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ANALYSIS OF THE FACTORS INFLUENCING DIGITAL PURCHASE DECISIONS ON BUSINESS PLATFORMS IN ECUADOR

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ABSTRACT

Digital commerce has expanded rapidly in Ecuador, but high traffic does not always translate into completed transactions. This study examined the factors associated with consumers' digital purchase decisions by combining the Technology Acceptance Model with constructs related to trust, emotion, social influence, and herding behavior. A cross-sectional quantitative design was used. An online questionnaire was completed by 666 Ecuadorian consumers who had purchased online during the previous twelve months. The instrument was reviewed by experts, piloted with 30 participants, and showed high internal consistency (Cronbach's alpha = 0.94). Descriptive statistics, Pearson correlations, exploratory factor analysis, and multiple linear regression were applied. Three latent factors emerged: trust and social influence, attitude toward the platform, and emotions and herding behavior. Together, they accounted for 76.8% of the variance identified in the factor solution. The regression model explained 76.1% of the variance in purchase intention. Platform trust, ease of use, perceived usefulness, post-purchase satisfaction, and anxiety when disclosing personal data were significant predictors, whereas demographic variables and most social-content indicators did not show direct effects. The findings indicate that Ecuadorian consumers respond most strongly to usable, useful, and trustworthy platforms. Social and emotional cues remain relevant, but much of their influence appears to operate through the broader experience of confidence and platform evaluation.

Keywords: e-commerce; consumer behavior; digital trust; digital marketing; emotions; technology acceptance; social media; Ecuador

1. INTRODUCTION

E-commerce has grown quickly across Latin America, and Ecuador is part of that shift. Mentinno's Digital Ecuador 2025 report estimates more than 18.2 million internet users in the country, social-media penetration of 74%, and annual e-commerce transactions approaching USD 4 billion. These figures point to a more mature digital market, but they do not by themselves explain why some visits become purchases while many others do not (Mentinno, 2025). The expansion of marketplaces, retail websites, social networks, and AI-supported business models has widened the range of channels through which Ecuadorian consumers discover and evaluate products. Large firms and small entrepreneurs now compete in the same digital environment, where customers move between search engines, social media, messaging applications, and online stores before deciding whether to buy. In this setting, attitudes toward the platform are central because consumers judge usefulness, usability, credibility, and risk at several points in the journey (Al Maalouf et al., 2025; Saxena & Thakur, 2024).

Platforms such as Mercado Libre, Fybeca, and DePrati attract substantial traffic, while TikTok and Instagram increasingly shape product discovery. The volume of exposure makes social influence difficult to ignore. Reviews, recommendations, and visible popularity can reduce uncertainty, but they can also encourage consumers to follow the behavior of others without conducting an independent evaluation. Ali and Amir (2024) describe this tendency as herding behavior and show that it can either accelerate or inhibit online purchases depending on the information available to the consumer.

Digital expectations have also changed. Convenience and speed remain important, but users increasingly expect personalized offers, transparent data practices, secure payment procedures, and a smooth navigation experience (Saxena & Thakur, 2024). These expectations are particularly relevant in Ecuador, where mobile access is widespread and Android devices predominate. At the same time, regional differences in connectivity, uneven levels of digital literacy, and persistent distrust of online transactions continue to affect adoption. International research helps clarify several of these tensions. Chen (2025) found that social-media interaction and micro-influencer activity can shape purchase intention, while Guan and Lin (2024) showed that online reviews serve as cues for quality and trust. Studies of luxury goods, sustainable products, and upcycled foods likewise report that platform credibility, perceived security, product familiarity, and emotional response influence digital decisions (Chernov & Gura, 2024; Dlamini & Mahowa, 2024; Jeon et al., 2024).

Ecuador's digital market has grown faster than the national research base devoted to consumer decision-making. General patterns are known: younger consumers are usually more willing to buy online, social-media use affects brand perceptions, and security concerns can interrupt a transaction. What remains less clear is the relative weight of these variables when they are examined together. A multivariate model is therefore needed to distinguish direct predictors from variables whose influence is indirect or shared with other constructs. The practical problem can be seen in the gap between site traffic and completed purchases. Mentinno (2025) reports that leading platforms receive considerable numbers of visits, yet conversion rates remain below their potential in several market segments. High bounce rates and short browsing paths on less optimized sites suggest that initial interest often fades before checkout. A visit may be motivated by a social-media post or a recommendation, but the final decision depends on whether the platform appears useful, easy to navigate, and safe enough to justify the transaction.

Emerging technologies make the picture more complex. Conversational agents, recommendation systems, live selling, and data-driven personalization alter the way consumers interact with online stores (Ong et al., 2024; Ong et al., 2025). These tools may improve convenience, but they also raise concerns about privacy, manipulation, and the use of personal data. Their adoption in Ecuador has outpaced systematic local analysis, leaving firms with limited evidence for decisions about user experience, digital advertising, and platform design. The study therefore examines digital purchase intention as the outcome of interconnected technological, social, and emotional processes. It draws on the Technology Acceptance Model (Davis, 1989), the Theory of Planned Behavior (Ajzen & Driver, 1991), and recent work on trust, technology readiness, and consumer emotion (Han et al., 2024). The central premise is that purchase intention cannot be reduced to a single preference. It develops from the consumer's evaluation of the platform, confidence in the transaction, exposure to other people's opinions, and emotional reaction to the experience.

1.1 Digital platforms and consumer evaluation

The Technology Acceptance Model offers a useful starting point because perceived usefulness and perceived ease of use have repeatedly been associated with the adoption of digital services. In an e-commerce setting, usefulness refers to the consumer's belief that the platform saves time, expands access, or improves the purchasing process. Ease of use concerns the effort required to search, compare, pay, and resolve problems. These evaluations become more important when consumers have several platforms offering similar products. Trust adds a distinct dimension. Online buyers cannot inspect every product, meet every seller, or observe what happens to their data after payment. They therefore rely on visible security measures, platform reputation, clear return policies, and previous experience. Saxena and Thakur (2024) found that trust mediates the relationship between web-assurance mechanisms and purchase intention. In Ecuador, where data-protection concerns and fear of fraud remain common, the quality of these signals may determine whether a user proceeds to checkout.

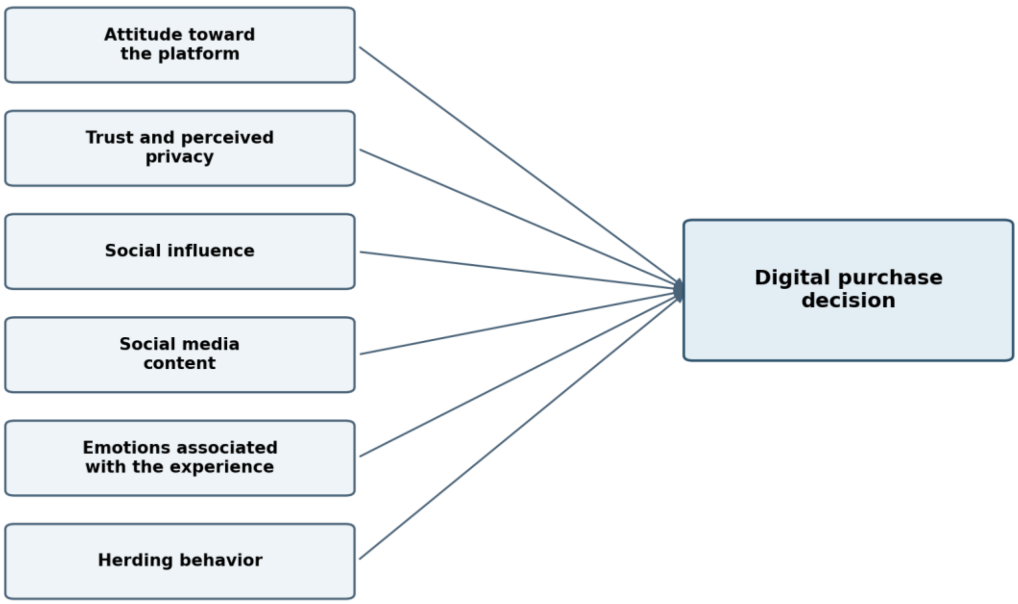
Social information works alongside these individual evaluations. Reviews, ratings, comments, and influencer recommendations can lower search costs and provide evidence about product performance. Guan and Lin (2024) show that consumer-generated content shapes judgments of quality and energy efficiency, while Zheng et al. (2024) warn that not every user-generated image is equally persuasive. The credibility, specificity, and relevance of the content matter more than its mere presence.Emotion is also part of the process. Satisfaction after a successful transaction can strengthen future purchase intention, whereas anxiety about disclosing personal information may discourage participation or make the consumer more dependent on familiar brands. Han et al. (2024) argue that emotional factors interact with technology readiness and subjective norms. This interaction is plausible in Ecuador, where consumers may appreciate the convenience of digital shopping while remaining cautious about payment security and data use.

Herding behavior captures a related but different response. When consumers face uncertainty, they may treat popularity as evidence and imitate the choices of a visible majority. Product rankings, high review counts, and viral content can therefore influence attention and perceived legitimacy. However, a popular product is not necessarily a direct cause of purchase. Its effect may be absorbed by trust, satisfaction, or the consumer's broader attitude toward the platform.

1.2 Digital purchase decision

The proposed model treats digital purchase intention as the result of six related domains: attitude toward the platform, trust and perceived privacy, social influence, social-media content, emotions associated with the experience, and herding behavior. Figure 1 presents the conceptual relationship. The model does not assume that every domain has an independent effect. Instead, it allows the variables to cluster and overlap, which is consistent with the way consumers evaluate online transactions.

Figure 1. *Proposed theoretical model*



Source: Authors' own elaboration (2025).

The operational definitions and questionnaire items are summarized in Table 1. All attitudinal items used a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The table was designed to connect the theoretical constructs with observable responses and to make the statistical model auditable.

Table 1. *Operationalization of the study variables*

Variable	Conceptual definition	Dimension	Questionnaire item (Likert)
Digital purchase decision (DV)	Consumer action that culminates in the acquisition of a product or service through a digital platform.	Purchase intention	I intend to purchase goods or services online in the coming months.
Attitude toward the platform	Cognitive and affective evaluation of the platform's usefulness and ease of use.	Perceived usefulness	I consider online shopping platforms useful.
Attitude toward the platform	Cognitive and affective evaluation of the platform's usefulness and ease of use.	Ease of use	I find online shopping platforms easy to navigate and use.
Attitude toward the platform	Cognitive and affective evaluation of the platform's usefulness and ease of use.	Platform trust	I trust online shopping platforms.
Trust and perceived privacy	The level of security the consumer perceives regarding personal data and the transaction.	Privacy	I feel secure about how my personal data are handled during online purchases.
Trust and perceived privacy	The level of security the consumer perceives regarding personal data and the transaction.	Payment security	I trust the security of payments made on e-commerce platforms.
Social influence	The degree to which peers, influencers, and comments affect the purchase decision.	Peer recommendations	Other users' opinions and reviews influence my online purchase decision.
Social influence	The degree to which peers, influencers, and comments affect the purchase decision.	Recommendations	I follow recommendations from influencers or people I know when buying online.
Social-media content	Exposure to and influence of social-media content on purchase intention.	Interaction	The content I see on social media influences my online purchase decision.
Emotions associated with the experience	The consumer's affective state while interacting with the platform.	Positive emotions	I feel satisfied after making online purchases.
Emotions associated with the experience	The consumer's affective state while interacting with the platform.	Negative emotions	I feel anxious when providing personal data for online purchases.
Herding behavior	The tendency to imitate or follow other consumers' behavior.	Observable behavior	When many people buy a product online, I feel more inclined to buy it.
Herding behavior	The tendency to imitate or follow other consumers' behavior.	Majority opinion	A product's popularity on social media encourages me to buy it.

Source: Authors' own elaboration (2025).

A multivariate approach is appropriate because the constructs are conceptually related and may share explanatory variance. It can identify latent groupings, estimate the strength of association with purchase intention, and show whether demographic differences remain relevant after the attitudinal variables are considered. The general objective was to analyze the factors that influence Ecuadorian consumers' digital purchase decisions on e-commerce platforms. The specific objectives were to identify the main sociodemographic, technological, and behavioral variables; examine the interaction of emotional, social, and technological dimensions; and develop an explanatory model that can inform customer-acquisition and conversion strategies.

2. MATERIALS AND METHODS

2.1 Design and participants

The research used a quantitative, non-experimental, cross-sectional, and correlational design. This design was selected because the purpose was to estimate relationships among several variables at a single point in time rather than to manipulate the purchasing environment. The target population consisted of Ecuadorian internet users aged 18 years or older who had completed at least one online purchase during the previous twelve months. Mentinno (2025) estimates approximately 18.2 million active internet users in Ecuador, of whom 20.4% participate in digital purchasing. This produced a potential population of about 3.7 million online consumers. A minimum sample close to 666 was obtained using a 99% confidence level and a 5% margin of error. Recruitment was conducted through Facebook, Instagram, LinkedIn, online forums related to e-commerce, and digital consumer communities.

Convenience sampling was used because a complete national sampling frame of online buyers was not available. A total of 702 responses were received. Thirty-six incomplete or inconsistent records were removed during data cleaning, leaving 666 valid cases. This sample also exceeds the common recommendation of at least ten observations per independent variable in multivariate analysis (Hair et al., 2013). Participants were included when they lived in Ecuador, were at least 18 years old, had purchased online within the previous year, and provided digital informed consent. People without prior online purchasing experience were excluded. Participation was voluntary, and the questionnaire did not request information that could directly identify respondents.

2.2 Instrument and data collection

Data were collected through a self-administered online questionnaire derived from the operationalization matrix in Table 1. The instrument contained three sections: sociodemographic questions, items measuring the independent constructs, and one item measuring digital purchase intention. Most responses were recorded on a five-point Likert scale from strongly disagree to strongly agree. Semantic-differential prompts were used where needed to capture emotional reactions.

Three academics with experience in digital marketing and consumer behavior reviewed the questionnaire for content validity. A pilot test with 30 participants was then conducted to assess clarity and internal consistency. The preliminary Cronbach's alpha was 0.94, indicating that the set of items was sufficiently consistent for the main study. Google Forms was used to administer the survey on mobile and desktop devices. Respondents who expressly agreed could also share basic browsing indicators, such as visit duration, bounce rate, and pages per session, through analytics tools. These optional indicators were used only as contextual information and were not treated as identifying data. Automatic and manual checks were applied to detect duplicate, incomplete, and contradictory responses.

2.3 Statistical analysis

The analysis proceeded in four stages. First, descriptive statistics were calculated for the sociodemographic variables and questionnaire items. Second, internal consistency was assessed with Cronbach's alpha. Third, Pearson correlations were used to examine bivariate associations with purchase intention. Spearman coefficients were checked when distributional assumptions were questionable. An exploratory factor analysis was then conducted using minimum residual extraction and oblimin rotation. An oblique rotation was chosen because the theoretical constructs were expected to correlate. Sampling adequacy was evaluated with the Kaiser-Meyer-Olkin statistic, and Bartlett's test of sphericity was used to determine whether the correlation matrix was suitable for factor analysis. Finally, multiple linear regression was used to estimate the unique contribution of each predictor to digital purchase intention while controlling for age and gender. Jamovi was used for descriptive and inferential analyses, AMOS 26 was available for multivariate model checks, and Microsoft Excel 365 was used for data management and cleaning. Statistical significance was assessed at $p < .05$.

3. RESULTS

The final sample included 666 Ecuadorian residents with online purchasing experience during the previous twelve months. After the cleaning procedure, no missing values remained in the variables used for the principal analyses.

3.1 Descriptive statistics

Table 2 presents the descriptive statistics. Digital purchase intention was high ($M = 3.98$, $SD = 1.07$). Perceived usefulness, ease of use, and platform trust all had means close to or above 4.00. Payment security also averaged 4.00. The lowest mean was observed for confidence in the handling of personal data ($M = 3.43$, $SD = 1.27$), suggesting that privacy remained a more uncertain aspect of the experience than usefulness or navigation.

Table 2. *Descriptive statistics for the model variables*

Variable	Mean	SD	Minimum	Maximum
I intend to purchase goods or services online.	3.98	1.07	1	5
I consider online shopping platforms useful.	3.94	1.06	1	5
I find online shopping platforms easy to navigate and use.	3.96	1.02	1	5
I trust online shopping platforms.	4.04	1.04	1	5
I feel secure about how my personal data are handled.	3.43	1.27	1	5
I trust the security of e-commerce payments.	4.00	1.17	1	5
Other users' opinions and reviews influence my decision.	4.12	1.08	1	5
I follow recommendations from influencers or people I know.	4.05	1.09	1	5
Social-media content influences my purchase decision.	4.01	1.13	1	5
I feel satisfied after shopping online.	4.00	1.07	1	5
I feel anxious when providing personal data online.	3.84	1.10	1	5
I am more inclined to buy when many other people do so.	3.90	1.07	1	5
A product's popularity on social media encourages me to buy it.	3.82	1.01	1	5

Source: Authors' own elaboration (2025).

3.2 Correlations

All variables were positively correlated with digital purchase intention (Table 3). The strongest relationships involved platform trust ($r = .825$), ease of use ($r = .798$), perceived usefulness ($r = .791$), and other users' opinions and reviews ($r = .774$). Post-purchase satisfaction also showed a strong association ($r = .763$). These coefficients indicate that favorable platform evaluations and confidence are closely connected to the consumer's intention to buy.

Table 3. *Pearson correlations with digital purchase intention*

Variable	r with purchase intention
Trust in online shopping platforms	0.825
Perceived usefulness	0.791
Ease of navigation and use	0.798

Variable	r with purchase intention
Influence of opinions and reviews	0.774
Trust in payment security	0.726
Influence of social-media content	0.702
Post-purchase satisfaction	0.763
Anxiety when providing personal data	0.706
Inclination to buy when many others do so	0.714
Influence of social-media popularity	0.689

Note: The table reports the principal bivariate coefficients with the dependent variable.

3.3 Exploratory factor analysis

The exploratory factor analysis used minimum residual extraction with oblimin rotation. The data were well suited to the procedure: the overall KMO was .966, and Bartlett's test was significant, chi-square(78) = 9637, $p < .001$. Three factors were retained, accounting for 76.8% of the total variance. Factor 1 explained 27.4% of the variance and combined trust in payment security with social influence. The largest loading was observed for payment security (.923), followed by social-media content (.843), recommendations from influencers or acquaintances (.713), and online opinions and reviews (.695). The pattern suggests that social information and transaction confidence form a common evaluative domain for many respondents.

Factor 2 explained 27.3% of the variance and contained the core platform-attitude variables. Ease of use loaded at .975, platform trust at .840, purchase intention at .745, and perceived usefulness at .727. This factor is consistent with the Technology Acceptance Model and shows that usability, usefulness, and trust are closely related in the Ecuadorian context.Factor 3 explained 22.1% of the variance and represented emotions and herding behavior. The inclination to purchase a product when many others bought it loaded at .907, social-media popularity at .815, anxiety about providing personal data at .724, and post-purchase satisfaction at .497. The factor captures a mixture of affective response and sensitivity to collective behavior.The factor correlations were high: .869 between Factors 1 and 2, .818 between Factors 1 and 3, and .848 between Factors 2 and 3. These values support the use of oblique rotation and show that the three domains are interdependent rather than separate stages of the decision process.

Table 4. *Exploratory factor loadings*

Item	Factor 1	Factor 2	Factor 3	Uniqueness
Trust in the security of e-commerce payments	0.923			0.167
Social-media content influences my decision	0.843			0.201
I follow recommendations from influencers or acquaintances	0.713			0.191
Other users' opinions and reviews influence my decision	0.695			0.141
Online platforms are easy to navigate and use		0.975		0.166
I trust online shopping platforms		0.840		0.146
I intend to purchase online in the coming months		0.745		0.213
Online shopping platforms are useful		0.727		0.225
I feel secure about how my personal data are handled				0.735
I am more inclined to buy when many other people do so			0.907	0.145
A product's popularity on social media encourages me to buy it			0.815	0.238
I feel anxious when providing personal data online			0.724	0.269
I feel satisfied after making online purchases	0.414		0.497	0.182

Note: Minimum residual extraction with oblimin rotation. Loadings below the reported threshold are blank.
Source: Authors' own elaboration (2025).

3.4 Multiple linear regression

The regression model used digital purchase intention as the dependent variable and included demographic, attitudinal, emotional, and social predictors. The model explained 76.1% of the variance, with an adjusted R-squared of .757 (Table 5). The small difference between the two coefficients indicates limited shrinkage after adjustment for the number of predictors.

Table 5. *Overall regression model statistics*

Statistic	Value
R-squared	0.761
Adjusted R-squared	0.757

Source: Authors' own elaboration (2025).

Platform trust was the strongest direct predictor (B = 0.2772, p < .001), followed by ease of use (B = 0.2022, p < .001) and perceived usefulness (B = 0.1599, p < .001). Post-purchase satisfaction (B = 0.1033, p = .016) and anxiety when providing personal data (B = 0.1083, p = .001) were also significant. Gender, age, perceived privacy, payment security, reviews, influencer recommendations, social-media content, and the two herding items did not retain statistically significant direct effects after the other predictors entered the model.

Table 6. *Multiple linear regression coefficients*

Predictor	Estimate	SE	t	p
Intercept	0.0238	0.0979	0.243	0.808
Gender: male vs. female	0.0733	0.0927	0.790	0.430
Age 26-35 vs. 18-25	0.0639	0.0548	1.165	0.244
Age 36-45 vs. 18-25	0.0132	0.0627	0.210	0.833
Age 46-55 vs. 18-25	0.1334	0.1112	1.200	0.230
Age 56 or older vs. 18-25	-0.1976	0.3853	-0.513	0.608
Perceived usefulness	0.1599	0.0378	4.230	< .001
Ease of use	0.2022	0.0426	4.752	< .001
Platform trust	0.2772	0.0452	6.134	< .001
Confidence in personal-data handling	0.0324	0.0196	1.652	0.099
Trust in payment security	0.0385	0.0376	1.023	0.306
Influence of opinions and reviews	0.0518	0.0468	1.108	0.268
Recommendations from influencers or acquaintances	0.0525	0.0417	1.260	0.208
Influence of social-media content	-0.0383	0.0376	-1.019	0.308
Post-purchase satisfaction	0.1033	0.0428	2.413	0.016
Anxiety when providing personal data	0.1083	0.0339	3.199	0.001
Inclination to buy when many others do so	-0.0295	0.0409	-0.721	0.471
Influence of social-media popularity	0.0278	0.0384	0.724	0.469

Note: The dependent variable was intention to purchase goods or services online in the coming months. The intercept represents the reference categories.

Source: Authors' own elaboration (2025).

4. DISCUSSION

The analysis identified three related dimensions of digital purchasing behavior in Ecuador: trust and social influence, attitude toward the platform, and emotions and herding behavior. The factor solution accounted for 76.8% of the variance, and the regression model explained roughly three quarters of the variance in purchase intention. The results support a multidimensional explanation, but they also show that not every variable that clusters with purchase intention is an independent predictor.The first factor joined payment security with social information. This combination is consistent with the argument that consumers use other people's behavior as a cue when they cannot fully evaluate a transaction. The very high loading for payment security (.923) confirms that confidence in the transaction remains central. Social-media content, influencer recommendations, and reviews also loaded on the factor, yet none of them was significant in the regression. Their role may therefore be indirect: they help consumers form an impression of credibility, but do not necessarily produce a purchase once platform trust and usability are taken into account (Ali & Amir, 2024; Saxena & Thakur, 2024).

The second factor contained the main Technology Acceptance Model variables and had the clearest relationship with purchase intention. Platform trust was the strongest predictor, followed by ease of use and perceived usefulness. These results agree with Han et al. (2024) and with research showing that consumers prefer digital services that reduce effort and uncertainty. For Ecuadorian firms, the implication is concrete. A complicated checkout, unclear information, or weak security communication can offset the attention generated by advertising and social networks.The third factor combined anxiety, satisfaction, and herding. This finding shows that emotion and collective behavior are part of the same decision environment, although their direct effects differed. Post-purchase satisfaction increased purchase intention, while anxiety about personal data also showed a positive coefficient. The latter result should not be interpreted as anxiety encouraging purchase. A more plausible reading is that active online buyers can remain worried about data practices even while they continue to use digital platforms. Their concern coexists with purchase behavior rather than preventing it entirely.

Herding items had substantial factor loadings but no unique regression effect. Popularity and visible adoption appear to influence how consumers interpret a product, yet those cues may lose explanatory power once trust, ease of use, usefulness, and satisfaction are controlled. Chen (2025) similarly notes that social signals operate within a larger network of beliefs and contextual cues. The present results therefore caution against treating virality as a substitute for a reliable purchasing experience. The high correlations among the three factors also deserve attention. Consumers do not evaluate technology, emotion, and social information in isolation. A positive review may strengthen trust; a clear interface may reduce anxiety; a successful purchase may make social recommendations more credible. This interdependence explains why an oblique factor solution was more appropriate than a model that forced the dimensions to remain unrelated. The findings extend the use of the Technology Acceptance Model in a Latin American market while showing where it benefits from additional variables. Usefulness and ease of use remain powerful, but trust is not merely another platform attribute. It links technical design, perceived security, reputation, and previous experience. Emotional and social variables add context to that relationship, especially when the consumer has limited information or is considering an unfamiliar seller.

4.1 Study limitations

Several limitations affect the interpretation of the results. The convenience sample was large but not probabilistic, so the estimates cannot be generalized to every Ecuadorian online consumer with a known sampling error. The measures were self-reported and may reflect social desirability, memory, or individual interpretations of the items. The cross-sectional design does not establish causal direction. In addition, the model did not directly measure newer practices such as conversational AI, live commerce, or algorithmic personalization. Future studies should use probability-based or stratified samples, compare regions and age groups, and collect longitudinal or behavioral data alongside survey responses.

4.2 Practical implications

For e-commerce managers, the results place platform quality ahead of superficial popularity. Security indicators, transparent privacy explanations, clear prices, reliable payment options, and accessible return procedures should be visible at the point where consumers make decisions. These measures address the strongest predictor in the model: trust in the platform. Usability requires similar attention. Navigation, search, product comparison, and checkout should work consistently on mobile devices and under varying connection speeds. The effect of perceived usefulness suggests that platforms should also communicate the practical value they provide, such as time savings, product availability, delivery information, and after-sales support.

Social content remains useful when it supports credibility rather than replacing it. Reviews should be authentic, specific, and easy to verify. Influencer partnerships are more likely to help when the recommendation matches the product and the audience. Firms should also manage the post-purchase stage because satisfaction has a direct association with future intention. Clear confirmation messages, delivery tracking, responsive support, and straightforward complaint procedures can turn one transaction into a repeat relationship. Public policy can contribute by improving digital literacy, promoting understandable privacy practices, and supporting secure payment infrastructure. These actions are particularly relevant for consumers who have internet access but remain hesitant to transact online.

5. CONCLUSIONS

Digital purchase intention among the surveyed Ecuadorian consumers was best explained by three connected domains: trust and social influence, attitude toward the platform, and emotions and herding behavior. The statistical model showed that platform trust, ease of use, perceived usefulness, satisfaction, and concern about personal-data disclosure were the variables with significant direct effects. The results do not support a simple view in which social popularity automatically converts attention into sales. Reviews, influencers, social-media content, and herding were present in the factor structure, but most did not retain an independent effect in the regression. Their contribution appears to depend on the consumer's broader judgment of the platform and transaction.For businesses, the most effective priorities are therefore practical: trustworthy payment and data practices, clear navigation, useful platform functions, and consistent post-purchase service. For researchers, the findings support further integration of technology-acceptance models with emotional and social constructs. Longitudinal research and the inclusion of conversational AI, live commerce, and observed transaction data would help determine how these relationships change as Ecuador's digital market develops.

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