Persuasion Knowledge and Psychological Reactance as Divergent Predictors of Consumer Vulnerability Among Digital Consumers in Honduras

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Abstract*– Digital consumers increasingly face algorithmic personalization and influencer marketing that require them to recognize and cope with persuasive intent, yet little research has examined whether this recognition protects consumers or leaves them more exposed. This study examined structural associations among Persuasion Knowledge, Psychological Reactance, and three dimensions of Consumer Vulnerability (digital cognitive, digital economic, and situational) among adult digital consumers in Honduras. Data were collected through an online cross-sectional survey of a non-probabilistic convenience sample recruited via social media (N = 201). Persuasion Knowledge was modeled as a second-order factor comprising cognitive, evaluative, and tactical dimensions; Psychological Reactance was modeled as a unidimensional first-order factor. Structural equation modeling with robust maximum likelihood estimation showed adequate model fit. Persuasion Knowledge was positively associated with Psychological Reactance (β = .728, p < .001) and negatively associated with digital economic (β = −.302, p = .013) and situational vulnerability (β = −.264, p = .015), but not significantly with digital cognitive vulnerability (β = −.179, p = .068). Psychological Reactance, by contrast, was positively associated with all three vulnerability dimensions (β = .385 to .696, p < .001). These findings indicate that persuasion knowledge and psychological reactance, though positively related, are not interchangeable forms of consumer resistance and may carry opposite implications for consumer protection in emerging Latin American digital markets.

***Keywords*– persuasion knowledge, psychological reactance, consumer vulnerability, digital consumers, structural equation modeling**

I. Introduction

Recommendation algorithms now shape a considerable share of what digital consumers see, click, and ultimately buy, tailoring offers, product suggestions, and promotional messages to inferred preferences rather than presenting a common commercial environment to every user. This architecture is usually promoted as a convenience, yet a growing empirical record documents its less comfortable counterpart: once consumers sense that a system is steering their choices, personalization can provoke resistance instead of acceptance, ranging from purchase reluctance to outright algorithm aversion [1]–[3]. Pahari et al. [4] describe this pushback as a patterned response to perceived emotional manipulation and diminished autonomy rather than a wholesale rejection of digital commerce, which suggests that the tension is not simply about algorithms themselves but about what consumers understand, and feel, when they recognize an attempt to influence them. That recognition, and its consequences, is the problem this study addresses.

Two literatures bear on this problem without, for the most part, meeting each other. One treats persuasion knowledge as a cognitive resource, an accumulated understanding of marketers' goals and tactics that allows consumers to identify persuasion attempts and adjust their responses accordingly [5]. Research building on the persuasion knowledge model has linked its activation to more cautious evaluation of covert marketing [6], reduced susceptibility to manipulation depending on the time of day [7], and, at the aggregate level, to consumer protection, since persuasion knowledge is presumed to buffer exactly those consumer groups who would otherwise be most exposed to marketer influence [8]. A second literature examines psychological reactance, the motivational state aroused when a persuasive message is perceived as a threat to one's freedom of choice [9]. Reactance research has traced consequences ranging from ad avoidance on social media [10] to revenge buying under conditions of restricted autonomy [11] and hostility toward retailers [12]. Both processes are commonly described as forms of resistance, but they are not obviously equivalent: persuasion knowledge is typically framed as a stable competency that helps consumers navigate the marketplace, whereas reactance is an acute, affectively charged reaction that need not leave the consumer better positioned to make sound decisions. Whether these two forms of resistance converge on the same outcomes for consumers, or pull in different directions, remains an open question.

Persuasion knowledge, as originally conceptualized by Friestad and Wright [13], encompasses consumers' beliefs about how, why, and by whom they are being persuaded. Later operationalizations informed by advertising literacy

research have decomposed this capacity into cognitive, evaluative, and tactical facets, which respectively involve recognizing that a message carries commercial intent, judging the honesty and legitimacy of the tactics used, and identifying specific persuasive devices such as artificial urgency or fabricated scarcity [14]. These tactics are not incidental to digital retail; scarcity cues and time-limited offers are documented drivers of impulsive buying, particularly among younger consumers navigating unfamiliar digital marketplaces [15], and visual and narrative framing choices shape how readily consumers infer manipulative intent from an advertisement in the first place [16]. Importantly, activating consumers' awareness of persuasive intent does not uniformly produce skepticism; one-sided interventions that emphasize only the suspicious side of persuasion knowledge can overstate its effects relative to more balanced accounts of marketers' motives [17], a caveat that argues for treating persuasion knowledge as a differentiated capacity rather than a single undifferentiated alarm signal.

The link between recognizing persuasive intent and experiencing reactance has direct theoretical grounding. Pergelova and Hachey [18] argue that disclosure of persuasive intent in influencer advertising activates reactance precisely because it makes consumers aware that they are the target of an influence attempt; De Keyzer [19] reaches a compatible conclusion in the context of sustainability-themed influencer posts, where recognizing selling intent undermines perceived source credibility. Ham [20] integrated the persuasion knowledge model with reactance as a cognitive processing variable to explain coping with online behavioral advertising, and more recent work on manipulative consent interfaces shows that ambiguous, low-transparency designs activate persuasion knowledge and reactance jointly by heightening perceived threats to control [21]. Yet this activation is not unconditional: Ziegler et al. [22] show that whether persuasion knowledge translates into resistance depends on its accessibility and on consumers' own sense of power in the interaction, indicating that the persuasion-knowledge–reactance link, though theoretically expected, is neither automatic nor uniform across contexts. Foundational accounts of reactance itself go back to forced-exposure research on early web advertising, where perceived intrusiveness of pop-up ads was shown to provoke irritation and avoidance [23], [24], and subsequent work has continued to model reactance as a composite of anger and counterarguing that mediates responses to freedom-threatening communication [9], [25].

What remains comparatively underexamined is what these two resistance processes mean for consumer vulnerability, a construct defined by Baker et al. [26] as a state of powerlessness arising from the interaction of personal characteristics, individual states, and external conditions that leave consumption goals unmet. Vulnerability, on this account, is not a fixed trait attached to demographic categories but a condition that can affect otherwise capable consumers depending on circumstances, and one that recent theorizing frames as dynamic rather than static, moving consumers toward or away from vulnerable states over time [27]. In digital markets specifically, vulnerability has been characterized as architectural and relational, arising from the very design of automated commerce rather than solely from individual deficits [28], and as layered, in the sense that structural risks inherent to algorithmic marketing apply to all users while additional personal and situational factors compound exposure for some more than others [29]. A systematic review of digital consumer vulnerability similarly converges on a multidimensional model distinguishing personal, external, and behavioral triggers rather than a single undifferentiated risk factor [30], and typologies of platform-based vulnerability further separate what consumers themselves recognize from disadvantages that remain structurally invisible [31]. Within this literature, financial exposure in digital transactions has been treated as a distinct source of vulnerability shaped importantly by age and familiarity with digital payment tools [32], while reduced skepticism under conditions of heavy technology reliance has been shown to heighten susceptibility to deception [33], and low digital literacy has been found to amplify the harm consumers experience from deceptive advertising claims [34]. Because cognitive, economic, and situational vulnerability rest on partly distinct mechanisms (information-processing limitations, constraints on financial self-regulation, and context-dependent susceptibility, respectively), there is little basis for assuming that persuasion knowledge and reactance would relate to all three in the same way or with the same strength; collapsing consumer vulnerability into a single global outcome risks obscuring differences of this kind.

The theoretical expectation that persuasion knowledge protects consumers, evident in its treatment as a resource that shields groups otherwise exposed to marketer influence [8], [35], sits uneasily alongside evidence that the resistance captured by reactance does not always leave consumers better off. Reactance-driven responses documented in the consumer literature include revenge buying [11] and hostile disengagement expressed as shopping hate [12], patterns that look less like protective vigilance than like emotionally charged, and potentially poorly regulated, reactions to perceived pressure. If persuasion knowledge and reactance indeed diverge in this way, a model that examines both simultaneously, against a differentiated vulnerability outcome, offers a more informative test of how digital consumers actually fare than one that treats resistance as a single, uniformly beneficial response.

Most of the evidence reviewed above originates in North American, European, and East Asian samples, with Japanese social media users [36], Facebook users in the United States [10], and short-form video platform users in China [1], [3] figuring prominently, while evidence from Latin American digital markets remains comparatively scarce. This is not a trivial omission: digitalization in the region has been shown to unfold unevenly across vulnerable populations, with infrastructural and digital-literacy conditions that differ meaningfully from those documented elsewhere [37], and the adoption of digital marketing and financial technologies in Latin American settings continues to be constrained by

socioeconomic inequality and uneven digital preparedness [38], even as tools such as digital wallets extend into populations with heterogeneous familiarity with digital instruments [39]. Examining persuasion knowledge, reactance, and consumer vulnerability among digital consumers in a Honduran market therefore extends this literature to a setting where the conditions that shape digital consumption differ from those of the samples on which the underlying theories were largely built.

The present study addresses these gaps by testing a structural model in which persuasion knowledge, modeled through its cognitive, evaluative, and tactical dimensions, is examined as an antecedent of psychological reactance, and both persuasion knowledge and psychological reactance are examined, in turn, as predictors of three dimensions of consumer vulnerability: digital cognitive, digital economic, and situational. The study contributes to the persuasion knowledge and reactance literatures by testing them within a single structural framework rather than in isolation, to consumer vulnerability research by evaluating a differentiated rather than global outcome, and to the broader evidence base by drawing on a sample of digital consumers in Honduras, a market underrepresented in this literature.

A. Hypotheses

The hypothesized model comprises seven structural paths linking the three constructs. Fig. 1 (Section III) depicts this model together with the standardized estimates obtained.

H1. Persuasion Knowledge will be positively associated with Psychological Reactance.

H2. Persuasion Knowledge will be negatively associated with (a) Digital Cognitive Vulnerability, (b) Digital Economic Vulnerability, and (c) Situational Vulnerability.

H3. Psychological Reactance will be positively associated with (a) Digital Cognitive Vulnerability, (b) Digital Economic Vulnerability, and (c) Situational Vulnerability.

II. METHODS

This study followed a cross-sectional, quantitative, correlational design, in which confirmatory factor analysis and structural equation modeling (SEM) were used to examine the measurement properties and structural associations among Persuasion Knowledge, Psychological Reactance, and Consumer Vulnerability. Reporting follows the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines for cross-sectional studies.

A. Setting

Data were collected online in Honduras between May and June 2026, using a self-administered questionnaire distributed through Microsoft Forms. Respondents were geographically distributed across 12 of the country's 18 departments.

B. Participants

A non-probabilistic convenience sample was recruited through social media and personal networks, following a snowball sampling strategy in which initial contacts were invited to complete the questionnaire and to share the survey link with other potential participants. Eligible participants were adults aged 18 to 70 years residing in Honduras who provided electronic informed consent before accessing the questionnaire; no additional eligibility restrictions were applied. Data collection yielded 238 initial responses. The screening procedure applied to this initial pool, including the criteria and case counts that produced the final analytic sample, is reported in Section III-A.

C. Variables and Operational Definitions

1) Persuasion Knowledge: defined as the set of beliefs, attitudes, and knowledge that consumers develop about the goals, tactics, and processes of persuasion used in digital advertising and influencer marketing, enabling them to identify, evaluate, and resist commercial influence attempts in digital environments [13], [40]. Three dimensions were assessed: Cognitive Persuasion Knowledge, consumers' ability to recognize that a message carries persuasive or commercial intent; Evaluative Persuasion Knowledge, consumers' ability to render critical judgments about the honesty and legitimacy of advertising tactics; and Tactical Persuasion Knowledge, recognition of specific persuasion strategies such as artificial urgency, simulated scarcity, or fabricated social proof.

2) Psychological Reactance: defined as a motivational state, both emotional and cognitive, experienced when consumers perceive that advertising messages, algorithmic recommendations, or marketing communications threaten their freedom of consumption choice [9], [23]. Two components were assessed at the item level: Emotional Reactivity to Advertising Pressure (negative affect, primarily anger and irritation) and Cognitive Counterarguing (active generation of thoughts opposing a persuasive message). As reported in Section III-B, these components were retained as indicators of a single first-order Psychological Reactance factor in the final structural model.

3) Consumer Vulnerability: defined as consumers' susceptibility to experiencing adverse outcomes in their interactions with the digital marketplace, arising from information asymmetry, personal characteristics, or situational circumstances that reduce their capacity to make informed and protected consumption decisions [26]. Three dimensions were assessed: Digital Cognitive Vulnerability (difficulty processing and evaluating digital information), Digital Economic Vulnerability (financial limitations affecting balanced online purchasing, including susceptibility to impulsive purchases), and Situational Vulnerability (temporal or contextual circumstances increasing susceptibility to unfavorable digital consumption decisions).

D. Data Sources and Measurement

All variables were assessed through self-report on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), administered as part of a single online questionnaire.

1) Persuasion Knowledge: measured with items adapted from the Advertising Literacy Scale [14] and from Persuasion Knowledge Model-based scales [40], grounded in the

Persuasion Knowledge Model [13]. Fifteen items (five per dimension) were originally administered; Cognitive, Evaluative, and Tactical Persuasion Knowledge retained four, three, and four items, respectively, in the final measurement model.

2) Psychological Reactance: measured with items adapted from the Hong Psychological Reactance Scale [41] and from Dillard and Shen's [9] dual-process framework, grounded in Reactance Theory [9], [23], [42]. Ten items (five per component) were originally administered; three and four items, respectively, were retained in the final measurement model.

3) Consumer Vulnerability: assessed with an ad hoc scale developed for this study, grounded in the Consumer Vulnerability Framework [26], [43] and informed by [44], [45], and Information Asymmetry Theory [46], because no single validated instrument for vulnerability in digital consumption was available for the Honduran context. Fifteen items (five per dimension) were originally administered; four, four, and three items, respectively, were retained in the final measurement model.

4) Item refinement: Two kinds of modification were applied and are reported separately. Theoretically motivated modifications took place before data collection and were limited to adapting the wording of items from the source instruments to digital advertising, algorithmic recommendation, and influencer-marketing contexts; every instrument was administered in its full form (15, 10, and 15 items). Data-driven refinement took place afterward, during confirmatory factor analysis: indicators were removed when their standardized loadings were weak (below .50) or when modification indices showed substantial residual covariance with other indicators or loading on a non-target dimension, signaling redundant or ambiguous content. After each removal, the retained indicators were checked against the conceptual definition of their dimension, so that every dimension kept at least three indicators covering its core content. In total, 11 of the 40 administered items were removed (four for Persuasion Knowledge, three for Psychological Reactance, and four for Consumer Vulnerability), leaving 29 indicators in the final models. Because item selection and model evaluation were conducted on the same sample, the final structures may capitalize on sample-specific variance and should be regarded as provisional until they are confirmed in independent samples. This requirement applies with particular force to the ad hoc Consumer Vulnerability instrument, for which no prior validation evidence exists.

E. Bias

Careless-response bias was addressed by removing records exhibiting straight-lining on at least 80% of the 35 Likert items and by excluding responses completed in implausibly short or long times. Because recruitment relied on non-probabilistic, snowball-based convenience sampling conducted entirely online, the sample is subject to self-selection bias and to coverage bias associated with differential digital access. Because all measures were collected through a single self-administered instrument at one point in time, the design is also subject to common-method bias.

F. Study Size

Sample size was determined by the number of eligible responses obtained during the data-collection window rather than by an a priori power or sample-size calculation. Of 238 initial responses, a final analytic sample of 202 participants remained after data screening, and the final structural model was estimated on 201 complete cases following listwise deletion of one case with a missing value on a model indicator.

The adequacy of N = 201 was therefore evaluated against established criteria for SEM. The sample reaches the level of about 200 cases often treated as a practical threshold for SEM with continuous indicators, but the ratio of cases to freely estimated parameters (201 to 100, about 2:1) is below the ratios of 10:1 or higher sometimes recommended [47]; relative to the complexity of the model, the sample is modest. Simulation evidence indicates, however, that the sample size SEM requires depends less on fixed rules of thumb than on features of the model, with requirements ranging from about 30 to 460 cases across conditions: strong standardized loadings and three or more indicators per factor reduce the required sample, whereas missing data increase it [48]. The final model met these favorable conditions. All first-order loadings were at least .603, every first-order factor had three or more indicators, and only one case was lost to missing data. The model also converged normally, without improper estimates, and the upper bound of the RMSEA confidence interval (.059) remained below .08. These features support the stability of the estimates reported here, although a Monte Carlo power analysis for this model remains a task for future studies with larger samples.

G. Quantitative Variables

All indicators were treated as continuous ordinal (Likert) variables and modeled as reflective indicators of their respective latent factors. No items were dichotomized and no continuous variable was categorized for analysis.

H. Statistical Methods

Analyses proceeded in two stages. First, confirmatory factor analysis (CFA) was conducted separately for the Persuasion Knowledge and Consumer Vulnerability measurement models and for a preliminary second-order specification of Psychological Reactance. Second, a structural equation model integrating all latent constructs was estimated to test the hypothesized associations. All models were estimated using maximum likelihood estimation with robust (Huber–White) standard errors and the Yuan–Bentler scaled test statistic, using NLMINB optimization. Model fit was evaluated using the robust comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). Composite reliability was estimated using Cronbach's α and McDonald's ω, convergent validity via the average variance extracted (AVE), and discriminant validity using the heterotrait-monotrait (HTMT) ratio. Missing data

were handled through listwise deletion. All analyses were performed in jamovi (Version 2.7) [49] using the SEMLj module [50], which implements SEM through the lavaan package [51] in R (Version 4.5) [52]; reliability and discriminant-validity indices were computed with the semTools package [53].

I. Ethical Considerations

This study was approved by the institutional ethics committee prior to data collection and was conducted in accordance with the ethical principles of the Declaration of Helsinki. All participants were informed of the study's purpose, voluntary nature, and anonymity, and provided electronic informed consent before accessing the questionnaire.

III. Results

A. Data Screening and Analytic Sample

Data collection via Microsoft Forms yielded 238 initial responses. Twelve records were removed for withholding or omitting consent, leaving 226 eligible records. Response time showed a median of 444 s (7.4 min); records were flagged as excessively fast below the median divided by three (148 s) and as excessively slow above Q3 + 1.5 × IQR (1,102.3 s). Eighteen records were removed on this basis (2 speeders, 16 slow outliers), followed by five records removed for straight-lining and one record removed for implausible age. This screening procedure reduced the initial 238 records to 202 eligible cases. The final SEM was estimated with 201 complete cases because one participant had a missing value on a model indicator, handled through listwise deletion.

B. Measurement Model

1) Persuasion Knowledge: The initial measurement model specified three correlated first-order factors. This CFA showed excellent robust fit (robust CFI = .992, robust TLI = .989, robust RMSEA = .041, 95% CI [.000, .077], SRMR = .032), and standardized loadings ranged from .599 to .913. Reliability and convergent validity were adequate: Cognitive (α = .869, ω ≈ .873, AVE = .636), Evaluative (α = .824, ω ≈ .823, AVE = .609), and Tactical (α = .920, ω ≈ .921, AVE = .745). Standardized latent correlations ranged from .822 to .879, and HTMT ratios ranged from .845 to .881, consistent with modeling under a second-order factor.

2) Psychological Reactance: A preliminary second-order specification, in which emotional reactivity and cognitive counterarguing loaded on a higher-order factor, produced an inadmissible solution: the information matrix could not be inverted, a negative latent variance was estimated, and the standardized loading of the emotional dimension exceeded 1. This diagnosis has a structural explanation. A higher-order factor defined by only two first-order factors is not identified without additional constraints [47], and a standardized loading above 1 together with a negative variance (a Heywood case) indicates that the emotional component was empirically almost indistinguishable from the higher-order factor, leaving no unique variance to separate the two levels. The statistical result converges with the theoretical literature. Dillard and Shen [9] compared alternative representations of reactance and found that anger and counterarguing were best modeled as intertwined indicators of a single latent reactance construct rather than as distinct factors, and a later meta-analysis supported this intertwined, composite conceptualization [54]. Consequently, the final structural model specified Psychological Reactance as a first-order factor measured directly by its seven retained emotional and cognitive indicators, the representation that both the statistical diagnosis and the theoretical literature support.

3) Consumer Vulnerability: The three-factor structure showed excellent robust fit (robust CFI = 1.000, robust TLI = 1.009, robust RMSEA = .000, 95% CI [.000, .044], SRMR = .027), with standardized loadings ranging from .631 to .911. Reliability and convergent validity were adequate: Digital Cognitive (α = .857, ω = .857, AVE = .601), Digital Economic (α = .873, ω = .877, AVE = .644), and Situational (α = .892, ω = .896, AVE = .742). Standardized latent correlations were .809 (cognitive–economic), .674 (cognitive–situational), and .866 (economic–situational); HTMT ratios were .793, .698, and .883, respectively, all below the more permissive .90 criterion. Because these properties were estimated in the same sample used to select the items, they constitute initial rather than independent validity evidence for this instrument. Table I summarizes the measurement quality of all constructs.

TABLE I
Measurement Quality and Standardized Factor Loadings

Construct / Dimension	k	Loadings	α	ω	AVE
Cognitive PK	4	.599–.887	.869	.873	.636
Evaluative PK	3	.753–.805	.824	.823	.609
Tactical PK	4	.819–.913	.920	.921	.745
PK (second-order)	3 dim.	.895–.963	.924	.925	.639
Psychological Reactance	7	.690–.868	.855	.856	.597
Digital Cognitive V.	4	.740–.803	.857	.857	.601
Digital Economic V.	4	.631–.878	.873	.877	.644
Situational V.	3	.806–.909	.892	.896	.742

Note. PK = Persuasion Knowledge; V. = Vulnerability; k = indicators retained. Loadings, α, and ω for first-order PK and CV dimensions from independent CFAs (N = 202); PK second-order and Psychological Reactance reliability from the final SEM (N = 201); Situational Vulnerability reliability from the independent CFA.

C. Structural Equation Model

The final structural model was estimated using maximum likelihood with robust standard errors and the Yuan–Bentler scaled test statistic (NLMINB optimization; 201 complete cases; 100 free parameters; 58 iterations). Persuasion Knowledge was modeled as a second-order factor; Psychological Reactance as a unidimensional first-order factor; and the three Consumer Vulnerability dimensions as correlated endogenous outcomes with correlated residuals.

1) Model fit: Yuan–Bentler scaled $\chi^2(364) = 504$, $p < .001$; robust CFI = .960, robust TLI = .956, robust RMSEA = .049, 95% CI [.038, .059], SRMR = .055, PNFI = .774. Taken together, the robust incremental and residual-based fit indices supported an adequate fit of the proposed structural model.

2) Measurement model within the final SEM: All standardized loadings were significant, $p < .001$. Cognitive Persuasion Knowledge: .603–.887; Evaluative: .748–.810; Tactical: .819–.915. Second-order loadings of Persuasion Knowledge: .895 (Cognitive), .963 (Evaluative), .920 (Tactical). Psychological Reactance: .690–.868. Digital Cognitive Vulnerability: .759–.795; Digital Economic Vulnerability: .632–.895; Situational Vulnerability: .806–.909.

D. Structural Paths

Persuasion Knowledge was positively associated with Psychological Reactance, $\beta = .728$, 95% CI [.628, .829], $z = 6.09$, $p < .001$ ($R^2 = .530$), supporting H1. Predictors accounted for 33.4% of the variance in Digital Cognitive Vulnerability ($R^2 = .334$): Persuasion Knowledge showed no significant direct association, $\beta = -.179$, 95% CI [−.361, .002], $z = -1.82$, $p = .068$, while Psychological Reactance was positively associated, $\beta = .696$, 95% CI [.518, .873], $z = 5.61$, $p < .001$. Predictors accounted for 12.3% of the variance in Digital Economic Vulnerability ($R^2 = .123$): Persuasion Knowledge showed a negative association, $\beta = -.302$, 95% CI [−.521, −.082], $z = -2.48$, $p = .013$, whereas Psychological Reactance showed a positive association, $\beta = .502$, 95% CI [.255, .749], $z = 3.55$, $p < .001$. Predictors accounted for 7.0% of the variance in Situational Vulnerability ($R^2 = .070$): Persuasion Knowledge showed a negative association, $\beta = -.264$, 95% CI [−.460, −.069], $z = -2.43$, $p = .015$, whereas Psychological Reactance showed a positive association, $\beta = .385$, 95% CI [.185, .584], $z = 3.45$, $p < .001$. H2 was therefore supported for economic and situational vulnerability but not for cognitive vulnerability (H2b and H2c supported; H2a not supported), and H3 was fully supported. Table II reports the full structural estimates and Table III the fit indices of all models. Fig. 1 presents the standardized estimates for the final structural model.

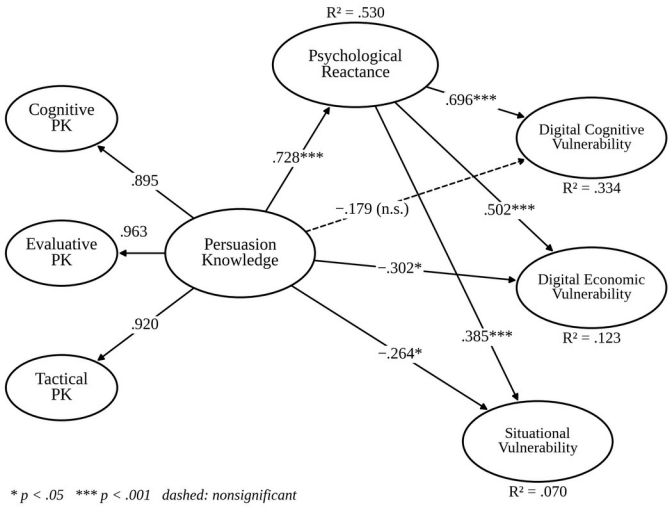


Fig. 1 Standardized estimates of the final structural model (N = 201). Solid arrows denote significant paths and the dashed arrow a nonsignificant path. Observed indicators, disturbances, and residual covariances among the vulnerability dimensions are omitted for clarity.

TABLE II
Structural Model Estimates

Path	B (SE)	β [95% CI]	z	p
PK → PR	0.963 (0.158)	.728 [.628, .829]	6.09	<.001
PK → DCV	−0.251 (0.138)	−.179 [−.361, .002]	−1.82	.068
PR → DCV	0.736 (0.131)	.696 [.518, .873]	5.61	<.001
PK → DEV	−0.520 (0.210)	−.302 [−.521, −.082]	−2.48	.013
PR → DEV	0.655 (0.185)	.502 [.255, .749]	3.55	<.001
PK → SV	−0.450 (0.185)	−.264 [−.460, −.069]	−2.43	.015
PR → SV	0.495 (0.144)	.385 [.185, .584]	3.45	<.001

Note. N = 201. PK = Persuasion Knowledge; PR = Psychological Reactance; DCV = Digital Cognitive Vulnerability; DEV = Digital Economic Vulnerability; SV = Situational Vulnerability. Maximum likelihood, robust SE, Yuan–Bentler scaled test statistic. $R^2 = .530$ (PR), .334 (DCV), .123 (DEV), .070 (SV).

TABLE III
Fit Indices for the Confirmatory and Structural Models

Model	χ^2 (df)	p	CFI	TLI	RMSEA [95% CI]	SRMR
PK CFA	49.5 (41)	.170	.992	.989	.041 [.000, .077]	.032
CV CFA	34.6 (41)	.748	1.000	1.009	.000 [.000, .044]	.027
Final SEM	504 (364)	<.001	.960	.956	.049 [.038, .059]	.055

Note. PK = Persuasion Knowledge; CV = Consumer Vulnerability. All indices are robust; χ^2 values are the Yuan–Bentler scaled test statistic. The preliminary second-order CFA of Psychological Reactance is not reported because it produced an inadmissible solution.

IV. Discussion

This study examined how Persuasion Knowledge and Psychological Reactance relate to one another and to three dimensions of Consumer Vulnerability among digital consumers in Honduras. The pattern of results supports a picture in which these two forms of resistance to persuasion are closely linked yet functionally distinct: Persuasion Knowledge was strongly associated with Psychological Reactance, was negatively associated with two of the three vulnerability dimensions, and was unrelated to the third, whereas Psychological Reactance was positively associated with all three. Read together, these findings speak directly to the question posed in the introduction: whether recognizing and resisting persuasion leaves consumers better protected or more exposed depends on which form of resistance is at issue.

The association between Persuasion Knowledge and Psychological Reactance was the strongest structural path in the model and accounted for over half of the variance in reactance. This result is consistent with theoretical accounts holding that recognizing a communication as an attempt at influence is what activates reactance in the first place: once consumers detect commercial intent behind a personalized recommendation, an algorithmic suggestion, or an influencer post, that recognition itself constitutes a perceived threat to their freedom of choice [18], [21]. The size of this association suggests that, in the algorithmic and influencer-driven persuasion environments most familiar to this sample, knowledge and reactance are tightly coupled rather than loosely related processes, extending prior evidence obtained mostly in traditional online-advertising settings [19], [20] to a context defined more by recommendation systems than by discrete advertisements.

Persuasion Knowledge showed the theoretically expected negative association with digital economic and situational vulnerability, consistent with its treatment in the literature as a resource that buffers consumers who might otherwise be more exposed to marketer influence [8], [35]. Consumers who more readily recognize commercial intent, judge the legitimacy of digital tactics, and identify specific devices such as artificial urgency or fabricated scarcity appear correspondingly less prone to the kind of impulsive, financially strained, or context-driven purchasing that these two dimensions capture. The association with digital cognitive vulnerability, however, did not reach significance. This dimension concerns difficulty processing and evaluating the information digital platforms present, such as parsing terms and conditions or judging whether a website is trustworthy, a competency that plausibly draws on general digital literacy and information-processing capacity more than on the ability to recognize persuasive intent as such. A consumer can be well aware that a website is trying to persuade them and still struggle to evaluate the technical or contractual information that platform presents; the two capacities are related but not the same. This distinction is consistent with characterizations of digital vulnerability as partly architectural, arising from features of platform design that individual awareness alone does not resolve [28], and it reinforces the broader argument that consumer vulnerability should not be treated as a single, homogeneous outcome [26], [30].

Psychological Reactance, in contrast, was positively associated with all three vulnerability dimensions, including digital cognitive vulnerability, where it was the only significant predictor. Because Persuasion Knowledge positively predicted Psychological Reactance while showing negative associations with two of the same vulnerability dimensions that Psychological Reactance predicted positively, the overall pattern of direct coefficients resembles what would conventionally be described as a competitive, or inconsistent, configuration: the route running from knowledge through reactance points in the opposite direction from knowledge's own direct association with vulnerability. This study did not estimate indirect effects or apply bootstrap resampling, so this description should be read as an interpretation of the pattern of direct paths rather than as a tested mediation result. Substantively, it suggests that reactance does not function as a protective competency in the way persuasion knowledge does. Where persuasion knowledge is typically framed as a relatively stable form of consumer literacy, reactance is, by definition, an acute and affectively charged motivational state [9], [23], and the present results are compatible with the possibility that this aroused state leaves consumers less rather than more equipped to navigate a transaction carefully. Such a reading fits with prior evidence linking heightened reactance to impulsive and defensively motivated consumption responses, including revenge buying under conditions of restricted autonomy [11] and hostile disengagement from retailers [12], outcomes that plausibly share more with vulnerability than with protection against it.

Table IV sets these results against the evidence reported in other settings. Three differences stand out. First, prior work describes the link between recognizing persuasive intent and reactance as conditional, dependent on disclosure, accessibility, and consumers' sense of power [18], [22]; in the Honduran sample the link was strong and explained over half of the variance in reactance. Second, the protective role usually attributed to persuasion knowledge [8], [35] was only partly replicated: it held for economic and situational vulnerability but not for cognitive vulnerability. Third, and most distinctively, studies conducted mainly in the United States and East Asia have examined reactance as a driver of resistance behaviors such as ad avoidance, purchase resistance, and algorithm aversion [1]–[3], [10], outcomes generally read as consumers pushing back against marketers. In the present sample, reactance instead accompanied greater vulnerability on all three dimensions, a pattern closer to the evidence on revenge buying and shopping hate [11], [12] than to that on protective avoidance. The present design cannot establish whether these differences reflect the Honduran market, the platforms examined, or the measures used, but they show that the protective or harmful character of each form of resistance should not be assumed to transfer across settings.

TABLE IV
Present Findings Compared With Evidence From Other Settings

Relationship	Prior evidence (settings)	Present study (Honduras)
PK → PR	Recognizing persuasive intent activates reactance, but conditionally, depending on disclosure, accessibility, and consumer power [18], [20]–[22]	Strong positive association (β = .728); PK explains 53% of variance in PR
PK → vulnerability	PK treated as a protective resource that buffers exposed consumers [8], [35]; one-sided activation may overstate skepticism [17]	Protective for economic and situational vulnerability; no significant association with cognitive vulnerability
PR → outcomes	Reactance drives ad avoidance (United States) [10] and purchase resistance or algorithm aversion (China) [1]–[3], read as pushback against marketers; also revenge buying and shopping hate [11], [12]	Positive association with all three vulnerability dimensions (β = .385 to .696)

Note. PK = Persuasion Knowledge; PR = Psychological Reactance.

A related methodological observation concerns the structure of Psychological Reactance itself. The preliminary higher-order specification proved inadmissible, and the final model represented reactance as a single first-order factor. As explained in Section III-B, this outcome combines an identification problem inherent to a higher-order factor with only two components and an empirical overlap between the emotional component and the overall construct. It is also consistent with the way reactance has been operationalized since early work on the construct, which favored an intertwined, composite representation of anger and negative

cognitions over a strictly hierarchical two-factor structure [9], [54]. The results reported here add one more observation in favor of that composite conceptualization in digital consumption contexts, although the two components may still be distinguishable with larger item pools or experimental manipulations of freedom threat.

These associations emerged in a market that differs in relevant ways from the North American, European, and East Asian settings where most persuasion knowledge and reactance research has been conducted. Honduras, like much of Latin America, combines expanding digital-platform use with documented unevenness in digital literacy and infrastructure across its population [37], [38], conditions that could plausibly shape how consumers develop persuasion knowledge and experience reactance in the first place. That the basic pattern (knowledge as broadly protective, reactance as broadly associated with vulnerability) emerged even in this setting is a useful data point, though a single cross-sectional study in one country does not establish that the pattern generalizes; that determination will require replication across other Latin American digital markets, including those where financial-technology access itself remains uneven [39].

For consumer protection and digital literacy efforts, these results caution against treating all forms of resistance to digital persuasion as equally beneficial. Interventions that build consumers' capacity to recognize, evaluate, and name specific persuasive tactics may plausibly support protection against economic and situational vulnerability, in line with their treatment elsewhere as a form of consumer capability [8]. Interventions or platform features that instead provoke an angry or defensive reaction, without building that underlying capacity, may not carry the same benefit and could, on the pattern observed here, coincide with greater rather than lesser vulnerability. Efforts to increase transparency in algorithmic and influencer marketing should therefore be evaluated not only for whether they make consumers more resistant, but for what kind of resistance they produce.

Several limitations qualify these conclusions. The cross-sectional design does not support claims about the temporal order or causal direction of the associations reported. Because participants were recruited through a non-probabilistic, snowball-based convenience sample distributed on social media, the sample likely overrepresents digitally active and connected segments of the Honduran population, which may have attenuated rather than inflated the vulnerability levels observed; the findings should not be generalized to the broader population without further evidence. All variables were collected through a single self-administered instrument, which leaves the results open to common-method influences. The sample size was not determined a priori and, although the model conditions described in Section II-F favor stable estimates, it is modest relative to the number of estimated parameters. Item refinement and model evaluation were carried out on the same sample, so the final measurement structures of all three instruments require confirmation in independent samples; this applies above all to the Consumer Vulnerability measure, which was developed for this study in the absence of a validated instrument for the Honduran digital context and whose adequate properties here have not been cross-validated. Finally, because indirect effects were not formally estimated, the competitive-pattern interpretation offered above remains provisional and should be tested directly in future work.

Longitudinal or experimental designs would help establish whether persuasion knowledge and reactance precede changes in vulnerability, or arise alongside it, and would allow formal mediation and moderation tests, including bootstrap-based indirect effects and potential moderators such as digital literacy, age, or platform type. Future studies should also plan sample size a priori through Monte Carlo simulation and validate the Consumer Vulnerability instrument in a new sample, preferably through a split-sample or cross-validation design that separates item selection from confirmatory testing. Cross-national replication within and beyond Latin America would further clarify how much of the pattern observed here reflects the specific market examined and how much reflects a more general feature of digital persuasion resistance.

V. Conclusions

This study set out to determine whether recognizing and resisting digital persuasion leaves consumers better protected or more exposed, and the answer depends on which form of resistance is considered. Persuasion Knowledge and Psychological Reactance were positively related to each other, yet they diverged in their associations with consumer vulnerability: knowledge was protective for economic and situational vulnerability, whereas reactance was associated with greater vulnerability on every dimension. This divergence is the study's central contribution. By testing both constructs together, rather than in the separate literatures where they are usually studied, and by treating consumer vulnerability as three distinguishable dimensions rather than a single outcome, the study offers a more differentiated account of what digital resistance means for consumers than either literature provides on its own.

Extending this account to Honduras further shows that a theoretical architecture developed largely in North American, European, and East Asian markets can be applied, and can yield theoretically coherent results, in an underrepresented Latin American digital market, while also revealing where the results depart from those settings. The practical implication is that building consumers' knowledge of persuasion tactics and provoking their emotional resistance to those tactics are not equivalent strategies for consumer protection, and policies or educational efforts that conflate the two may not achieve the protective effect they intend. Confirming the direction and mechanism of these associations, validating the measures in independent samples, and testing whether the associations hold across other markets and platforms remain tasks for future longitudinal and experimental research.

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