Consumer Vulnerability in Digital Environments: Technological Capabilities, Online Shopping Participation, and Payment System Inclusion

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***Abstract*– This study examines digital consumer vulnerability among Honduran consumers as an applied problem linked to digital transformation, technological capability, and participation in online commerce and payment systems, rather than as a psychometric validation exercise. Grounded in the Consumer Vulnerability Framework and its digital extensions, the construct was operationalized across three dimensions, cognitive, economic, and situational, and examined in relation to six contextual variables: age, perceived technological skills, educational level, income, payment method, and employment status. Using a cross-sectional observational design, data were collected online from 210 adult consumers (18 to 70 years) recruited through non-probability convenience sampling in Honduras between May and June 2026; the final analytic sample for the structural model was 205 after listwise deletion of missing values. A confirmatory factor analysis and a MIMIC structural equation model were estimated in Jamovi using robust maximum likelihood. The measurement model showed adequate properties, with standardized loadings between .570 and .899, and the structural model showed acceptable fit. Educational level and payment participation were associated with cognitive vulnerability, perceived technological skill was associated with situational vulnerability, and no contextual variable showed a significant association with economic vulnerability. The predictive power of the model was, however, clearly limited: the contextual variables explained only 3.4% to 6.5% of the variance in the three dimensions, so the associations reported here should be read as exploratory signals rather than as an explanatory account of digital consumer vulnerability. Within these limits, the findings indicate that digital consumer vulnerability is not a uniform condition but a differentiated one, shaped by distinct contextual pathways across its cognitive, economic, and situational components. The study contributes context-specific evidence from an underexplored Central American digital market, obtained from a young and predominantly university-educated convenience sample, and offers a dimension-specific framework for interpreting consumer vulnerability in emerging digital economies.**

***Keywords*— digital consumer vulnerability, digital transformation, payment method adoption, technological literacy, structural equation modeling.**

I. Introduction

Digital transformation has rapidly changed the way consumers access information, compare products, and carry out economic transactions. E-commerce, digital payment systems, and, more recently, artificial-intelligence-based personalization mechanisms have expanded consumers' options for market participation, but have also introduced new forms of exposure to risk [1], [2]. In emerging Latin American economies, this process has been particularly asymmetric: the adoption of digital platforms and electronic payment methods coexists with segments of the population that continue to rely on traditional payment mechanisms, such as cash or cash-on-delivery, and with marked differences in technological capabilities, educational level, and income [3], [4].

The concept of consumer vulnerability offers a useful framework for analyzing these asymmetries. Baker, Gentry, and Rittenburg [5] defined consumer vulnerability as a state of susceptibility to experiencing negative consequences in the marketplace, arising from the interaction between individual characteristics, contextual conditions, and market practices, rather than as a fixed or permanent attribute of certain consumer groups. This perspective has been expanded by the public policy and marketing literature on vulnerable consumers [6]–[8], and has given rise to different operationalization proposals, ranging from scales centered on product knowledge, social pressure, and purchasing power [9] to theoretical frameworks that integrate personal, external, and behavioral triggers specific to the digital environment [10]. More recently, the notion has been extended to the digital environment under the idea of digital vulnerability: a state of relational, architectural, and data-driven defenselessness that arises from the automation of commerce and the growing information asymmetry between platforms and consumers [1], [2]. This information asymmetry, described in general economic terms by Akerlof [11], takes on a particular expression in digital markets, where personalization algorithms and exposure to new artificial intelligence technologies can intensify, rather than reduce, consumers' informational disadvantage and sense of defenselessness [12].

In line with this framework, digital consumer vulnerability can be understood as a multidimensional construct. The cognitive dimension refers to difficulties in accessing, processing, and evaluating information available on digital platforms, a problem that intensifies when consumers lack the skills or knowledge needed to navigate these environments [13], [14]. The economic dimension refers to susceptibility to negative financial consequences stemming from digital consumption, including the propensity toward impulsive

purchases and indebtedness associated with online payment facilities [15], [16]. Finally, the situational dimension captures how temporary or contextual states, such as stress, urgency, sadness, loneliness, or boredom, can induce unfavorable digital consumption decisions, regardless of consumers' permanent characteristics [16], [17].

Available evidence suggests that these three dimensions do not respond uniformly to the same contextual factors. Digital literacy or competence, for example, has been associated with greater confidence and lower uncertainty toward digital financial services [4], although its protective effect is not automatic: studies on the digital divide show that even users with reasonable levels of technological competence remain exposed to certain risks, and that age and access to infrastructure remain robust determinants of digital exclusion [18]. Similarly, educational level and the type of participation in payment systems, traditional or digital, have been linked to different patterns of financial inclusion and consumption [3], [19]. Likewise, perceived vulnerability does not operate in isolation: in cross-border commerce contexts, it interacts with consumer trust toward the platform or seller, moderating its effect on purchase intention [20], which suggests that the relationship between consumer capabilities and digital vulnerability depends on the type of vulnerability examined rather than on a uniform protective effect.

Much of this literature has been developed in European, Asian, or high-income contexts, while empirical evidence on digital consumer vulnerability in Central American economies remains scarce. Honduras represents a particularly relevant context for this discussion: the adoption of e-commerce and digital payment methods coexists with a considerable proportion of consumers who still rely on traditional payment mechanisms or do not participate in online commerce at all, within a setting of wide educational and income heterogeneity. This study does not aim to propose a theoretical reconceptualization of digital consumer vulnerability, but rather to provide contextualized empirical evidence on how capabilities, resources, and forms of participation in the digital market are differentially associated with its three dimensions, in an understudied Latin American emerging market.

Within this framework, the present study examines the association between contextual consumer variables, namely age, perceived technological skills, educational level, income, payment method, and employment status, and three dimensions of digital consumer vulnerability (cognitive, economic, and situational) in a sample of Honduran consumers. A confirmatory factor analysis and a MIMIC structural equation model are used as analytical tools to address this applied question, rather than as a psychometric validation exercise. The three vulnerability dimensions are expected to exhibit distinct patterns of association with the contextual variables evaluated, reinforcing the idea that digital consumer vulnerability is not a uniform phenomenon, but a process differentiated by consumers' capabilities, resources, and forms of participation in digital markets.

II. Method

A. Design and Participants

An observational cross-sectional study was conducted, following the STROBE recommendations for reporting observational studies. Within the framework of the digital transformation of consumption in Honduras, the study examines the association between contextual consumer variables (age, perceived technological skills, educational level, income, payment method, and employment status) and three dimensions of digital consumer vulnerability.

The population of interest consisted of adult Honduran consumers (18 to 70 years old) with experience interacting in digital commerce environments. Data were collected between May and June 2026 through a self-administered online questionnaire (Microsoft Forms), disseminated through a non-probability convenience sampling procedure via social media and personal contacts. Because of this recruitment strategy, the sample should not be interpreted as representative of the general Honduran population; the findings should be read as associative evidence within the sample studied.

A total of 247 initial responses were collected. The final analytic sample, after the data-cleaning process described in the Procedure section, consisted of 210 participants. For the estimation of the measurement model and the structural model (Model 3), the software reduced the sample to n = 205 through listwise deletion, excluding observations with missing values on variables included in the model, mainly Likert-scale items with isolated non-response and the “Prefer not to answer” category for Income, treated as missing.

B. Procedure

The questionnaire was self-administered online through Microsoft Forms. Before starting the instrument, an informed consent question was presented (“Do you wish to participate in this research?”); records with a negative response or no response were excluded (n = 5), reducing the sample from 247 to 242 records.

On this basis, a sequential data-quality control process was applied. First, response time in seconds was calculated from the start and completion timestamps automatically recorded by the form, excluding respondents with response times below one-third of the median (speeders) [21] and cases with times exceeding Q3 + 1.5 times the interquartile range, which eliminated 6 and 10 records, respectively (resulting sample = 226). Second, straight-lining response patterns were identified and excluded, defined as selecting the same option on at least 80% of the 38 Likert-type items in the full instrument [21]–[23], which eliminated 11 additional records (resulting sample = 215). Third, records with ages outside the plausible range of 18 to 70 years, or that were null or clearly erroneous, were excluded (n = 5), yielding the final analytic sample of 210 participants.

C. Variables and Instruments

The central construct of the study is Consumer Vulnerability, defined as consumers' state of susceptibility to experiencing negative consequences in their interactions with the digital

market, arising from information asymmetries, cognitive or economic limitations, or specific contextual circumstances that reduce their ability to make informed and protected consumption decisions [5]. The instrument was built based on the Consumer Vulnerability Framework [5], [7] and on the consumer vulnerability literature by Adkins and Ozanne [6] and Shultz and Holbrook [8], adapted to the context of digital information asymmetry, impulsive online purchasing, and consumption experiences on digital platforms in Honduras.

The construct was operationalized across three dimensions: cognitive vulnerability (difficulty accessing, processing, and evaluating information available in digital consumption environments), economic vulnerability (limited financial resources affecting online purchase decision-making, including susceptibility to impulsive purchases), and situational vulnerability (temporary or contextual circumstances, such as stress, fatigue, urgency, sadness, frustration, loneliness, or boredom, that increase the likelihood of unfavorable digital consumption decisions). Each dimension was originally measured with 5 items on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

During the evaluation of the measurement model, 3 of the 15 original items were excluded for showing cross-loadings, local dependence, or insufficient differentiation from other indicators. The final measurement model retained 12 items: 4 for cognitive vulnerability, 3 for economic vulnerability, and 5 for situational vulnerability. The measurement model showed adequate properties for structural analysis (see Results); this should not be interpreted as definitive psychometric validation of the scale.

D. Coding of Contextual Variables

Age and perceived technological skills were treated as continuous variables. Educational level and income were coded as ordinal variables in increasing order; for income, the "Prefer not to answer" category was treated as missing. Payment method was recoded into two dummy variables: Traditional_payment (1 = cash-on-delivery or another traditional method, 0 = other) and Digital_payment (1 = digital wallet, credit card, debit card, or bank transfer, 0 = other), with people who do not shop online as the reference category. Employment status was recoded into Salaried_employment (1 = employment in the public or private sector, 0 = other) and Independent_employment (1 = self-employment, 0 = other), with unemployed people as the reference category (unemployed individuals, students without paid work, and homemakers).

E. Analytic Strategy

Analyses were performed in Jamovi using its Structural Equation Modeling (SEM) module. A confirmatory factor analysis (CFA) was first estimated to evaluate the three-factor structure of the construct, followed by a MIMIC-type SEM model with the contextual variables specified as observed predictors of the three dependent latent variables (Model 3). Estimation was performed using robust maximum likelihood (Robust ML / MLR), with robust standard errors and a Yuan-Bentler scaled chi-square test. Exogenous covariates were specified as observed predictors, without their own measurement model.

Model fit was evaluated using CFI, TLI, RMSEA (with a 95% confidence interval), and SRMR. Standardized factor loadings, standardized β coefficients, 95% confidence intervals, p values, and R^2 for the dependent latent variables are reported. The statistical significance criterion was set at .05.

Two residual covariances were included between situational vulnerability indicators (cv_Sit_1 with cv_Sit_2; cv_Sit_3 with cv_Sit_4), conceptually justified by the content similarity between item pairs referring to related emotional or temporal states, and not as the result of an automatic search based on modification indices.

F. Ethical Considerations

The study was approved by an institutional ethics committee. Participation was voluntary and conditional upon obtaining explicit informed consent at the beginning of the form. Data were collected and analyzed anonymously.

III. Results

A. Sample Characteristics

The analytic sample consisted of 210 participants, with a mean age of 32.0 years (SD = 11.1; range 18–62) and a mean perceived technological skills score of 2.71 (SD = 1.07) on a 1-to-5 scale. Table I presents the distribution of the contextual variables relevant to the model. Incomplete and completed university levels predominated, and a considerable proportion of participants (21.9%) preferred not to report their income level. Regarding payment method, 47.6% of participants reported using some form of digital payment, 29.0% a traditional payment method, and 23.3% do not shop online. Regarding employment status, 51.0% held salaried employment, 16.7% worked independently, and 32.4% were not employed.

The composition of the sample should be kept in mind when interpreting the results that follow. Participants were comparatively young (M = 32.0 years) and educationally advantaged, with 58.2% reporting at least some university education and only 21.0% reporting incomplete or complete primary education as their highest level. In addition, the 21.9% of participants who declined to report their income were treated as missing, which reduced the effective information available for the paths involving that variable.

TABLE I
CHARACTERISTICS OF THE ANALYTIC SAMPLE (N = 210)

Variable / category	n	%
Age, M (SD); range	32.0 (11.1); 18–62	—
Tech. skills, M (SD); 1–5	2.71 (1.07)	—
Educational level		
Incomplete primary	26	12.4
Complete primary	18	8.6
Incomplete secondary	15	7.1
Complete secondary	29	13.8

Incomplete university	64	30.5
Complete university	44	21.0
Graduate studies	14	6.7
Monthly income (Lempiras)		
Less than 5,000	33	15.7
5,001–10,000	18	8.6
10,001–15,000	26	12.4
15,001–20,000	39	18.6
20,001–30,000	29	13.8
30,001–50,000	14	6.7
More than 50,000	5	2.4
Prefer not to answer	46	21.9
Payment method (recoded)		
Digital payment	100	47.6
Traditional payment	61	29.0
Does not shop online (ref.)	49	23.3
Employment status (recoded)		
Salaried (public/private)	107	51.0
Independent	35	16.7
Not employed (ref.)	68	32.4

Note. n = 210 is the total analytic sample after data cleaning. The measurement and structural models were estimated with n = 205 due to listwise deletion of missing data.

B. Measurement Model

The confirmatory factor analysis of three correlated dimensions showed adequate standardized factor loadings: between .570 and .844 for cognitive vulnerability, between .767 and .846 for economic vulnerability, and between .653 and .899 for situational vulnerability (Table II). The final measurement model retained 12 of the 15 original instrument items, after excluding 3 items during evaluation for showing cross-loadings, local dependence, or insufficient differentiation. Two residual covariances were included between situational vulnerability indicators: one statistically significant (cv_Sit_1 with cv_Sit_2, r = .446, p < .001) and one non-significant (cv_Sit_3 with cv_Sit_4, r = .214, p = .095). Overall, the measurement model showed adequate properties for structural analysis. Fig. 1 depicts the complete structural model, including standardized loadings, path coefficients, R^2, factor correlations, residual covariances, and overall fit indices.

TABLE II
MEASUREMENT MODEL: STANDARDIZED FACTOR LOADINGS

Factor	Indicator	β	z	p
Cognitive vuln.	cv_cog_1	.570	—	(ref.)
	cv_cog_3	.792	7.92	<.001
	cv_cog_4	.834	7.56	<.001
	cv_cog_5	.844	7.53	<.001
Economic vuln.	cv_Eco_1	.767	—	(ref.)
	cv_Eco_2	.846	12.14	<.001
	cv_Eco_3	.826	11.18	<.001
Situational vuln.	cv_Sit_1	.840	—	(ref.)
	cv_Sit_2	.877	19.31	<.001
	cv_Sit_3	.653	10.24	<.001
	cv_Sit_4	.663	9.69	<.001
	cv_Sit_5	.899	16.28	<.001

Note. Indicators marked (ref.) are the reference item of each factor (loading fixed to 1 in the unstandardized metric); they do not report z or p.

C. Structural Model Fit

Model 3 converged successfully with 205 observations and 55 free parameters, estimated using robust maximum likelihood with robust standard errors. The Yuan-Bentler scaled chi-square test was statistically significant, $\chi^2(131) = 233$, $p < .001$, an expected result given the sample size and model complexity. Incremental and absolute fit indices indicated acceptable fit: robust CFI = .932, robust TLI = .915, robust RMSEA = .064 (95% CI [.050, .077]), SRMR = .052.

The three vulnerability dimensions correlated significantly with one another: cognitive–economic, r = .644, p < .001; cognitive–situational, r = .493, p < .001; economic–situational, r = .768, p < .001. The variance explained by the contextual variables was limited across all three dimensions: cognitive vulnerability, $R^2 = .065$; economic vulnerability, $R^2 = .034$; situational vulnerability, $R^2 = .048$. In substantive terms, the six contextual variables jointly account for between 3.4% and 6.5% of the variance in each dimension, leaving more than 93% of that variance unexplained; this constraint frames the interpretation of all the associations reported below.

D. Associations with the Vulnerability Dimensions

Table III presents the complete structural paths of Model 3. Regarding cognitive vulnerability, educational level showed a positive association (β = .203, p = .005), while traditional payment (β = -.256, p = .006) and digital payment (β = -.226, p = .022) showed negative associations, both statistically significant relative to the reference category (does not shop online). Age and perceived technological skills were not significantly associated with this dimension.

For economic vulnerability, none of the contextual variables evaluated (income, traditional payment, digital payment, salaried or independent employment status) showed a statistically significant association.

For situational vulnerability, perceived technological skills showed a statistically significant negative association (β = -.157, p = .009). Age, traditional payment, and digital payment were not significantly associated with this dimension. Table III summarizes all coefficients.

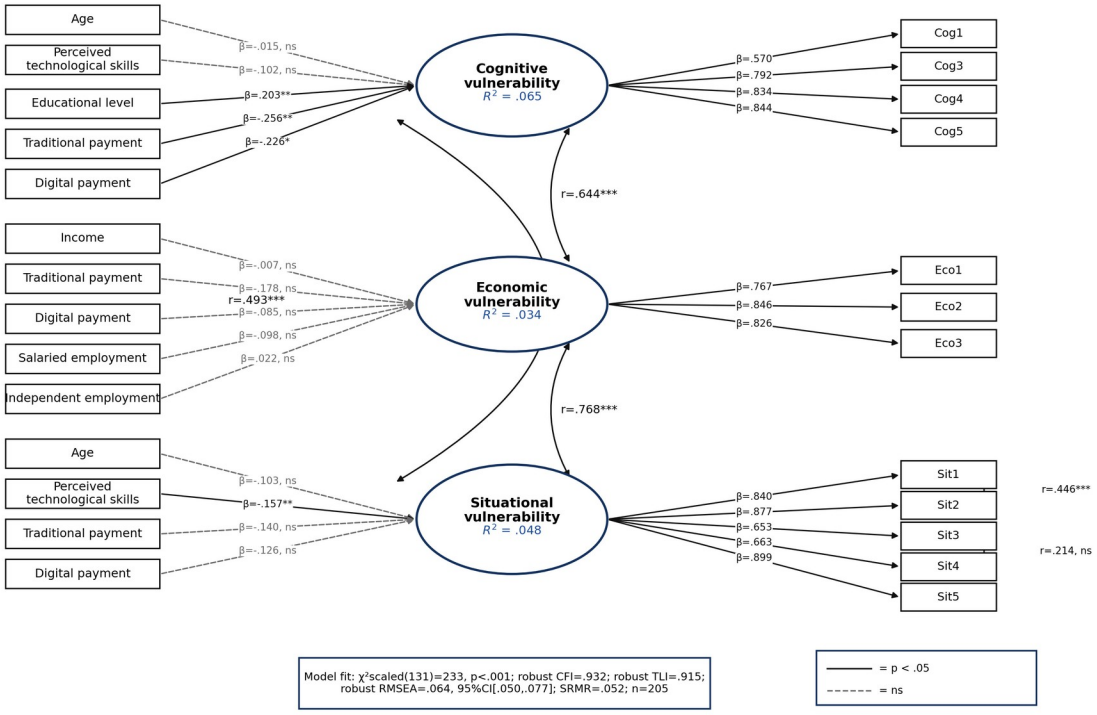


Fig. 1 Structural model of consumer vulnerability (Model 3).

TABLE III
STRUCTURAL PATHS OF MODEL 3

Dep. var.	Predictor	B	SE	95% CI	β	p
CV Cognitive	Age	-0.001	0.004	[-0.009, 0.007]	-.015	.822
	Perceived tech. skills	-0.068	0.047	[-0.160, 0.025]	-.102	.151
	Educational level	**0.081**	**0.029**	**[0.024, 0.139]**	**.203**	**.005**
	Traditional payment	**-0.397**	**0.143**	**[-0.677, -0.117]**	**-.256**	**.006**
	Digital payment	**-0.321**	**0.140**	**[-0.596, -0.046]**	**-.226**	**.022**
CV Economic	Income	-0.003	0.019	[-0.040, 0.034]	-.007	.884
	Traditional payment	-0.350	0.194	[-0.730, 0.031]	-.178	.072
	Digital payment	-0.152	0.182	[-0.509, 0.204]	-.085	.403
	Salaried employment	-0.176	0.105	[-0.381, 0.030]	-.098	.095
	Independent employment	0.052	0.139	[-0.220, 0.325]	.022	.707
CV Situational	Age	-0.010	0.006	[-0.021, 0.002]	-.103	.097
	Perceived tech. skills	**-0.152**	**0.058**	**[-0.265, -0.039]**	**-.157**	**.009**
	Traditional payment	-0.316	0.220	[-0.747, 0.116]	-.140	.152
	Digital payment	-0.260	0.208	[-0.667, 0.147]	-.126	.210

Note. B = unstandardized coefficient; SE = robust standard error; 95% CI = 95% confidence interval for B; β = standardized coefficient. Bold indicates statistically significant paths ($p < .05$). Model fit: χ^2scaled(131) = 233, $p < .001$; robust CFI = .932; robust TLI = .915; robust RMSEA = .064, 95% CI [.050, .077]; SRMR = .052; n = 205.

IV. Discussion

This study examined how contextual resources and forms of participation in digital markets relate to three dimensions of consumer vulnerability among Honduran consumers. Taken together, the pattern of findings indicates that cognitive, economic, and situational vulnerability are shaped by largely distinct sets of contextual conditions, rather than by a single common set of protective or risk factors. This differentiation is itself a central finding: it suggests that digital consumer vulnerability, at least as captured in this sample, does not behave as a unitary phenomenon that responds uniformly to education, technological competence, or market participation, but as a multidimensional condition in which each component may be activated by different mechanisms. It should be stressed from the outset, however, that the contextual variables examined explained only a small fraction of the variance in each dimension, so the discussion below interprets the direction and plausibility of small associations, not the determinants of digital consumer vulnerability as a whole.

A. Differentiated Pathways across Dimensions of Vulnerability

The differentiated pattern observed here is consistent with the conceptualization of consumer vulnerability as an outcome of the interaction between individual characteristics, contextual conditions, and market practices, rather than a fixed attribute of certain consumer groups [5]. It also aligns with more recent accounts that describe digital vulnerability as relational, architectural, and data-driven, emerging from the structure of digital markets rather than residing solely in the consumer [2]. Read against the multidimensional framework proposed by Capone et al. [10], which distinguishes personal, external, and behavioral triggers of digital vulnerability, the present results suggest that the contextual variables examined in this study operate mainly as personal and participation-related triggers, and that their influence is not evenly distributed across the cognitive, economic, and situational components of vulnerability.

B. Cognitive Vulnerability: Education and Market Participation

The positive association between educational attainment and cognitive vulnerability runs counter to the assumption, often implicit in digital divide framings, that more education should uniformly reduce difficulty navigating digital markets. Several non-exclusive mechanisms may plausibly account for this pattern. First, more educated consumers may engage more frequently and extensively with digital platforms, increasing their exposure to promotional content, information volume, and interface complexity, which can raise the cognitive demands involved in comparing and evaluating options. Second, greater awareness of risk and information asymmetry among more educated consumers may make them more attentive to inconsistencies, opacity, or manipulative design in digital platforms; because information asymmetry is a structural feature of digital markets rather than a deficiency that awareness alone resolves [1], [11], heightened awareness could translate into greater perceived difficulty rather than a false sense of mastery. Third, because cognitive vulnerability was assessed through self-report, more educated respondents may be more accustomed to metacognitive self-assessment and therefore more likely to notice and report subtle difficulties that other respondents may not recognize as such. This measurement-sensitive account does not require assuming that less educated consumers are, in an objective sense, less vulnerable. The pattern also stands in contrast to accounts of literacy-driven exclusion in analog retail contexts, such as the coping strategies documented among low-literate consumers [6], suggesting that the relationship between education and vulnerability may operate differently for a self-reported, digitally mediated construct than for functional literacy in traditional commerce.

A fourth consideration concerns the composition of the sample itself. Because participants were recruited through non-probability convenience sampling and were comparatively young and educationally advantaged, with 58.2% reporting at least some university education and a mean age of 32.0 years, the upper categories of the education variable are well represented while the lower categories are comparatively thin. The positive association between education and cognitive vulnerability may therefore partly reflect the internal composition of this particular sample, in which the effective contrast is largely between moderately and highly educated digital consumers rather than between educated consumers and those with minimal formal schooling. A sample with a wider educational spread, and one that better represents older and less connected consumers, could yield a different, possibly non-linear, pattern. Given the cross-sectional design and the limited variance explained, this finding should be read as a question for replication in a more balanced sample rather than as a population-level regularity, and certainly not as evidence that education increases actual susceptibility to harm; it remains equally compatible with heightened detection or reporting of pre-existing difficulty.

The lower cognitive vulnerability observed among consumers who use either traditional or digital payment methods, relative to those who do not purchase online at all, is consistent with an experiential-familiarity account: repeated exposure to the practical steps of a remote transaction, such as comparing prices, verifying legitimacy, or completing a payment, may build procedural confidence that reduces perceived difficulty. This interpretation is broadly consistent with evidence linking digital literacy to greater behavioral confidence in digital financial contexts [4] and with accounts that frame vulnerability partly as a function of limited skills or experiential knowledge rather than of formal education alone [13]. An equally plausible, non-exclusive explanation is self-selection: consumers who already perceive themselves as capable of navigating remote commerce may be more likely to participate in the first place, while those who anticipate difficulty may avoid online purchasing altogether, which would produce a similar association without implying that participation itself is protective. Because both traditional and digital payment users showed a comparable advantage over

non-participants, the relevant contrast in this sample appears to be participation versus non-participation in remote commerce broadly, rather than a specific advantage of digital over traditional payment channels. This nuance is consistent with the coexistence of digital and traditional payment infrastructures described earlier, and echoes evidence from other markets where cash-based or delivery-based transactions remain a dominant and trusted alternative to card- or wallet-based payment [19].

C. Situational Vulnerability and the Boundaries of Technological Competence

Perceived technological competence was associated with lower situational vulnerability but showed no comparable association with cognitive or economic vulnerability, suggesting that its protective scope is bounded rather than general. A plausible interpretation is that technological competence operates specifically as a buffer against decisions made under time pressure, emotional strain, or perceived urgency, for instance by supporting quicker verification of a platform's legitimacy or a more measured response to countdown-style promotions, without necessarily extending to the evaluation of complex information or to the self-regulation of spending. This pattern is consistent with the conceptual distinction between competence and dependence proposed by Stewart et al. [17]: whereas heightened technology dependence has been associated with reduced skepticism and greater susceptibility to deception, the present findings suggest that perceived competence, when it reflects confidence and self-efficacy rather than reliance, may instead support more composed responses under pressure. The absence of a parallel association for the cognitive and economic dimensions indicates that technological competence should not be treated as a general-purpose safeguard against digital consumer vulnerability, but as a dimension-specific resource whose relevance is bounded by the particular demands, whether attentional, emotional, or analytical, that each form of vulnerability entails.

D. Economic Vulnerability: An Unresolved Dimension

None of the contextual variables examined, including income, payment method, and employment status, showed a statistically significant association with economic vulnerability, although the estimate for traditional payment approached conventional significance thresholds. This pattern should not be read as evidence that economic vulnerability is unrelated to consumers' material circumstances; rather, the available evidence did not support the proposed associations within this model and this sample. The sociodemographic and participation variables captured here may be too distal to explain a dimension centered on impulsivity, indebtedness, and immediate financial strain. More proximal behavioral and financial variables, such as credit versus debit card usage, financial literacy, existing debt burden, purchase frequency, and household financial responsibilities, may carry more explanatory weight for economic vulnerability than broad income brackets or employment categories. This possibility is consistent with research linking e-commerce-related financial vulnerability to behavioral and structural channels beyond income alone [15], and with evidence that indebtedness associated with online shopping is better explained by psychosocial mechanisms, such as stress, loneliness, or coping-driven consumption, than by socioeconomic status per se [16]. The modest sample size available for structural estimation also limited statistical power to detect small effects, and the marginal association observed for traditional payment is compatible with a real but underpowered effect rather than with a confirmed absence of relationship.

The interpretation of these null results is further complicated by non-response on the income variable. Because 21.9% of participants preferred not to report their income and these cases were treated as missing, the income path was estimated on a reduced and potentially self-selected subset of the sample. Non-response to income questions is rarely random: consumers under financial strain, those with irregular or informal earnings, and those at the upper end of the distribution are all plausibly over-represented among non-respondents, and the first two groups are precisely those in whom economic vulnerability would be expected to be highest. If this is the case, the restricted variance and the loss of the most financially strained respondents would attenuate any true association between income and economic vulnerability, so the null finding reported here is compatible with an underpowered or truncated test rather than with an actual absence of relationship. A design that retains income information, for example through broader brackets, indirect elicitation, or a complementary measure of perceived financial adequacy, would provide a fairer test of this dimension.

E. Shared Variance across Dimensions and the Limits of Explanatory Power

The three latent dimensions were substantially correlated with one another, particularly economic and situational vulnerability, even though they responded to different contextual predictors and were explained by small proportions of variance. This combination suggests that, while cognitive, economic, and situational vulnerability follow distinct pathways in relation to the contextual variables examined, they may still share an underlying susceptibility or tend to co-occur within the same individuals, consistent with the view that these dimensions represent interrelated facets of a broader vulnerability syndrome rather than fully independent processes [9], [10]. At the same time, the explained variance of 3.4% to 6.5% indicates that sociodemographic and participation variables capture only a marginal part of what shapes digital consumer vulnerability. This is consistent with frameworks describing digital vulnerability as emerging from the interaction of personal, external, and behavioral triggers [10]: the present model addressed mainly personal and participation-related conditions, leaving relational and behavioral triggers, such as trust in specific platforms, exposure to manipulative design, or emotional regulation strategies, unexamined and likely to account for the greater part of the unexplained variance.

F. Contextualizing the Findings in the Honduran Digital Market

These results can be tentatively read against the coexistence of traditional and digital payment infrastructures, structural informality, and uneven access to digital and financial education that characterizes the Honduran market described earlier. In such a setting, consumers' capacity to compare, evaluate, and trust digital transactions may depend more on their accumulated practical exposure to any form of remote commerce than on their income or formal employment status, which could help explain why participation, rather than economic standing, was associated with cognitive vulnerability. This pattern parallels evidence from other markets with significant informality and historically cash-reliant consumer behavior, where trust and prior transactional experience, rather than income, shape payment-related decisions [19]. This contextual interpretation is offered cautiously, given the non-probabilistic nature of the sample and the limited variance explained, and should be understood as a plausible reading of the pattern observed rather than as a population-level claim about Honduran consumers.

G. Artificial Intelligence and Algorithmic Personalization as an Unexamined Layer

Artificial intelligence was treated in this study as part of the context that makes digital consumer vulnerability a timely concern, but it was not measured or tested empirically, and no claim about AI effects can be derived from these data. The dimensional pattern observed here nevertheless suggests specific, testable ways in which AI-driven personalization and recommendation systems could interact with each component of vulnerability. For the cognitive dimension, recommendation and ranking systems compress the choice set and mediate what consumers can compare, which may either reduce perceived difficulty by simplifying decisions or deepen informational asymmetry by concealing the criteria behind the ordering [1], [2]; the association observed here between education and reported cognitive difficulty makes the second possibility worth testing, since consumers who are more aware of algorithmic mediation may also be the ones who most readily perceive it as opacity. For the economic dimension, personalized pricing, dynamic offers, and AI-assisted credit or deferred-payment prompts operate directly on the impulsivity and indebtedness mechanisms that this dimension captures, and are considerably more proximal to it than the sociodemographic variables that produced null results in this model [15], [16]. For the situational dimension, systems that infer affective or contextual states and time their prompts accordingly convert transient states, such as stress, fatigue, or boredom, into commercially actionable signals, which is precisely the mechanism the situational dimension was designed to capture, and which the literature on emotional data and automated decision environments identifies as a distinctive source of digital defenselessness [12]. Incorporating measures of exposure to and awareness of algorithmic personalization, such as perceived recommendation influence, awareness of personalized pricing, or reliance on AI-based assistants, would allow future studies to test whether these systems amplify vulnerability, redistribute it across dimensions, or add a further explanatory layer to a model that, as shown here, leaves the greater part of the variance unaccounted for.

H. Theoretical and Practical Contributions

Theoretically, this study contributes context-specific evidence on digital consumer vulnerability from a Central American market that has received limited empirical attention in a literature concentrated mainly on European, Asian, or high-income settings [1], [2]. It also extends the multidimensional conceptualization of digital consumer vulnerability [9], [10] by showing that cognitive, economic, and situational vulnerability can be predicted by largely non-overlapping sets of contextual variables within the same sample, which refines the interpretation of vulnerability as a differentiated rather than unitary condition. The counterintuitive association between education and cognitive vulnerability suggests a possible boundary condition for assumptions that formal education uniformly reduces digital consumer vulnerability, and points to self-reported cognitive vulnerability as a construct that may be sensitive to awareness and reporting processes, not only to underlying capability. These contributions are exploratory in nature, given the limited explanatory power of the model and the characteristics of the sample.

Practically, the findings may inform platform design practices that prioritize clarity of information and pricing, given that reported cognitive difficulty was not limited to less educated or less resourced consumers; interface transparency and safeguards against manipulative design [1], [12] may therefore be broadly relevant rather than targeted only at ostensibly vulnerable segments. The experiential pattern observed for payment participation suggests that guided first-time-user support, such as structured onboarding or verification checklists, could help infrequent or first-time online shoppers build the procedural confidence associated with more experienced users. Given the protective but narrow role of perceived technological competence for situational vulnerability, consumer education addressing urgency-based and emotionally driven purchasing tactics may usefully complement general digital-skills training, which on its own may not extend to economic self-regulation. Finally, the absence of significant associations for income and employment on economic vulnerability suggests that consumer-protection efforts in this domain may benefit from evaluating behavioral and financial-literacy-oriented interventions rather than relying primarily on income-based targeting, although this possibility warrants direct empirical testing, on more representative samples, before implementation.

I. Limitations and Directions for Future Research

Several limitations restrict the interpretation of these findings. The most important is the limited explanatory power of the model: the contextual variables examined accounted for 6.5%, 3.4%, and 4.8% of the variance in cognitive, economic, and

situational vulnerability, respectively, which means that more than 93% of the variance in each dimension remains unexplained. The associations reported here therefore identify statistically detectable but substantively small contextual signals, and they should not be read as an explanatory model of digital consumer vulnerability.

The sample also limits what can be claimed. Recruitment relied on non-probability convenience sampling through social media and personal contacts, and the resulting sample was comparatively young (M = 32.0 years, SD = 11.1) and educationally advantaged, with 58.2% reporting at least some university education. The sample therefore over-represents connected, digitally active consumers and under-represents older adults, rural consumers, and those with lower educational attainment, who are among the segments most often identified as vulnerable in the digital divide literature [18]. A more representative sample, ideally probabilistic or at least quota-based on age, education, region, and connectivity, would be required before any of these associations could be attributed to Honduran consumers as a population. In addition, 21.9% of participants declined to report their income, a gap that directly affects the dimension for which no significant association was found.

The remaining limitations concern design and measurement. The cross-sectional design cannot establish temporal precedence or rule out reciprocal association, a concern that is particularly relevant for the education–cognitive vulnerability finding, which is equally compatible with education shaping reported vulnerability and with unmeasured factors jointly influencing both. Reliance on self-report measures raises the possibility of common method variance and social desirability bias, which may be especially relevant for a self-assessed construct such as cognitive vulnerability. The measurement instrument was adapted and constructed ad hoc for this study; although the measurement model showed adequate properties for structural analysis, three items were excluded during measurement evaluation, and the scale has not undergone independent psychometric validation beyond the present study. The single-country context, while relevant to an underexplored regional gap, limits generalizability to other Central American or Latin American digital markets, which may differ in payment infrastructure, regulatory environment, and digital adoption. The limited variance explained and the null findings for economic vulnerability point to the likely relevance of financial-behavior variables not captured in this model, including credit use, existing debt, financial literacy, purchase frequency, and household financial responsibilities, consistent with vulnerability frameworks that emphasize behavioral, not only sociodemographic, triggers [10]. Finally, employment and payment method were operationalized as broad dummy categories, which may mask heterogeneity within each group that a more granular measurement could reveal.

These limitations point to several directions for future research. The priority is a study with a larger and more representative sample and a validated instrument, capable of supporting population-level inference and of detecting the small effects that the present design could not. Longitudinal or experimental designs are needed to disentangle whether education elevates actual cognitive difficulty, heightens its detection, or both. Incorporating proximal behavioral and financial variables, such as financial literacy, credit use, impulsivity, and indebtedness, together with measures of exposure to algorithmic personalization as outlined above, would help clarify the drivers of economic vulnerability left unexplained in this model and would substantially raise the share of variance accounted for. Comparative studies across other Central American markets would help determine whether the differentiated pattern observed here generalizes regionally or reflects conditions specific to the present sample. Finally, qualitative or mixed-method research examining how educated consumers interpret and report cognitive difficulty in digital environments could help adjudicate between the exposure, awareness, and measurement-artifact explanations proposed above.

V. Conclusion

This study examined how contextual resources and participation in digital markets relate to consumer vulnerability among Honduran consumers, addressing cognitive, economic, and situational dimensions separately rather than as a single construct. The findings indicate that these three dimensions are not shaped by a common set of predictors: educational attainment and participation in either traditional or digital payment methods were associated with cognitive vulnerability, perceived technological competence was associated with situational vulnerability, and none of the contextual variables examined showed a significant association with economic vulnerability. This differentiated pattern suggests that digital consumer vulnerability should be treated as a multidimensional condition whose components may respond to distinct mechanisms, rather than as a single trait that education, income, or technological skill can uniformly offset.

These conclusions must be stated with the explanatory limits of the model in view. The contextual variables examined explained only 3.4% to 6.5% of the variance across the three dimensions, so the greater part of what drives digital consumer vulnerability lies outside the set of variables modeled here, plausibly in behavioral, financial, relational, and algorithmic factors that were not measured. The evidence was moreover obtained from a young, predominantly university-educated convenience sample in a single Central American market, which precludes population-level inference. Within these limits, the study provides exploratory, context-specific evidence that complicates simple assumptions about digital literacy and formal education as uniformly protective factors, and points toward the need for dimension-specific approaches, in research and in consumer-protection practice, that account for the distinct cognitive, economic, and situational pathways through which digital markets may place consumers at a disadvantage. Confirming and extending this account will require a larger and more representative sample, a validated instrument, and the inclusion of behavioral,

financial, and AI-related variables capable of explaining a substantially larger share of the variance.

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