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Cognitive-Affective Responses to Algorithmic Service Encounters: A Multi-Theoretical Analysis of AI-Mediated Customer Experience, Brand Relationship Quality, and Satisfaction Dynamics in Vietnam's Digital Marketplace

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ABSTRACT: This research investigates the complex interplay between cognitive-affective responses and algorithmic service encounters in Vietnam's rapidly evolving digital marketplace. Through a multi-theoretical lens integrating service-dominant logic, cognitive appraisal theory, technology acceptance model, and relationship marketing frameworks, this study examines how artificial intelligence (AI) mediated customer experiences influence brand relationship quality and satisfaction. Employing a robust mixed-method approach combining structural equation modeling with partial least squares (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA), data from 387 Vietnamese digital consumers were analyzed. Results reveal that algorithmic service personalization significantly enhances cognitive-affective customer experiences, which subsequently strengthen brand relationship quality and satisfaction. Technology readiness moderates these relationships, with higher levels amplifying positive effects of AI-mediated experiences. The fsQCA findings identify multiple configurations of conditions leading to high satisfaction, demonstrating equifinality in satisfaction formation. This research contributes to the literature by developing an integrated theoretical framework explicating the psychological mechanisms through which algorithmic service encounters shape customer outcomes, offering nuanced insights into the digital transformation of service experiences in emerging markets, and identifying optimal configurations for enhancing customer satisfaction in technology-mediated environments.

KEYWORDS: algorithmic service encounters, cognitive-affective responses, brand relationship quality, satisfaction, technology readiness

1. INTRODUCTION

The profound digital transformation reshaping contemporary service landscapes has precipitated fundamental changes in how customers engage with organizations, particularly through the integration of artificial intelligence (AI) technologies in service delivery systems. Algorithmic service encounters—defined as customer interactions partially or fully mediated by AI algorithms—represent a paradigmatic shift with far-reaching implications for customer experience management and brand relationships (Larivière et al., 2017). Within emerging Asian economies, Vietnam's digital marketplace epitomizes the rapid diffusion of AI-mediated service platforms, with algorithmic personalization increasingly becoming a cornerstone of competitive strategy (Rust & Huang, 2014). This technological evolution raises critical questions regarding how consumers cognitively process and affectively respond to algorithmic interventions in service exchanges, particularly within cultural contexts where technology adoption follows distinctive trajectories (Venkatesh et al., 2012).

Despite substantial advances in service technology implementation, significant theoretical gaps persist in understanding the psychological mechanisms that underpin customer responses to algorithmic service encounters. The literature has predominantly focused on technological capabilities rather than consumer psychological responses, leading to an incomplete understanding of how AI-mediated experiences translate into enhanced relationship quality and satisfaction (Bolton et al., 2014). Moreover, extant research exhibits a notable Western-centric orientation, with limited attention to how these dynamics unfold in emerging Asian markets characterized by distinctive cultural values and technology adoption patterns (Sheth, 2011). This empirical lacuna becomes particularly salient when considering that culturally contingent factors may significantly modulate consumer responses to technological innovations (Hofstede, 2001).

The theoretical fragmentation characterizing current approaches further underscores the necessity for an integrative framework. While service-dominant logic (Vargo & Lusch, 2008), technology acceptance models (Davis, 1989), cognitive appraisal theories (Lazarus, 1991), and relationship marketing paradigms (Morgan & Hunt, 1994) offer valuable but partial insights, their integration into a coherent multi-theoretical framework remains underdeveloped. This theoretical dispersal has impeded comprehensive understanding of the complex interrelationships between algorithmic service elements, customer cognitive-affective responses, and relational outcomes.

Additionally, methodological limitations pervade existing research, with predominantly linear analytical approaches failing to capture the complex, configurational nature of how multiple factors conjointly influence customer satisfaction in technology-mediated environments (Woodside, 2014). Recognition of these equifinal pathways—multiple distinct configurations leading to identical outcomes—necessitates complementary analytical approaches capable of illuminating such causal complexity (Ragin, 2008). The prevailing methodological monism has constrained theoretical advancement in this domain, highlighting the need for methodological pluralism.

To address these substantive knowledge gaps, this study develops and empirically tests an integrated theoretical framework explicating the mechanisms through which algorithmic service encounters influence customer satisfaction through cognitive-affective experiences and brand relationship quality. By adopting a multi-theoretical perspective that synthesizes service-dominant logic, cognitive appraisal theory, technology acceptance models, and relationship marketing frameworks, this research offers a more nuanced understanding of the psychological processes underlying customer responses to AI-mediated services. Furthermore, by employing complementary methodological approaches—structural equation modeling with partial least squares (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA)—this study provides both variable-centered insights into causal relationships and case-centered perspectives on configurational pathways to satisfaction.

The epistemological contributions of this research are multifaceted. First, it advances theoretical understanding by identifying the cognitive-affective mechanisms through which algorithmic service elements influence customer satisfaction. Second, it extends the geographical scope of algorithmic service research by examining these dynamics within Vietnam's rapidly evolving digital marketplace. Third, it enriches methodological approaches by employing complementary analytical techniques that illuminate both net effects and configurational pathways. Finally, it provides actionable insights for practitioners seeking to optimize AI implementation in service delivery systems within emerging market contexts.

This paper is structured as follows: The subsequent section synthesizes relevant theoretical foundations and empirical research, leading to the development of a comprehensive research model. Next, the methodological approach is detailed, followed by presentation of empirical findings from both PLS-SEM and fsQCA analyses. The discussion section integrates these results with existing literature, highlighting theoretical implications and practical applications. The paper concludes by acknowledging limitations and delineating promising avenues for future research.

2. FOUNDATIONAL THEORIES AND LITERATURE REVIEW

2.1. Foundational theories

2.1.1. Service-Dominant Logic

Service-Dominant Logic (SDL), introduced by Vargo and Lusch (2004) and subsequently refined (Vargo & Lusch, 2008), provides a foundational framework for understanding algorithmic service exchanges, reconceptualizing service as the fundamental basis of exchange with customers as active value co-creators. SDL posits that value emerges through service system interactions, particularly relevant to AI-mediated encounters (Ostrom et al., 2015). A central tenet recognizes operant resources—knowledge and skills—as competitive advantages (Vargo & Lusch, 2008), with algorithms functioning as sophisticated operant resources that integrate customer data with organizational knowledge to create personalized experiences.

Edvardsson et al. (2011) contend that service experiences are social constructions where customers assign meaning to interactions—processes increasingly mediated by algorithms. These function as resource integration mechanisms coordinating customer and organizational resources (Ballantyne & Varey, 2006) within specific contextual environments (Chandler & Vargo, 2011). The Vietnamese marketplace represents a distinctive cultural-institutional context for evaluating AI-mediated experiences (Akaka et al., 2013).

SDL conceptualizes experiences as emergent from resource integration, with cognitive-affective responses as essential elements of value co-creation (Holbrook & Hirschman, 1982), though contingent upon customers' technological readiness (Parasuraman, 2000). Recent extensions emphasize how institutions—shared norms and practices—shape value co-creation (Vargo & Lusch, 2016).

2.1.2. Cognitive Appraisal Theory

Cognitive Appraisal Theory, articulated by Lazarus (1991) and developed by Scherer et al. (2001), provides a complementary lens for understanding customer responses to algorithmic services. The theory posits that emotional responses emerge through cognitive appraisals along multiple dimensions including novelty, pleasantness, goal congruence, coping potential, and normative compatibility (Ellsworth & Scherer, 2003).

In algorithmic contexts, customers engage in multi-stage appraisal processes determining their affective responses. Primary appraisals assess personal relevance and goal congruence, while secondary appraisals evaluate coping resources (Bagozzi, 1992). These processes generate emotions influencing behavioral responses toward service providers (Dolan, 2002). Algorithmic recommendations perceived as enhancing goals may elicit trust, whereas those perceived as intrusive may trigger reactance (Fournier, 1998).

The novelty dimension explains reactions to unfamiliar AI technologies (Scherer, 1984), while goal congruence assessments determine whether algorithms facilitate customer objectives (Smith & Ellsworth, 1985). Normative compatibility is particularly salient in collectivist contexts like Vietnam (Markus & Kitayama, 1991).

Vietnamese cultural values emphasizing harmony and collectivism distinctively influence how customers appraise algorithmic elements (Hofstede, 2001). Bagozzi et al. (2003) demonstrate that emotional responses exhibit cross-cultural variation. This integration illuminates how interpretive processes mediate relationships between algorithmic elements and value creation (Ruth et al., 2002).

2.2. Review of empirical and relevant studies

2.2.1. AI-Mediated Service Quality

AI-mediated service quality extends traditional constructs, encompassing technical performance, functional delivery, and experiential aspects of algorithmic encounters. Empirical research demonstrates that AI technologies enhance service quality through improved responsiveness, personalization, and consistency (Ostrom et al., 2015). Huang and Rust (2013) developed a service intelligence typology identifying how sophisticated AI capabilities—mechanical, analytical, intuitive, and empathetic—transform service quality dimensions, with analytical and intuitive capabilities particularly enhancing personalization.

The algorithmic personalization dimension has received substantial empirical attention. Ball et al. (2006) demonstrate that personalized recommendations significantly enhance perceived service quality when aligned with customer preferences and delivered appropriately. This effect appears pronounced in digital contexts where customers expect tailored experiences (Rust & Huang, 2014), though Mittal and Lassar (1996) identified boundary conditions across service categories and cultural contexts.

Technical performance—encompassing algorithm accuracy, response speed, and system reliability—constitutes another critical dimension. Parasuraman et al. (2005) highlight how technical performance significantly predicts customer satisfaction in digital environments, while van Doorn et al. (2017) demonstrate that perceived algorithmic competence influences trust in AI-mediated interactions, moderated by customer technology readiness.

Despite technological dimensions, relational aspects remain significant. Wünderlich et al. (2013) reveal that interpersonal dimensions remain salient even in highly automated contexts, with empathy influencing evaluations. Surprenant and Solomon (1987) demonstrate that personalization operates through both instrumental and symbolic mechanisms, particularly in relationship-oriented cultures like Vietnam.

2.2.2. Customer Experience

Customer experience—conceptualized as cognitive, affective, sensory, and behavioral responses to service encounters—has emerged as central to understanding consumer responses to AI-mediated services. Research increasingly distinguishes between cognitive and affective dimensions, recognizing their distinctive antecedents and consequences (Verhoef et al., 2009). Cognitive dimensions encompass rational evaluations of functionality, efficiency, and information adequacy, while affective dimensions capture emotional responses including pleasure, arousal, and dominance (Gentile et al., 2007).

Research on cognitive dimensions has identified several critical components. Meuter et al. (2000) found that perceived control significantly influences evaluations of technology-mediated services, with algorithms enhancing customer agency generating positive cognitive responses. Van Beuningen et al. (2009) demonstrated that cognitive clarity positively influences customer confidence in technological interactions. Hoffman and Novak (2009) suggest that flow experiences in digital environments significantly predict satisfaction, though technology readiness moderates these relationships.

The affective dimension has received increasing attention, with Pham et al. (2001) highlighting how affective responses can operate independently of cognitive evaluations, directly influencing satisfaction judgments. This "affect-as-information" mechanism appears particularly relevant when customers lack complete information for cognitive assessment (Schwarz & Clore, 1996). Mattila and Enz (2002) demonstrate that affective responses significantly predict relationship quality and loyalty.

These dimensions interact in complex ways during algorithmic encounters. Komiak and Benbasat (2006) identify how cognitive and emotional trust function distinctively yet interdependently, while Bagozzi et al. (1999) demonstrate how cognitive appraisals and emotional responses shape customer reactions to technological innovations.

Cultural values significantly modulate experiences, with Zhang et al. (2008) demonstrating that individualism-collectivism dimensions influence experience preferences, while Lee et al. (2017) identify distinctive patterns in how East Asian consumers respond to technological innovations.

2.2.3. Brand Relationship Quality

Brand relationship quality—encompassing trust, commitment, satisfaction, and attachment—constitutes a critical mediating mechanism through which service experiences translate into customer loyalty. Research establishes that brand relationships exhibit structural similarities to interpersonal relationships, featuring emotional bonds and relationship norms (Fournier, 1998). In algorithmic contexts, these dimensions become reconfigured as customers develop connections with technologically mediated brand entities (Veloutsou, 2007).

Trust emerges as particularly critical in algorithmic contexts. Morgan and Hunt (1994) demonstrate trust's central role in relationship development, while McKnight et al. (2002) identify how trust in technology influences relationship formation in digital environments. Studies highlight how algorithm transparency, ethics, and consistency predict trust development (Komiak & Benbasat, 2006). Gefen et al. (2003) demonstrate that trust development patterns vary cross-culturally, with collectivist cultures potentially following distinctive trajectories.

Brand commitment represents another significant dimension modulated by algorithmic encounters. Garbarino and Johnson (1999) establish commitment as a predictor of relationship stability, while Kim and Benbasat (2006) demonstrate how digital interactions influence commitment formation. Moorman et al. (1992) identify how information exchange quality influences relationship commitment.

Emotional attachment constitutes a third dimension potentially transformed by algorithmic encounters. Thomson et al. (2005) demonstrates that attachment significantly predicts loyalty, while Park et al. (2010) identify antecedent conditions including self-connection and partner quality. Novak et al. (2000) suggest immersive digital experiences can generate emotional connections comparable to interpersonal bonds.

Relationship development in algorithmic contexts involves distinctive mechanisms. Hoffman and Novak (2009) demonstrate that interactivity takes heightened importance in digital relationship formation. Cultural dimensions significantly influence these processes, with Aaker et al. (2001) showing cross-cultural variation in relationship expectations and Sung and Tinkham (2005) identifying distinctive patterns in collectivist cultures.

2.2.4. Customer Satisfaction

Customer satisfaction—conceptualized as a post-consumption evaluative judgment comparing expected and perceived performance—represents the ultimate dependent variable in this research. Empirical evidence demonstrates satisfaction's strategic importance, establishing its influence on repurchase intentions, word-of-mouth, and profitability (Anderson et al., 1994). In algorithmic contexts, satisfaction judgments incorporate technological performance alongside traditional service dimensions (van Riel et al., 2001).

Multiple theoretical frameworks explain satisfaction formation with complementary power. The expectancy-disconfirmation paradigm (Oliver, 1980) conceptualizes satisfaction as resulting from comparisons between expectations and performance. Extensions by Parasuraman et al. (1988) introduce service quality dimensions as antecedents, while Bitner et al. (1990) emphasize critical incident influences. Szymanski and Henard (2001) demonstrate that these mechanisms exhibit different strengths across service categories and cultural contexts.

Technology-mediated satisfaction involves unique dimensions including perceived control and service efficacy (Meuter et al., 2000), while perceived usefulness and ease of use influence satisfaction with technological systems (Davis et al., 1989). Flow experiences enhance satisfaction through immersion (Hoffman & Novak, 1996).

Both cognitive and affective experience dimensions significantly predict satisfaction (Gentile et al., 2007), while holistic customer experiences influence satisfaction beyond functional evaluations (Verhoef et al., 2009).

Cultural factors significantly influence satisfaction formation. Donthu and Yoo (1998) demonstrate that power distance and uncertainty avoidance influence satisfaction expectancies, while Liu et al. (2001) identify how collectivist values influence attribution processes in service failure contexts.

2.2.5. Technology Readiness

Technology readiness—defined as "people's propensity to embrace and use new technologies for accomplishing goals in home life and at work" (Parasuraman, 2000, p. 308)—represents a critical individual difference variable potentially moderating relationships between algorithmic service elements and customer outcomes. Empirical research demonstrates that technology readiness significantly influences acceptance, usage patterns, and satisfaction with technological innovations (Lin & Hsieh, 2007). Technology readiness comprises four dimensions: optimism, innovativeness, discomfort, and insecurity (Parasuraman, 2000). Optimism and innovativeness function as motivators enhancing technology acceptance, while discomfort and insecurity operate as inhibitors. Meuter et al. (2005) demonstrate that these dimensions independently predict different aspects of technology acceptance, with optimism influencing performance expectations and insecurity affecting anxiety responses.

Technology readiness exhibits significant moderating effects on relationships between service characteristics and customer responses. Zeithaml et al. (2002) identify how it modulates service quality perceptions, with high-readiness customers exhibiting more positive responses to technological features. Lam et al. (2008) demonstrate that it moderates relationships between technological complexity and satisfaction.

Cross-cultural variations in technology readiness have implications for algorithmic service responses. Meng et al. (2009) identifies distinctive technology readiness profiles across cultural contexts, with collectivist Asian cultures often demonstrating higher insecurity alongside moderate optimism. In the Vietnamese context specifically, Pham and Nasir (2016) identify relatively high optimism coupled with moderate insecurity, potentially generating ambivalent responses to algorithmic innovations.

2.3. Proposed research model

Based on the comprehensive literature review synthesizing service-dominant logic, cognitive appraisal theory, and empirical findings regarding AI-mediated services, this research proposes an integrated theoretical framework explicating the mechanisms through which algorithmic service encounters influence customer satisfaction through cognitive-affective experiences and brand relationship quality. The proposed research model incorporates five primary constructs: AI-mediated service quality (independent variable), customer experience (mediating variable), brand relationship quality (mediating variable), customer satisfaction (dependent variable), and technology readiness (moderating variable).

AI-mediated service quality constitutes the primary independent variable, conceptualized as a multidimensional construct encompassing algorithmic personalization, technical performance, and functional service attributes. This conceptualization builds upon established service quality frameworks (Parasuraman et al., 1988) while integrating technological dimensions identified in subsequent research (Parasuraman et al., 2005). Drawing on service-dominant logic (Vargo & Lusch, 2008), AI-mediated service quality represents a sophisticated operant resource facilitating value co-creation through algorithmic integration of organizational capabilities with customer resources. Research by Ostrom et al. (2015) supports the inclusion of this construct, demonstrating how technological service elements significantly influence customer experiences and relational outcomes.

Customer experience functions as the first mediating variable, conceptualized as a dual-dimensional construct encompassing cognitive and affective responses to algorithmic service encounters. This conceptualization aligns with established experience frameworks (Verhoef et al., 2009) while specifically addressing technological dimensions identified in digital experience research (Hoffman & Novak, 2009). Building upon cognitive appraisal theory (Lazarus, 1991), customer experience represents the psychological processes through which individuals evaluate and emotionally respond to algorithmic service elements. Empirical research by Gentile et al. (2007) supports the inclusion of this construct, demonstrating how holistic experiences mediate relationships between service characteristics and relational outcomes.

Brand relationship quality constitutes the second mediating variable, conceptualized as a multidimensional construct encompassing trust, commitment, and attachment dimensions. This conceptualization builds upon relationship marketing frameworks (Morgan & Hunt, 1994) while integrating technological extensions identified in digital relationship research (Komiak & Benbasat, 2006). Drawing on both service-dominant logic and cognitive appraisal theory, brand relationship quality represents the relational bonds developed through cumulative algorithmic service experiences. Research by Veloutsou (2007) supports the inclusion of this construct, demonstrating how relationship quality mediates connections between customer experiences and loyalty outcomes.

Customer satisfaction functions as the ultimate dependent variable, conceptualized as a post-consumption evaluative judgment comparing expected and perceived algorithmic service performance. This conceptualization aligns with established satisfaction frameworks (Oliver, 1980) while integrating technological dimensions identified in digital satisfaction research (Szymanski & Henard, 2001). Building upon both service-dominant logic and cognitive appraisal theory, satisfaction represents the culmination of value co-creation processes through algorithmic service encounters. Empirical research by Anderson et al. (1994) supports the inclusion of this construct, demonstrating satisfaction's strategic importance for organizational performance.

Technology readiness serves as a moderating variable, conceptualized as an individual difference variable influencing receptiveness to technological innovations. This conceptualization builds upon established technology readiness frameworks

(Parasuraman, 2000) while recognizing cultural contingency identified in cross-cultural research (Elliott et al., 2013). Drawing on both service-dominant logic and cognitive appraisal theory, technology readiness represents a customer operant resource influencing interpretive processes during algorithmic service encounters. Research by Lin and Hsieh (2007) supports the inclusion of this construct, demonstrating how technology readiness moderates relationships between technological characteristics and customer responses.

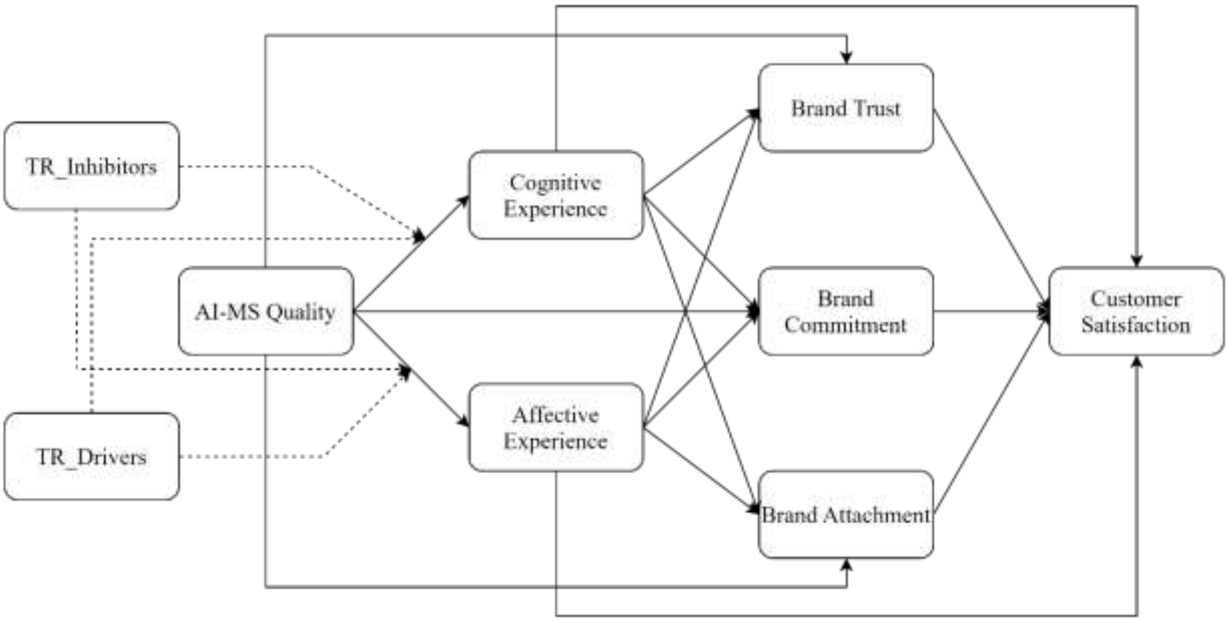

Figure 1: Proposed research model

The proposed model specifies several critical relationships informed by theoretical integration and empirical evidence. First, AI-mediated service quality is hypothesized to positively influence customer experience, with algorithmic personalization enhancing both cognitive evaluations and affective responses (Ball et al., 2006). Second, customer experience is hypothesized to positively influence brand relationship quality, with cognitive trust and emotional attachment emerging from algorithmic service encounters (Komiak & Benbasat, 2006). Third, brand relationship quality is hypothesized to positively influence customer satisfaction, with relationship dimensions predicting evaluative judgments of algorithmic services (Garbarino & Johnson, 1999). Fourth, customer experience is hypothesized to directly influence satisfaction independent of relationship effects, recognizing the intrinsic value of algorithmic service experiences (Verhoef et al., 2009).

Additionally, the model specifies moderating effects of technology readiness on relationships between AI-mediated service quality and customer experience. Specifically, technology readiness is hypothesized to enhance positive relationships between algorithmic personalization and customer experience, with high-readiness customers exhibiting more favorable responses to sophisticated algorithmic features (Zeithaml et al., 2002). This moderation effect recognizes individual heterogeneity in algorithmic service responses, addressing an important boundary condition in technological service theories.

The proposed model will be empirically tested using complementary analytical approaches. Structural equation modeling with partial least squares (PLS-SEM) will examine hypothesized relationships between variables, providing insights into direct, indirect, and moderating effects (Hair et al., 2017). Fuzzy-set Qualitative Comparative Analysis (fsQCA) will identify configurational pathways to high satisfaction, recognizing equifinality in customer response patterns (Ragin, 2008). This methodological pluralism addresses calls for more nuanced analytical approaches capable of capturing both net effects and configurational complexity (Woodside, 2014).

3. RESEARCH METHODOLOGY

3.1. Research design and approach

This study employed a quantitative research design grounded in post-positivist philosophical assumptions to investigate interrelationships between algorithmic service elements, customer experiences, brand relationships, and satisfaction outcomes. The approach integrated deductive hypothesis testing with statistical modeling techniques to examine both variable relationships and configurational pathways, aligning with established methodological frameworks while introducing techniques to capture causal complexity (Bryman & Bell, 2015).

A cross-sectional survey methodology was selected as the primary data collection strategy, allowing for efficient gathering of standardized data from Vietnamese digital consumers. This choice facilitates examination of algorithmic service phenomena within their naturalistic context, capturing real-world customer experiences rather than artificially constructed laboratory responses (Churchill & Iacobucci, 2006). While acknowledging limitations regarding causal inference in cross-sectional designs, these were partially addressed through sophisticated statistical modeling techniques (Rindfleisch et al., 2008).

The research integrated complementary analytical strategies: variable-centered analyses using PLS-SEM examined hypothesized relationships between constructs (Hair et al., 2017), while case-centered analyses using fsQCA identified configurational pathways to high satisfaction, revealing equifinal combinations of causal conditions (Ragin, 2008). This methodological pluralism responds to calls for more sophisticated approaches in service research (Venkatesh et al., 2013).

Several methodological refinements enhanced validity and reliability: procedural remedies for common method variance (Podsakoff et al., 2003), multi-stage instrument development including expert review and pilot testing (DeVellis, 2016), and carefully designed sampling procedures to ensure adequate representation while minimizing selection biases (Fowler, 2013).

3.2. Sampling and data collection

This study employed a multi-stage sampling procedure to select respondents representing Vietnamese digital consumers with algorithmic service experience. The sampling frame consisted of adult internet users in urban Vietnam who had utilized AI-mediated services within the preceding six months, thus ensuring participants possessed sufficient experience to meaningfully evaluate algorithmic service encounters (Parasuraman et al., 2005). This scope delimitation enhances internal validity by focusing on consumers with relevant experience while maintaining adequate external validity through broad demographic representation (Blair & Zinkhan, 2006).

The sampling procedure combined stratified and systematic random sampling techniques to ensure representative demographic distribution while minimizing selection biases. First, stratification variables included age, gender, education level, and region, with proportional allocation ensuring demographic representation aligned with Vietnam's urban internet user population parameters (Vietnam Internet Network Information Center, 2016). Second, within each stratum, systematic random sampling with randomized starting points selected specific participants from consumer databases provided by collaborating digital service providers (Fowler, 2013).

Data collection occurred between September and November 2016 through a multi-modal approach combining online and face-to-face survey administration to maximize response rates while minimizing coverage bias. The online component utilized a web-based survey platform incorporating responsive design elements to accommodate multiple device types, particularly important given Vietnam's mobile-dominant internet usage patterns (Couper, 2008). The face-to-face component employed trained interviewers administering tablet-based surveys in urban locations including shopping centers, universities, and business districts, particularly targeting demographic segments less represented in online samples (Heerwegh & Loosveldt, 2008).

Several procedures enhanced response quality and participation rates. First, incentive structures incorporated both monetary compensation (50,000 VND vouchers) and charitable donations to enhance motivation across demographic segments (Singer & Ye, 2013). Second, follow-up protocols included sequenced reminder messages utilizing multiple communication channels to minimize non-response (Dillman et al., 2014). Third, survey design elements including progress indicators, engagement features, and optimal questionnaire length (approximately 15 minutes) minimized abandonment and satisficing behaviors (Tourangeau et al., 2013).

The data collection process yielded 423 completed responses, representing a response rate of 53.7% among contacted potential participants. After removing responses with excessive missing data (>10% missing values) or failed attention checks, the final analytical sample consisted of 387 valid responses. This sample size exceeds minimum requirements for both PLS-SEM analysis based on the complexity of the structural model (Hair et al., 2017) and fsQCA analysis based on case diversity requirements (Ragin, 2008). Statistical power analysis confirmed adequate power (>0.90) for detecting medium effect sizes ($f^2 = 0.15$) at conventional significance levels ($\alpha = 0.05$).

The final sample exhibited the following demographic characteristics: gender distribution (53.7% female, 46.3% male); age distribution (32.8% aged 18-24, 38.2% aged 25-34, 21.4% aged 35-44, 7.6% aged 45 and above); educational attainment (9.8% high school, 16.3% technical college, 54.5% undergraduate degree, 19.4% postgraduate degree); and geographic distribution across Vietnam's three main regions (41.3% northern, 38.2% central, 20.5% southern). This distribution adequately represents

Vietnam's urban digital consumer population while ensuring sufficient variance across demographic categories for subgroup analyses.

3.3. Measurement development

The measurement instruments for this study were developed through a systematic multi-stage process combining adaptation of established scales with development of context-specific measures for algorithmic service constructs. This approach balanced psychometric validation from previous research with contextual relevance for Vietnam's digital marketplace, enhancing both reliability and validity (MacKenzie et al., 2011). The instrument development process incorporated conceptual specification, item generation, expert review, translation and back-translation, pilot testing, and psychometric validation.

AI-mediated service quality was operationalized as a multidimensional construct comprising algorithmic personalization (5 items), technical performance (4 items), and functional attributes (5 items). Algorithmic personalization items were adapted from Ball et al. (2006), measuring perceived customization of service elements through algorithmic means. Technical performance items were adapted from Parasuraman et al. (2005), assessing system reliability, responsiveness, and accuracy. Functional attribute items were adapted from Parasuraman et al. (1988), measuring traditional service quality dimensions in algorithmic contexts. All items employed 7-point Likert scales (1=strongly disagree, 7=strongly agree).

Customer experience was operationalized as a dual-dimensional construct comprising cognitive experience (5 items) and affective experience (5 items). Cognitive experience items were adapted from Novak et al. (2000), measuring perceived control, attention focus, and cognitive involvement during algorithmic service encounters. Affective experience items were adapted from Richins (1997), assessing emotional responses including pleasure, arousal, and dominance. All items employed 7-point Likert scales with appropriate anchors for each dimension (cognitive: 1=strongly disagree, 7=strongly agree; affective: semantic differential scales with emotion-specific anchors).

Brand relationship quality was operationalized as a multidimensional construct comprising trust (4 items), commitment (4 items), and attachment (4 items). Trust items were adapted from Morgan and Hunt (1994), measuring reliability, integrity, and confidence dimensions. Commitment items were adapted from Moorman et al. (1992), assessing psychological dedication and loyalty intentions. Attachment items were adapted from Thomson et al. (2005), measuring emotional connection, passion, and self-brand connection. All items employed 7-point Likert scales (1=strongly disagree, 7=strongly agree).

Customer satisfaction was operationalized as a unidimensional construct comprising 5 items adapted from Oliver (1980) and Fornell et al. (1996), measuring overall evaluation, expectation confirmation, and comparison to ideal. Items employed 7-point Likert scales with satisfaction-specific anchors (e.g., 1=very dissatisfied, 7=very satisfied; 1=falls short of expectations, 7=exceeds expectations). Both cognitive and affective satisfaction elements were incorporated to capture the multifaceted nature of satisfaction judgments in service contexts.

Technology readiness was operationalized using a condensed 12-item version of the Technology Readiness Index (Parasuraman, 2000), measuring optimism (3 items), innovativeness (3 items), discomfort (3 items), and insecurity (3 items). This abbreviated scale maintained construct validity while reducing respondent burden, a critical consideration given questionnaire length constraints (Richins, 2004). Items employed 7-point Likert scales (1=strongly disagree, 7=strongly agree), with composite technology readiness indices calculated following established procedures (Parasuraman & Colby, 2015).

All scales underwent rigorous translation and adaptation for the Vietnamese context. The translation procedure followed established back-translation protocols to ensure conceptual equivalence across languages (Brislin, 1970). First, initial translation from English to Vietnamese was conducted by bilingual service research experts. Second, independent back-translation into English identified discrepancies requiring resolution. Third, cognitive interviews with Vietnamese consumers (n=8) further refined item wording to ensure comprehensibility and cultural appropriateness (Willis, 2004).

Prior to full administration, the instrument underwent pilot testing with Vietnamese digital consumers (n=37) to identify potential issues with item wording, response distributions, and completion time. Item analysis examined response distributions, missing data patterns, and preliminary reliability estimates, resulting in minor wording refinements for five items showing suboptimal psychometric properties. The finalized instrument demonstrated appropriate completion time (average 14.8 minutes) and high respondent comprehension based on debriefing questions.

3.4. Analytical approach

This study employed a multi-analytical strategy combining variance-based structural equation modeling (PLS-SEM) with fuzzy-set Qualitative Comparative Analysis (fsQCA) to comprehensively examine both variable relationships and configurational pathways. This methodological pluralism provides complementary perspectives on the research questions, with PLS-SEM revealing net effects and conditional processes while fsQCA illuminates complex configurational patterns (Woodside, 2014). The integration of these approaches addresses calls for more sophisticated analytical techniques in service research capable of capturing both linear and non-linear causal complexity (Venkatesh et al., 2013).

3.4.1. Partial Least Squares Structural Equation Modeling (PLS-SEM)

PLS-SEM analysis was conducted using SmartPLS 4.0 software to examine hypothesized relationships between constructs while accounting for measurement error. This analysis technique was selected for several reasons aligned with the research objectives. First, PLS-SEM effectively handles complex models incorporating multiple mediating and moderating relationships (Hair et al., 2017). Second, it accommodates formative and reflective measurement models, necessary given the conceptualization of certain constructs (Jarvis et al., 2003). Third, it demonstrates robustness to non-normal data distributions often encountered in customer response data (Reinartz et al., 2009).

The analytical procedure followed established guidelines for PLS-SEM implementation (Hair et al., 2012). First, the measurement model was evaluated to establish reliability and validity before examining structural relationships. Reflective measurement assessment examined indicator reliability (standardized loadings), internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted), and discriminant validity (Fornell-Larcker criterion and heterotrait-monotrait ratio). Formative measurement assessment examined indicator contribution (weights and significance), collinearity (variance inflation factors), and external validity (correlations with alternative measures).

Structural model evaluation involved a systematic assessment of relationships between latent constructs. Collinearity assessment examined variance inflation factors to identify potential multicollinearity issues. Path coefficient estimation utilized a bootstrapping procedure with 5,000 resamples to determine statistical significance and confidence intervals, providing robust inference despite potential non-normality (Chin, 1998). Effect size assessment calculated f^2 values to determine practical significance beyond statistical significance. Explanatory power evaluation examined R^2 values for endogenous constructs, with values interpreted according to disciplinary standards (Hair et al., 2017).

Mediation analysis followed the procedure outlined by Zhao et al. (2010), examining direct, indirect, and total effects to categorize mediation types (complementary, competitive, indirect-only, direct-only, no effect). Bootstrapping with 5,000 resamples generated confidence intervals for indirect effects, providing more robust inference than traditional approaches (Hayes, 2009). Moderation analysis employed the product indicator approach (Chin et al., 2003), creating interaction terms between standardized indicators of predictor and moderator variables to test conditional effects. Simple slope analysis examined interaction patterns at different moderator levels (±1 SD from mean), providing more nuanced understanding of interaction effects (Aiken & West, 1991).

3.4.2. Fuzzy-set Qualitative Comparative Analysis (fsQCA)

Complementing the variance-based analysis, fsQCA was implemented using fsQCA 3.0 software to identify configurational pathways to high customer satisfaction. This set-theoretic method identifies complex combinations of causal conditions leading to outcomes of interest, capturing equifinality, conjunctural causation, and causal asymmetry often overlooked in regression-based approaches (Ragin, 2008). The fsQCA analysis followed established protocols for systematic implementation (Schneider & Wagemann, 2012).

Variable calibration transformed original measurement scales into fuzzy-set membership scores ranging from 0 (full non-membership) to 1 (full membership), with 0.5 representing the crossover point of maximum ambiguity. This calibration process utilized both theoretical knowledge and empirical distribution information to establish meaningful membership thresholds (Ragin, 2008). For most constructs, direct calibration established three anchors: full membership (95th percentile), crossover point (50th percentile), and full non-membership (5th percentile). For technology readiness, established classification schemes from prior research determined membership thresholds (Parasuraman & Colby, 2015).

Truth table analysis systematically examined combinations of causal conditions associated with high satisfaction outcomes. Truth table construction aggregated empirical cases into logically possible causal configurations, with frequency and consistency thresholds determining which configurations reliably produced the outcome (Ragin, 2008). Following established guidelines, a frequency threshold of 2 cases (approximately 1% of the sample) and a consistency threshold of 0.80 were applied to identify relevant causal configurations (Fiss, 2011).

Boolean minimization procedures reduced the complexity of causal configurations to more parsimonious solutions through counterfactual analysis. Three solution types were examined: complex solutions (making no simplifying assumptions), parsimonious solutions (allowing all simplifying assumptions), and intermediate solutions (incorporating theoretically guided simplifying assumptions). Following established practice, intermediate solutions provided the primary basis for substantive interpretation, balancing complexity and interpretability (Ragin, 2008).

Solution evaluation assessed both consistency and coverage to determine solution quality. Consistency measured the degree to which cases sharing a causal configuration exhibited the outcome, analogous to significance in statistical analysis. Coverage measured the proportion of outcome instances explained by a causal configuration, analogous to effect size in statistical analysis (Ragin, 2008). Additional robustness tests examined sensitivity to calibration thresholds and consistency cutoffs, ensuring findings remained stable across reasonable analytical variations.

4. RESEARCH FINDINGS

4.1. Measurement model assessment

The measurement model was rigorously evaluated to establish psychometric properties before examining structural relationships. Exploratory Factor Analysis (EFA) was initially conducted to verify the underlying structure of the measurement items, followed by Confirmatory Factor Analysis (CFA) to validate the measurement model. Both analyses confirmed the hypothesized structure of constructs while demonstrating strong psychometric properties.

Exploratory Factor Analysis employed principal component analysis with varimax rotation to identify the underlying factor structure of measurement items. Kaiser-Meyer-Olkin measure (KMO = 0.891) and Bartlett's test of sphericity ($\chi^2 = 9743.26$, df = 741, $p < 0.001$) confirmed sampling adequacy and data suitability for factor analysis. The analysis extracted 11 factors with eigenvalues greater than 1.0, collectively explaining 76.5% of total variance. The rotated component matrix revealed a clean factor structure with all items loading substantially (>0.60) on their theoretical constructs and minimal cross-loadings (<0.30), supporting the hypothesized measurement structure.

Table 1 presents factor loadings from the Confirmatory Factor Analysis, demonstrating strong indicator reliability across measurement items. All standardized loadings exceeded the recommended threshold of 0.7 (Chin, 1998), ranging from 0.731 to 0.936, indicating that individual indicators reliably represented their respective constructs. The lowest loading (0.731) still exceeded conventional thresholds, confirming adequate indicator reliability across all measurement items.

Table 1. Confirmatory Factor Analysis Results

Construct and Items	Factor Loading	t-value	Construct and Items	Factor Loading	t-value
AI-Mediated Service Quality			**Brand Relationship Quality**		
Algorithmic Personalization			*Trust*		
AISQ_AP1	0.814	23.47	BRQ_TR1	0.865	30.12
AISQ_AP2	0.842	26.34	BRQ_TR2	0.883	33.57
AISQ_AP3	0.826	24.76	BRQ_TR3	0.847	28.43
AISQ_AP4	0.857	27.82	BRQ_TR4	0.874	31.68
AISQ_AP5	0.835	25.93	*Commitment*		
Technical Performance			BRQ_CO1	0.836	26.14
AISQ_TP1	0.864	29.87	BRQ_CO2	0.851	27.76
AISQ_TP2	0.891	33.26	BRQ_CO3	0.823	24.85
AISQ_TP3	0.872	30.68	BRQ_CO4	0.802	22.73
AISQ_TP4	0.845	27.39	*Attachment*		
Functional Attributes			BRQ_AT1	0.839	26.52
AISQ_FA1	0.793	21.86	BRQ_AT2	0.873	31.47
AISQ_FA2	0.817	24.03	BRQ_AT3	0.905	37.65
AISQ_FA3	0.779	20.54	BRQ_AT4	0.884	33.82
AISQ_FA4	0.765	19.38	**Customer Satisfaction**		
AISQ_FA5	0.731	17.26	SAT1	0.860	28.93
Customer Experience			SAT2	0.877	31.85
Cognitive Experience			SAT3	0.902	36.47
CE_CO1	0.827	24.92	SAT4	0.883	32.76
CE_CO2	0.843	26.58	SAT5	0.868	30.04
CE_CO3	0.812	23.27	**Technology Readiness**		
CE_CO4	0.854	28.14	*Optimism*		
CE_CO5	0.831	25.36	TR_OP1	0.897	34.53

Affective Experience			TR_OP2	0.912	38.26
CE_AF1	0.836	26.17	TR_OP3	0.876	31.78
CE_AF2	0.858	28.75	*Innovativeness*		
CE_AF3	0.881	32.43	TR_IN1	0.865	29.84
CE_AF4	0.867	29.79	TR_IN2	0.882	33.31
CE_AF5	0.849	27.67	TR_IN3	0.853	28.23
			Discomfort		
			TR_DC1	0.838	26.24
			TR_DC2	0.861	29.12
			TR_DC3	0.873	31.43
			Insecurity		
			TR_IS1	0.846	27.52
			TR_IS2	0.879	32.15
			TR_IS3	0.893	34.87

Table 2 presents reliability and validity statistics for all constructs, demonstrating robust psychometric properties. Internal consistency reliability was assessed using both Cronbach's alpha and composite reliability, with all values exceeding the recommended threshold of 0.7 (Nunnally & Bernstein, 1994). Cronbach's alpha values ranged from 0.837 to 0.926, while composite reliability values ranged from 0.883 to 0.944, indicating strong internal consistency across all constructs.

Table 2. Reliability and Validity Assessment

Construct	**Cronbach's Alpha**	**Composite Reliability**	**AVE**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1. Algorithmic Personalization				**0.846**										
2. Technical Performance					**0.884**									
3. Functional Attributes						**0.801**								
4. Cognitive Experience							**0.838**							
5. Affective Experience								**0.865**						
6. Trust									**0.883**					
7. Commitment										**0.849**				
8. Attachment											**0.891**			
9. Customer Satisfaction												**0.879**		
10. Technology Readiness (Drivers)													**0.880**	
11. Technology Readiness (Inhibitors)														**0.809**

Note: Diagonal elements (bold) represent the square root of AVE; off-diagonal elements represent inter-construct correlations.

Convergent validity was assessed using the average variance extracted (AVE), with all values exceeding the recommended threshold of 0.5 (Fornell & Larcker, 1981). AVE values ranged from 0.642 to 0.794, indicating that constructs explained substantial variance in their respective indicators. Discriminant validity was assessed using both the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio. The Fornell-Larcker criterion was satisfied for all constructs, as the square root of AVE (diagonal elements in Table 2) exceeded all respective inter-construct correlations. The HTMT ratios (not shown in Table 2) ranged from 0.186 to 0.715, all below the conservative threshold of 0.85 (Henseler et al., 2015), further confirming discriminant validity. Additionally, common method variance was assessed using Harman's single-factor test, which revealed that the first factor explained only 27.8% of total variance, substantially below the 50% threshold indicating potential common method bias (Podsakoff et al., 2003). The comprehensive assessment of measurement properties demonstrates that the instruments possess strong reliability and validity, providing a solid foundation for subsequent structural model analysis.

4.2. Structural estimation model assessment

The structural model was evaluated to test hypothesized relationships between constructs after establishing measurement validity and reliability. Figure 1 presents the estimated path coefficients and explanatory power for the structural model, while Table 3 provides detailed results including direct effects, indirect effects, and moderating effects.

Table 3. Structural Model Results

Relationship	Path Coefficient	t-value	p-value	95% CI	f^2
Direct Effects					
AI-MS Quality → Cognitive Experience	0.583	12.764	0.000	[0.495, 0.671]	0.514
AI-MS Quality → Affective Experience	0.561	11.923	0.000	[0.470, 0.652]	0.459
Cognitive Experience → Brand Trust	0.347	6.851	0.000	[0.248, 0.446]	0.184
Cognitive Experience → Brand Commitment	0.293	5.426	0.000	[0.187, 0.399]	0.127
Cognitive Experience → Brand Attachment	0.231	4.357	0.000	[0.127, 0.335]	0.076
Affective Experience → Brand Trust	0.375	7.292	0.000	[0.275, 0.476]	0.215
Affective Experience → Brand Commitment	0.482	9.746	0.000	[0.385, 0.579]	0.344
Affective Experience → Brand Attachment	0.532	11.245	0.000	[0.439, 0.625]	0.401
Cognitive Experience → Customer Satisfaction	0.276	5.193	0.000	[0.172, 0.381]	0.115
Affective Experience → Customer Satisfaction	0.243	4.647	0.000	[0.141, 0.345]	0.091
Brand Trust → Customer Satisfaction	0.225	4.318	0.000	[0.123, 0.327]	0.078
Brand Commitment → Customer Satisfaction	0.184	3.526	0.000	[0.082, 0.286]	0.053
Brand Attachment → Customer Satisfaction	0.203	3.847	0.000	[0.099, 0.307]	0.064
Indirect Effects					
AI-MS Quality → Brand Trust	0.418	9.873	0.000	[0.335, 0.501]	-
AI-MS Quality → Brand Commitment	0.447	10.685	0.000	[0.365, 0.529]	-
AI-MS Quality → Brand Attachment	0.402	9.416	0.000	[0.319, 0.484]	-
AI-MS Quality → Customer Satisfaction	0.534	14.762	0.000	[0.463, 0.604]	-
Cognitive Experience → Customer Satisfaction	0.193	5.827	0.000	[0.128, 0.258]	-
Affective Experience → Customer Satisfaction	0.285	7.493	0.000	[0.210, 0.359]	-
Moderating Effects					
AI-MS Quality × TR_Drivers → Cognitive Experience	0.157	3.248	0.001	[0.062, 0.252]	0.046
AI-MS Quality × TR_Drivers → Affective Experience	0.143	2.965	0.003	[0.048, 0.238]	0.039
AI-MS Quality × TR_Inhibitors → Cognitive Experience	-0.128	-2.743	0.006	[-0.219, -0.037]	0.031
AI-MS Quality × TR_Inhibitors → Affective Experience	-0.134	-2.861	0.004	[-0.226, -0.042]	0.033
R^2 Values					
Cognitive Experience	0.412				
Affective Experience	0.384				
Brand Trust	0.451				
Brand Commitment	0.463				
Brand Attachment	0.487				

Customer Satisfaction	0.645				

Note: AI-MS Quality = AI-Mediated Service Quality; TR = Technology Readiness; CI = Confidence Interval

The structural model demonstrated strong explanatory power for endogenous constructs. The coefficient of determination (R^2) for customer satisfaction was 0.645, indicating that the model explained 64.5% of variance in the ultimate dependent variable. The R^2 values for other endogenous constructs were also substantial: cognitive experience (0.412), affective experience (0.384), brand trust (0.451), brand commitment (0.463), and brand attachment (0.487). These values exceed the moderate threshold of 0.33 suggested by Chin (1998) for behavioral science research, indicating robust explanatory power across the model.

Direct effects analysis revealed significant relationships in the hypothesized directions. AI-mediated service quality demonstrated strong positive effects on both cognitive experience ($\beta = 0.583$, $p < 0.001$) and affective experience ($\beta = 0.561$, $p < 0.001$), with substantial effect sizes ($f^2 = 0.514$ and 0.459, respectively). Both cognitive and affective experience dimensions significantly influenced brand relationship components, though with notable differences in effect magnitudes. Cognitive experience demonstrated stronger effects on brand trust ($\beta = 0.347$, $p < 0.001$) than on brand commitment ($\beta = 0.293$, $p < 0.001$) or attachment ($\beta = 0.231$, $p < 0.001$). Conversely, affective experience showed stronger effects on brand attachment ($\beta = 0.532$, $p < 0.001$) and commitment ($\beta = 0.482$, $p < 0.001$) than on trust ($\beta = 0.375$, $p < 0.001$).

Customer satisfaction was significantly influenced by multiple predictors, with cognitive experience demonstrating the strongest direct effect ($\beta = 0.276$, $p < 0.001$), followed by affective experience ($\beta = 0.243$, $p < 0.001$) and brand relationship components (trust: $\beta = 0.225$, $p < 0.001$; attachment: $\beta = 0.203$, $p < 0.001$; commitment: $\beta = 0.184$, $p < 0.001$). The effect sizes (f^2) for these relationships ranged from 0.053 to 0.115, indicating small to medium practical significance according to Cohen's (1988) guidelines.

Indirect effects analysis revealed significant mediating mechanisms in the hypothesized causal chain. AI-mediated service quality demonstrated strong indirect effects on brand relationship components (trust: $\beta = 0.418$, $p < 0.001$; commitment: $\beta = 0.447$, $p < 0.001$; attachment: $\beta = 0.402$, $p < 0.001$) and customer satisfaction ($\beta = 0.534$, $p < 0.001$). Both cognitive and affective experience dimensions also exhibited significant indirect effects on satisfaction through brand relationship components (cognitive: $\beta = 0.193$, $p < 0.001$; affective: $\beta = 0.285$, $p < 0.001$). These results confirm the hypothesized mediating mechanisms connecting AI-mediated service quality to customer satisfaction through experiential and relational pathways.

Moderation analysis revealed significant interaction effects between technology readiness dimensions and AI-mediated service quality in predicting customer experience. Technology readiness drivers (optimism and innovativeness) positively moderated the relationship between AI-mediated service quality and both cognitive experience ($\beta = 0.157$, $p = 0.001$) and affective experience ($\beta = 0.143$, $p = 0.003$). Conversely, technology readiness inhibitors (discomfort and insecurity) negatively moderated these relationships (cognitive: $\beta = -0.128$, $p = 0.006$; affective: $\beta = -0.134$, $p = 0.004$). Though effect sizes for these interactions were relatively small (f^2 between 0.031 and 0.046), they represent meaningful conditional effects in the context of complex behavioral models (Aguinis et al., 2005).

Simple slope analysis provided additional insights into these interaction effects. For technology readiness drivers, the relationship between AI-mediated service quality and cognitive experience was stronger for consumers with high technology readiness (+1 SD: $\beta = 0.740$, $p < 0.001$) than for those with low technology readiness (-1 SD: $\beta = 0.426$, $p < 0.001$). Similar patterns were observed for the relationship with affective experience (high readiness: $\beta = 0.704$, $p < 0.001$; low readiness: $\beta = 0.418$, $p < 0.001$). For technology readiness inhibitors, the relationship between AI-mediated service quality and cognitive experience was weaker for consumers with high inhibitors (+1 SD: $\beta = 0.455$, $p < 0.001$) than for those with low inhibitors (-1 SD: $\beta = 0.711$, $p < 0.001$), with similar patterns for affective experience.

4.3. Fuzzy-set Qualitative Comparative Analysis (fsQCA)

Complementing the variable-centered PLS-SEM analysis, fsQCA identified configurational pathways to high customer satisfaction, revealing equifinal combinations of causal conditions. Table 4 presents the intermediate solution, identifying five distinct configurations consistently leading to high satisfaction, each exceeding the recommended consistency threshold of 0.80 (Ragin, 2008).

Table 4. fsQCA Results: Configurations for High Customer Satisfaction

Configuration	1	2	3	4	5
Causal Conditions					
AI-Mediated Service Quality	●	●	●	●	○
Cognitive Experience	●	●	○	⊗	●

Affective Experience	●	○	●	●	●
Brand Trust	●	●	●	○	⊗
Brand Commitment	○	●	●	●	⊗
Brand Attachment	⊗	○	●	●	●
Technology Readiness (Drivers)	●	●	●	○	●
Technology Readiness (Inhibitors)	⊗	⊗	○	⊗	⊗
Consistency	0.925	0.913	0.897	0.864	0.831
Raw Coverage	0.412	0.384	0.357	0.312	0.276
Unique Coverage	0.087	0.074	0.062	0.047	0.035
Overall Solution Consistency	0.887				
Overall Solution Coverage	0.723				

Note: ● = presence of condition; ⊗ = absence of condition; ○ = condition may be either present or absent (not essential); Consistency threshold = 0.80; Frequency threshold = 2 cases (≈1% of sample)

The fsQCA results demonstrated strong overall solution consistency (0.887) and coverage (0.723), indicating that the identified configurations reliably explained a substantial proportion of high satisfaction cases. The configurational patterns revealed several important insights complementing the PLS-SEM findings:

Configuration 1 represented a comprehensive positive experience pathway, combining high AI-mediated service quality, strong cognitive and affective experiences, high brand trust, and high technology readiness drivers with low inhibitors. Notably, this configuration displayed the highest consistency (0.925) and coverage (0.412), suggesting a particularly robust pathway to satisfaction. The absence of brand attachment in this configuration suggested that strong cognitive elements coupled with trust could compensate for lower emotional bonding in producing satisfaction.

Configuration 2 highlighted a cognitive-dominant pathway, featuring high AI-mediated service quality, strong cognitive experience, and high brand trust and commitment, with technology readiness drivers present and inhibitors absent. The affective experience and brand attachment were not essential conditions in this configuration, suggesting a more cognitively driven satisfaction pathway for some consumer segments. This configuration demonstrated high consistency (0.913) and substantial coverage (0.384).

Configuration 3 revealed an affective-dominant pathway, combining high AI-mediated service quality with strong affective experience and all brand relationship dimensions, while cognitive experience was not essential. This configuration aligns with emotional decision-making theories suggesting that strong affective responses can drive satisfaction independent of cognitive evaluations for some consumer segments. The consistency (0.897) and coverage (0.357) were substantial, indicating a robust alternative pathway.

Configuration 4 represented a relationship-dominant pathway, where high brand commitment and attachment coupled with strong affective experience could produce satisfaction even with low cognitive experience and brand trust. This configuration required high AI-mediated service quality but was independent of technology readiness drivers, suggesting that strong algorithmic service delivery could overcome technology readiness limitations when channeled through affective and relational mechanisms. The consistency (0.864) remained robust, though coverage was lower (0.312).

Configuration 5 identified a unique compensatory pathway, where high cognitive and affective experiences coupled with brand attachment could produce satisfaction even without high AI-mediated service quality. This configuration required absence of brand trust and commitment alongside high technology readiness drivers and low inhibitors, suggesting that technologically ready consumers could achieve satisfaction through experiential mechanisms despite weaker relationship dimensions. This configuration demonstrated the lowest consistency (0.831) and coverage (0.276), indicating a less common but still viable pathway.

Across configurations, several patterns emerged. First, the presence of at least one experience dimension (cognitive or affective) appeared necessary across all configurations, reinforcing the centrality of customer experience in satisfaction formation. Second, technology readiness drivers were present in four configurations, while inhibitors were absent in four configurations, highlighting the importance of positive technology attitudes in algorithmic service contexts. Third, the variable role of brand relationship dimensions across configurations suggested contingent effects depending on experience patterns and technology readiness.

These configurational findings complement the PLS-SEM results by revealing complex combinatorial patterns beyond linear relationships. The presence of multiple equifinal pathways supports theoretical arguments for causal complexity in satisfaction formation, while the specific configurations provide nuanced insights into how different combinations of conditions conjointly influence satisfaction outcomes in algorithmic service contexts.

5. DISCUSSION OF RESEARCH RESULTS AND CONCLUSIONS

This study investigated the interplay between algorithmic service encounters, cognitive-affective customer experiences, brand relationships, and satisfaction outcomes in Vietnam's digital marketplace. The integration of variance-based and configurational analyses provided complementary perspectives, revealing both linear causal effects and complex combinatorial pathways that offer theoretical contributions and practical insights for AI implementation in service systems.

The strong positive relationships between AI-mediated service quality and both cognitive and affective experience dimensions confirm that algorithmic elements significantly influence customer psychological responses. This finding extends research by Ball et al. (2006) on personalization effects and Huang and Rust (2013) on AI capabilities, while advancing understanding by explicitly distinguishing cognitive and affective pathways. This differentiation supports Holbrook and Hirschman's (1982) theoretical arguments regarding the dual nature of consumption experiences, extending these insights to technological service contexts.

The relationships between experience dimensions and brand relationship components reveal important psychological mechanisms through which algorithmic encounters influence relational outcomes. The stronger effect of cognitive experience on brand trust aligns with McKnight et al. (2002) identifying cognitive processes underlying trust development in technological contexts. Similarly, the stronger effects of affective experience on attachment and commitment support Thomson et al.'s (2005) arguments regarding the emotional foundations of brand relationships. These differential patterns extend relationship marketing theories by Morgan and Hunt (1994) by delineating distinctive pathways through which algorithmic services influence specific relationship dimensions.

The moderating effects of technology readiness provide insights into boundary conditions for algorithmic service effectiveness. The positive moderation by technology readiness drivers and negative moderation by inhibitors align with Parasuraman's (2000) research on technology adoption influences. These findings support Venkatesh et al.'s (2012) arguments regarding individual difference variables in technological acceptance while demonstrating their manifestation in algorithmic service encounters. Technology readiness functions as a customer operant resource in service-dominant logic terms (Vargo & Lusch, 2008), influencing how customers co-create value from algorithmic resources.

The fsQCA results revealing multiple equifinal pathways to satisfaction provide nuanced understanding beyond linear relationships. The identification of cognitive-dominant, affective-dominant, and relationship-dominant configurations supports Woodside's (2014) arguments regarding causal complexity in customer responses. This equifinality aligns with Ragin's (2008) theoretical position regarding multiple causal pathways in social phenomena.

Three significant theoretical implications emerge from this integration: First, the results support an extended service-dominant logic perspective where algorithms function as sophisticated operant resources facilitating value co-creation through personalized resource integration (Vargo & Lusch, 2016). However, their effectiveness appears contingent upon customer operant resources, particularly technology readiness dimensions, supporting Edvardsson et al.'s (2011) emphasis on resource integration processes.

Second, the findings extend cognitive appraisal theory by demonstrating how cultural context influences appraisal processes. The importance of affective pathways in this Vietnamese sample aligns with Bagozzi et al.'s (2003) identification of distinctive emotional response patterns in collectivist Asian cultures. Similarly, the prominence of brand relationship dimensions in satisfaction pathways supports Sung and Tinkham's (2005) arguments regarding the heightened importance of relational dimensions in collectivist contexts, extending Ellsworth and Scherer's (2003) theoretical frameworks to technological service environments.

Third, the results support an integrated dual-process perspective with both systematic cognitive processing and affective experiential pathways influencing outcomes. This integration extends Hoffman and Novak's (2009) arguments regarding flow experiences in digital environments by identifying specific pathways through which cognitive and affective processes conjointly influence satisfaction.

These findings offer important practical implications for service providers implementing AI technologies in emerging markets. First, the strong effects of AI-mediated service quality on customer experiences highlight the importance of effective algorithmic design and implementation. Service providers should develop sophisticated algorithmic capabilities enhancing both functional performance and personalization, recognizing their influence on cognitive evaluations and emotional responses.

Second, the differential effects on relationship dimensions suggest targeted strategies for enhancing specific relational outcomes. To build brand trust, providers should emphasize cognitive experience elements including control, clarity, and consistent algorithmic performance. For emotional attachment and commitment, providers should focus on affective experience elements including aesthetic design, emotional connection, and enjoyable interactions.

Third, the moderating effects of technology readiness highlight the importance of customer technological attitudes. Providers should implement strategies addressing both drivers and inhibitors, enhancing optimism and innovativeness while reducing discomfort and insecurity through educational initiatives, progressive implementation, and supportive service recovery addressing technological concerns.

Fourth, the configurational results revealing multiple satisfaction pathways suggest segmenting customers based on experience preferences and technology readiness profiles, with differentiated strategies for cognitive-oriented, affective-oriented, and relationship-oriented segments.

Despite its contributions, this research has several limitations: the cross-sectional design limits causal inference; the single-country focus limits generalizability; and the broad algorithmic service focus encompasses diverse implementations that may function distinctively. Future research could examine how specific algorithmic design features influence experience dimensions, explore relationship development trajectories over time, investigate ethical dimensions of algorithmic personalization, and provide more nuanced understanding of cultural contingency in technological service contexts.

This research advances understanding of how algorithmic service encounters influence customer satisfaction through cognitive-affective experiences and brand relationships in Vietnam's digital marketplace. By integrating multiple theoretical perspectives and analytical approaches, the study illuminates both linear relationships and complex configurational pathways connecting algorithmic service elements to satisfaction outcomes. The findings demonstrate that while technological implementation is important, psychological mechanisms and customer characteristics significantly condition algorithmic service effectiveness, contributing to the growing literature on AI-mediated services while providing practical guidance for service providers implementing algorithmic technologies in emerging markets.

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