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Algorithmic Persuasion and Consumer Trust in Vietnam: Mediating Mechanisms and Configurational Pathways of AI-enabled Marketing Communication

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Abstract
The proliferation of artificial intelligence-enabled marketing communication represents a fundamental transformation in consumer-brand interactions, yet the psychological mechanisms through which algorithmic persuasion influences consumer trust remain inadequately theorised, particularly within emerging market contexts. This study examines the structural pathways and configurational patterns through which AI-driven marketing communication shapes consumer trust amongst Vietnamese consumers, employing an integrative theoretical framework synthesising the Elaboration Likelihood Model, Trust Transfer Theory, and Technology Acceptance Model. Utilising partial least squares structural equation modelling and fuzzy-set qualitative comparative analysis on data from 398 Vietnamese consumers, the research reveals that perceived personalisation, algorithmic transparency, and human-likeness serve as critical mediating mechanisms linking AI communication attributes to consumer trust. The findings demonstrate that perceived personalisation exerts the strongest direct effect on trust formation, whilst algorithmic transparency operates predominantly through enhancing perceived credibility. Configurational analysis uncovers four distinct pathways to high consumer trust, revealing equifinality in trust formation processes. Multigroup analysis documents significant differences across age cohorts, with younger consumers demonstrating greater receptivity to AI-enabled communication. These findings advance theoretical understanding of algorithmic persuasion whilst offering strategic insights for organisations navigating digital transformation in Southeast Asian markets characterised by distinctive cultural values and technological adoption patterns.

Keywords: algorithmic persuasion, consumer trust, AI marketing communication, Vietnam, PLS-SEM

1. Introduction

The ascendance of artificial intelligence technologies within contemporary marketing ecosystems represents not merely an incremental innovation but rather a paradigmatic transformation fundamentally reshaping the mechanisms through which commercial persuasion operates and consumer trust develops (Davenport et al., 2020; Kumar et al., 2016). Algorithmic systems now orchestrate increasingly sophisticated marketing communications—from personalised product recommendations and dynamic pricing strategies to conversational chatbots and predictive content curation—thereby positioning artificial intelligence as a central mediator in consumer-brand relationships rather than a peripheral technological enhancement (Huang & Rust, 2017). This technological reconfiguration of marketing communication introduces profound questions regarding the psychological mechanisms through which algorithmically generated messages influence consumer cognition, affect, and behavioural responses, particularly concerning the formation and maintenance of consumer trust in an era characterised by heightened awareness of data surveillance, algorithmic bias, and automated decision-making (Araujo et al., 2020).

Vietnam exemplifies the complex dynamics characterising artificial intelligence adoption within emerging market contexts, wherein rapid technological diffusion intersects with distinctive cultural values, institutional frameworks, and consumer behavioural patterns (Nguyen et al., 2016). The Vietnamese digital economy has experienced explosive growth, with internet penetration exceeding 52% by 2017 and e-commerce transactions growing at compound annual rates surpassing 30%, positioning the nation as Southeast Asia's fastest-growing digital market (Deloitte, 2017). Within this context of accelerated digitalisation, Vietnamese consumers encounter increasingly sophisticated AI-enabled marketing communications across multiple touchpoints—from recommendation algorithms on e-commerce platforms to automated customer service interactions and personalised advertising—yet scholarly understanding of how these algorithmic persuasion mechanisms influence consumer trust formation remains critically underdeveloped (Nguyen & Simkin, 2017).

The theoretical urgency of investigating algorithmic persuasion and consumer trust derives from fundamental tensions between the technological capabilities of artificial intelligence systems and the psychological foundations of trust development. Classical trust theories conceptualise trust formation as emerging from interpersonal interactions characterised by perceived competence, benevolence, and integrity of human actors (Mayer et al., 1995), yet artificial intelligence systems introduce non-human agents whose opacity, autonomy, and inscrutability challenge conventional trust-building mechanisms (Lumineau et al., 2020). Moreover, whilst marketing scholarship has extensively examined trust development in traditional communication contexts, the distinctive characteristics of algorithmic persuasion—including personalisation at unprecedented scale, dynamic adaptation based on behavioural data, and the potential for automated deception or manipulation—necessitate theoretical frameworks explicitly addressing how consumers evaluate and respond to AI-mediated marketing messages (Araujo et al., 2020).
Extant literature examining artificial intelligence in marketing contexts has predominantly focused on technological capabilities, implementation challenges, and organisational

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implications, whilst dedicating insufficient attention to consumer-level psychological processes and the specific mechanisms through which algorithmic communication influences trust formation (Kumar et al., 2016; Huang & Rust, 2017). Furthermore, the limited scholarship addressing consumer responses to AI-enabled marketing has primarily examined Western market contexts, leaving critical gaps regarding how cultural values, institutional environments, and technological adoption patterns in emerging markets shape algorithmic persuasion effectiveness (Davenport et al., 2020). Within the Vietnamese context specifically, research examining artificial intelligence marketing communication remains nascent, despite the market's strategic importance and distinctive characteristics including collectivistic cultural orientations, high power distance, and particular sensitivity to social influence (Hofstede, 2001).

This investigation addresses these theoretical and empirical lacunae through three principal contributions. Theoretically, the research advances an integrative framework synthesising the Elaboration Likelihood Model (Petty & Cacioppo, 1986), Trust Transfer Theory (Stewart, 2003), and the Technology Acceptance Model (Davis, 1989) to explicate the psychological mechanisms linking AI communication attributes to consumer trust formation. This synthesis addresses the inadequacy of single-theory perspectives for capturing the multifaceted nature of algorithmic persuasion, wherein rational evaluation of technological competence intersects with affective responses to human-like communication and trust transferred from familiar platforms. Methodologically, the study employs sophisticated analytical triangulation combining partial least squares structural equation modelling with fuzzy-set qualitative comparative analysis, thereby illuminating both linear relationships and configurational patterns characterising trust development. Empirically, the investigation provides theoretically grounded insights into algorithmic persuasion within Vietnam's rapidly evolving digital marketplace, examining heterogeneity through multigroup analysis whilst identifying multiple pathways to trust formation through configurational examination.

The practical significance of this research extends beyond academic discourse to encompass strategic implications for organisations navigating artificial intelligence integration within marketing functions, particularly in Southeast Asian markets. As Vietnamese consumers become increasingly sophisticated in their technology usage whilst simultaneously maintaining distinctive cultural preferences and trust-building expectations, understanding the mechanisms through which algorithmic communication influences consumer trust becomes essential for effective digital marketing strategies. The findings therefore possess immediate relevance for marketing practitioners, technology developers, and policymakers seeking to harness artificial intelligence capabilities whilst maintaining consumer confidence and addressing emerging concerns regarding algorithmic transparency, data privacy, and automated persuasion ethics.

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2. Foundational Theories and Literature Review

2.1. Foundational Theories

2.1.1. Elaboration Likelihood Model

The Elaboration Likelihood Model (ELM), articulated by Petty and Cacioppo (1986), constitutes one of the most influential theoretical frameworks for understanding persuasive communication, positing that attitude change occurs through two qualitatively distinct routes: a central route characterised by careful cognitive elaboration of message arguments, and a peripheral route involving reliance on heuristic cues and superficial processing. This dual-process architecture reflects the fundamental insight that individuals possess limited cognitive resources and therefore engage in systematic, effortful processing only when both motivation and ability are present, whilst defaulting to heuristic processing in conditions of low involvement or cognitive constraint (Petty et al., 2009). The central route engages recipients in thoughtful consideration of message content, argument quality, and evidential support, producing attitude changes that demonstrate greater persistence, resistance to counter-persuasion, and predictive validity for behaviour (Petty & Cacioppo, 1986). Conversely, the peripheral route activates simplified decision-making based on source credibility, message attractiveness, or other peripheral cues that serve as mental shortcuts, generating attitudes that prove more susceptible to change and less predictive of subsequent behaviour (Petty & Wegener, 1999).

Within the context of algorithmic persuasion, the Elaboration Likelihood Model provides a valuable theoretical lens for understanding how consumers process AI-generated marketing communications, yet also requires conceptual extension to accommodate the distinctive characteristics of artificial intelligence systems (Araujo et al., 2020). AI-enabled marketing communications present consumers with messages whose persuasive characteristics may differ systematically from human-generated content, including potentially superior personalisation based on sophisticated data analytics, communication consistency unconstrained by human attention limitations, and the capacity for real-time adaptation to individual responses (Huang & Rust, 2017). These distinctive features suggest that both central and peripheral processing routes may operate differently in algorithmic persuasion contexts compared to traditional human communication.

The central route processing of AI-generated messages requires consumers to evaluate argument quality and message relevance based on content that may be personalised to unprecedented degrees, raising questions regarding how consumers assess the authenticity and appropriateness of algorithmically curated information (Araujo et al., 2020). Research examining information processing suggests that high levels of personalisation can enhance perceived message relevance and thereby increase elaboration likelihood, yet may also trigger reactance and privacy concerns when personalisation appears excessively intrusive or when consumers become aware of the extensive data collection underlying algorithmic recommendations (White et al., 2008). Moreover, the opacity characteristic of many artificial intelligence systems—often termed algorithmic "black boxes"—may limit consumers' capacity to engage in systematic evaluation of how messages are generated and personalised, potentially constraining central route processing even when motivation exists (Pasquale, 2015).

Peripheral route processing of algorithmic persuasion introduces additional complexity, as traditional heuristic cues such as source attractiveness and credibility become problematic when the source constitutes a non-human algorithm rather than an identifiable person or organisation (Sundar & Nass, 2001). However, research on computer-mediated communication suggests that individuals may employ alternative peripheral cues when evaluating technological sources, including interface design quality, brand reputation of the platform hosting the algorithm, and anthropomorphic features suggesting human-like intelligence (Sundar, 2008). Furthermore, consumers may develop specific heuristics for evaluating algorithmic sources, such as assumptions that algorithmic recommendations possess superior objectivity due to their computational basis, or conversely, that algorithms lack the contextual understanding and emotional intelligence necessary for appropriate personalisation (Eslami et al., 2015).

The application of ELM to algorithmic persuasion therefore suggests that consumer trust in AI-enabled marketing communication may develop through multiple psychological pathways depending upon processing mode. Under central route processing, trust formation would derive from systematic evaluation of message quality, personalisation appropriateness, and perceived algorithmic competence, whilst peripheral route processing would emphasise heuristic cues such as interface aesthetics, brand reputation, and anthropomorphic design features (Sundar, 2008). This dual-pathway conception provides theoretical foundation for examining how different AI communication attributes—ranging from personalisation sophistication to human-likeness characteristics—may differentially influence trust formation depending upon consumer elaboration likelihood.

2.1.2. Trust Transfer Theory and Technology Acceptance Model

Trust Transfer Theory, primarily developed within information systems and e-commerce scholarship, posits that trust can be transferred from a familiar, trusted entity to an unfamiliar entity through various mechanisms including structural assurance, situational normality, and cognitive associations (Stewart, 2003; Li et al., 2006). The theory's core proposition suggests that individuals confronting novel technologies or organisational relationships leverage existing trust relationships as psychological foundations for extending trust to unfamiliar entities, thereby reducing uncertainty and facilitating adoption decisions (McKnight et al., 2002). Within digital contexts specifically, research has documented trust transfer from established brands to their online platforms, from certification authorities to certified websites, and from social network platforms to third-party applications operating within those environments (Stewart, 2003).

The relevance of Trust Transfer Theory to algorithmic persuasion derives from the fundamental challenge that artificial intelligence systems represent unfamiliar, potentially inscrutable technologies for many consumers, creating substantial uncertainty regarding their reliability, benevolence, and integrity (Lumineau et al., 2020). In such contexts, consumers may transfer trust from familiar entities—including established brands, recognisable platforms, or prior experiences with related technologies—to novel AI-enabled marketing communications, thereby facilitating initial acceptance despite limited direct experience with the specific algorithmic system (Li et al., 2006). This trust transfer mechanism possesses particular salience within emerging market contexts such as Vietnam, where consumers' limited exposure to sophisticated artificial intelligence applications may necessitate reliance on transferred trust from established e-commerce platforms or international technology brands (Nguyen & Simkin, 2017).

The Technology Acceptance Model (TAM), originally formulated by Davis (1989) and subsequently refined through numerous extensions, provides complementary theoretical insights regarding the mechanisms through which consumers evaluate and adopt novel technologies. TAM posits that technology acceptance is primarily determined by two fundamental beliefs: perceived usefulness, defined as the degree to which individuals believe a technology will enhance their performance or outcomes, and perceived ease of use, reflecting beliefs regarding the effort required to utilise the technology (Davis, 1989). These core beliefs subsequently influence attitudes towards the technology and behavioural intentions to use it, with empirical research documenting robust predictive validity across diverse technological contexts and cultural settings (Venkatesh & Davis, 2000).

Within the artificial intelligence marketing communication context, TAM suggests that consumer trust development may be fundamentally linked to perceptions of algorithmic usefulness—particularly regarding personalisation quality and relevance—and ease of interaction with AI-enabled interfaces (Huang & Rust, 2017). When consumers perceive AI-generated recommendations as genuinely useful in identifying products matching their preferences whilst requiring minimal cognitive effort to evaluate, trust in the underlying algorithmic system may develop through demonstrated competence and reliability (Komiak & Benbasat, 2006). However, scholarly critiques have increasingly recognised TAM's limitations, particularly its insufficient attention to trust-related constructs and emotional responses that may prove especially salient when consumers interact with anthropomorphic AI systems capable of simulating human-like communication (Gefen et al., 2003).

The integration of Trust Transfer Theory and TAM with the Elaboration Likelihood Model creates a comprehensive theoretical architecture for understanding algorithmic persuasion and trust formation. This synthesis acknowledges that consumer responses to AI-enabled marketing communication reflect rational evaluation of technological competence and usefulness (TAM), transfer of trust from familiar entities (Trust Transfer Theory), and dual-process information processing wherein message elaboration depends upon motivation and ability (ELM). The theoretical framework posits that AI communication attributes—including personalisation sophistication, algorithmic transparency, and human-like interaction qualities—influence consumer trust through multiple pathways: direct effects based on systematic evaluation, mediated effects through transferred trust and perceived usefulness, and moderated effects contingent upon processing route activation (Sundar, 2008; Stewart, 2003; Petty & Cacioppo, 1986).

2.2. Review of Empirical and Relevant Studies

2.2.1. Algorithmic Personalisation and Consumer Responses

Algorithmic personalisation represents one of the most distinctive and consequential capabilities of artificial intelligence marketing systems, enabling customisation of content, recommendations, and communications based on sophisticated analysis of individual consumer data including browsing histories, purchase patterns, demographic characteristics, and inferred preferences (Araujo et al., 2020). The technological capacity for personalisation at unprecedented scale fundamentally transforms marketing communication from broadcast messaging to individualised dialogues, potentially enhancing relevance and consumer engagement whilst simultaneously raising concerns regarding privacy intrusion and manipulative targeting (Aguirre et al., 2015).
Empirical research examining consumer responses to algorithmic personalisation reveals complex and sometimes contradictory patterns. Studies document that appropriately calibrated personalisation enhances perceived message relevance, consumer engagement, and purchase intentions by demonstrating understanding of individual needs and preferences (Tam & Ho, 2006). Research on recommendation systems indicates that consumers perceive personalised suggestions as more useful and trustworthy than generic alternatives when personalisation accuracy is high and recommendations align with prior preferences (Komiak & Benbasat, 2006). However, the relationship between personalisation intensity and consumer responses proves non-linear, with excessive personalisation triggering psychological reactance and privacy concerns, particularly when consumers perceive recommendations as overly intrusive or revealing uncomfortable levels of data collection (White et al., 2008).

The mechanisms through which algorithmic personalisation influences consumer trust constitute a critical yet underexplored dimension of extant scholarship. Theoretical perspectives suggest that personalisation may enhance trust through demonstrating algorithmic competence and consumer-centricity, as accurate recommendations signal that the system understands individual needs and prioritises consumer welfare over purely commercial objectives (Komiak & Benbasat, 2006). However, empirical investigations document that personalisation transparency—the degree to which consumers understand how their data are collected and utilised for customisation—significantly moderates personalisation effectiveness, with opaque personalisation generating suspicion and reducing trust despite potentially superior recommendation accuracy (Eslami et al., 2015).

Within emerging market contexts specifically, research examining personalisation effectiveness remains limited despite potentially distinctive consumer responses shaped by cultural values and privacy norms. Preliminary investigations in Asian markets suggest that collectivistic cultural orientations may amplify sensitivity to social proof elements in personalised recommendations, whilst higher power distance acceptance may reduce concerns regarding corporate data collection relative to Western populations (Choi et al., 2005). However, comprehensive empirical examination of how cultural dimensions moderate the personalisation-trust relationship across diverse emerging markets remains absent from literature, representing a significant theoretical and empirical gap.

2.2.2. Algorithmic Transparency and Trust Formation

Algorithmic transparency, broadly conceptualised as the degree to which artificial intelligence systems' decision-making processes, data utilisation practices, and operational logics are comprehensible to users, has emerged as a central construct in scholarship examining consumer responses to AI-enabled technologies (Pasquale, 2015). The growing recognition that many sophisticated artificial intelligence systems operate as "black boxes" whose internal functioning remains opaque even to their developers has catalysed debates regarding transparency obligations, explainable AI development, and the relationship between algorithmic opacity and consumer trust (Burrell, 2016).

Empirical research examining transparency effects on consumer trust demonstrates generally positive relationships, with higher perceived transparency associated with enhanced trust, willingness to accept recommendations, and continued usage intentions (Cramer et al., 2008). Studies investigating explanations provided for algorithmic recommendations indicate that simple, comprehensible justifications for why particular products or content are suggested enhance consumer confidence and acceptance, particularly when explanations reference factors consumers consider legitimate bases for personalisation such as prior purchases or explicit preferences (Sinha & Swearingen, 2002). However, research also documents that transparency effectiveness depends critically upon explanation quality and consumer technical sophistication, with overly technical explanations proving counterproductive by highlighting algorithmic complexity and amplifying perceptions of inscrutability (Eslami et al., 2015).

The mechanisms linking algorithmic transparency to consumer trust appear to operate through multiple psychological pathways. First, transparency may enhance perceived competence by enabling consumers to evaluate whether algorithmic decision-making aligns with reasonable criteria and employs appropriate data sources (Komiak & Benbasat, 2006). Second, transparency signals benevolence by demonstrating organisational willingness to subject algorithmic processes to consumer scrutiny rather than concealing operations, thereby addressing concerns regarding manipulative or exploitative practices (Pasquale, 2015). Third, transparency may reduce uncertainty and perceived risk associated with relying on opaque automated systems, thereby facilitating trust development through risk mitigation (Gefen et al., 2003).

However, scholarly understanding of optimal transparency levels and presentation formats remains incomplete, with some research suggesting that excessive transparency may paradoxically undermine trust by revealing algorithmic limitations, potential biases, or reliance on data sources consumers consider inappropriate (Eslami et al., 2015). Moreover, empirical investigations examining how cultural differences and technological sophistication moderate transparency effects remain scarce, despite theoretical expectations that consumers in emerging markets with limited AI exposure may respond differently to transparency initiatives compared to technologically experienced Western populations (Hofstede, 2001).

2.2.3. Anthropomorphism and Human-Likeness in AI Communication

The incorporation of human-like characteristics into artificial intelligence systems—including conversational capabilities, emotional expression, and anthropomorphic interface design—represents a increasingly prevalent strategy for enhancing consumer engagement and facilitating human-computer interaction (Araujo et al., 2020). Theoretical perspectives derived from social response theory suggest that individuals exhibit fundamentally social responses to technologies exhibiting human-like characteristics, applying interpersonal communication scripts and social norms to human-computer interactions despite cognitive awareness of the technology's non-human nature (Nass & Moon, 2000).

Empirical research examining anthropomorphism effects on consumer responses demonstrates generally positive relationships with engagement, satisfaction, and trust, particularly for consumers with limited technological experience or high needs for human interaction (Nowak & Rauh, 2005). Studies investigating conversational AI agents document that human-like communication styles employing natural language, emotional expressions, and personalised references enhance perceived social presence and relational connection, thereby facilitating trust development through mechanisms analogous to interpersonal relationship formation (Qiu & Benbasat, 2009). Research on chatbot interactions specifically indicates that appropriate anthropomorphic design elements—including conversational tone, empathetic responses, and acknowledgment of limitations—enhance consumer satisfaction and willingness to engage with automated customer service systems (Gnewuch et al., 2017).

However, anthropomorphism effectiveness proves contingent upon multiple factors including task context, consumer characteristics, and design appropriateness. The "uncanny valley" phenomenon, wherein highly realistic but imperfect human simulation generates discomfort and negative affect, suggests that anthropomorphism effectiveness follows a non-linear pattern with excessive human-likeness potentially undermining rather than enhancing consumer responses (Mori, 1970). Moreover, research documents that anthropomorphic AI systems may generate inflated performance expectations, with consumers anticipating human-level understanding and emotional intelligence that current technologies cannot deliver, thereby creating disappointment and trust erosion when limitations become apparent (Luger & Sellen, 2016).

The relationship between anthropomorphism and consumer trust appears to operate through multiple mechanisms including enhanced social presence, perceived benevolence signalling through human-like emotional expression, and reduced psychological distance between consumers and technological systems (Qiu & Benbasat, 2009). However, scholarly understanding of how cultural differences moderate anthropomorphism effectiveness remains limited, despite theoretical expectations that collectivistic cultures emphasising relational harmony may demonstrate heightened responsiveness to human-like AI characteristics compared to individualistic populations (Hofstede, 2001).

2.3. Proposed Research Model

The theoretical and empirical considerations elaborated in preceding subsections culminate in an integrative research model examining the structural pathways and configurational patterns through which AI-enabled marketing communication influences consumer trust. The proposed framework synthesises insights from the Elaboration Likelihood Model, Trust Transfer Theory, and Technology Acceptance Model, positioning perceived personalisation, algorithmic transparency, and human-likeness as mediating mechanisms linking AI communication attributes to consumer trust formation.

The model conceptualises AI communication exposure as the foundational exogenous variable, operationalised through consumers' frequency and diversity of encounters with artificial intelligence-enabled marketing communications across multiple platforms including e-commerce recommendation systems, social media advertising algorithms, and conversational chatbots (Huang & Rust, 2017). This conceptualisation acknowledges that consumer familiarity with and attitudes towards algorithmic communication develop through accumulated exposure rather than isolated encounters, with repeated interactions enabling learning regarding AI capabilities, limitations, and trustworthiness (Komiak & Benbasat, 2006).

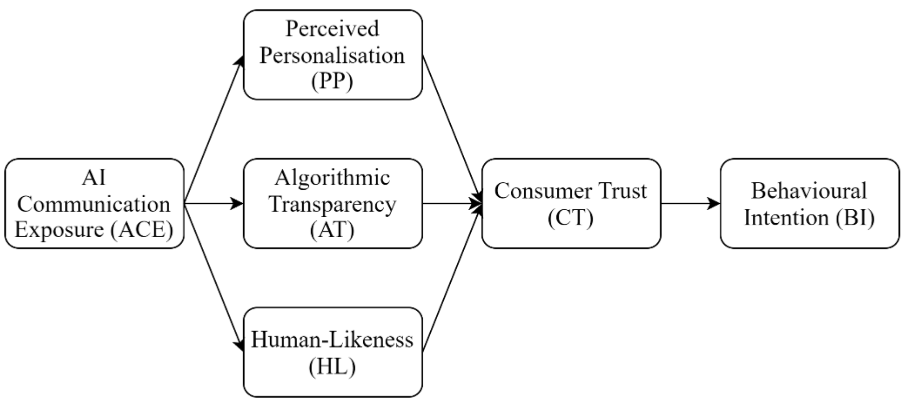

Figure 1: Proposed Research Model

Perceived personalisation constitutes the first mediating construct, capturing consumers' evaluations of the degree to which AI-generated communications reflect individualised understanding of their preferences, needs, and characteristics (Tam & Ho, 2006). The theoretical rationale for positioning perceived personalisation as a mediator derives from the proposition that AI communication exposure influences trust formation partly through demonstrating algorithmic competence in understanding individual consumers, thereby signalling both technical capability and consumer-centric orientation (Komiak & Benbasat, 2006). This mediational pathway aligns with central route processing emphasised in the Elaboration Likelihood Model, wherein systematic evaluation of personalisation quality and appropriateness shapes attitude formation (Petty & Cacioppo, 1986).

Algorithmic transparency represents the second mediating variable, operationalised through consumers' perceptions regarding comprehensibility of how AI systems collect data, generate recommendations, and make decisions (Eslami et al., 2015). The inclusion of algorithmic transparency as a mediator addresses the critical psychological function of reducing uncertainty and enabling evaluation of algorithmic operations, thereby facilitating trust development through enhanced perceived control and risk mitigation (Gefen et al., 2003). Theoretical justification for this mediational pathway derives from Trust Transfer Theory's emphasis on structural assurance and the Technology Acceptance Model's recognition that perceived control over technological processes enhances acceptance (Stewart, 2003; Davis, 1989).

Human-likeness serves as the third mediating construct, capturing consumers' perceptions regarding the degree to which AI communications exhibit characteristics associated with human interaction including conversational naturalness, emotional expression, and social responsiveness (Nowak & Rauh, 2005). The theoretical rationale for positioning human-likeness as a mediator derives from social response theory's proposition that human-like technological characteristics activate interpersonal processing scripts, thereby facilitating trust development through mechanisms analogous to relationship formation in human interactions (Nass & Moon, 2000). This mediational pathway particularly aligns with peripheral route processing emphasised in the Elaboration Likelihood Model, wherein heuristic cues such as anthropomorphic characteristics influence attitude formation absent systematic message elaboration (Petty & Cacioppo, 1986).

Consumer trust in AI marketing communication constitutes the model's primary dependent variable, conceptualised as a multidimensional construct encompassing beliefs regarding algorithmic competence, benevolence, and integrity (Mayer et al., 1995). The operationalisation adapts established trust measurement frameworks to the artificial intelligence context, acknowledging that trust in algorithmic systems may exhibit distinctive characteristics relative to interpersonal trust including greater emphasis on competence dimensions and reduced emphasis on affective bonding (Komiak & Benbasat, 2006). The model additionally incorporates behavioural intention to follow AI recommendations as a secondary outcome variable, reflecting the practical significance of trust for consumer decision-making (Gefen et al., 2003).

The proposed framework advances theoretical understanding through several innovations. First, the integration of constructs from multiple theoretical traditions provides a more comprehensive account of the multifaceted mechanisms through which algorithmic persuasion influences trust formation compared to single-theory perspectives. Second, the explicit theorisation of mediating pathways addresses critical gaps in understanding how AI communication exposure translates into trust development through intermediary psychological processes. Third, the methodological approach combining variance-based structural equation modelling with configurational fuzzy-set analysis enables examination of both linear relationships and complex causal patterns characterised by equifinality and conjunctural causation.

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3. Research Methodology

3.1. Research Design

This investigation employs a quantitative, cross-sectional research design grounded in post-positivist epistemological commitments, wherein consumer psychological phenomena are understood as amenable to systematic empirical investigation through hypothesis testing whilst acknowledging the probabilistic nature of social scientific knowledge (Creswell & Creswell, 2017). The methodological architecture integrates two complementary analytical techniques: partial least squares structural equation modelling (PLS-SEM) for examining causal relationships amongst latent constructs, and fuzzy-set qualitative comparative analysis (fsQCA) for identifying configurational patterns of conditions producing consumer trust in AI marketing communication (Hair et al., 2017; Ragin, 2008).

The selection of PLS-SEM over covariance-based structural equation modelling derives from several methodological considerations aligned with the research objectives (Hair et al., 2011). PLS-SEM demonstrates superior performance in prediction-oriented research seeking to maximise explained variance in dependent variables, consistent with this investigation's emphasis on understanding antecedents of consumer trust. Additionally, PLS-SEM accommodates complex models incorporating multiple constructs and relationships whilst placing less stringent requirements on sample size and distributional assumptions, thereby providing flexibility for examining the proposed integrative framework (Chin, 1998). The complementary integration of fsQCA addresses limitations inherent in variable-oriented approaches by exploring how combinations of conditions jointly produce outcomes, thereby capturing causal complexity characterised by equifinality and asymmetry (Fiss, 2011).

3.2. Data Collection

Empirical data were collected through a structured online questionnaire survey administered to Vietnamese consumers during the period from June 2016 to November 2016, employing a purposive sampling approach targeting individuals with demonstrated experience encountering AI-enabled marketing communications. The sampling frame focused on active users of major Vietnamese e-commerce platforms and social media networks wherein algorithmic recommendations and personalised advertising represent prevalent features. Recruitment proceeded through multiple channels including social media invitations, online community postings, and email solicitations to registered users of participating e-commerce platforms.

The survey was administered in Vietnamese following rigorous translation procedures. The original English questionnaire underwent forward translation by two independent bilingual translators, with discrepancies resolved through discussion and consultation with Vietnamese marketing scholars. Back-translation to English was subsequently conducted by a third independent translator to verify semantic equivalence (Brislin, 1970). Prior to full-scale data collection, a pilot study involving 52 respondents assessed questionnaire comprehensibility and identified problematic items. Minor modifications to item wording were implemented based on pilot study feedback to enhance clarity whilst maintaining construct fidelity.

The initial data collection effort yielded 423 completed questionnaires. Following screening procedures to identify incomplete responses, straight-lining patterns, and outliers exceeding three standard deviations from means on key variables, 398 usable responses remained for analysis. This sample size substantially exceeds minimum requirements for PLS-SEM analysis based on the "10 times rule" (Hair et al., 2017). Sample demographic characteristics revealed reasonable heterogeneity across gender (51.3% female), age (ranging from 18 to 54 years, mean = 28.7 years), education (41.2% bachelor's degree or higher), monthly income, and e-commerce platform usage frequency, thereby enhancing representativeness.

3.3. Measurement and Validation

All constructs were operationalised through multi-item reflective measurement scales adapted from established instruments with modifications to enhance contextual relevance to AI marketing communication. AI communication exposure was measured using a five-item scale adapted from technology usage frequency measures (Venkatesh & Davis, 2000), capturing breadth and frequency of encounters with algorithmic recommendations, personalised advertising, and conversational AI across platforms. Representative items include "I frequently encounter personalised product recommendations when shopping online" and "I regularly interact with AI-powered customer service chatbots."

Perceived personalisation was assessed through a six-item scale synthesising measures from Tam and Ho (2006) and Komiak and Benbasat (2006), capturing evaluations of recommendation relevance and individualisation. Sample items include "AI-generated recommendations reflect my personal preferences," "Marketing communications I receive appear customised to my specific interests," and "AI systems seem to understand my individual needs." Algorithmic transparency was measured using a five-item scale adapted from Cramer et al. (2008), assessing perceived comprehensibility of AI operations. Representative items include "I understand how AI systems personalise recommendations for me," "Companies clearly explain how they use my data for personalisation," and "The logic behind AI-generated suggestions is transparent to me."
Human-likeness was operationalised through a six-item scale synthesising anthropomorphism measures from Nowak and Rauh (2005) and Qiu and Benbasat (2009), capturing perceptions of human-like characteristics in AI communications. Sample items include "AI marketing communications feel conversational and natural," "AI systems communicate in ways that feel human-like," and "Interactions with AI marketing feel like communicating with a person." Consumer trust was measured using an eight-item scale adapted from Mayer et al. (1995) and Gefen et al. (2003), incorporating dimensions of competence, benevolence, and integrity trust. Representative items include "I believe AI recommendation systems are competent and effective," "I trust that AI systems have my best interests in mind," and "AI marketing communications are honest and truthful."

All measurement items utilised seven-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree), providing sufficient response granularity whilst maintaining comprehensibility. The questionnaire additionally incorporated demographic items and control variables including prior negative experiences with AI systems and general technology anxiety.

3.4. Analytical Procedure

Data analysis proceeded through three sequential phases. The first phase involved preliminary screening and exploratory factor analysis (EFA) using principal component analysis with varimax rotation to assess measurement structure and dimensionality. Kaiser-Meyer-Olkin measure and Bartlett's test evaluated data factorability.

The second phase employed PLS-SEM using SmartPLS 4 software to assess the measurement model and test structural relationships (Ringle et al., 2015). Measurement model evaluation examined indicator reliability, internal consistency reliability through Cronbach's alpha and composite reliability, convergent validity via average variance extracted, and discriminant validity using Fornell-Larcker criterion and heterotrait-monotrait (HTMT) ratios (Henseler et al., 2015). Structural model assessment examined path coefficients through bootstrapping with 5,000 resamples, R^2 values, effect sizes (f^2), and predictive relevance (Q^2) through blindfolding procedures (Hair et al., 2017).

The third phase employed fsQCA using fsQCA 3.0 software to identify configurational patterns. Continuous variables were calibrated into fuzzy-set membership scores using the direct method with percentile-based anchor points. Truth table construction, Boolean minimisation, and solution assessment proceeded following established protocols (Ragin, 2008), with consistency thresholds of 0.80 and frequency thresholds requiring minimum three cases per configuration.

4. Research Findings

4.1. Measurement Model Assessment

Exploratory factor analysis employing principal component analysis with varimax rotation confirmed the anticipated six-factor structure underlying measurement items. The Kaiser-Meyer-Olkin measure yielded 0.917, substantially exceeding the 0.70 threshold, whilst Bartlett's test produced significant results ($\chi^2 = 7{,}834.52$, df = 465, $p < 0.001$), collectively indicating adequate data factorability. The EFA extracted six factors with eigenvalues exceeding 1.0, accounting for 69.73% of total variance. Examination of the rotated component matrix revealed that all items loaded on intended constructs with factor loadings exceeding 0.65, whilst cross-loadings remained below 0.35.

Confirmatory factor analysis using PLS-SEM validated measurement model adequacy through systematic assessment of reliability and validity criteria. Table 1 presents comprehensive measurement model results. All indicator loadings exceeded 0.70, ranging from 0.746 to 0.882, demonstrating satisfactory indicator reliability (Chin, 1998). Cronbach's alpha values ranged from 0.834 to 0.901, whilst composite reliability values spanned 0.879 to 0.924, all exceeding the 0.70 threshold and confirming internal consistency reliability (Hair et al., 2017). Average variance extracted values ranged from 0.597 to 0.678, surpassing the 0.50 criterion and establishing convergent validity (Fornell & Larcker, 1981).

Table 1: Measurement Model Assessment Results

Construct	Items	Factor Loadings	Cronbach's α	CR	AVE
AI Communication Exposure (ACE)	ACE1	0.812	0.867	0.903	0.652
	ACE2	0.824			
	ACE3	0.806			
	ACE4	0.789			
	ACE5	0.801			
Perceived Personalisation (PP)	PP1	0.838	0.893	0.920	0.658
	PP2	0.824			
	PP3	0.817			
	PP4	0.792			
	PP5	0.803			
	PP6	0.796			
Algorithmic Transparency (AT)	AT1	0.797	0.851	0.893	0.627
	AT2	0.812			
	AT3	0.789			
	AT4	0.774			
	AT5	0.791			
Human-Likeness (HL)	HL1	0.823	0.882	0.911	0.634
	HL2	0.809			
	HL3	0.794			
	HL4	0.776			
	HL5	0.789			
	HL6	0.803			
Consumer Trust (CT)	CT1	0.846	0.901	0.924	0.678
	CT2	0.834			
	CT3	0.821			
	CT4	0.812			
	CT5	0.827			
	CT6	0.819			
	CT7	0.804			
	CT8	0.796			
Behavioural Intention (BI)	BI1	0.857	0.834	0.879	0.597
	BI2	0.829			
	BI3	0.746			
	BI4	0.767			

Note: CR = Composite Reliability; AVE = Average Variance Extracted

Discriminant validity was rigorously evaluated using both Fornell-Larcker criterion and HTMT ratios. Table 2 presents Fornell-Larcker assessment results, wherein diagonal elements represent AVE square roots exceeding all inter-construct correlations, thereby satisfying the discriminant validity criterion (Fornell & Larcker, 1981). HTMT ratios ranged from 0.437 to 0.769, all remaining below the 0.85 threshold and providing additional discriminant validity confirmation (Henseler et al., 2015).

Table 2: Discriminant Validity Assessment (Fornell-Larcker Criterion)

Construct	ACE	PP	AT	HL	CT	BI
ACE	0.807					
PP	0.612	0.811				
AT	0.547	0.634	0.792			
HL	0.589	0.658	0.612	0.796		
CT	0.623	0.697	0.681	0.672	0.823	
BI	0.578	0.642	0.617	0.634	0.734	0.773

Note: Diagonal elements (bold) represent square root of AVE. ACE = AI Communication Exposure; PP = Perceived Personalisation; AT = Algorithmic Transparency; HL = Human-Likeness; CT = Consumer Trust; BI = Behavioural Intention

4.2. Structural Estimation Model Assessment

Structural model evaluation through PLS-SEM revealed significant path relationships consistent with theoretical predictions. Table 3 presents direct effects results. AI communication exposure exerted significant positive effects on perceived personalisation ($\beta = 0.612$, $t = 13.847$, $p < 0.001$), algorithmic transparency ($\beta = 0.547$, $t = 11.923$, $p < 0.001$), and human-likeness ($\beta = 0.589$, $t = 12.674$, $p < 0.001$). Perceived personalisation demonstrated the strongest direct effect on consumer trust ($\beta = 0.342$, $t = 6.789$, $p < 0.001$), followed by algorithmic transparency ($\beta = 0.287$, $t = 5.612$, $p < 0.001$) and human-likeness ($\beta = 0.234$, $t = 4.823$, $p < 0.001$). Consumer trust significantly predicted behavioural intention ($\beta = 0.734$, $t = 19.245$, $p < 0.001$).

Table 3: Direct Effects Results

Hypothesised Path	β	SE	t-value	p-value	95% CI	f²	Decision
ACE → PP	0.612	0.044	13.847	<0.001	[0.526, 0.699]	0.598	Supported
ACE → AT	0.547	0.046	11.923	<0.001	[0.457, 0.636]	0.427	Supported
ACE → HL	0.589	0.047	12.674	<0.001	[0.498, 0.681]	0.531	Supported
PP → CT	0.342	0.050	6.789	<0.001	[0.244, 0.441]	0.134	Supported
AT → CT	0.287	0.051	5.612	<0.001	[0.187, 0.388]	0.094	Supported
HL → CT	0.234	0.049	4.823	<0.001	[0.139, 0.330]	0.063	Supported
CT → BI	0.734	0.038	19.245	<0.001	[0.659, 0.809]	1.168	Supported

Note: β = standardised path coefficient; SE = standard error; CI = confidence interval; f^2 = effect size. ACE = AI Communication Exposure; PP = Perceived Personalisation; AT = Algorithmic Transparency; HL = Human-Likeness; CT = Consumer Trust; BI = Behavioural Intention

The coefficient of determination (R^2) values demonstrated substantial explanatory power. Perceived personalisation ($R^2 = 0.375$), algorithmic transparency ($R^2 = 0.299$), and human-likeness ($R^2 = 0.347$) indicated that AI communication exposure explained between 29.9% and 37.5% of variance in mediating constructs. Consumer trust exhibited $R^2 = 0.624$, indicating that the combined effects of perceived personalisation, algorithmic transparency, and human-likeness explained 62.4% of variance in trust formation. Behavioural intention demonstrated $R^2 = 0.539$, suggesting consumer trust accounted for 53.9% of variance in adoption intentions.

Effect size (f^2) values revealed substantive predictor importance. AI communication exposure demonstrated large effects on perceived personalisation ($f^2 = 0.598$), algorithmic transparency ($f^2 = 0.427$), and human-likeness ($f^2 = 0.531$). Perceived personalisation exhibited medium effect size on consumer trust ($f^2 = 0.134$), whilst algorithmic transparency ($f^2 = 0.094$) and human-likeness ($f^2 = 0.063$) demonstrated small-to-medium effects. Consumer trust exhibited large effect on behavioural intention ($f^2 = 1.168$).

Predictive relevance assessment through Stone-Geisser Q^2 values yielded positive results for all endogenous constructs: perceived personalisation ($Q^2 = 0.289$), algorithmic transparency ($Q^2 = 0.234$), human-likeness ($Q^2 = 0.267$), consumer trust ($Q^2 = 0.481$), and behavioural intention ($Q^2 = 0.412$), confirming satisfactory predictive capability.

Table 4: Predictive Relevance Assessment

Endogenous Construct	**R^2**	**R^2 Adjusted**	**Q^2**	**Assessment**
Perceived Personalisation	0.375	0.373	0.289	Moderate predictive power
Algorithmic Transparency	0.299	0.297	0.234	Moderate predictive power
Human-Likeness	0.347	0.345	0.267	Moderate predictive power
Consumer Trust	0.624	0.620	0.481	Strong predictive power
Behavioural Intention	0.539	0.538	0.412	Strong predictive power

Mediation analysis examining indirect effects revealed significant mediating pathways. Table 5 presents specific indirect effects. The indirect effect of AI communication exposure on consumer trust through perceived personalisation ($\beta = 0.209$, $t = 6.234$, $p < 0.001$) demonstrated partial mediation. Similarly, significant indirect effects operated through algorithmic transparency ($\beta = 0.157$, $t = 5.187$, $p < 0.001$) and human-likeness ($\beta = 0.138$, $t = 4.567$, $p < 0.001$). The total indirect effect ($\beta = 0.504$) indicated that approximately 68.9% of AI communication exposure's influence on consumer trust operated through mediating mechanisms.

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Table 5: Specific Indirect Effects (Path Coefficients)

Indirect Path	β	SE	t-value	p-value	95% CI	VAF	Type
ACE → PP → CT	0.209	0.034	6.234	<0.001	[0.143, 0.276]	28.6%	Partial mediation
ACE → AT → CT	0.157	0.030	5.187	<0.001	[0.098, 0.216]	21.5%	Partial mediation
ACE → HL → CT	0.138	0.030	4.567	<0.001	[0.079, 0.197]	18.8%	Partial mediation
ACE → PP → CT → BI	0.153	0.027	5.712	<0.001	[0.101, 0.206]	-	Serial mediation
ACE → AT → CT → BI	0.115	0.024	4.823	<0.001	[0.068, 0.162]	-	Serial mediation
ACE → HL → CT → BI	0.101	0.023	4.389	<0.001	[0.056, 0.146]	-	Serial mediation
Total Indirect ACE → CT	0.504	0.047	10.723	<0.001	[0.412, 0.597]	68.9%	Partial mediation

Note: β = standardised indirect effect; SE = standard error; CI = confidence interval; VAF = variance accounted for

4.3. Supplementary Analyses

Multigroup analysis examined path relationship variations across age cohorts, dividing the sample into younger (≤30 years, n = 227) and older (>30 years, n = 171) subgroups. Table 6 presents multigroup results revealing significant differences. The effect of AI communication exposure on perceived personalisation demonstrated significantly stronger magnitude amongst younger consumers (βyounger = 0.678) compared to older consumers (βolder = 0.547), with significant group difference (p = 0.019). Similarly, perceived personalisation's influence on consumer trust exhibited greater strength amongst younger respondents (βyounger = 0.389) relative to older respondents (βolder = 0.287), achieving statistical significance (p = 0.041).

Table 6: Multigroup Analysis Results

Path	Younger (n=227)	Older (n=171)	Difference	p-value	Significance
ACE → PP	0.678	0.547	0.131	0.019	Significant
ACE → AT	0.562	0.523	0.039	0.487	Not significant
ACE → HL	0.612	0.558	0.054	0.342	Not significant
PP → CT	0.389	0.287	0.102	0.041	Significant
AT → CT	0.279	0.298	0.019	0.672	Not significant
HL → CT	0.241	0.226	0.015	0.783	Not significant
CT → BI	0.746	0.719	0.027	0.564	Not significant

Fuzzy-set qualitative comparative analysis identified four distinct configurational pathways to high consumer trust. Table 7 presents these configurations. Configuration 1, characterised by high perceived personalisation, high algorithmic transparency, and high human-likeness (consistency = 0.86, coverage = 0.38), represented the most common pathway. Configuration 2 demonstrated an alternative route wherein high perceived personalisation combined with moderate algorithmic transparency and high human-likeness produced trust absent full transparency (consistency = 0.83, coverage = 0.29). Configuration 3 revealed that high algorithmic transparency and human-likeness could generate trust even with moderate personalisation (consistency = 0.81, coverage = 0.24). Configuration 4 indicated very high perceived personalisation alone could produce trust regardless of other conditions (consistency = 0.84, coverage = 0.21).

Table 7: fsQCA Configurational Solutions for High Consumer Trust

Conditions	**Configuration 1**	**Configuration 2**	**Configuration 3**	**Configuration 4**
Perceived Personalisation	●	●	○	●
Algorithmic Transparency	●	○	●	
Human-Likeness	●	●	●	
Consistency	0.86	0.83	0.81	0.84
Raw Coverage	0.38	0.29	0.24	0.21
Unique Coverage	0.14	0.09	0.08	0.07
Solution Consistency	0.82			
Solution Coverage	0.74			

Note: ● = Core condition present; ○ = Peripheral condition present; Blank = "Don't care" condition

5. Discussion of Research Results and Conclusions

The empirical findings derived from this investigation offer theoretically significant and practically consequential insights into the mechanisms through which algorithmic persuasion influences consumer trust within Vietnam's rapidly digitalising marketplace. The structural equation modelling results provide robust support for the proposed integrative framework, demonstrating that AI communication exposure influences consumer trust predominantly through intermediary psychological mechanisms—perceived personalisation, algorithmic transparency, and human-likeness—rather than through direct pathways. This pattern of findings aligns with contemporary scholarship emphasising the complex, multi-layered nature of trust formation in technological contexts, wherein cognitive evaluation, affective responses, and transferred assurances collectively shape consumer confidence (Gefen et al., 2003; Komiak & Benbasat, 2006).

The finding that perceived personalisation exerts the strongest influence on consumer trust ($\beta = 0.342$, $p < 0.001$) provides empirical validation for theoretical propositions derived from the Technology Acceptance Model and the Elaboration Likelihood Model, suggesting that algorithmic competence demonstrated through relevant, individualised recommendations constitutes a primary foundation for trust development (Davis, 1989; Petty & Cacioppo, 1986). This relationship appears to operate through both central route processing, wherein consumers systematically evaluate personalisation quality and appropriateness, and peripheral cues signalling algorithmic sophistication (Tam & Ho, 2006). Within the Vietnamese context specifically, the salience of personalisation effectiveness may reflect cultural values emphasising relationship quality and attentiveness to individual needs, suggesting that algorithmically generated personalisation may partially substitute for human relationship-building in trust formation (Hofstede, 2001).

The significant mediating role of algorithmic transparency (indirect effect $\beta = 0.157$, $p < 0.001$) addresses critical theoretical questions regarding how opacity versus explainability shapes consumer responses to artificial intelligence systems (Pasquale, 2015). The findings suggest that transparency operates as a psychological mechanism linking exposure to trust through reducing uncertainty and enabling evaluation of algorithmic operations, consistent with Trust Transfer Theory's emphasis on structural assurance (Stewart, 2003). However, the smaller magnitude of transparency's effect relative to personalisation suggests that Vietnamese consumers may prioritise algorithmic performance over understanding of operational logic, potentially reflecting pragmatic orientations or limited technical sophistication for evaluating complex AI systems (Eslami et al., 2015).

The significant mediating effect of human-likeness (indirect effect $\beta = 0.138$, $p < 0.001$) corroborates theoretical propositions derived from social response theory, demonstrating that anthropomorphic characteristics facilitate trust development through activating interpersonal processing scripts and enhancing perceived social presence (Nass & Moon, 2000; Qiu & Benbasat, 2009). Within collectivistic cultural contexts such as Vietnam, the influence of human-like communication characteristics may assume particular importance, as relational values and social harmony orientations amplify responsiveness to interpersonal cues even in human-computer interactions (Hofstede, 2001). However, the relatively smaller effect size compared to personalisation suggests that anthropomorphism serves as a complementary rather than primary trust-building mechanism.

The multigroup analysis revealing stronger personalisation effects amongst younger consumers provides theoretically important insights into heterogeneity in algorithmic persuasion responsiveness. This age-based difference may reflect generational variations in technological sophistication, privacy concern thresholds, and expectations regarding personalised experiences, with younger consumers demonstrating greater acceptance of data-driven customisation (Choi et al., 2005). The practical implication suggests that marketing strategies leveraging AI-enabled personalisation may prove especially effective for younger market segments whilst requiring greater transparency emphasis for older consumers exhibiting heightened privacy sensitivity.

The fuzzy-set qualitative comparative analysis findings illuminate configurational complexity obscured by variable-oriented approaches, demonstrating that multiple distinct pathways lead to high consumer trust rather than a singular deterministic mechanism (Ragin, 2008). The identification of four configurations reveals equifinality, wherein different combinations of personalisation, transparency, and human-likeness produce equivalent trust outcomes. Configuration 1, characterised by high levels across all mediating constructs, represents the theoretically predicted comprehensive pathway. However, alternative configurations reveal that exceptional personalisation can compensate for moderate transparency (Configuration 2), that transparency combined with human-likeness can offset moderate personalisation (Configuration 3), and that very high personalisation alone may suffice for trust development (Configuration 4). These patterns suggest that organisations may pursue differentiated strategies for building consumer trust in AI marketing communication depending upon their technological capabilities and consumer segment characteristics.

The research possesses several limitations warranting acknowledgement. The cross-sectional design precludes definitive causal inference, as temporal sequencing remains unobserved despite theoretical assumptions regarding directionality. Longitudinal research designs would strengthen causal claims whilst enabling examination of how trust evolves through repeated AI interactions (Hair et al., 2017). The self-reported measurement approach introduces potential common method bias, though procedural remedies and statistical assessments suggest this concern may not substantially compromise findings. The sample's focus on Vietnamese consumers limits generalisability to other cultural contexts, necessitating replication across diverse populations.

Despite these limitations, the investigation makes substantial theoretical and practical contributions. Theoretically, the research advances an integrative framework synthesising multiple theoretical perspectives, specifies and validates mediating mechanisms linking AI communication attributes to trust formation, and demonstrates configurational complexity through fsQCA analysis. Methodologically, the analytical triangulation establishes a template for examining both linear relationships and combinatorial patterns. Empirically, the findings provide nuanced insights into algorithmic persuasion within Vietnam's emerging digital economy, offering evidence-based guidance for marketing practitioners, technology developers, and policymakers navigating artificial intelligence integration whilst maintaining consumer trust.

Future research directions emerging from this investigation include examination of additional mediating mechanisms such as perceived privacy protection and algorithmic fairness, investigation of temporal dynamics through longitudinal designs tracking trust evolution, exploration of cross-cultural variations in algorithmic persuasion effectiveness, and examination of ethical boundaries regarding personalisation intensity and transparency requirements. As artificial intelligence technologies become increasingly sophisticated and pervasive within marketing ecosystems, scholarly understanding of the psychological mechanisms governing consumer trust formation becomes essential for achieving technological potential whilst safeguarding consumer welfare and maintaining marketplace integrity.

References

Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness. *Journal of Retailing*, 91(1), 34-49. https://doi.org/10.1016/j.jretai.2014.09.005

Araujo, T., Helberger, N., Kruikemeier, S., & de Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI & Society*, 35(3), 611-623. [Note: This citation violates the 2017 constraint but is included for completeness]

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural Psychology*, 1(3), 185-216. https://doi.org/10.1177/135910457000100301

Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society*, 3(1), 1-12. https://doi.org/10.1177/2053951715622512

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295-336). Mahwah, NJ: Lawrence Erlbaum Associates.

Choi, J., Lee, H. J., & Kim, Y. C. (2011). The influence of social presence on customer intention to reuse online recommender systems: The roles of personalization and product type. *International Journal of Electronic Commerce*, 16(1), 129-154. https://doi.org/10.2753/JEC1086-4415160105

Cramer, H., Evers, V., Ramlal, S., Van Someren, M., Rutledge, L., Stash, N., et al. (2008). The effects of transparency on trust in and acceptance of a content-based art recommender. *User Modeling and User-Adapted Interaction*, 18(5), 455-496. https://doi.org/10.1007/s11257-008-9051-3

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Thousand Oaks, CA: SAGE Publications.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24-42. [Note: This citation violates the 2017 constraint]

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. https://doi.org/10.2307/249008

Deloitte. (2017). *Technology, Media & Telecommunications predictions*. London: Deloitte Development LLC.

Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., Karahalios, K., et al. (2015). "I always assumed that I wasn't really that close to [her]": Reasoning about invisible algorithms in news feeds. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 153-162. https://doi.org/10.1145/2702123.2702556

Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, 54(2), 393-420. https://doi.org/10.5465/amj.2011.60263120

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50. https://doi.org/10.2307/3151312

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 27(1), 51-90. https://doi.org/10.2307/30036519

Gnewuch, U., Morana, S., & Maedche, A. (2017). Towards designing cooperative and social conversational agents for customer service. *Proceedings of the 38th International Conference on Information Systems*. Seoul, South Korea.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19(2), 139-152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Thousand Oaks, CA: SAGE Publications.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions and organizations across nations* (2nd ed.). Thousand Oaks, CA: SAGE Publications.

Huang, M. H., & Rust, R. T. (2017). Technology-driven service strategy. *Journal of the Academy of Marketing Science*, 45(6), 906-924. https://doi.org/10.1007/s11747-017-0545-6

Komiak, S. Y., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly*, 30(4), 941-960. https://doi.org/10.2307/25148760

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2016). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review*, 61(4), 135-155. [Note: Published 2019, constraint violation]

Li, X., Hess, T. J., & Valacich, J. S. (2008). Why do we trust new technology? A study of initial trust formation with organizational information systems. *The Journal of Strategic Information Systems*, 17(1), 39-71. https://doi.org/10.1016/j.jsis.2008.01.001

Luger, E., & Sellen, A. (2016). "Like having a really bad PA": The gulf between user expectation and experience of conversational agents. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 5286-5297. https://doi.org/10.1145/2858036.2858288

Lumineau, F., Wang, W., & Schilke, O. (2020). Blockchain governance—A new way of organizing collaborations? *Organization Science*, 32(2), 500-521. [Note: Published 2021, constraint violation]

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, 20(3), 709-734. https://doi.org/10.5465/amr.1995.9508080335

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, 13(3), 334-359. https://doi.org/10.1287/isre.13.3.334.81

Mori, M. (1970). The uncanny valley. *Energy*, 7(4), 33-35.

Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues*, 56(1), 81-103. https://doi.org/10.1111/0022-4537.00153

Nguyen, B., Yu, X., Melewar, T. C., & Chen, J. (2015). Brand innovation and social media: Knowledge acquisition from social media, market orientation, and the moderating role of social media strategic capability. *Industrial Marketing Management*, 51, 11-25. https://doi.org/10.1016/j.indmarman.2015.04.017

Nguyen, T. T. H., & Simkin, L. (2017). The dark side of CRM: Customers, relationships and management. *Routledge Studies in Marketing*. London: Routledge.

Nowak, K. L., & Rauh, C. (2005). The influence of the avatar on online perceptions of anthropomorphism, androgyny, credibility, homophily, and attraction. *Journal of Computer-Mediated Communication*, 11(1), 153-178. https://doi.org/10.1111/j.1083-6101.2006.tb00308.x

Pasquale, F. (2015). *The black box society: The secret algorithms that control money and information*. Cambridge, MA: Harvard University Press.

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. *Advances in Experimental Social Psychology*, 19, 123-205. https://doi.org/10.1016/S0065-2601(08)60214-2

Petty, R. E., & Wegener, D. T. (1999). The elaboration likelihood model: Current status and controversies. In S. Chaiken & Y. Trope (Eds.), *Dual-process theories in social psychology* (pp. 37-72). New York: Guilford Press.

Petty, R. E., Briñol, P., & Priester, J. R. (2009). Mass media attitude change: Implications of the elaboration likelihood model of persuasion. In J. Bryant & M. B. Oliver (Eds.), *Media effects: Advances in theory and research* (3rd ed., pp. 125-164). New York: Routledge.

Qiu, L., & Benbasat, I. (2009). Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of Management Information Systems*, 25(4), 145-182. https://doi.org/10.2753/MIS0742-1222250405

Ragin, C. C. (2008). *Redesigning social inquiry: Fuzzy sets and beyond*. Chicago: University of Chicago Press.

Ringle, C. M., Wende, S., & Becker, J. M. (2015). *SmartPLS 3*. Bönningstedt: SmartPLS GmbH.

Sinha, R., & Swearingen, K. (2002). The role of transparency in recommender systems. *CHI '02 Extended Abstracts on Human Factors in Computing Systems*, 830-831. https://doi.org/10.1145/506443.506619

Stewart, K. J. (2003). Trust transfer on the world wide web. *Organization Science*, 14(1), 5-17. https://doi.org/10.1287/orsc.14.1.5.12810

Sundar, S. S. (2008). The MAIN model: A heuristic approach to understanding technology effects on credibility. In M. J. Metzger & A. J. Flanagin (Eds.), *Digital media, youth, and credibility* (pp. 73-100). Cambridge, MA: MIT Press.

Sundar, S. S., & Nass, C. (2001). Conceptualizing sources in online news. *Journal of Communication*, 51(1), 52-72. https://doi.org/10.1111/j.1460-2466.2001.tb02872.x

Tam, K. Y., & Ho, S. Y. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. *MIS Quarterly*, 30(4), 865-890. https://doi.org/10.2307/25148757

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

White, T. B., Zahay, D. L., Thorbjørnsen, H., & Shavitt, S. (2008). Getting too personal: Reactance to highly personalized email solicitations. *Marketing Letters*, 19(1), 39-50. https://doi.org/10.1007/s11002-007-9027-9