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ALGORITHMIC PERSUASION, TRUST EROSION, AND THE TRUST–BEHAVIOR GAP IN DIGITAL COMMERCE

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ABSTRACT

Algorithmic personalization shapes how consumers encounter persuasive messages in digital commerce. Platform success is often inferred from behavioral engagement metrics, treating continued engagement as indicating healthy platform-consumer relationships. Drawing on Persuasion Knowledge Theory and attribution theory, this study examines how consumers interpret algorithmic persuasion cues and their impact on trust and disengagement intentions. Survey data from 737 digital commerce users in India, analyzed through structural equation modeling, shows that perceived algorithmic manipulation predicts inferred manipulative intent, which erodes relational trust. Advertising skepticism weakens this relationship by attenuating the effect of inferred intent on trust erosion. Trust erosion does not predict platform disengagement intentions, revealing a trust-behavior gap in algorithmic environments. Continued engagement may coexist with declining relational evaluations, suggesting engagement metrics can mislead as indicators of communicative effectiveness. This study advances research on trust and algorithmic influence by reframing algorithmic persuasion as an interpretive process rather than purely behavioral.

Keywords: *Algorithmic Personalization, Digital Commerce Platforms, Consumer Trust, Persuasion Knowledge, Advertising Skepticism.*

1. INTRODUCTION

Algorithmic personalization has become a dominant mode of marketing communication in digital commerce, with platforms relying on recommendation systems, targeted messages, and behavioral nudges to shape consumer attention and engagement. Unlike traditional advertising, these persuasive cues are embedded within platform interfaces and delivered continuously, often without explicit disclosure, rendering persuasive intent less visible to consumers [1-2].

Existing research on algorithmic personalization has primarily focused on issues of privacy, transparency, fairness, and trust [3-4]. This literature often assumes that negative evaluations of algorithmic practices—such as perceived manipulation or declining trust—lead to avoidance, disengagement, or platform switching. However, accumulating evidence suggests that consumers frequently continue using digital platforms despite recognizing persuasive or self-serving algorithmic intent, challenging the assumed alignment between attitudes and behavior in algorithmically mediated environments [5-6].

From a marketing communication perspective, algorithmic personalization constitutes persuasive communication that consumers actively interpret rather than passively receive. Persuasion Knowledge Theory explains how consumers infer persuasive intent and evaluate communicator motives [7], while attribution theory explains how individuals infer intentionality behind observed actions under conditions of uncertainty [8]. These interpretive processes are particularly salient in algorithmic contexts, where persuasive intent is opaque and agency is attributed to automated systems rather than identifiable human communicators [6,9].

Importantly, continued platform engagement does not necessarily imply acceptance of algorithmic persuasion. Consumers may remain active due to habit, convenience, switching costs, or ecosystem dependence, even while holding critical evaluations of algorithmic communication practices [10]. This coexistence of skepticism and engagement reflects a trust–behavior gap, in which the erosion of relational trust does not automatically translate into disengagement. While related inconsistencies, such as the privacy paradox, have been documented, this

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trust–behavior gap in algorithmic persuasion contexts remains underexplored theoretically.

Prior studies largely conceptualize trust erosion as a behavioral antecedent, overlooking the possibility that trust erosion functions primarily as a psychological and relational evaluation rather than a direct trigger for disengagement in structurally embedded digital environments. Addressing this gap, the present study distinguishes among experiential evaluations of algorithmic behavior, attribution-based inferences of manipulative intent, and disengagement intentions to examine whether negative interpretations of algorithmic persuasion lead to behavioral withdrawal or coexist with continued engagement.

This study contributes to the literature in four ways. First, it recognizes that the process of perceived algorithmic manipulation is a sequential, but conceptually different, process for the consumer to interpret. Secondly, it is an extension of Persuasion Knowledge Theory in algorithmic communication environments. Third, it finds and empirically substantiates a trust erosion–disengagement gap, in which trust erosion doesn't always result in disengagement intentions. Third, it illustrates the flaws of engagement as a platform–consumer relationship measure.

While previous research has considered privacy issues, transparency, and trust in algorithmic settings, less has been focused on how consumers process algorithmic persuasion and its connections with behavioral withdrawal when they lack confidence in that persuasion. While previous research has considered privacy concerns, transparency, and trust in algorithmic settings, few has focused on how consumers process algorithmic persuasion and its connections with behavioral withdrawal when they lack confidence in that persuasion. Previous studies generally take the assumption that the relationship between trust and behavior is direct, neglecting the possibility that consumers might still use platforms even when they have a negative evaluation of the relationship. As a result, the psychological processes between algorithmic manipulation, manipulative intent, loss of trust and disengagement are still poorly understood.

The present study is situated in India, a context characterized by high algorithmic exposure, rapid digital platform adoption, and strong platform dependence across e-commerce and digital services, this study provides a theoretically relevant setting for examining trust–behavior decoupling beyond Western contexts. Accordingly, it investigates how perceived algorithmic manipulation shapes inferred manipulative intent, erosion of trust, and disengagement intentions, while accounting for individual differences in advertising skepticism. Specifically, the study addresses the following research questions:

RQ1: How does perceived algorithmic manipulation influence consumers' inferences of manipulative intent?
RQ2: How do such inferences contribute to erosion of relational trust toward digital commerce platforms?
RQ3: Does trust erosion translate into disengagement intentions or coexist with continued engagement?
RQ4: How does advertising skepticism moderate consumers' interpretive responses to algorithmic persuasion cues?

It is assumed that users have adequate exposure to algorithmically personalized shopping contexts and can make evaluations about the influence of the platform. The study focuses on self-reported perceptions and intentions of active digital commerce users in India and does not quantify actual outcomes of behaviors. Thus, the findings need to be understood in relation to the algorithm mediated consumer experience.

By jointly examining psychological and behavioral outcomes, the study advances marketing communication theory by extending persuasion knowledge to automated contexts and clarifying the limits of behavioral engagement as an indicator of communicative effectiveness.

2. LITERATURE REVIEW

Digital platforms increasingly shape user experiences through algorithmic personalization, targeted content delivery, and automated recommendation systems [11,6]. In marketing communication contexts, these systems' structure information exposure, embed persuasive cues, and influence how users interpret commercial messages [12-13]. While algorithmic personalization offers functional benefits, prior research has consistently linked it to concerns around autonomy, fairness, transparency, and trust, particularly when persuasive influence is perceived as opaque or self-serving [1,14,4].

Existing research has examined algorithmic personalization across domains such as privacy, system performance, and trust, yet these streams remain weakly integrated within a unified marketing communication framework explaining how users interpret algorithmic persuasion [15]. As a result, the psychological processes through which users infer persuasive intent and form relational trust judgments remain underdeveloped. Addressing this gap, the present review synthesizes prior research around five constructs central to algorithmic persuasion in marketing communication: perceived algorithmic manipulation (PAM), perceived manipulative intent (PMI), erosion of trust (EOT), platform disengagement intentions (PDI), and skepticism toward advertising (STA).

2.1 REVIEW OF KEY CONSTRUCTS

PAM refers to users' judgments about whether personalization enhances relevance or constrains autonomy by prioritizing platform objectives [16-17][9]. Prior research shows that highly precise recommendations, continuous behavioral monitoring, and opaque personalization practices can signal hidden influence and reduce perceived control [18-20].

PMI reflects beliefs that platforms deliberately deploy persuasive tactics to advance self-serving goals [21]. In algorithmic contexts lacking identifiable human persuaders, users infer intent from system outputs and recurring recommendation patterns [6]. Such attributional judgments have been linked to distrust, resistance, and psychological reactance [2,22]. To clarify the conceptual distinction between PAM and PMI, a theory-driven comparison is provided in (Table 1).

[Table 1 About Here]

Although PAM and PMI are empirically related, attribution theory suggests they represent distinct stages of consumer interpretation. PAM reflects experiential evaluations of observable algorithmic behavior, whereas PMI captures higher-order attributions of intentionality and motive underlying that behavior [23,8]. This distinction parallels established separations between behavioral evaluations and intent attributions in persuasion research and explains why high correlations are theoretically expected without implying conceptual redundancy [24].

EOT denotes declining confidence in a platform's integrity, benevolence, and fairness as a communication partner [25-26]. When users infer exploitative motives, relational trust is undermined through perceptions of opportunism and violations of autonomy [4].

PDI captures users' willingness to reduce interaction, limit exposure, or switch platforms [27]. However, prior research indicates that such intentions do not consistently translate into disengagement, as habit, convenience, and structural dependence often sustain continued exposure to marketing communications [28-29].

STA reflects a stable tendency to question persuasive messages and critically evaluate marketers' motives [15]. Higher skepticism is associated with greater persuasion knowledge and reduced emotional susceptibility to manipulative cues, whereas lower skepticism is linked to stronger affective reactions when manipulation is perceived [30,5].

2.2 Relationships among Constructs

Prior research indicates that perceptions of manipulation activate persuasion knowledge, increasing the likelihood that users interpret algorithmic communication as self-serving [9]. Such interpretations undermine relational trust by signaling perceived violations of fairness and communicative legitimacy [31,4]. However, EOT does not consistently result in disengagement, as continued exposure is often sustained by habit and convenience [28]. Within this process, STA is expected to moderate the relationship between PMI and EOT.

2.3 Comparative Analysis of Existing Studies

[Table 2 About Here]

Although prior research consistently associates algorithmic personalization with trust-related concerns, existing studies remain fragmented. Most investigations focus either on algorithmic transparency or trust outcomes without explaining the attributional processes through which users infer manipulative intent. Furthermore, dominant trust models assume that declining trust necessarily results in disengagement, an assumption that has received limited empirical scrutiny in highly embedded digital platform environments. These limitations indicate the need for a more integrated framework linking algorithmic evaluations, intent attributions, trust erosion, and behavioral responses.

2.4 Identification of Research Gaps

This study addresses three gaps in research on algorithmic persuasion. First, limited attention has been paid to how PAM is translated into inferred manipulative intent and subsequent erosion of relational trust in algorithmic communication

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contexts [9]. Second, although advertising skepticism is well established, its role as a boundary condition shaping trust erosion remains underexplored in algorithmic persuasion research [13,32]. Third, dominant trust models continue to assume that EOT leads to PDI, overlooking contexts in which exposure to marketing communication persists despite negative relational evaluations [28-29].

3. THEORETICAL FOUNDATION

This study is grounded primarily in Persuasion Knowledge Theory (PKT) [7], complemented by attribution theory [23,8] and research on the trust–behavior gap in digitally embedded environments [28-29]. Together, these perspectives explain how consumers interpret algorithmic personalization as persuasive communication, how inferred intent shapes relational trust evaluations, and why erosion of trust does not necessarily result in behavioral disengagement.

PKT posits that consumers actively interpret persuasion attempts by inferring the motives and intentions of the persuasion source rather than responding passively to influence cues [7]. Although originally developed for human persuaders, PKT is theoretically applicable to algorithmic contexts because consumers frequently perceive algorithmic systems as intentional and goal-directed actors rather than neutral technical tools. Research on human–algorithm interaction shows that users attribute agency, responsibility, and motive to algorithmic systems based on observable behaviors such as recommendation patterns, repeated nudges, and personalization intensity, even in the absence of identifiable human communicators [1][33-34].

In algorithmic environments, persuasion knowledge operates through attributional sensemaking, whereby users infer persuasive intent from system outputs and interaction experiences rather than from explicit communicative disclosures [13,9]. Within this process, PAM reflects experiential evaluations of observable algorithmic behavior, whereas PMI captures higher-order motivational attributions regarding why such behavior occurs. PMI thus represents an attributional elaboration of perceived manipulation rather than a redundant construct [24].

Attribution theory further explains how these motivational inferences translate into trust outcomes. When users infer that algorithmic personalization prioritizes platform interests over user welfare, they attribute opportunism and value misalignment to the platform, undermining expectations of benevolence, fairness, and integrity [8,4]. EOT is therefore conceptualized as a relational and psychological evaluation reflecting dissatisfaction with how persuasion is communicated, rather than as an immediate rejection of platform functionality.

Importantly, declining trust does not necessarily lead to behavioral withdrawal in algorithmically embedded environments. Prior research shows that continued platform engagement may persist despite trust erosion due to habit formation, convenience, switching costs, and ecosystem dependence [10,28]. In this study, these conditions are theorized as structural boundary conditions that may decouple trust evaluations from disengagement intentions, giving rise to a trust–behavior gap.

Integrating these perspectives, the study adopts a hierarchical framework that distinguishes experiential evaluations of algorithmic behavior, attribution-based inferences of persuasive intent, and relational trust outcomes, while treating behavioral disengagement as an empirical rather than assumed consequence of trust erosion (see Figure 1).

4. HYPOTHESES DEVELOPMENT

Algorithmic personalization introduces multiple interpretive layers between users and digital platforms by shaping information exposure, choice sets, and decision sequences [12]. Although personalization is often associated with greater relevance and efficiency, reduced transparency, limited controllability, and low predictability can create uncertainty regarding platform motives, fairness, and accountability [1,14,35]. Such uncertainty encourages users to actively interpret algorithmic behavior rather than passively accept system outputs, particularly when personalization appears intrusive, overly targeted, or misaligned with users' interests [33,18,20].

Building on PKT, attribution theory, and digital trust research, this study adopts a hierarchical framework distinguishing experiential evaluations of algorithmic behavior, motivational inferences, and relational and behavioral outcomes [7,23,8]. This framework explains how users interpret algorithmic personalization as persuasive communication, how such interpretations shape trust judgments, and whether EOT translates into PDI under conditions of digital reliance [10,28].

a) Perceived Algorithmic Manipulation and Erosion of Trust

Trust in digital platforms is grounded in expectations of transparency, benevolence, and respect for user autonomy [19,36]. When algorithmic personalization appears manipulative—through opaque recommendations, excessive targeting, or restricted choice sets—users may experience reduced perceptions of control and procedural fairness, weakening trust even in the absence of explicit intent attributions [31,35,21,1,4]. Therefore, the following hypothesis is proposed:

H1: Perceived algorithmic manipulation is positively associated with erosion of trust.

b) Perceived Algorithmic Manipulation and Manipulative Intent Attribution

According to PKT, individuals actively interpret persuasive cues to recognize influence attempts and infer underlying motives [7]. In algorithmically mediated environments, highly personalized recommendations, repeated nudges, and opaque targeting mechanisms function as cues that activate persuasion knowledge and prompt motivational inferences about platform intent [24,18,37,9,17]. Therefore, the following hypothesis is proposed:

H2: Perceived algorithmic manipulation is positively associated with perceived manipulative intent.

c) Direct Effect of Perceived Manipulative Intent on Erosion of Trust

Beyond evaluations of algorithmic functionality, PMI intent plays a central role in shaping trust judgments. When users believe that platforms deliberately deploy algorithmic tactics for self-serving or exploitative purposes, they reassess platform integrity and benevolence, directly eroding relational trust even when technical performance appears adequate [38-39,26]. Therefore, the following hypothesis is proposed:

H3: Perceived manipulative intent is positively associated with erosion of trust.

d) Mediating Role of Perceived Manipulative Intent

Integrating PKT and attribution theory, perceived manipulative intent represents a key psychological mechanism through which experiential evaluations of algorithmic behavior translate into EOT. Observable algorithmic cues give rise to motivational attributions, which intensify suspicion and perceived exploitation, weakening relational trust [23,8,24,22,6]. Therefore, the following hypothesis is proposed:

H4: Perceived manipulative intent mediates the relationship between perceived algorithmic manipulation and erosion of trust.

e) Moderating Role of Advertising Skepticism

STA reflects a stable tendency to question persuasive messages and critically evaluate marketers' motives [15]. Higher skepticism is associated with greater persuasion knowledge and coping capacity, enabling individuals to regulate emotional responses to inferred persuasion attempts, whereas lower skepticism amplifies trust erosion when manipulative intent is perceived [7,13,30,32, 5]. Therefore, the following hypothesis is proposed:

H5: Advertising skepticism moderates the relationship between perceived manipulative intent and erosion of trust, such that the relationship is weaker at higher levels of skepticism.

f) Trust Erosion and Platform Disengagement: A Diagnostic Perspective

Traditional trust models assume that EOT leads to behavioral withdrawal [36]. However, research in digitally embedded environments indicates that platform engagement may persist despite declining trust due to habit formation, convenience, switching costs, and network externalities [10,28,29]. Accordingly, this study adopts a diagnostic perspective to examine whether erosion of trust is associated with platform disengagement intentions. Therefore, the following hypothesis is proposed:

H6: Erosion of trust is associated with platform disengagement intentions.

g) Sequential Psychological–Behavioral Pathway

Drawing on PKT, attribution theory, and trust-violation perspectives, disengagement may unfold through a sequential psychological–behavioral process in which PAM activates PMI, contributes to EOT, and subsequently shapes PDI [7-8,28,40,20]. Therefore, the following hypothesis is proposed:

H7: Perceived algorithmic manipulation is indirectly associated with platform disengagement intentions through perceived manipulative intent and erosion of trust in sequence.

[Figure 1 About Here]

5. MATERIAL AND METHODS

5.1 Sample

The study followed institutional ethical guidelines for human research. Participation was voluntary with informed consent obtained before surveys; responses were anonymous without personal identifiers. Data were stored securely, accessed only by researchers, and used for academic purposes. Participants could withdraw anytime, and the Ethics Committee approved the protocol.

A cross-sectional, descriptive design examined perceptions of algorithmic personalization among digital platform users, assessing whether trust erosion affects engagement under platform reliance. Data were collected across India via online questionnaires distributed through social media, email, and messaging apps. India was chosen for its high algorithmic exposure and digital platform dependence. The survey was conducted via Google Forms between May-September 2025, following a pilot study from February-May 2024. Of 764 responses, 737 were retained after screening. Non-response bias assessment showed no significant differences [41]. While non-probability sampling is well-suited to examining perceptual processes among active digital users, findings should be interpreted cautiously with respect to broader generalizability. Structural equation modeling employed a partial least squares approach (PLS-SEM) with SmartPLS, which is appropriate for mediation, moderation, and prediction with non-normally distributed data [42].

The study employed a sequential method comprising the following stages: (1) literature study and identification of constructs, (2) development of the questionnaire and adaptation of the items from the existing scales, (3) pilot testing of the questionnaire and refining the items, (4) online data collection, (5) data screening and cleaning, (6) test of the reliability and validity of the questionnaire, (7) estimation of the measurement model, (8) test of the structural model (PLS-SEM), and (9) evaluation of the hypotheses and interpretation.

5.2 Demographic Profile of The Respondents

The respondents consist of 411 males (55.80%) and 326 females (44.20%). The respondents' demographic information is presented in Table 3.

[Table 3 About Here]

5.3 Measures

All constructs were evaluated using a five-point Likert scale [‘5’ = strongly agree; ‘1’ = strongly disagree]. The indicators for these constructs were adapted and modified from established sources in the literature. Although some constructs included multiple indicators to capture nuanced perceptions, item retention was based on theory rather than fit, and no items were removed to improve model fit. All constructs and indicators are listed in (Table 4).

[Table 4 About Here]

5.4 Descriptive Statistics: Means, Standard Deviation, and Zero-Order Correlation

Descriptive statistics indicate moderate perceptions of EOT ($M = 2.93$, $SD = 0.59$), PAM ($M = 2.98$, $SD = 0.54$), and PMI ($M = 2.91$, $SD = 0.59$). Zero-order correlations show strong positive associations between EOT and PMI ($r = 0.726$) and PAM ($r = 0.673$), as well as between PAM and PMI ($r = 0.735$). Given the high correlation between PAM and PMI, alternative specifications such as higher-order or bifactor models were considered. However, consistent with attribution theory and research on persuasion knowledge, the constructs were retained as sequential yet conceptually distinct. In contrast, PDI shows weak and non-significant correlations with EOT ($r = -0.059$), PAM ($r = -0.028$), and PMI ($r = -0.052$), indicating a trust–behavior gap. Descriptive statistics and zero-order correlations are reported in Table 5, providing foundational evidence for construct relationships before multivariate analysis [43].

[Table 5 About Here]

5.5 Measurement Model Assessment

The measurement model was assessed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS. Indicator reliability was evaluated through standardized outer loadings exceeding 0.70. Internal consistency reliability was confirmed with composite reliability (CR) values above 0.70. Convergent validity was established as average variance extracted (AVE) values exceeded 0.50 for all constructs [44,42]. All indicators were retained on the basis of theoretical relevance.

Discriminant validity was assessed using the Fornell–Larcker criterion and heterotrait–monotrait ratio (HTMT). The square roots of AVE for each construct exceeded inter-construct correlations, satisfying the Fornell–Larcker criterion. While PAM and PMI are strongly correlated, their diagonal AVE values exceed shared variance. All HTMT values were below 0.85, with the highest value for PAM-PMI within acceptable limits [42]. The detailed HTMT were presented in (Table 6).

[Table 6 About Here]

Collinearity diagnostics indicated VIF values ranging from 1.000 to 2.183, which are below the threshold of 3.3 [45]. The standardized root mean square residual (SRMR) was 0.027, indicating acceptable model fit. Model evaluation emphasized measurement quality over global goodness-of-fit indices [42]. Bayesian Information Criterion (BIC) values are reported but not interpreted.

5.6 Common Method Bias (CMB)

Given the use of self-reported survey data, potential common method bias (CMB) was assessed using procedural and statistical remedies for PLS-SEM. Procedurally, anonymity was assured, items were refined through pilots, and item order was counterbalanced to reduce response bias. Harman's single-factor test indicated that a single factor accounted for 33.17% of the total variance, which is below the 50% threshold, suggesting that CMB is unlikely to be concerning. Although Harman's test has limitations, it serves as an initial screening tool [46]. A full collinearity assessment showed that all within-group VIF values were below 3.3, indicating that common method bias is unlikely to affect the relationships [45]. These checks suggest that common method bias does not significantly threaten the validity of the findings.

6. DATA ANALYSIS AND HYPOTHESIS TESTING

We used partial least squares structural equation modeling (PLS-SEM) to evaluate both the measurement and structural models, given its suitability for moderation analysis and prediction-oriented research. The results of the structural model are reported in (Table 7).

[Table 7 About Here]

Prior to estimating the structural model, a hierarchical regression analysis was conducted to assess the influence of demographic control variables on erosion of trust and platform disengagement intentions. As none of the control variables showed significant effects, they were excluded from the final model to preserve parsimony.

6.1 Direct Effects (Structural Relationships)

The structural model results support the proposed psychological relationships among the focal constructs. PAM is significantly positively associated with EOT ($\beta = 0.316$, $p < .001$), supporting H1. It also exhibits a strong positive association with PMI ($\beta = 0.734$, $p < .001$), supporting H2. In turn, PMI significantly predicts EOT ($\beta = 0.491$, $p < .001$), supporting H3. Collectively, these results indicate that algorithmic cues are associated with both direct and attribution-based sequential process through which trust erosion occurs.

6.2 Mediation Effects

Mediation analysis indicates that PMI significantly mediates the relationship between PAM and EOT ($\beta = 0.360$, $p < .001$), supporting H4. This finding suggests that motivational attribution constitutes an important psychological mechanism through which users interpret algorithmic manipulation and form negative trust judgments.

6.3 Moderation Effect

The interaction between STA and PMI is statistically significant ($\beta = -0.047$, $p = .045$), supporting H5. The negative interaction coefficient indicates that higher levels of skepticism weaken the positive association between PMI and EOT, suggesting that inferred manipulative motives exert a reduced emotional impact among more skeptical users. The interaction graph is shown in (Figure 4).

[Figure 4 About Here]

6.4 Behavioral Outcomes and Sequential Mediation

In contrast to the strong psychological relationships, the EOT does not significantly predict PDI ($\beta = -0.053$, $p = .144$), providing no support for H6. Consistent with this pattern, the sequential indirect effect of PAM → PMI → EOT → PDI is not statistically significant ($\beta = -0.019$, $p = .152$), providing no support for H7. These findings indicate that EOT does not necessarily translate into behavioral withdrawal in algorithmically embedded platform contexts.

6.5 Conditional Indirect Effects

Conditional process analysis shows that the indirect effect of PAM on EOT through PMI remains significant across low (−1 SD), mean, and high (+1 SD) levels of STA ($\beta = 0.325$ to 0.395, $p < .001$).

However, none of the conditional indirect effects leading to PDI reach statistical significance across levels of skepticism ($p > .15$). This pattern indicates that skepticism moderates psychological trust responses but does not alter the absence of behavioral disengagement.

The standardized structural model is illustrated in (Figure 2), and (Figure 3) illustrates the Structural and Conditional Process Model.

[Figure 2 & 3 About Here]

6.6 Explained Variance, Predictive Relevance, And Effect Sizes

[Insert Table 8 About Here]

In Table 8, the model accounts for substantial variance in EOT ($R^2 = 0.601$) and PMI ($R^2 = 0.540$), exceeding commonly cited thresholds for moderate explanatory power, yet explains negligible variance in PDI ($R^2 = 0.003$) [42]. Predictive relevance assessments further indicate strong in-sample prediction for EOT ($Q^2 = 0.422$) and PMI ($Q^2 = 0.361$), but minimal predictive relevance for PDI ($Q^2 = 0.002$), suggesting that the model captures psychological responses more effectively than behavioral outcomes [42].

Out-of-sample predictive assessment shows lower prediction errors for EOT (RMSE = 0.721; MAE = 0.571) and PMI (RMSE = 0.682; MAE = 0.542) than for PDI (RMSE = 1.003; MAE = 0.840), further indicating weaker behavioral predictability. Overall, these results suggest strong effects for psychological constructs and limited explanatory power for disengagement outcomes, consistent with prior research on trust–behavior divergence in digital platforms [36,10].

6.7 Predictive Assessment

[Table 9 About Here]

In Table 9, PLS predict results indicate that the model predicts EOT and PMI more accurately than the indicator-average benchmark EOT ($\Delta = -0.171$, $p < .001$), PMI ($\Delta = -0.156$, $p < .001$), whereas predictions for PDI do not differ from the benchmark ($\Delta = 0.001$, $p = .732$), reflecting limited behavioral predictability [42].

[Figure 5 About Here]

Consistent with these findings, the importance–performance map analysis, as shown in (Figure 5), identifies PAM as the most influential predictor of EOT, followed by PMI, whereas STA is of lower relative importance [36]. Overall, the results indicate that algorithmic and attributional mechanisms explain trust erosion but do not account for disengagement intentions, highlighting a persistent trust–behavior divergence in digital platform use [36,10].

7. DISCUSSION

This study examined algorithmic personalization as a form of marketing communication in digital commerce platforms. It explored how consumers interpret algorithmic persuasion cues and how these interpretations shape their evaluations of platforms. Drawing on PKT and attribution theory, the findings challenge the common assumption that negative evaluations of algorithmic practices lead to disengagement. Instead, algorithmic persuasion mainly affects how users perceive platforms at a relational level, not whether they stop using them.

Consistent with PKT, consumers do not passively accept algorithmic personalization. They actively interpret it as persuasive communication. Repeated recommendations, opaque targeting, and behavioral nudging function as cues that invite inferences of persuasive intent [1-2]. When these cues are perceived as intrusive or misaligned with users' interests, they are associated with stronger attributions of manipulative intent and greater erosion of trust. This supports prior research showing that consumers evaluate communicator motives even when persuasion originates from algorithmic systems rather than identifiable human agents [24,9].

The strong relationship between perceived algorithmic manipulation (PAM) and perceived manipulative intent (PMI) highlights the attributional nature of consumer sensemaking in opaque algorithmic environments. PMI does not represent a separate cognitive stage. Instead, it reflects an attributional elaboration of users' experiential evaluations of algorithmic behavior [23, 8]. Trust erosion is therefore driven less by technical system features and more by inferred platform motives and perceived misalignment of value.

Mediation results show that PMI is the key psychological mechanism linking PAM to erosion of trust (EOT). These findings extend PKT to automated and continuous persuasion contexts by demonstrating that persuasion knowledge operates primarily as an interpretive sensemaking process rather than as a direct trigger of resistance or avoidance [47,11]. Advertising skepticism moderates this process by weakening the effect of inferred manipulative intent on trust erosion. This suggests that skeptical consumers regulate emotional trust responses more effectively [48]. Although modest, this effect is theoretically meaningful, with skepticism acting as an emotional buffer rather than a driver of disengagement.

Despite strong psychological effects, trust erosion does not predict disengagement. It also does not mediate the relationship between algorithmic manipulation and behavioral withdrawal. This reveals a trust–behavior decoupling among active users and challenges dominant trust models that assume declining trust leads to exit [36]. Continued engagement appears sustained by habit, convenience, switching costs, and ecosystem dependence [10,28]. These forces are especially salient in the Indian digital commerce context, where everyday consumption is embedded within dominant platforms. Since disengagement was measured as intention, behavioral inertia may be even stronger than observed.

Overall, the findings show that algorithmic persuasion reshapes relational evaluations even when observable behavior remains unchanged. This underscores the limits of engagement metrics as indicators of relational health and ethical marketing communication.

8. THEORETICAL CONTRIBUTIONS

This study makes three interrelated theoretical contributions to marketing communication and digital trust research by directly addressing the gaps identified in Section 2.3 and by reframing how outcomes of algorithmic persuasion are theorized in digitally embedded environments.

8.1 Distinguishing Algorithmic Experience from Intent Attribution

First, the study advances research on algorithmic persuasion by empirically and conceptually distinguishing PAM from PMI. While prior studies often treat perceptions of algorithmic influence as a unified construct, the findings show that experiential evaluations of observable algorithmic behavior and attribution-based inferences regarding platform motives constitute analytically distinct yet sequential psychological processes [7,23,8]. Consistent with persuasion knowledge research, evaluations of algorithmic cues activate motivational attributions that subsequently intensify erosion of relational trust [24,9]. By clarifying this distinction, the study extends persuasion knowledge theory to algorithmic communication contexts and demonstrates that trust erosion arises through layered interpretive sensemaking rather than through direct stimulus–response effects.

8.2 Advertising Skepticism as an Interpretive Boundary Condition

Second, the study refines persuasion knowledge research by identifying advertising skepticism as an interpretive boundary condition that shapes how inferred manipulative intent translates into trust erosion. Although skepticism has been extensively examined in traditional advertising contexts [15], its role in algorithmic persuasion remains underexplored [13]. The findings indicate that skepticism does not prevent users from inferring manipulative intent but attenuates the relational impact of such inferences on trust erosion. This suggests that persuasion knowledge in algorithmic environments primarily functions as an emotional regulation and interpretive coping mechanism rather than as a trigger for behavioral resistance [7,32,8].

8.3 Reinterpreting Engagement Metrics Through the Trust–Behavior Gap

Third, and most importantly, this study contributes to marketing communication theory by reinterpreting behavioral engagement metrics through the lens of the trust–behavior gap. Contrary to dominant trust models that assume erosion of trust leads to behavioral withdrawal [36], the findings demonstrate that EOT does not reliably predict PDI among active users. Despite strong psychological effects of perceived manipulation and inferred intent on relational trust, behavioral engagement remains largely unaffected. This decoupling aligns with emerging evidence that continued platform use may be sustained by habit, convenience, switching costs, and structural dependence rather than by communicative legitimacy or relational trust [10,28-29]. By empirically demonstrating that behavioral persistence can coexist with relational erosion, the study challenges the assumption that engagement metrics serve as valid indicators of healthy platform–consumer relationships and calls for greater theoretical emphasis on relational and interpretive outcomes in evaluating algorithmic marketing communication.

9. PRACTICAL IMPLICATIONS

The findings suggest that platform managers should not equate sustained user engagement with relational trust or communicative legitimacy. Algorithmic personalization can preserve usage while simultaneously eroding trust, implying that reliance on engagement metrics alone may obscure emerging reputational and regulatory risks. Managers should therefore complement behavioral indicators with measures of perceived manipulation, inferred intent, and relational trust when evaluating algorithmic marketing effectiveness.

From a design perspective, reducing perceptions of manipulative intent requires more than improving personalization accuracy or transparency disclosures. Platforms can enhance user agency by enabling preference reversibility through features such as resetting recommendation histories, pausing personalization, or adjusting recommendation intensity without penalty. Such controls signal respect for autonomy and benevolent intent, mitigating trust erosion even when personalization remains active.

Ethical algorithmic persuasion should focus on proportional and user-aligned influence rather than short-term optimization. Limiting exploitative nudging, avoiding artificially induced scarcity cues, and aligning recommendation objectives with user welfare can help sustain long-term relational trust. Overall, platforms that prioritize relational outcomes alongside engagement are better positioned to achieve durable legitimacy in algorithmically mediated markets.

10. CONCLUSION

The study introduces algorithmic commerce contexts and extends PKT to such contexts and provides empirical evidence for a lack of trust–behaviour link in the algorithmic commerce domain. The results show that behavioral engagement can last despite a decrease in trust, an assumption commonly made about engagement measures reflecting the quality of relationship. In today's digital landscape, where algorithmic personalization is a growing feature of consumer experience and decisions about the governance of platforms, these findings are of special significance.

This study examined algorithmic personalization as marketing communication by distinguishing experiential evaluations of algorithmic behavior, attribution-based inferences of persuasive intent, and their relational and behavioral consequences. The findings show that PAM leads consumers to infer PMI, which erodes relational trust in digital platforms. However, trust erosion does not translate into disengagement intentions among active users, revealing a trust–behavior gap in algorithmically embedded environments. Continued platform use appears sustained by habit, convenience, switching costs, and structural dependence rather than by trust or perceived communicative legitimacy. By demonstrating that behavioral persistence can coexist with relational erosion, the study challenges the assumption that engagement metrics reliably indicate healthy platform–consumer relationships. Overall, the findings suggest that algorithmic persuasion may preserve usage while undermining relational trust, underscoring the need for marketing communication research to evaluate relational and interpretive outcomes alongside behavioral indicators when assessing the effectiveness and legitimacy of algorithmic influence.

The main contribution of this study is that it shows that algorithmic mediated spaces can experience both trust loss and engagement in behavior. The study expands the PKT theory to digital commerce and uncovers that consumers actively attribute meaning to the algorithmic influence. The results indicate that a platform's effectiveness is more likely to be determined by a combination of engagement measures, as firms increasingly see the market as digital, and in such a context, behavioral metrics might not be sufficient to assess the quality of consumers' relationships with the platform. The findings have significant implications for platform governance, ethical practices of personalisation, and discussions of regulatory transparency for algorithms.

11. LIMITATIONS AND FUTURE RESEARCH

This study relies on cross-sectional self-report data from a single national context, limiting causal inference and generalizability. The strong association between perceived algorithmic manipulation and perceived manipulative intent may partly reflect respondents' tendency to conflate evaluations of algorithmic behavior with motive attributions in opaque algorithmic environments.

In addition, disengagement was measured as intention rather than observed behavior. Given habit, convenience, and structural dependence, the absence of a trust–disengagement relationship should be interpreted as psychological–behavioral decoupling rather than definitive behavioral effects. Future research could use longitudinal or experimental designs to disentangle behavioral evaluations from motive attributions, examine boundary conditions such as switching costs and digital literacy, and extend the framework to emerging algorithmic systems, including generative AI, across diverse platform contexts.

Ethical Statement

This study involved an anonymous, non-invasive questionnaire survey of adult participants and did not involve any deception, clinical intervention, or collection of sensitive personal data. As per the institutional research ethics guidelines of SRM Institute of Science and Technology, formal Institutional Review Board approval is not required for such minimal-risk social science research. The study adhered to established ethical principles, including voluntary participation, informed consent, the right to withdraw, and protection of participant anonymity and confidentiality.

Funding Statement

The authors received no specific funding for this work.

Conflict of Interest Statement

The authors declare no conflict of interest.

Data Availability Statement

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Use of AI Tools

Generative artificial intelligence tools were employed solely to enhance language clarity, grammar, and readability of the manuscript. Research design, hypothesis development, data collection, data analysis, and interpretation of results were not conducted using any AI tools. The authors accept full responsibility for the manuscript.

REFERENCES

[1] Burrell J. How the Machine "thinks": Understanding Opacity in Machine Learning Algorithms. Big Data & Society. 2016 Jan 5;3(1):1–12.
[2] Cotte J, Coulter RA, Moore M. Enhancing or disrupting guilt: the role of ad credibility and perceived manipulative intent. Journal of Business Research. 2005 Mar;58(3):361–8.
[3] Jean Michel Sahut, Laroche M, Braune E. Antecedents and consequences of fake reviews in a marketing approach: An overview and synthesis. Journal of Business Research. 2024 Feb 1;175:114572–2.
[4] Schilke O, Reimann M. The transparency dilemma: How AI disclosure erodes trust. Organizational Behavior and Human Decision Processes. 2025 May;188:104405.
[5] Song Q, Guo Y, Ren Q, Ren Y, Lv H, Ma R, et al. Energizing, yet tiring: The dual impact of felt trust on employee creativity and work-to-family conflict. Journal of Business Research. 2025 Mar;190:115242.
[6] Wang X, Fu J, Tian Y, Chen H. Does food recall strategy have a positive or negative effect on trust repair? Moderation analysis based on trust violation types and trust disposition. China Economic Review. 2025 Dec;94:102512.
[7] Friestad M, Wright P. The persuasion knowledge model: How people cope with persuasion attempts. Journal of Consumer Research. 1994 Jun;21(1):1–31.
[8] Kelley HH. The processes of causal attribution. American Psychologist. 1973;28(2):107–28.
[9] Liu D, Wang H, Zhu Y. You plan to manipulate me: A persuasion knowledge perspective for understanding the effects of AI-assisted selling. Journal of Business Research. 2025 Jul 15;200:115598–8.
[10] Oestreicher-Singer G, Zalmanson L. Content or Community? A Digital Business Strategy for Content Providers in the Social Age. MIS Quarterly. 2013 Feb 2;37(2):591–616.
[11] Rhee CE, Choi J. Effects of personalization and social role in voice shopping: An experimental study on product recommendation by a conversational voice agent. Computers in Human Behavior. 2020 Aug;109:106359.
[12] Gouthier MHJ, Nennstiel C, Kern N, Wendel L. The more the better? Data disclosure between the conflicting priorities of privacy concerns, information sensitivity and personalization in e-commerce. Journal of Business Research. 2022 Sep;148:174–89.
[13] Ham CD, Nelson MR. The role of persuasion knowledge, assessment of benefit and harm, and third-person perception in coping with online behavioral advertising. Computers in Human Behavior. 2016 Sep;62:689–702.
[14] Mittelstadt BD, Allo P, Taddeo M, Wachter S, Floridi L. The Ethics of algorithms: Mapping the Debate. Big Data & Society. 2016 Dec;3(2):1–21.
[15] Obermiller C, Spangenberg ER. Development of a Scale to Measure Consumer Skepticism Toward Advertising. Journal of Consumer Psychology. 1998 Jan;7(2):159–86.
[16] Choi S, Song M, Jing L. Let your algorithm shine: The impact of algorithmic cues on consumer perceptions of price discrimination. Tourism Management. 2023 Dec 1;99:104792.

[17] Kim T, Im I. Understanding users' AI manipulation intention: An empirical investigation of the antecedents in the context of AI recommendation algorithms. Information & Management. 2025 Jan;62(1):104061.
[18] Boerman SC, Kruikemeier S, Bol N. When is personalized advertising crossing personal boundaries? How type of information, data sharing, and personalized pricing influence consumer perceptions of personalized advertising. Computers in Human Behavior Reports. 2021 Aug;4(4):100144.
[19] Micu A, Capatina A, Cristea DS, Munteanu D, Micu AE, Sarpe DA. Assessing an on-site customer profiling and hyper-personalization system prototype based on a deep learning approach. Technological Forecasting and Social Change. 2022 Jan;174:121289.
[20] Paliński M, Jusypenko B, Hardy W. Behind the screens. Privacy and advertising preferences in VoD —the role of privacy concerns, persuasion knowledge, and experience. Journal of Retailing and Consumer Services. 2025 Feb 1;84:104233.
[21] Arango-Kure M, Garz M. Manipulation: An integrative framework of unethical influence in marketing. Journal of Business Research. 2025 May 20;197:115476.
[22] Mucundorfeanu M, Balaban DC. Suspicious minds: Adolescents' inferences of manipulative intent in retouched influencer ads. PubMed. 2025 Oct 20;261:105780–0.
[23] Heider F. The psychology of interpersonal relations. Hoboken: John Wiley & Sons Inc; 1958.
[24] Campbell MC, Kirmani A. Consumers' Use of Persuasion Knowledge: The Effects of Accessibility and Cognitive Capacity on Perceptions of an Influence Agent. Journal of Consumer Research. 2000 Jun;27(1):69–83.
[25] McKnight DH, Choudhury V, Kacmar C. Developing and Validating Trust Measures for e-Commerce: An Integrative Typology. Information Systems Research. 2002 Sep;13(3):334–59.
[26] Ahn J, Kim S. Do Digital platform's Unethical Behaviors Influence users' Trust and Intention to Use Alternative platforms? Telecommunications Policy. 2025 May 16;102996.
[27] Tonta KE, Howell JA, Hasking PA, Boyes ME, Clarke PJF. Attention biases in perfectionism: Biased disengagement of attention from emotionally negative stimuli. Journal of Behavior Therapy and Experimental Psychiatry. 2019 Sep;64:72–9.
[28] Sultan P, Tarafder T, Pearson D, Henryks J. Intention-behaviour gap and perceived behavioural control-behaviour gap in theory of planned behaviour: moderating roles of communication, satisfaction and trust in organic food consumption. Food Quality and Preference. 2020 Apr;81(81):103838.
[29] Willekens M, Siongers J, Lievens J. Social stratification and social media disengagement. The effect of economic, cultural and social capital on reasons for non-use of social media platforms. Poetics. 2022 Jul;95:101708.
[30] Raziq MM, Ahmed QM, Ahmad M, Yusaf S, Sajjad A, Waheed S. Advertising skepticism, need for cognition and consumers' attitudes. Marketing Intelligence & Planning. 2018 Sep 3;36(6):678–93.
[31] Lankton NK, McKnight DH, Tripp J. Technology, Humanness, and Trust: Rethinking Trust in Technology. AIS Electronic Library (AISeL). 2015.
[32] Huang Y, Liu L. The impact of algorithm awareness on the acceptance of personalized social media content recommendation based on the technology acceptance model. Acta Psychologica. 2025 Aug 8;259:105383.
[33] Eslami M, Krishna Kumaran SR, Sandvig C, Karahalios K. Communicating Algorithmic Process in Online Behavioral Advertising. Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. 2018 Apr 21;
[34] Claure H, Kim S, Kizilcec R, Jung M. The social consequences of machine allocation behavior: Fairness, interpersonal perceptions and performance. Computers in Human Behavior. 2022 Dec;107628.
[35] Shin D, Park YJ. Role of fairness, accountability, and transparency in algorithmic affordance. Computers in Human Behavior. 2019 Sep;98(98):277–84.
[36] Gefen D, Karahanna E, Straub DW. Trust and TAM in Online shopping: an Integrated Model. MIS Quarterly. 2003;27(1):51–90.
[37] Simon F. Consumer adoption of No Junk Mail stickers: An extended planned behavior model assessing the respective role of store flyer attachment and perceived intrusiveness. Journal of Retailing and Consumer Services. 2016 Mar;29:12–21.
[38] Chi OH, Jia S, Li Y, Gursoy D. Developing a formative scale to measure consumers' trust toward interaction with artificially intelligent (AI) social robots in service delivery.

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Computers in Human Behavior. 2021 May;118:106700.
[39] Lambrecht A, Tucker C. Algorithmic Bias? An Empirical Study of Apparent Gender-Based Discrimination in the Display of STEM Career Ads. Management Science. 2019 Apr 10;65(7):2966–81.
[40] Quan S. Socioeconomic status and prosocial behaviors among Chinese emerging adults: Sequential mediators of parental warmth and personal belief in a just world. Children and Youth Services Review. 2020 Nov;105680.
[41] Armstrong JS, Overton TS. Estimating Nonresponse Bias in Mail Surveys. Journal of Marketing Research. 1977 Aug;14(3):396–402.
[42] Hair JF, Black WC, Babin BJ, Anderson RE. Multivariate data analysis. 8th ed. Boston: Cengage Learning; 2019. - Bing. Bing. 2019.
[43] Ne A, Ts S, Pearce J, Porter L, Hite P. CHOICE OF EMPLOYEE-ORGANIZATION RE LA Tl ON SH IP: I NFL UE NCE OF EXTERNAL AND INTERNAL ORGANIZATIONAL FACTORS.
[44] Fornell C, Larcker DF. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research. 1981 Feb;18(1):39–50.
[45] Kock N. Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration. 2015 Oct;11(4):1–10.
[46] Howard MC, Boudreaux M, Oglesby M. Can Harman's single-factor test reliably distinguish between research designs? Not in published management studies. European Journal of Work and Organizational Psychology. 2024 Aug 27;1–15.
[47] Fayyaz MS, Abbasi AZ, Kumar S, Qureshi A, Hussain K, Muhammad L. Integrating digital influencer persuasion model and theory of planned behavior: The mediating role of consumer involvement in endorsed brands. Journal of Retailing and Consumer Services. 2025 Apr 23;85:104309.
[48] Maddaloni FD, Meira LH, de Andrade MO, de Melo IR, Castro A, Locatelli G. The dark legacy of megaprojects: A case of local disengagement, missed opportunities, and social value dissipation. International Journal of Project Management. 2025 Jan 23;43(1):102676.

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Table 1. Conceptual distinction between PAM and PMI

Dimension	Perceived Algorithmic Manipulation (PAM)	Perceived Manipulative Intent (PMI)
Conceptual focus	Evaluation of observable algorithmic behavior	Attribution of underlying motive or intent
Theoretical basis	Experiential evaluation; early-stage persuasion knowledge	Attribution theory; motivational inference
Core question answered	*"What is the algorithm doing to me?"*	*"Why is the algorithm doing this?"*
Nature of judgment	Descriptive and experiential	Interpretive and inferential
Level of abstraction	Lower-order, surface-level evaluation	Higher-order, relational evaluation
Temporal position	Immediate response to system outputs	Subsequent elaboration based on interpretation
Source of inference	System features (e.g., targeting intensity, nudges, opacity)	Inferred platform goals (e.g., self-interest, exploitation)
Dependence on attribution	Not necessarily attribution-based	Explicitly attribution-based
Relation to trust	Can weaken trust through perceived loss of control or fairness	Directly erodes trust through perceived opportunism and value misalignment
Expected correlation	High (shared stimulus)	High (attributional elaboration), but conceptually distinct
Key theoretical anchors	Persuasion Knowledge Theory [18]	Attribution theory [25,30]
Illustrative example	"The app keeps pushing the same products at me."	"The app is doing this to manipulate me into spending more."

Table 2: Positioning of the Present Study Within Existing Literature

Study	Strength	Limitation	Contribution of Present Study
Ham & Nelson [21]	Examined algorithmic persuasion awareness	Did not investigate trust erosion	Introduces trust erosion mechanism
Liu et al. [35]	Focused on manipulative intent	No behavioral outcome examined	Tests trust–behavior relationship
Schilke & Reimann [48]	Strong trust perspective	Attribution mechanism absent	Integrates attribution theory
Sultan et al. [52]	Demonstrated platform dependence	No algorithmic persuasion focus	Explains trust–behavior gap

Table 3: Demographic Profile of the respondent

Variable	Category	Frequency	Percent
Gender	Male	411	55.8
	Female	326	44.2
Age	25–29	310	42.1
	30–34	263	35.7
	35–40	164	22.3
Educational Status	UG	227	30.8
	PG	243	33.0
	MPhil	101	13.7
	PhD	53	7.2
	Professional	92	12.5
	Others	21	2.8
Occupation	Student	85	11.5
	Private Employee	442	60.0
	Public Employee	85	11.5
	Homemaker	58	7.9
	Self Employee	67	9.1
Annual Income	< ₹250000	159	21.6
	₹250000–₹499999	236	32.0
	₹500000–₹749999	156	21.2
	₹750000–₹999999	104	14.1
	> ₹1000000	82	11.1
Frequency of Online Shopping	< Once a month	93	12.6
	1–2 times a month	232	31.5
	3–5 times a month	248	33.6
	> 5 times a month	164	22.3
Social Apps Usage per Day	< 1 hour	100	13.6
	2–3 hours	233	31.6
	3 hours	225	30.5
	3–4 hours	111	15.1
	> 5 hours	68	9.2
Platform Used for Shopping	Amazon	345	46.8
	Flipkart	183	24.8
	Myntra	111	15.1
	Ajio	39	5.3
	Meesho	37	5.0
	Nykaa	17	2.3
	Tata Cliq	5	0.7

Source: The Author's work

Table 4: Measurement Model: Reliability And Validity Results

Construct and Indicator	Factor Loading (λ)	Indicator Variance (λ²)	Error Variance (1–λ²)	VIF	Cronbach's Alpha (α)	Composite Reliability (CR)	AVE
Perceived Algorithmic Manipulation [5][21]					0.951	0.958	0.696
The shopping app I use most often appears to recommend specific products.	0.856	0.733	0.267	3.074			

It feels like the app uses my data to influence my choices.	0.839	0.704	0.296	2.778			
The product suggestions shown by the app seem engineered to steer my decisions.	0.828	0.686	0.314	2.631			
The app monitors my activity to manipulate what I see.	0.838	0.702	0.298	2.753			
Sometimes I feel controlled by the app’s recommendation system.	0.826	0.682	0.318	2.570			
The app often shows options that benefit it more than me.	0.830	0.689	0.311	2.651			
The app arranges products in a way that appears designed to influence my choices.	0.830	0.689	0.311	2.642			
Messages such as “limited stock” or countdown timers in the app appear artificial.	0.827	0.684	0.316	2.599			
The app’s algorithm feels intrusive and overly persuasive.	0.838	0.702	0.298	2.763			
The shopping app I use most often uses methods that manipulate my buying behavior.	0.829	0.687	0.313	2.598			
Perceived Manipulative Intent [9][14]					0.940	0.949	0.676
I believe the shopping app I use most often tries to manipulate my decisions.	0.827	0.684	0.316	2.539			
This app seems more focused on making me spend than helping me.	0.827	0.684	0.316	2.582			
The app employs techniques that appear to exploit users.	0.821	0.674	0.326	2.460			
Some of the app’s tactics feel ethically questionable.	0.811	0.658	0.342	2.355			
The app prioritizes profits over user well-being.	0.822	0.676	0.324	2.486			
The shopping app I use most often structures information to influence choices.	0.833	0.694	0.306	2.630			
I sometimes feel tricked by the app’s promotional strategies.	0.810	0.656	0.344	2.337			
The app’s practices appear manipulative and self-serving.	0.822	0.676	0.324	2.492			
Overall, I feel that the shopping app I use most often has manipulative intentions.	0.828	0.686	0.314	2.549			
Erosion of Trust in the Shopping App [29]					0.949	0.956	0.709
My trust in the shopping app I use most often has decreased over time.	0.857	0.734	0.266	3.011			
I feel less confident that this app is fair.	0.818	0.669	0.331	2.483			
I doubt the transparency of the shopping app I use most often.	0.825	0.681	0.319	2.515			
I believe this app may misuse my data.	0.852	0.726	0.274	2.967			
I feel that this app tries to influence or control my decisions.	0.848	0.719	0.281	2.853			
I increasingly question the honesty of the app I use most often.	0.847	0.717	0.283	2.867			
I worry that this app prioritizes profits over my best interests.	0.830	0.689	0.311	2.625			

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I feel less secure relying on the shopping app I use most often.	0.837	0.701	0.299	2.727			
Overall, my trust in the shopping app I use most often has deteriorated significantly.	0.862	0.743	0.257	3.068			
Skepticism Toward Advertising [41][45]					0.956	0.962	0.717
I generally do not trust advertising claims.	0.821	0.674	0.326	2.691			
Ads usually exaggerate product benefits.	0.842	0.709	0.291	2.794			
I often question the truthfulness of online ads.	0.852	0.726	0.274	3.043			
Many advertisements hide important information.	0.837	0.701	0.299	2.847			
I am skeptical about most brand promotions.	0.861	0.741	0.259	3.067			
I find many ads misleading.	0.858	0.736	0.264	3.072			
Advertising manipulates consumer emotions.	0.845	0.714	0.286	2.740			
I rarely accept advertisements without doubt.	0.851	0.724	0.276	2.968			
I assume most ads are biased or one-sided.	0.852	0.726	0.274	2.966			
In general, I treat advertising with suspicion.	0.846	0.716	0.284	3.029			
Platform Disengagement Intentions [26][53]					0.949	0.956	0.732
I intend to reduce the amount of time I spend on this platform in the near future.	0.845	0.714	0.286	2.928			
I am likely to use this platform less frequently than I do now.	0.835	0.697	0.303	2.806			
I am considering taking a break from this platform.	0.867	0.752	0.248	3.036			
I have considered discontinuing my use of this platform altogether.	0.850	0.723	0.278	3.096			
I am actively looking for alternative platforms to replace this one.	0.861	0.741	0.259	2.928			
I intend to rely less on this platform for my daily online activities.	0.852	0.726	0.274	3.063			
If I had a good alternative, I would switch away from this platform.	0.876	0.767	0.233	2.708			
I plan to avoid engaging with content on this platform as much as possible.	0.860	0.740	0.260	3.028			

Source: Author's own work

Table 5: Descriptive Statistics: Means, Standard Deviation, And Zero-Order Correlation

Construct	Mean	SD	1	2	3	4	5	VIF
Erosion of trust in the shopping app	2.93	0.59	0.842					1.000
Perceived algorithmic manipulation	2.98	0.54	0.673	0.834				2.177
Platform disengagement intentions	3.2	0.57	-0.059	-0.028	0.856			

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Perceived manipulative intent	2.91	0.59	0.726	0.735	-0.052	0.822		2.183
Skepticism toward advertising	3.01	1.05	0.161	-0.034	0.002	-0.004	0.847	1.002

Source: The author's own work
Note: ** P<0.001; CR Composite Reliability; AVE Average Variance Extracted; Diagonal elements are the square root of AVE.

Table 6: Heterotrait–Monotrait Ratio (Htmt) Matrix

Construct	**1**	**2**	**3**	**4**	**5**
Erosion of trust in the shopping app					
Perceived algorithmic manipulation	0.708				
Platform disengagement intentions	0.057	0.032			
Perceived manipulative intent	0.768	0.776	0.053		
Skepticism toward advertising	0.165	0.044	0.034	0.035	

Source: PLS-SEM

Table 7: Testing Of Hypothesis

Hypothesis	**Pathway**	**Original sample (O)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Result**
H1	PAM -> EOT	0.316	0.315	0.035	9.034	0.000	Significant
H2	PAM -> PMI	0.734	0.734	0.018	41.148	0.000	Significant
H3	PMI -> EOT	0.491	0.491	0.034	14.506	0.000	Significant
H4	PAM -> PMI -> EOT	0.360	0.361	0.027	13.363	0.000	Significant
H5	STA x PMI -> EOT	-0.047	-0.048	0.024	2.002	0.045	Significant
H6	EOT -> PDI	-0.053	-0.053	0.036	1.463	0.144	Not Significant
H7	PAM -> PMI -> EOT -> PDI	-0.019	-0.019	0.013	1.434	0.152	Not Significant
Conditional Indirect Effect							
		Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	
	PAM -> PMI -> EOT -> PDI conditional on STA at +1 SD	-0.017	-0.017	0.012	1.437	0.151	Not Significant

	PAM -> PMI -> EOT conditional on STA at +1 SD	0.325	0.326	0.032	10.093	0.000	Significant
	PMI -> EOT -> PDI conditional on STA at +1 SD	-0.023	-0.023	0.016	1.440	0.150	Not Significant
	PAM -> PMI -> EOT -> PDI conditional on STA at -1 SD	-0.021	-0.021	0.015	1.423	0.155	Not Significant
	PAM -> PMI -> EOT conditional on STA at -1 SD	0.395	0.395	0.032	12.433	0.000	Significant
	PMI -> EOT -> PDI conditional on STA at -1 SD	-0.028	-0.029	0.020	1.425	0.154	Not Significant
	PAM -> PMI -> EOT -> PDI conditional on STA at Mean	-0.019	-0.019	0.013	1.434	0.152	Not Significant
	PAM -> PMI -> EOT conditional on STA at Mean	0.360	0.361	0.027	13.363	0.000	Significant
	PMI -> EOT -> PDI conditional on STA at Mean	-0.026	-0.026	0.018	1.437	0.151	Not Significant

Source: PLS-SEM

Table 8: Predictive Accuracy And Effect Size Assessment Of The Structural Model

Construct	R^2	Adjusted R^2	Q^2	RMSE	MAE	Effect Size
EOT	0.601	0.599	0.422	0.721	0.571	Large
PDI	0.003	0.002	0.002	1.003	0.840	Small
PMI	0.540	0.539	0.361	0.682	0.542	Large

Source: PLS-SEM

Table 9: PLS Predict Model Comparison Results (PLS Vs. Indicator Average Benchmarks)

Construct	PLS loss	IA loss	Average loss difference	t value	p value
EOT	0.327	0.499	-0.171	11.421	0.000
PDI	1.494	1.493	0.001	0.343	0.732
PMI	0.274	0.43	-0.156	10.651	0.000
Overall	0.668	0.781	-0.113	12.04	0.000

Source: PLS Predict Model

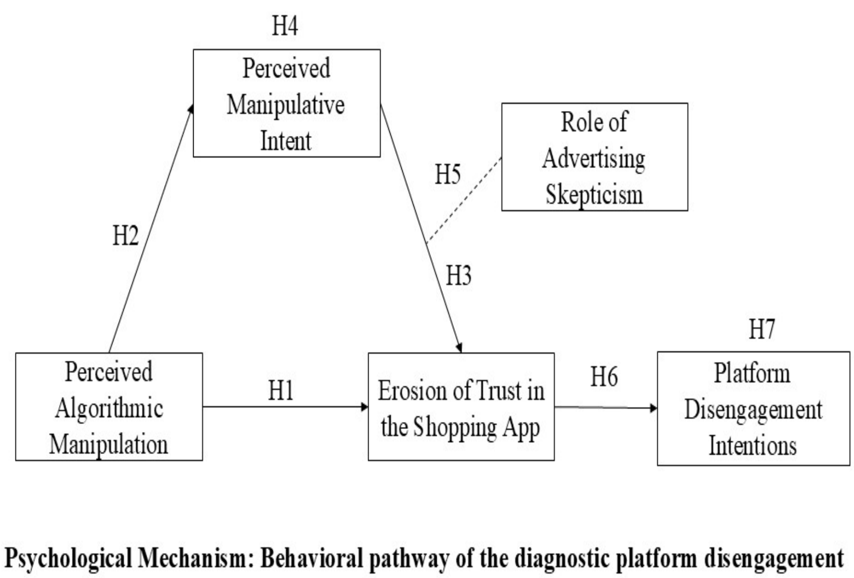

Figure 1: Conceptual Model

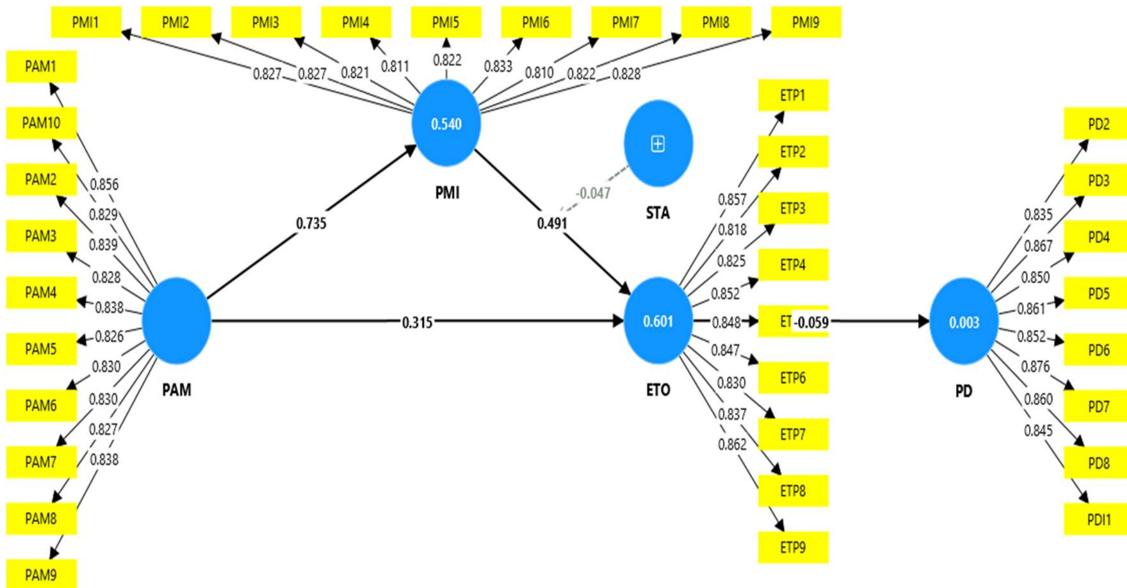

Figure 2: Empirical Model

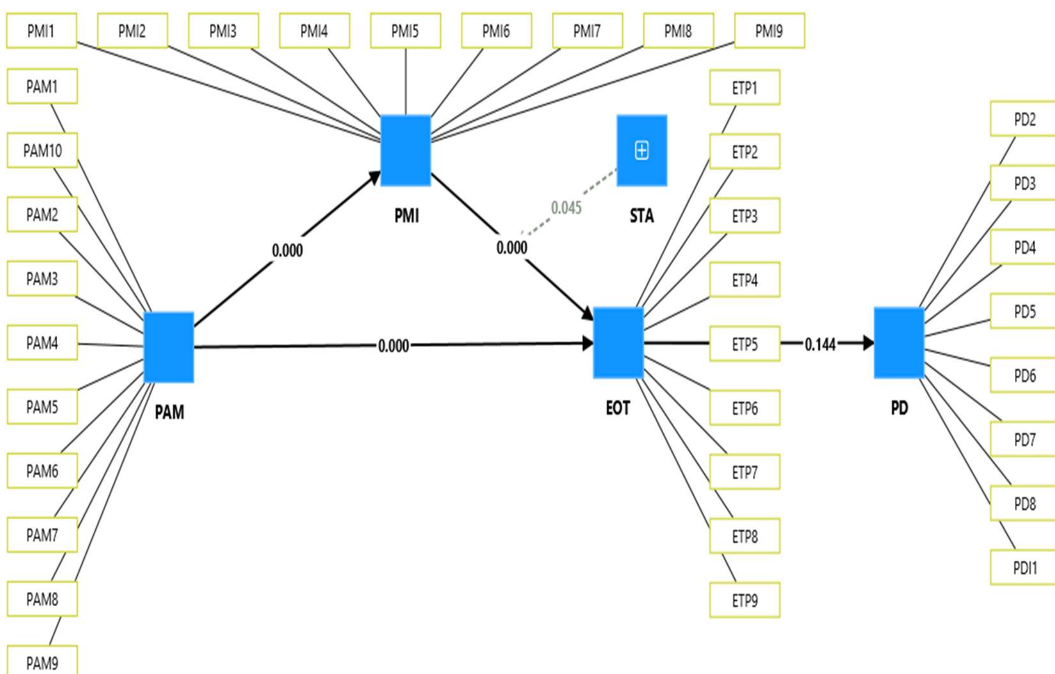

Figure 3: Bootstrapped Output

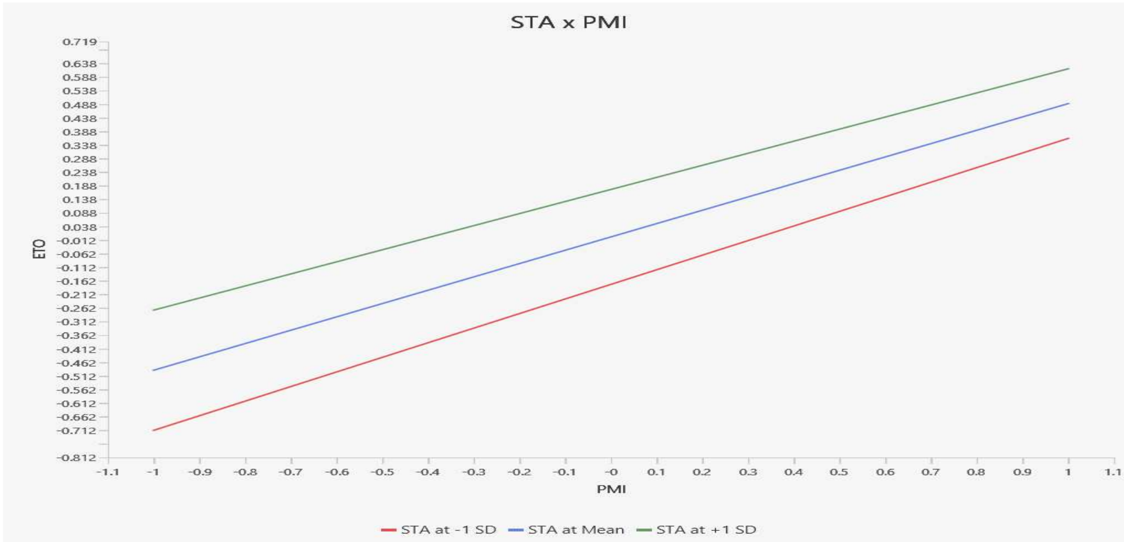

Figure 4: Moderation Graph

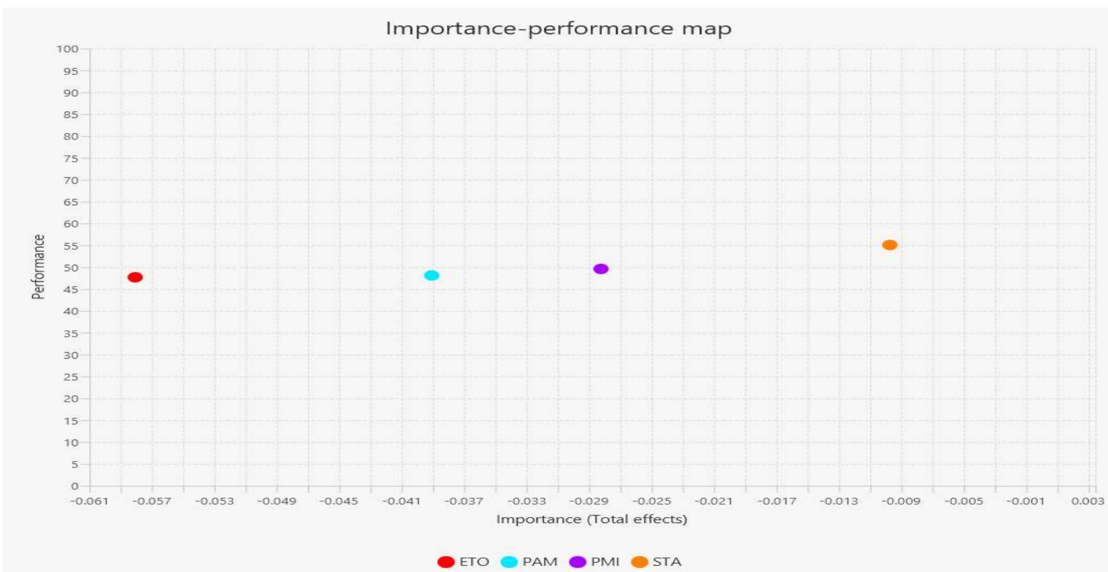

Figure 5: Importance–Performance Map

Note: Skepticism Toward Advertising (STA), Perceived Manipulative Intent (PMI), Erosion of Trust (EOT) and Perceived Algorithm Manipulation (PAM)