Perceived Digital Invasion and Consumer Resistance to Personalized Advertising: Evidence from Honduran Digital Consumers

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***Abstract*– Personalized digital advertising relies on continuous data collection that consumers may experience as invasive. Drawing on psychological reactance theory, this study examined whether perceived digital invasion, distinguished from advertising interruption, is associated with emotional reactivity and cognitive counterarguing. A cross-sectional online survey of 125 adult digital consumers in Honduras was analyzed with robust structural equation modeling. Perceived digital invasion was positively associated with emotional reactivity (β = .822), whereas interruption and personalization showed no stable associations with reactance. Because the two reactance dimensions overlapped substantially and the final specification was exploratory, the results support association rather than sequence, and highlight the value of treating intrusiveness as multidimensional.**

***Keywords*-- perceived digital invasion, psychological reactance, personalized advertising, structural equation modeling, digital consumers**

I. Introduction

Digital advertising no longer broadcasts generic messages; it infers what a specific person is likely to want, click on, or buy, and adjusts what it shows accordingly. That inference depends on the continuous collection and algorithmic processing of behavioral traces, such as browsing histories, purchase records, location signals, and social interactions, which firms convert into individually tailored offers [1], [2]. The same data practices that make an advertisement feel relevant to one user can make it feel like an unwarranted incursion into private space for another, and platforms have not resolved this tension so much as learned to operate inside it [3], [4]. The issue is how much data-driven visibility a commercial relationship can sustain before the person on the receiving end begins to resist it.

Empirical work on personalized advertising has established two findings that sit uneasily together. Personalization that consumers perceive as accurate tends to increase perceived relevance and favorable attitudes toward the advertisement and the platform, partly by reducing the sense of vulnerability that targeting can otherwise create [2], [5], [6]. The same tailoring, however, signals that a company has been watching, and this recognition can trigger privacy concern, skepticism, or avoidance [3], [7], [8]. Studies attempting to reconcile these pathways have sometimes found that personalization suppresses perceived intrusiveness by increasing relevance [6], and sometimes that intrusiveness dominates once consumers interpret targeting as surveillance rather than assistance [7], [8]. This inconsistency suggests that intrusiveness is not a single undifferentiated reaction but a judgment organized around distinct concerns.

Perceived intrusiveness has conventionally been operationalized around the disruption an advertisement causes to an ongoing task, following the scale developed by Li et al. [9]. Interruption of this kind is primarily an attentional and temporal cost: the ad arrives at the wrong moment. A conceptually distinct concern is the sense that an advertisement reveals more familiarity with the user's data than the user consented to, which is better described as invasion of a digital boundary than as interruption; consumers appear more attuned to this invasion when it originates from social media than from less visible technologies such as facial recognition or GPS-based targeting [10]. Adolescent consumers report that intrusive formats erode brand trust and prompt resistance once personalization and perceived vulnerability combine [11]. Treating intrusiveness as a single global factor may therefore obscure the difference between an advertisement that is poorly timed and one that is read as an incursion into informational privacy.

Psychological reactance theory offers one account of what happens once an advertisement is read as a boundary violation rather than a nuisance. People experience a motivational state aimed at restoring a threatened freedom, a state that carries an affective charge, commonly described as anger or irritation, and a cognitive component in which the person generates arguments against the source of the threat [12], [13]. In advertising, reactance has been measured as encompassing negative cognitions and anger as related but separable components [14], and threats to perceived freedom elevate reactance across message types and cultural settings [15].

Experiences read as violations of privacy or autonomy have been consistently linked to reactance. Retargeted ads that cue ongoing behavioral tracking increase perceived marketing surveillance, which heightens perceived threat and reactance before shaping attitudes and purchase intention [8]. Personalized email that feels too finely tuned, without an explicit justification, provokes personalization reactance rather than appreciation [16], and perceived intrusiveness in unsolicited commercial email has been linked to the strength of the reactance that follows [17]. Invasions that consumers

judge illegitimate generate anxiety through a loss of perceived control [18], the erosion of perceived autonomy under algorithmic personalization undermines trust by heightening reactance [19], and perceived intrusiveness has been associated with irritation and skepticism through a stimulus–organism–response logic [20].

How the affective and cognitive components of reactance relate to each other is less settled. Some accounts treat negative cognitions and anger as co-occurring dimensions of a single response [14], while research on ad blocking suggests that cognitive and affective antecedents can be distinguished empirically and jointly predict resistance [21]. Consumers who feel that intrusive advertising has stripped them of agency develop more negative evaluations of the brand behind the ad, an outcome consistent with an active rejection of the persuasive attempt [22]. Some theoretical accounts propose that irritation precedes and organizes counterarguing, but establishing such an order requires temporal or experimental evidence that a single cross-sectional measurement cannot provide.

Two gaps in this literature motivate the present study. First, most structural models of intrusiveness in digital advertising rely on composite or single-dimension measures rather than distinguishing interruption from invasion, so it remains unclear which facet carries the association with reactance. Second, the empirical base cited above is concentrated in North American, Western European, and East and South Asian markets, with Latin American digital consumers comparatively absent despite exposure to the same platforms, targeting infrastructure, and advertising formats. Honduran consumers interact with the same global advertising platforms and data-driven targeting practices, yet have not been part of the samples on which current understanding rests. Examining them does not assume that they will respond differently; it tests whether an association documented in other markets is observed in a setting not yet examined.

The present study therefore evaluates the Digital Invasion–Reactance Model, a structural specification in which perceived digital invasion, defined as consumers' sense that personalized advertising and algorithmic targeting intrude on their digital privacy without adequate control, is associated with emotional reactivity to advertising pressure, which is in turn associated with cognitive counterarguing against persuasive marketing attempts. The model was estimated with cross-sectional data, so its paths are interpreted as statistical associations, not as causal or temporal relations.

A. Hypotheses

H1. Perceived digital invasion will be positively associated with consumers' emotional reactivity to advertising pressure.

H2. Emotional reactivity to advertising pressure will be positively associated with consumers' cognitive counterarguing against advertising.

The direction of the second path follows accounts that treat the affective component of reactance as the more immediate response [13], [14]. The design does not test this ordering: no indirect effect was estimated and no temporal order was observed, so the hypotheses concern associations only.

II. Method

A. Study Design

This study followed a quantitative, non-experimental, cross-sectional design with a correlational-explanatory scope. Data were collected at a single point in time, without manipulation of variables or longitudinal follow-up; consequently, the findings do not support causal inferences. Reporting followed the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines for cross-sectional studies.

B. Setting and Data-Collection Period

Data were collected through a self-administered online questionnaire, designed and distributed via Microsoft Forms, targeting digital consumers residing in Honduras, between May and June 2026. Participants came from 13 of the 18 departments of Honduras, which indicates geographic dispersion but not proportional representativeness. The instrument was part of a broader project on algorithmic personalization, perceived intrusiveness, and psychological reactance among Honduran digital consumers.

C. Participants

Individuals aged 18 to 70 years, residing in Honduras, who voluntarily agreed to participate through informed consent were eligible. Recruitment used non-probabilistic convenience sampling, disseminating the questionnaire link on social media, without a predefined sampling frame or random selection. A total of 174 responses were collected; after the data-cleaning criteria described below, the final analytic sample comprised 125 participants.

D. Variables

Three latent constructs were measured with 5-point Likert items (1 = strongly disagree, 5 = strongly agree), together with sociodemographic and digital-behavior variables used exclusively for descriptive purposes.

Perceived Personalization (PP): consumers' perception that the content, products, offers, and communications they receive on digital platforms have been tailored to their individual preferences, needs, and characteristics [23]. It was operationalized through two dimensions of five items each: perceived relevance of content and perceived adaptation of the experience.

Perceived Intrusiveness (PI): consumers' perception that digital advertising, automated notifications, and marketing communications interrupt, invade, or interfere with their online experience in an unwanted manner [9], [17]. It was operationalized through two dimensions of five items each: perceived advertising interruption and perceived digital invasion.

Psychological Reactance (PR): the affective and cognitive motivational state experienced when consumers perceive that advertising messages or algorithmic recommendations threaten their freedom of consumption choice [12], [13]. It was operationalized through two

dimensions of five items each: emotional reactivity to advertising pressure and cognitive counterarguing.

Sociodemographic variables included age, gender, educational level, marital status, employment status, monthly household income, department of residence, and the person responsible for household purchases. Digital-behavior variables included primary connection device, type of connection, years and daily hours of internet use, self-perceived digital skills, shopping and social media platforms used, and preferred payment method. These variables characterized the sample and were not included in the measurement or structural models.

E. Data Sources and Measurement

All data were self-reported through a single online instrument, with no secondary sources. The questionnaire included a consent question ("Do you wish to participate in this research?"), the 30 Likert items, and the sociodemographic and digital-behavior variables. The platform recorded the start and completion time of each response, which was used for data-quality control.

F. Bias

The design was exposed to several potential sources of bias. Convenience sampling through social media entailed self-selection, whereby individuals more willing to answer online surveys or more interested in digital consumption may have been overrepresented. Online administration introduced a digital-coverage bias that excludes individuals without internet access or with low digital literacy. Self-report introduced possible social-desirability and recall bias. Because predictors and outcomes were measured in the same instrument and session, common method variance is also a plausible source of inflated associations; no procedural separation of measures, marker variable, or statistical control for method variance was implemented, and this is treated as a limitation.

To mitigate bias from careless responding, data-cleaning criteria based on response time and invariant response patterns (straight-lining) were applied, following Meade and Craig [24], Krosnick [25], and Zhang and Conrad [26]. No external verification procedures (e.g., IP address or geolocation) were implemented beyond the native controls of the platform.

G. Sample Size

Sample size was not determined through a formal power calculation or a prior heuristic rule for structural equation models. A convenience sample bounded by the data-collection period yielded 174 initial responses and a final analytic sample of 125 cases. This size is admissible for a parsimonious three-factor model but modest for structural equation modeling, which limits statistical power and the precision of the estimates.

H. Treatment of Quantitative Variables

Age was treated as continuous. The 30 Likert items were used as indicators of their latent variables in the confirmatory factor analysis (CFA) and structural equation modeling (SEM), without constructing composite scores. Categorical sociodemographic variables were summarized with frequencies and percentages, and multiple-response platform variables coded 0/1 were treated as independent dichotomous indicators.

I. Statistical Methods

1) Data Cleaning: A sequential procedure was applied to the 174 responses. Records without valid consent were excluded (n = 4). Response time was computed from the platform's start and completion fields, and two time-based criteria were applied: speeders, with a time below the median divided by three, and excessively slow responses, with a time above Q3 + 1.5 × IQR (n = 23 combined). Records with the same value on 80% or more of the 30 Likert items were then excluded as straight-lining [24], [25], [26] (n = 21). Finally, 1 record was excluded for implausible age. The final sample comprised 125 cases, with no missing values.

2) Measurement Analysis: Three two-factor confirmatory models were evaluated separately for perceived personalization, perceived intrusiveness, and psychological reactance. All models, including the structural model, were estimated by maximum likelihood with robust standard errors and the Yuan-Bentler scaled test statistic, given the ordinal nature of the indicators and possible multivariate non-normality. Robust fit indices were prioritized for interpretation.

Fit was evaluated with the scaled χ^2, the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA, with 95% CI), and the standardized root mean square residual (SRMR), following conventional criteria [27]: CFI and TLI $\geq .95$ adequate ($\geq .90$ acceptable), RMSEA $\leq .06$ ($\leq .08$ acceptable), and SRMR $\leq .08$. Reliability was assessed with Cronbach's alpha and McDonald's omega, convergent validity with average variance extracted (AVE $\geq .50$), and discriminant validity with the heterotrait-monotrait ratio (HTMT $< .85$ strict, $< .90$ liberal [28]).

3) Structural Model: A structural model linking perceived digital invasion, emotional reactivity, and cognitive counterarguing, termed the Digital Invasion–Reactance Model, was then estimated. This final specification is exploratory rather than confirmatory. It was reached after preliminary structural tests in which perceived personalization and perceived advertising interruption did not show stable relationships with the reactance dimensions and were therefore not retained, and it incorporates residual covariances between items with related content identified through modification indices. Because the specification was shaped by the same data used to estimate it, its fit and coefficients are likely to be optimistic and require replication in an independent sample.

No indirect effect was estimated, and no subgroup, interaction, or measurement-invariance analyses were conducted. A single-factor alternative for psychological reactance was not estimated. There were no missing values, so imputation was not required.

Analyses were conducted in jamovi (version 2.7 [29]) with the SEMLj module [30], which relies on R (version 4.5 [31]) and the lavaan package [32], and the semTools package [33] for reliability, AVE, and HTMT.

J. Ethical Considerations

The study adhered to the Declaration of Helsinki. The protocol was reviewed and approved by an institutional ethics committee before data collection. All participants provided voluntary informed consent through an explicit question. Participation was anonymous: no personal identifiers were collected or analyzed, and identifying metadata were removed from the analytic database once they had served their quality-control function.

III. Results

A. Data Cleaning and Sample Characteristics

Of 174 initial responses, 4 were removed for lack of consent, 23 by the response-time filter (4 speeders and 19 excessively slow cases), 21 for straight-lining, and 1 for implausible age, leaving 125 cases with no missing values.

Participants' age ranged from 18 to 55 years (M = 28.40, SD = 8.40). Most identified as women (70.4%), reported incomplete (44.8%) or complete/graduate (27.2%) university studies, were single (60.8%), and browsed mainly on a smartphone (80.0%). The sample is therefore young, highly educated, and predominantly female (Table I).

TABLE I
SAMPLE CHARACTERISTICS

Variable	Category or statistic	n	%
Age	M = 28.40, SD = 8.40, range = 18–55	—	—
Gender	Male	35	28.0
	Female	88	70.4
	Non-binary	1	0.8
	Prefer not to answer	1	0.8
Educational level[a]	Basic or incomplete secondary	10	8.0
	Complete secondary	25	20.0
	Incomplete university	56	44.8
	Complete university or graduate	34	27.2
Marital status	Single	76	60.8
	Married	14	11.2
	In a relationship	31	24.8
	Divorced or separated	4	3.2
Primary device[b]	Computer (desktop or laptop)	6	4.8
	Smartphone	100	80.0
	Several devices equally	19	15.2

Note. N = 125. [a]Basic or incomplete secondary combines incomplete primary, complete primary, and incomplete secondary; complete university or graduate combines bachelor's/engineering degrees and graduate studies. [b]Computer includes desktop and laptop; no participant reported a tablet as primary device. "In a relationship" includes cohabiting and dating.

B. Assessment of the Measurement Models

The perceived personalization model showed adequate fit (scaled $\chi^2 = 27.1$, df = 26, p = .404; robust CFI = .997; robust TLI = .995; robust RMSEA = .022, 95% CI [.000, .089]; SRMR = .051), with standardized loadings from .672 to .803. Item PP_RP1 was not included; perceived relevance was estimated from PP_RP2 to PP_RP5. Reliability and convergent validity were adequate for perceived relevance (α = .800, ω = .804, AVE = .507) and perceived adaptation (α = .875, ω = .877, AVE = .589), with HTMT = .717.

The perceived intrusiveness model showed mixed fit (scaled $\chi^2 = 62.5$, df = 34, p = .002; robust CFI = .960; robust TLI = .947; robust RMSEA = .090, 95% CI [.054, .125]; SRMR = .064). Loadings ranged from .547 to .953 for advertising interruption and from .675 to .868 for digital invasion. Both dimensions showed adequate reliability and convergent validity (interruption: α = .884, ω = .883, AVE = .609; invasion: α = .893, ω = .893, AVE = .628), and HTMT = .737 supported their discrimination. The RMSEA exceeded .08, so fit is acceptable with reservations.

The psychological reactance model showed poor fit (scaled $\chi^2 = 96.6$, df = 34, p < .001; robust CFI = .894; robust TLI = .860; robust RMSEA = .146, 95% CI [.112, .180]; SRMR = .064). Loadings ranged from .750 to .798 for emotional reactivity and from .713 to .860 for cognitive counterarguing, and reliability and convergent validity were adequate (emotional reactivity: α = .883, ω = .884, AVE = .603; counterarguing: α = .894, ω = .899, AVE = .645). However, the HTMT between the two dimensions was .910, above both the strict (.85) and liberal (.90) criteria [28]. Discriminant validity between emotional reactivity and cognitive counterarguing was therefore not established: in these data the two dimensions share most of their variance and may reflect a single, undifferentiated reactance response. The two-dimensional structure was retained in the structural model on theoretical grounds [13], [14], and any path between the two dimensions is interpreted with this limitation in view (Table II).

TABLE II
FIT, RELIABILITY, AND VALIDITY OF THE MEASUREMENT MODELS

Model	CFI	TLI	RMSEA [95% CI]	SRMR
Panel A. Fit of the two-factor models				
Personalization	.997	.995	.022 [.000, .089]	.051
Intrusiveness	.960	.947	.090 [.054, .125]	.064
Reactance	.894	.860	.146 [.112, .180]	.064

Panel B. Dimension	α	ω	AVE	HTMT
Perceived relevance[c]	.800	.804	.507	.717
Perceived adaptation	.875	.877	.589	
Advertising interruption	.884	.883	.609	.737
Digital invasion	.893	.893	.628	
Emotional reactivity	.883	.884	.603	.910
Cognitive counterarguing	.894	.899	.645	

Note. Robust fit indices from models estimated with ML and the Yuan-Bentler scaled test. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; AVE = average variance extracted; HTMT = heterotrait-monotrait ratio, reported once per pair of dimensions of the same construct. The HTMT of .910 exceeds the .85 and .90 criteria [28]. [c]Estimated without item PP_RP1.

C. Digital Invasion–Reactance Model

The exploratory structural model specified perceived digital invasion (PI_IDP1–PI_IDP5) as associated with emotional reactivity (PR_EMO1–PR_EMO5), which was in turn associated with cognitive counterarguing (PR_CONTRA1–PR_CONTRA5); n = 125, 51 free parameters, convergence after 44 iterations.

Fit was mixed: scaled $\chi^2 = 156$, df = 84, $p < .001$; robust CFI = .936; robust TLI = .921; robust RMSEA = .091, 95% CI [.068, .113], close-fit p = .003; SRMR = .051. CFI, TLI, and SRMR met the acceptable criteria, but the RMSEA of .091 exceeded the .08 threshold adopted above, and its confidence interval did not include values consistent with close fit. The model should therefore be regarded as a marginally fitting, exploratory representation of the data.

All standardized loadings were adequate and significant ($p < .001$), except the reference indicators, whose unstandardized loadings were fixed to 1 for identification (Table III, Panel A).

Perceived digital invasion was positively associated with emotional reactivity (B = 0.934, SE = 0.169, 95% CI [0.603, 1.260]; β = .822, 95% CI [.716, .928]; z = 5.54, $p < .001$), supporting H1. Emotional reactivity was positively associated with cognitive counterarguing (B = 1.018, SE = 0.142, 95% CI [0.741, 1.300]; β = .922, 95% CI [.876, .967]; z = 7.19, $p < .001$), supporting H2 (Table III, Panel B; Fig. 1). The model explained 67.6% of the variance in emotional reactivity and 84.9% in cognitive counterarguing. Given the HTMT of .910, the second coefficient is close to the latent correlation between two dimensions that were not empirically distinguished and should not be read as an effect of one on the other. No indirect effect was estimated, so no mediation is claimed.

The final model included four residual correlations identified through modification indices: PR_EMO1 ~~ PR_EMO2, PR_EMO2 ~~ PR_EMO3, PI_IDP1 ~~ PI_IDP2, and PR_EMO5 ~~ PR_CONTRA1. The first three were significant ($p < .001$, p = .027, and p = .008). The cross-dimension correlation PR_EMO5 ~~ PR_CONTRA1 was not significant (estimate = 0.121, SE = 0.076, p = .111) and was retained without substantive interpretation.

TABLE III
PARAMETERS OF THE DIGITAL INVASION–REACTANCE MODEL

Indicator	Factor	β	p
Panel A. Standardized factor loadings			
PI_IDP1[d]	Digital invasion	.633	—
PI_IDP2	Digital invasion	.729	<.001
PI_IDP3	Digital invasion	.798	<.001
PI_IDP4	Digital invasion	.869	<.001
PI_IDP5	Digital invasion	.884	<.001
PR_EMO1[d]	Emotional reactivity	.727	—
PR_EMO2	Emotional reactivity	.740	<.001
PR_EMO3	Emotional reactivity	.696	<.001
PR_EMO4	Emotional reactivity	.832	<.001
PR_EMO5	Emotional reactivity	.781	<.001
PR_CONTRA1[d]	Cognitive counterarguing	.785	—
PR_CONTRA2	Cognitive counterarguing	.863	<.001
PR_CONTRA3	Cognitive counterarguing	.763	<.001
PR_CONTRA4	Cognitive counterarguing	.712	<.001
PR_CONTRA5	Cognitive counterarguing	.846	<.001

Panel B. Path	Invasion → Emotional reactivity	Emotional reactivity → Counterarguing
B (SE)	0.934 (0.169)	1.018 (0.142)
95% CI of B	[0.603, 1.260]	[0.741, 1.300]
β	.822	.922
95% CI of β	[.716, .928]	[.876, .967]
z	5.54	7.19
p	<.001	<.001
R^2 of outcome	.676	.849

Note. B = unstandardized coefficient; SE = standard error; CI = confidence interval; β = standardized coefficient; z = critical ratio. Because the two reactance dimensions were not empirically distinguished (HTMT = .910), the second path approximates their latent correlation. [d]Reference indicator; unstandardized loading fixed to 1 for identification, so no z or p is reported.

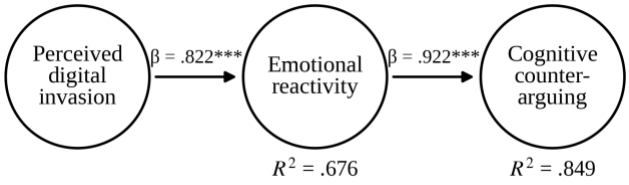


Fig. 1 Digital Invasion–Reactance Model with standardized coefficients and explained variance (N = 125). Paths are associations estimated from cross-sectional data; no indirect effect was estimated. $p < .001$.

Preliminary structural analyses did not show stable relationships between perceived personalization or advertising interruption and the reactance dimensions; documentation of the alternative specifications can be provided as supplementary material.

IV. DISCUSSION

The central finding is that, among the facets of intrusiveness examined, perceived digital invasion, and not advertising interruption or personalization, was the one associated with consumers' emotional reactivity to advertising, and that emotional reactivity was closely associated with cognitive counterarguing. These results are associations from a single cross-sectional measurement within an exploratory specification. They are compatible with

accounts that place affect before cognition in reactance, but they cannot establish that order, and the measurement evidence leaves open whether the two reactance dimensions are distinct at all.

The association between perceived digital invasion and emotional reactivity supports H1 and is consistent with the proposition that a perceived threat to informational freedom activates an affective response aimed at restoring that freedom [12]. What distinguishes invasion from ordinary advertising friction is what it signals: an advertisement that interrupts a task is a momentary cost, whereas one that seems to know more than the user disclosed suggests that control over one's data has already been lost. This echoes findings in which tracking cues heighten perceived surveillance and threat [8], in which unjustified personalization provokes reactance [16], in which eroded autonomy under algorithmic personalization undermines trust [19], and in which intrusiveness translates into irritation and skepticism [20]. The present data add a case in which invasion, separated from other facets of intrusiveness, shows a substantial association with emotional reactivity in a market that had not contributed to this evidence base.

The distinction between invasion and interruption is the study's clearest contribution. Both dimensions showed adequate reliability and convergent validity and were empirically discriminable (HTMT = .737), yet only invasion was retained as structurally related to reactance. Interruption appears closer to a transient attentional cost: an ad that disrupts a task can be dismissed once the task resumes, whereas an ad that signals unauthorized use of personal data leaves the sense of exposure in place after it is gone. Personalization, for its part, has been shown to carry countervailing effects, increasing relevance and favorable attitudes while sometimes heightening intrusiveness and privacy concern [2], [3], [5], [6], [7]; if both pathways were present without one dominating, no stable net association would be expected. These null results do not show that personalization or interruption are irrelevant, only that their relationship with reactance was not direct or stable in this sample. A composite intrusiveness score would have concealed this pattern.

The association between emotional reactivity and cognitive counterarguing supports H2 but requires the most caution. The two dimensions were not empirically distinguished (HTMT = .910) and their two-factor measurement model fit poorly. Under these conditions, the path of $\beta = .922$ is best read as the latent correlation between two closely overlapping measures of reactance rather than as evidence that one drives the other. This is consistent with accounts that treat anger and negative cognitions as co-occurring aspects of a single reactance state [14], and does not contradict the conceptual distinction between them, which remains theoretically meaningful [13]. Whether an affective response precedes and organizes counterarguing is a question for designs that can separate the two in time.

The magnitude of the coefficients ($\beta > .80$) and of the explained variance (up to 84.9%) also warrants caution. All constructs were self-reported in one instrument and one session, which is the condition under which common method variance is most likely to inflate associations. No procedural or statistical remedy was applied, so part of the shared variance may reflect method rather than substance. In addition, the final model was reached through specification search, including the removal of two constructs and the addition of residual covariances from modification indices, which tends to produce optimistic fit and coefficients. The RMSEA of .091, above the .08 criterion, confirms that the model is a reasonable but not the only plausible representation of these data.

With these qualifications, the study contributes in two ways. Theoretically, it indicates that the boundary-violation facet of intrusiveness, rather than intrusiveness in general, is the facet associated with reactance, which argues for multidimensional measurement of the construct. Empirically, it provides evidence from a Latin American digital-consumer population largely absent from the literature, allowing mechanisms documented in North American, European, and Asian samples to be examined in a different regulatory and market setting.

For firms relying on personalized advertising, the results suggest that the greater risk to consumer goodwill may lie less in how often an advertisement appears and more in how clearly it signals the collection and use of personal data. Mechanisms that restore a sense of agency, such as explaining why an ad is shown, allowing adjustment of targeting preferences, or limiting repetition, have been associated elsewhere with reduced reactance [22] and may deserve attention. These implications should be evaluated against specific formats and platforms rather than treated as a general prescription.

Several limitations restrict how far these results extend. The cross-sectional design does not establish temporal precedence, and no indirect effect was estimated, so neither sequence nor mediation can be inferred. Discriminant validity between the two reactance dimensions was not established, and a single-factor alternative was not tested. The final specification is exploratory and was shaped by the data. Common method variance was not controlled. The sample of 125 is modest for SEM and limits power and precision, and its composition, mostly young, university-educated women recruited through social media in one country, limits generalization to the broader Honduran population and to other regulatory or market conditions.

Future research should first resolve the measurement question by comparing single-factor and two-factor models of reactance, ideally with items revised to sharpen the distinction between affect and cognition. Experimental designs that manipulate perceived invasion, or longitudinal designs with repeated measurement, could then test whether emotional reactivity precedes counterarguing. Procedural separation of measures or marker variables would help estimate method variance, and larger probabilistic samples would allow confirmatory replication of the model and tests of whether the

effects of personalization depend on perceived legitimacy, user control, trust in the brand, or transparency about data use.

V. Conclusion

This study examined whether perceived digital invasion is associated with Honduran consumers' emotional reactivity to advertising and, in turn, with cognitive counterarguing against personalized advertising. Perceived digital invasion, distinguished from advertising interruption and personalization, was the facet of intrusiveness associated with emotional reactivity, a result that supports treating intrusiveness as a multidimensional construct. Emotional reactivity and counterarguing were strongly associated, but their limited discriminant validity, the cross-sectional design, the exploratory specification, and possible common method variance mean that this association cannot be read as a sequence or as evidence that the two are distinct processes. The study extends reactance research to a Latin American consumer population that had received little empirical attention and identifies the measurement and design steps needed to test the ordering of affective and cognitive resistance.

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