues with longer average dwell times where dynamic content has more time to register with viewers.

The mediation results support the organism gateway at the core of S-O-R theory [8], [12]: in the hypothesized specification, the stimuli reach engagement through perceived relevance, and the serial path to purchase intention ($\beta = 0.486$) reproduces, in a public-space field setting, the relevance-to-response chain established for online advertising [16]. The engagement-to-intention path ($\beta = 0.717$) is consistent with the hierarchy-of-effects sequence [20] and with engagement research that identifies purchase intent as a principal consequence of engagement [19], [23]. That four content-side stimuli explain roughly half the variance in relevance and intention indicates how much of DOOH effectiveness is settled before creative execution begins, by whom the content addresses and when it appears.

The mediation analysis in Section 4.6 tested a fully mediated structural specification, in which the four targeting stimuli influence engagement and purchase intention only indirectly, through perceived ad relevance. Full mediation was the a priori theoretical expectation rather than an assumption imposed after the fact: within the S-O-R logic underlying the model, targeting stimuli are properties of the environmental input, and the ELM literature treats perceived relevance as the elaboration trigger through which content properties translate into downstream engagement [9], [14]; no direct stimulus-to-engagement or stimulus-to-intention paths were therefore specified a priori. As a robustness check on this specification, a competing partial-mediation model adding direct paths from each stimulus to audience engagement was estimated. The direct paths were statistically significant for demographic targeting precision ($\beta = 0.211$, $p < 0.001$) and interactive content dynamism ($\beta = 0.258$, $p < 0.001$), and smaller but still significant for psychographic fit ($\beta = 0.064$, $p = 0.022$) and behavioral alignment ($\beta = 0.069$, $p = 0.007$); the direct path from perceived relevance to engagement remained the largest single coefficient ($\beta = 0.443$, $p < 0.001$) but dropped from its fully mediated value ($\beta = 0.678$), and explained variance in engagement increased from $R^2 = 0.459$ to $R^2 = 0.567$ ($\Delta R^2 = 0.108$). Partial, rather than full, mediation is therefore the more accurate description of the data: perceived relevance is the dominant pathway from targeting stimuli to engagement, but demographic precision and, notably, interactive content dynamism also reach engagement directly, independent of perceived relevance. A plausible reading is that these two stimuli carry attentional

or salience value (precision targeting signals and real-time visual change) that registers as engaging even when it is not consciously coded as personally relevant, a nuance the original fully mediated specification could not capture. We retain the fully mediated model as the primary specification for parsimony and consistency with the ELM-based hypotheses (H1–H6), and report the partial-mediation estimates here as an acknowledged refinement for future model development.

The campaign-condition comparison adds practical weight to these paths. Differences between the data-driven and conventional conditions grow monotonically along the causal chain, from d = 0.75–1.01 on the stimulus constructs to d = 2.07–3.06 on relevance, engagement, and intention. This amplification is what a mediated model predicts: modest improvements in congruence compound as they propagate through relevance to downstream responses. The pattern is consistent with the data-driven marketing proposition of Wedel and Kannan [21] and with Davenport et al. [4], and it extends the descriptive account of algorithmic audience planning by Beauvisage et al. [3] with quantified audience-side outcomes.

Section 4.5 additionally tested whether these stimulus-to-relevance paths are homogeneous across audience segments rather than uniform, as the baseline structural model assumes. None of the six paths differed significantly by age band, income group, or on-site movement pattern (Table 9; all $p > 0.05$). This is itself a substantively useful finding for practice: it indicates that the relative priority of psychographic fit, demographic precision, behavioral alignment, and content dynamism established in Section 4.4 holds broadly across the audience segments observed in this sample, so advertisers do not need segment-specific targeting-weight strategies to capture the bulk of the effect documented here. This finding should be read alongside the sample's composition, five central-business-district corridors in a single metropolitan market (Section 5); heterogeneity may emerge in samples spanning a wider range of income strata, age structures, or mobility contexts than the present study captured.

Several alternative explanations deserve mention. Because all constructs were measured by self-report within a single questionnaire, common-method variance could inflate the structural paths, although Harman's test (31.4%), the full-collinearity and marker-variable checks, and the sizable between-condition differences obtained from independently timed surveys argue against a purely methodological account [36]. The sequential rather than randomized assignment of campaign conditions leaves room for seasonal and order effects, and the Jakarta central-business-district setting, with its dense commuter flows, may amplify behavioral-alignment effects relative to lower-traffic environments. These caveats bound the claims but do not overturn the central pattern: audience-content congruence, not display technology or exposure volume, is the dominant lever of DOOH effectiveness.

5. Conclusion

This study set out to explain, with a simple and fully quantitative design, how audiences respond to data-driven DOOH advertising. Using survey data from 800 respondents at five Jakarta protocol-road locations and PLS-SEM with 5,000 bootstrap subsamples, all six hypotheses derived from the S-O-R, ELM, and TAM frameworks were supported. Psychographic fit ($\beta = 0.392$) and demographic targeting precision ($\beta = 0.365$) were the dominant antecedents of perceived ad relevance ($R^2 = 0.528$); relevance drove engagement ($\beta = 0.678$), and engagement drove purchase intention ($\beta = 0.717$, $R^2 = 0.513$). Respondents exposed to data-driven campaigns reported significantly more favorable responses on every construct than those exposed to conventional campaigns.

Theoretically, the study validates a parsimonious S-O-R model in which perceived relevance is the single organismic gateway between targeting stimuli and behavioral response, extending ELM evidence to incidental, public-space exposure. Practically, the results direct advertisers and DOOH operators to prioritize audience-content congruence, investing in demographic and psychographic audience intelligence before investing in display interactivity, and provide regulators with evidence that privacy-preserving, aggregated telecommunications data can create measurable advertising value without individual-level profiling [24], [25]. In practical terms, the relative effect sizes translate into a straightforward prioritization rule for campaign budgets: because psychographic fit and demographic targeting precision jointly account for the two largest effect sizes on perceived relevance ($f^2 = 0.300$ and 0.256, against 0.123 for behavioral alignment and 0.020 for content dynamism), advertisers working with a fixed data and technology budget should sequence investment as follows: first, psychographic and demographic audience-intelligence acquisition;

second, behavioral and time-of-day alignment capability; and only third, and at comparatively low priority, interactive display technology. DOOH operators marketing programmatic inventory can use this same ordering to advise clients on where an incremental data-licensing outlay produces the largest expected return in relevance, engagement, and purchase intention.

Several limitations bound these conclusions and define the research agenda. The design is cross-sectional, so the mediational ordering, although theory-driven, bootstrap-supported, and checked against a competing partial-mediation specification (Section 4.8), is not strictly causal. The data are self-reported perceptions, and interactive content dynamism in particular relies on respondents' brief, incidental recall of display behavior, a measurement-sensitivity concern discussed in Section 4.8. Sampling relied on intercept quotas at five high-traffic protocol-road corridors within Jakarta's central business district, selected under the criteria described in Section 3.2; although temporal quotas balanced time-of-day and day-type within each site, the design cannot rule out unmeasured differences between corridor commuters and the broader, non-metropolitan population, and the structural relationships reported here should be treated as bounded to dense, high-traffic urban corridors until replicated elsewhere. The conceptual model also does not include consumer privacy perceptions, perceived intrusiveness, or psychological reactance, constructs central to the personalization paradox literature [15], [16], [17], because the present instrument was designed around content-and-timing congruence rather than privacy cognition; Section 4.8 offers audience-level abstraction as a theoretical account of why reactance was plausibly muted, but this remains an unmeasured proposition pending future work. Finally, purchase intention, rather than actual purchase, is the terminal outcome.

Future research should proceed along six directions. First, longitudinal and field-experimental designs randomizing data-driven versus conventional scheduling across matched locations and tracking the same audiences over time would convert the present associational evidence into causal estimates. Second, replication across cities, display formats, and cultures is needed to establish the model's boundary conditions, particularly outside high-density urban corridors. Third, the model should be extended with moderators this single-market sample could not adequately range-test: although age band, income group, and on-site movement pattern showed no significant moderation within this Jakarta sample (Section 4.5), the limited socioeconomic and geographic range of a single central-business-district population means this null result should be treated as provisional rather than conclusive; creative design quality on the response side, and audience heterogeneity across cities, income distributions, and cultures more broadly, remain open questions requiring wider-range replication. Fourth, hybrid designs that pair this survey instrument with objective telecommunications-derived measures (machine learning audience segmentation, footfall analytics, and content-affinity scoring) would allow perceived and actual targeting precision to be modeled jointly [22], [39]. Fifth, linking the model's terminal construct to observed behavior (mobile conversions, store visits, sales lift) would close the intention-behavior gap that the present design leaves open. Sixth, directly measuring consumer privacy perceptions, perceived intrusiveness, and psychological reactance alongside the present targeting stimuli would allow a formal test of whether audience-level abstraction (Section 4.8), rather than construct-level differences in stimulus design, explains the muted reactance implied by the present results. Together, these steps would move the field from demonstrating that data-driven DOOH works toward a predictive theory of when, where, and for whom it works best.

6. Declarations

6.1. Author Contributions

Conceptualization: O.U. and A.K.; Methodology: O.U. and A.K.; Software: A.K.; Validation: O.U., A.K., and A.K.R.P.; Formal Analysis: O.U. and A.K.; Investigation: O.U. and A.K.; Resources: O.U. and A.K.R.P.; Data Curation: A.K.; Writing Original Draft Preparation: O.U. and A.K.; Writing Review and Editing: O.U., A.K., and A.K.R.P.; Visualization: A.K.; Supervision: O.U.; Project Administration: O.U. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author, O.U. Individual-level BTS data, which contain information that could compromise the privacy of research participants, are not publicly available due to restrictions under Indonesia's Personal Data Protection Law (Law No. 27 of 2022). Aggregated, non-identifiable analytical data will be deposited at Zenodo upon acceptance.

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6.4. Institutional Review Board Statement

The study involving human participants complied with all relevant national regulations and institutional policies, was conducted in accordance with the tenets of the Declaration of Helsinki and was approved by the Research Ethics Committee of Universitas Negeri Jakarta.

6.5. Informed Consent Statement

Informed consent was obtained from all individual participants included in the study.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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