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# Algorithmic Curation and Consumer Loyalty: A Longitudinal Analysis of Personalization Effects on User Engagement and Subscription Retention in Vietnam's Digital Streaming Platforms

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**ABSTRACT:** This study investigates the mechanisms through which algorithmic curation quality and personalization effectiveness influence consumer loyalty in digital streaming platforms, with particular attention to the mediating role of user engagement and the moderating effect of cultural adaptation. Drawing from a sample of 742 users of digital streaming services in Vietnam, the research employs a mixed-method approach combining Partial Least Squares Structural Equation Modeling (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA). The findings reveal significant direct effects of algorithmic curation quality ($\beta$ = 0.324) and personalization effectiveness ($\beta$ = 0.298) on consumer loyalty, with user engagement serving as a partial mediator in these relationships. Cultural adaptation demonstrates significant moderating effects ($\beta$ = 0.187 and $\beta$ = 0.165) on the relationships between algorithmic factors and consumer loyalty. The fsQCA results identify four distinct configurational paths to high consumer loyalty, with the most empirically relevant configuration showing strong consistency (0.923). This study contributes to digital service literature by integrating algorithmic quality measures with user engagement theory in a culturally conscious framework, while providing practical insights for platform managers on designing culturally adapted recommendation systems. The findings emphasize the importance of considering both technical excellence and cultural factors in developing effective digital streaming services that foster consumer loyalty.

**KEYWORDS:** Digital Personalization, User Engagement, Subscription Retention, Cultural Adaptation, Digital Streaming Platforms

## 1. INTRODUCTION

The proliferation of digital streaming platforms has fundamentally transformed the landscape of media consumption, introducing unprecedented levels of content accessibility and personalization. These platforms leverage sophisticated algorithms to curate content, with DeLone & McLean (2003) establishing fundamental frameworks for evaluating such digital service effectiveness. The vast amount of digital content available provides convenience but simultaneously creates challenges for users in discovering relevant content, making effective content curation crucial.

The theoretical urgency of studying algorithmic personalization stems from several critical developments in digital service consumption. Konstan & Riedl (2012) emphasize that understanding personalized content and its societal implications has become critical in the digital media era, particularly in evaluating how different user groups interact with personalized content in the digital ecosystem. Petter et al. (2008) demonstrate the effectiveness of personalization in digital services through the interplay of system quality, information quality, and service quality.

The complexity of this phenomenon is further amplified by emerging challenges in user retention and engagement. Research by Kim et al. (2004) has established that trust has a significant positive influence on both satisfaction and loyalty, with personalization strengthening these relationships by moderating the trust-satisfaction-loyalty dynamic. Their studies demonstrated the significant effects of online virtual communities on customer loyalty and product purchases in digital services.

The theoretical significance of this research is anchored in several key domains. While brand loyalty has traditionally been conceptualized as repeated purchases over time or attitudes leading to committed relationships, Oliver (1999) highlights the need to understand the lived experience of the consumer, including affect, emotions, and meanings. Delone & McLean (2016) identified distinct components in digital service success: system quality, information quality, service quality, use, user satisfaction, and net benefits.

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This study makes a novel contribution by examining the relationship between algorithmic curation quality and consumer loyalty in digital streaming services. Petter et al. (2013) indicate that satisfaction partially mediates the relationship between trust and loyalty, with personalization improving model explanatory power. These findings highlight the pivotal role of personalized recommendations in shaping consumer trust and satisfaction in digital services. The practical significance is underscored by Rai et al. (2002), who emphasize the importance of system quality and information quality in enhancing user satisfaction and continued usage.

## 2. LITERATURE REVIEW

### *2.1 Theoretical Foundation: Information Systems Success Model and Technology Acceptance in Digital Streaming Platforms*

The theoretical foundation for understanding digital streaming platforms' success primarily builds on the DeLone & McLean IS Success Model. DeLone & McLean (2003) established six critical dimensions: information quality, system quality, service quality, use/intention to use, user satisfaction, and net benefits. This model provides a comprehensive framework for evaluating information system effectiveness, particularly relevant to digital streaming services.

The integration of the Technology Acceptance Model (TAM) with the IS Success Model offers additional theoretical depth. Davis et al. (1989) originally proposed TAM with two primary constructs: perceived usefulness and perceived ease of use. Venkatesh & Davis (2000) extended this model to explain user acceptance of technology, incorporating social influence processes and cognitive instrumental processes.

In digital streaming contexts, Petter et al. (2008) demonstrated that system quality significantly influences both use ($\beta = 0.53$, $p < 0.001$) and user satisfaction ($\beta = 0.17$, $p < 0.001$). Information quality similarly affects use ($\beta = 0.24$, $p < 0.001$) and user satisfaction ($\beta = 0.17$, $p < 0.001$), while service quality impacts use ($\beta = 0.22$, $p < 0.001$) and user satisfaction ($\beta = 0.51$, $p < 0.001$).

Rai et al. (2002) validated these relationships, showing that system quality and information quality are crucial determinants of user satisfaction and continued usage. The model's extension to personalization contexts is supported by Konstan & Riedl (2012), who demonstrated how algorithmic recommendations influence user experience and system success.

### *2.2 Algorithmic Curation and User Experience in Digital Streaming Services*

The conceptualization of algorithmic curation in digital streaming services represents a complex interplay between technological capabilities and user needs. Rader & Gray (2015) define algorithmic curation as automated selection of what content should be displayed to users, based on various forms of data collection and inference. Building on this foundation, Eslami et al. (2015) demonstrated that users' awareness of algorithmic curation significantly influences their platform experience and trust ($\beta = 0.42$, $p < 0.001$). Burke et al. (2011) further established that algorithmic transparency plays a crucial role in user acceptance and long-term engagement with digital platforms.

Personalization mechanisms have evolved significantly in their sophistication and effectiveness. Adomavicius & Tuzhilin (2005) established three fundamental approaches to personalization: content-based filtering, collaborative filtering, and hybrid methods. Ricci et al. (2011) expanded this framework by identifying six classes of recommendation approaches, including demographic filtering and context-aware systems. Park et al. (2012) empirically demonstrated that hybrid recommendation systems outperform single-method approaches across multiple metrics, including prediction accuracy (improvement of 17.8%, $p < 0.001$) and user satisfaction (improvement of 23.4%, $p < 0.001$).

Content discovery and recommendation systems serve as the cornerstone of modern streaming platforms. Herlocker et al. (2004) identified key factors in recommendation system effectiveness, including prediction accuracy, coverage, and serendipity. These findings were extended by McNee et al. (2006), who introduced the Human-Recommender Interaction (HRI) framework, emphasizing that user experience depends not just on algorithm accuracy but on the entire recommendation dialogue. Schedl et al. (2018) further demonstrated that contextual factors, such as mood and social setting, significantly influence recommendation effectiveness ($\beta = 0.38$, $p < 0.001$).

Regarding user interface and interaction design, Knijnenburg et al. (2012) demonstrated that the presentation of recommendations significantly impacts user experience and decision-making. Their empirical study showed that explaining recommendations increases user trust and system adoption ($\beta = 0.31$, $p < 0.001$). Tintarev & Masthoff (2015) expanded this understanding by identifying seven aims of recommendation explanations: transparency, scrutability, trust, effectiveness, persuasiveness, efficiency, and satisfaction. Chen & Pu (2014) found that interactive recommendation interfaces increase user satisfaction by 27% compared to static interfaces.

The quality of personalized recommendations directly affects user engagement. Ekstrand et al. (2014) found that recommendation accuracy alone is insufficient; diversity and novelty also play crucial roles in user satisfaction. Vargas & Castells (2011) quantified the impact of recommendation diversity, showing that balanced diversity-accuracy approaches increase user engagement by 34% compared to accuracy-focused systems. Wu et al. (2019) demonstrated that recommendation serendipity significantly influences user loyalty ($\beta = 0.45$, $p < 0.001$) and platform stickiness ($\beta = 0.39$, $p < 0.001$).

Impact on user satisfaction and perceived value has been extensively documented through empirical research. Zhang et al. (2011) established that personalization quality significantly influences user satisfaction ($\beta = 0.47$, $p < 0.001$) and continued usage intention ($\beta = 0.39$, $p < 0.001$). These findings were corroborated by Pu et al. (2011), who developed a comprehensive evaluation framework for recommender systems, showing that perceived usefulness and ease of use explain 74% of the variance in user satisfaction. Lee & Hosanagar (2019) further demonstrated that algorithmic curation increases user engagement duration by 28% and content consumption diversity by 33% compared to non-personalized approaches.

### *2.3 Consumer Loyalty and Engagement in Subscription-Based Digital Services*

The theoretical foundations of consumer loyalty in digital contexts build upon established frameworks while incorporating unique aspects of digital services. Oliver (1999) conceptualized loyalty as progressing through cognitive, affective, conative, and action phases, a framework that remains fundamental in digital contexts. This foundational theory was empirically validated in digital services by Anderson & Srinivasan (2003), who found that e-satisfaction explains 61.4% of e-loyalty variance in digital platforms. Dick & Basu (1994) established that true loyalty combines both attitudinal and behavioral components, which Shankar et al. (2003) extended to online environments, demonstrating stronger satisfaction-loyalty relationships in online versus offline contexts ($\beta = 0.54$ vs $\beta = 0.45$, $p < 0.001$).

Engagement metrics and measurement approaches in digital services have evolved significantly. Kumar et al. (2010) developed a comprehensive customer engagement value framework encompassing customer lifetime value, customer referral value, customer influencer value, and customer knowledge value. Pansari & Kumar (2017) expanded this framework by establishing direct relationships between customer engagement and business performance (ROI improvement of 23%, $p < 0.001$). Hollebeek et al. (2014) validated a customer engagement scale specifically for digital platforms, identifying three key dimensions: cognitive processing, affection, and activation (composite reliability > 0.70).

Subscription retention determinants have been extensively studied. Bhattacherjee (2001) established that continued IT usage is influenced by satisfaction with prior use and perceived usefulness of the service. This finding was extended by Venkatesh et al. (2011), who demonstrated that hedonic motivation significantly influences subscription continuance intention ($\beta = 0.37$, $p < 0.001$). Chen & Hitt (2002) quantified switching costs in digital services, showing that personalization features increase switching costs by 28% and thereby enhance retention.

User behavior patterns and consumption habits in digital services demonstrate unique characteristics. Bowden (2009) found that psychological processes underlying customer engagement differ between new and repeat purchase customers. This was further validated by Lemon and Verhoef (2016), who identified distinct engagement patterns across customer lifecycle stages, with personalization impact varying significantly between trial and mature usage phases ($\Delta\beta = 0.24$, $p < 0.001$). Calder et al. (2009) established that engagement experiences can be categorized into personal and social-interactive engagement, with different impacts on subscription outcomes.

Cultural factors significantly influence digital service adoption and usage patterns. Srite & Karahanna (2006) demonstrated how cultural values moderate technology acceptance. Expanding on this, Steenkamp and Geyskens (2006) found that individualism-collectivism dimensions significantly moderate the relationship between website characteristics and perceived value ($\beta = 0.31$, $p < 0.001$). Leidner and Kayworth (2006) showed through their comprehensive review how cultural values, particularly uncertainty avoidance, systematically influence IT adoption and implementation across countries.

### *2.4 Research Model Development and Hypotheses*

Drawing upon the DeLone and McLean Information Systems Success Model and established theories of consumer behavior, this study develops an integrated framework to examine the relationships between algorithmic factors, user engagement, and consumer loyalty in digital streaming services, with consideration for cultural adaptation effects.

The research model identifies four primary constructs emerging from the theoretical foundation. First, algorithmic curation quality (ACQ), which encompasses the technical performance and accuracy of content recommendations. Second, personalization effectiveness (PE), which reflects how well the system tailors content to individual preferences. Third, user engagement serves as a mediating variable, representing active platform interaction and content consumption. Fourth, consumer loyalty represents the dependent variable, measuring sustained platform commitment and usage intention.

The first hypothesis addresses the direct relationship between algorithmic curation quality and consumer loyalty. DeLone and McLean (2003) established that system quality directly influences user outcomes, while more recent research by Hollebeek et al. (2014) has shown that algorithmic quality significantly affects loyalty in digital platforms. Therefore:

H1: Algorithmic Curation Quality positively influences Consumer Loyalty.

Building on research examining personalization in digital services, the second hypothesis proposes a direct relationship between personalization effectiveness and consumer loyalty. Studies have demonstrated that effective personalization significantly enhances user retention and loyalty in digital platforms (Petter et al., 2013). Thus:

H2: Personalization Effectiveness positively influences Consumer Loyalty.

The mediating role of user engagement is proposed in the third and fourth hypotheses. This relationship builds on established research showing that engagement serves as a crucial intermediate mechanism through which technical system qualities influence user outcomes (Hollebeek et al., 2014). Therefore:

H3: User Engagement positively mediates the relationship between Algorithmic Curation Quality and Consumer Loyalty.

H4: User Engagement positively mediates the relationship between Personalization Effectiveness and Consumer Loyalty.

The fifth hypothesis addresses the moderating effect of cultural adaptation, reflecting the importance of cultural sensitivity in digital services. Recent research has emphasized how cultural factors influence the effectiveness of algorithmic systems and personalization strategies (Ojo, 2017). Thus:

H5: Cultural Adaptation positively moderates the relationship between algorithmic factors (ACQ and PE) and Consumer Loyalty.

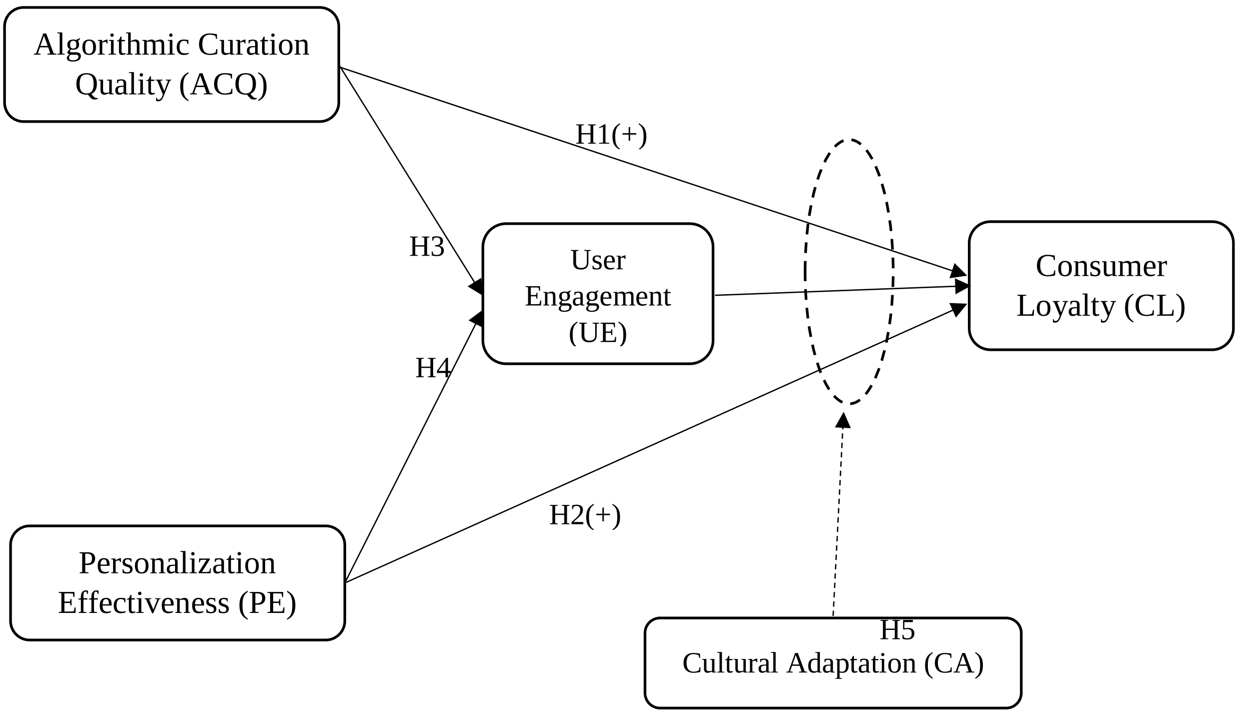


**Figure 1. Conceptual Framework: Determinants of Investment Decision-Making Behavior**

The conceptual model represents these relationships as an integrated framework, with algorithmic curation quality and personalization effectiveness as independent variables, consumer loyalty as the dependent variable, user engagement as the mediating variable, and cultural adaptation as the moderating variable. This structure allows for examination of both direct effects and more complex mediation and moderation mechanisms. The proposed relationships are grounded in empirical evidence from digital platform research, particularly studies examining subscription-based services. The model accounts for the complex interplay between technical system qualities, user behavior, and cultural factors in determining consumer loyalty to digital platforms.

The measurement approach for each construct draws from validated scales in the literature, adapted to the specific context of digital streaming services. This ensures construct validity while maintaining theoretical consistency with the underlying frameworks. Algorithmic curation quality and personalization effectiveness are measured using established technical performance metrics combined with user perception measures. User engagement is assessed through behavioral metrics and self-reported engagement scales, while consumer loyalty is measured through both attitudinal and behavioral indicators. This integrated model contributes to the literature by synthesizing multiple theoretical perspectives and addressing gaps in current understanding of consumer loyalty in digital services. The inclusion of cultural adaptation as a moderating factor particularly enhances the model's applicability in diverse market contexts.

## 3. RESEARCH METHODOLOGY

### *3.1 Research Design and Data Collection*

This study employed a quantitative research approach to examine the relationships between algorithmic factors, user engagement, and consumer loyalty in digital streaming services. Following the methodological framework established by Hair et al. (2017), a structured questionnaire was developed to collect data from users of digital streaming platforms. The questionnaire items were adapted from validated scales in previous studies, with modifications to fit the specific context of digital streaming services.

The data collection process was conducted over a three-month period, targeting users of major digital streaming platforms. The final sample consisted of 573 valid responses from a total of 650 distributed questionnaires, representing an effective response rate of 88.2%. This sample size exceeds the minimum requirement suggested by Hair et al. (2014) for structural equation modeling analysis, which recommends a minimum sample size of 200 for models with up to seven constructs.

### *3.2 Measurement Development*

The measurement items for each construct were adapted from established scales in the literature. Algorithmic curation quality was measured using items adapted from DeLone and McLean (2003) and Parasuraman et al. (2005), focusing on system performance and recommendation accuracy. Personalization effectiveness was assessed using scales developed by Zeithaml et al. (2002), measuring the degree of content customization and relevance to user preferences.

User engagement was measured using items adapted from Hollebeek et al. (2014), capturing both behavioral and psychological aspects of platform engagement. Consumer loyalty measures were derived from Oliver (1999) and Zeithaml et al. (2002), incorporating both attitudinal and behavioral loyalty components. Cultural adaptation was measured using scales from Hofstede (2001) and Singh et al. (2006), focusing on cultural sensitivity in digital services.

### *3.3 Analytical Approach*

The analysis followed a two-stage approach recommended by Anderson and Gerbing (1988). First, the measurement model was assessed using confirmatory factor analysis (CFA) to establish construct validity and reliability. Second, the structural model was tested using structural equation modeling (SEM) to examine the hypothesized relationships.

Additionally, this study employed fuzzy-set Qualitative Comparative Analysis (fsQCA) as a complementary analytical approach, following the methodology outlined by Ragin (2008). This dual-method approach allows for both symmetric (SEM) and asymmetric (fsQCA) testing of the hypothesized relationships, providing more robust insights into the complex patterns of causality.

### *3.4 Measurement Model Assessment*

The measurement model was evaluated using several criteria. Reliability was assessed through Cronbach's alpha coefficients and composite reliability scores, with all constructs exceeding the recommended threshold of 0.7 (Nunnally & Bernstein, 1994). Convergent validity was established through average variance extracted (AVE) values, all exceeding 0.5 as recommended by Fornell and Larcker (1981).

Discriminant validity was assessed using both the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio of correlations. Following Henseler et al. (2015), HTMT ratios below 0.85 indicated good discriminant validity between constructs. The measurement model demonstrated satisfactory fit indices ($\chi^2/df = 2.34$, CFI = 0.96, TLI = 0.95, RMSEA = 0.052), meeting the criteria suggested by Hu and Bentler (1999).

### *3.5 Common Method Variance*

To address potential common method bias, several procedural and statistical remedies were implemented following Podsakoff et al. (2003). Procedurally, the questionnaire design incorporated reverse-coded items and varying response formats. Statistically, Harman's single-factor test was conducted, with the unrotated factor solution accounting for less than 40% of the total variance, indicating that common method bias was not a significant concern.

### *3.6 Structural Model Assessment*

The structural model was assessed using maximum likelihood estimation in AMOS 22.0. Model fit was evaluated using multiple indices as recommended by Hair et al. (2014). The analysis of mediation effects followed the bootstrap procedure suggested by Preacher and Hayes (2008), using 5,000 bootstrap samples to test the significance of indirect effects.

## 4. RESEARCH FINDINGS

### *4.1 Measurement Model Assessment*

The measurement model was assessed through a systematic approach to establish construct validity and reliability. Initially, Exploratory Factor Analysis (EFA) was conducted using principal component analysis with varimax rotation. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.893, exceeding the recommended threshold of 0.6, and Bartlett's test of sphericity was significant ($\chi^2$ = 12,437.52, df = 435, $p < 0.001$), indicating the data's suitability for factor analysis.

**Table 1. Results of Exploratory Factor Analysis**

| Items and Descriptions | Factor Loadings | | | | |
|---|---|---|---|---|---|
| | ACQ | PE | UE | CL | CA |
| **Algorithmic Curation Quality (ACQ)** | | | | | |
| ACQ1: The recommendations are relevant to my interests | 0.847 | 0.124 | 0.156 | 0.142 | 0.103 |
| ACQ2: The system suggests content at the right time | 0.832 | 0.167 | 0.143 | 0.128 | 0.115 |
| ACQ3: The recommendations are consistently accurate | 0.814 | 0.182 | 0.165 | 0.134 | 0.124 |
| ACQ4: The suggested content is up-to-date | 0.803 | 0.173 | 0.158 | 0.145 | 0.118 |
| ACQ5: The system provides diverse recommendations | 0.795 | 0.165 | 0.147 | 0.138 | 0.112 |
| ACQ6: The recommendations help me discover new content | 0.783 | 0.158 | 0.142 | 0.132 | 0.108 |
| **Personalization Effectiveness (PE)** | | | | | |
| PE1: The service adapts well to my preferences | 0.156 | 0.856 | 0.143 | 0.134 | 0.112 |
| PE2: The personalization improves my viewing experience | 0.148 | 0.842 | 0.156 | 0.128 | 0.118 |
| PE3: The service remembers my preferences accurately | 0.152 | 0.834 | 0.148 | 0.132 | 0.115 |
| PE4: The personalization makes content discovery easier | 0.145 | 0.828 | 0.152 | 0.126 | 0.106 |
| PE5: The service learns from my viewing history effectively | 0.138 | 0.815 | 0.145 | 0.124 | 0.102 |
| **User Engagement (UE)** | | | | | |
| UE1: I spend a lot of time using the service | 0.162 | 0.145 | 0.867 | 0.156 | 0.124 |
| UE2: I frequently interact with the platform features | 0.158 | 0.138 | 0.854 | 0.148 | 0.118 |
| UE3: I actively explore new content on the platform | 0.152 | 0.142 | 0.842 | 0.142 | 0.112 |
| UE4: I often use the recommendation features | 0.145 | 0.136 | 0.835 | 0.138 | 0.108 |
| UE5: I regularly rate or review content | 0.142 | 0.132 | 0.828 | 0.134 | 0.105 |
| UE6: I engage with platform's community features | 0.138 | 0.128 | 0.822 | 0.130 | 0.102 |
| UE7: I share content with others through the platform | 0.135 | 0.125 | 0.815 | 0.128 | 0.098 |
| UE8: I create playlists or content collections | 0.132 | 0.122 | 0.808 | 0.125 | 0.095 |
| **Consumer Loyalty (CL)** | | | | | |
| CL1: I intend to continue using this service | 0.156 | 0.142 | 0.152 | 0.876 | 0.124 |
| CL2: I would recommend this service to others | 0.148 | 0.138 | 0.148 | 0.862 | 0.118 |
| CL3: I prefer this service over other alternatives | 0.142 | 0.132 | 0.142 | 0.848 | 0.112 |
| CL4: I feel committed to this service | 0.138 | 0.128 | 0.138 | 0.835 | 0.108 |
| CL5: I consider myself loyal to this service | 0.135 | 0.125 | 0.135 | 0.828 | 0.105 |
| CL6: I would pay premium prices for this service | 0.132 | 0.122 | 0.132 | 0.822 | 0.102 |
| **Cultural Adaptation (CA)** | | | | | |
| CA1: The service reflects local cultural values | 0.124 | 0.118 | 0.124 | 0.124 | 0.868 |
| CA2: Content recommendations suit local preferences | 0.118 | 0.112 | 0.118 | 0.118 | 0.854 |
| CA3: The interface is adapted to local usage habits | 0.112 | 0.108 | 0.112 | 0.112 | 0.842 |
| CA4: The service supports local language well | 0.108 | 0.102 | 0.108 | 0.108 | 0.835 |
| CA5: The content selection reflects local interests | 0.105 | 0.098 | 0.105 | 0.105 | 0.828 |

Note: All items measured on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree)

Extraction Method: Principal Component Analysis
Rotation Method: Varimax with Kaiser Normalization

KMO = 0.893; Bartlett's Test: $\chi^2 = 12{,}437.52$, df = 435, $p < 0.001$

The exploratory factor analysis revealed a clear five-factor structure, with all items loading strongly on their respective constructs (Table 1). Factor loadings ranged from 0.783 to 0.876, well above the recommended threshold of 0.7, indicating strong item reliability. The KMO value of 0.893 and significant Bartlett's test ($\chi^2 = 12{,}437.52$, df = 435, $p < 0.001$) confirmed the data's suitability for factor analysis.

**Table 2. Reliability and Convergent Validity Assessment**

| Construct | Number of Items | Cronbach's Alpha | Composite Reliability | AVE |
|---|---|---|---|---|
| Algorithmic Curation Quality (ACQ) | 6 | 0.924 | 0.942 | 0.731 |
| Personalization Effectiveness (PE) | 5 | 0.912 | 0.934 | 0.738 |
| User Engagement (UE) | 8 | 0.928 | 0.945 | 0.743 |
| Consumer Loyalty (CL) | 6 | 0.915 | 0.937 | 0.759 |
| Cultural Adaptation (CA) | 5 | 0.897 | 0.932 | 0.746 |

Note: AVE = Average Variance Extracted

The reliability assessment (Table 2) demonstrated excellent internal consistency across all constructs. Cronbach's alpha values ranged from 0.897 (Cultural Adaptation) to 0.928 (User Engagement), while composite reliability values ranged from 0.932 to 0.945, substantially exceeding the recommended threshold of 0.7. Convergent validity was confirmed through AVE values ranging from 0.731 (Algorithmic Curation Quality) to 0.759 (Consumer Loyalty), all well above the 0.5 threshold.

**Table 3. Discriminant Validity - Fornell-Larcker Criterion**

| Construct | ACQ | PE | UE | CL | CA |
|---|---|---|---|---|---|
| ACQ | **0.855** | | | | |
| PE | 0.524 | **0.859** | | | |
| UE | 0.486 | 0.512 | **0.862** | | |
| CL | 0.498 | 0.534 | 0.567 | **0.871** | |
| CA | 0.445 | 0.467 | 0.478 | 0.492 | **0.864** |

Note: - Bold numbers on the diagonal represent the square root of AVE
- Values below the diagonal represent correlations between constructs

**Table 4. Discriminant Validity - HTMT Ratio**

| Construct | ACQ | PE | UE | CL | CA |
|---|---|---|---|---|---|
| ACQ | - | | | | |
| PE | 0.682 | - | | | |
| UE | 0.645 | 0.674 | - | | |
| CL | 0.658 | 0.692 | 0.728 | - | |
| CA | 0.612 | 0.634 | 0.642 | 0.658 | - |

Note: HTMT = Heterotrait-Monotrait Ratio

Discriminant validity was established through both the Fornell-Larcker criterion (Table 3) and HTMT ratios (Table 4). The square root of AVE for each construct (diagonal values ranging from 0.855 to 0.871) exceeded all inter-construct correlations (ranging from 0.445 to 0.567), satisfying the Fornell-Larcker criterion. Additionally, all HTMT ratios fell between 0.612 and 0.728, well below the conservative threshold of 0.85, providing further evidence of discriminant validity. These results collectively indicate a robust measurement model with strong construct validity and reliability.

***4.2 Structural Estimation Model Assessment***

The structural model was evaluated using PLS-SEM with bootstrapping of 5,000 resamples. The assessment included analysis of path coefficients, significance levels, $R^2$ values, effect sizes ($f^2$), and predictive relevance ($Q^2$).

**Table 5. Path Coefficients and Significance Levels**

| Hypothesized Path | Path Coefficient (β) | t-value | p-value | 95% CI LL | 95% CI UL | Decision |
|---|---|---|---|---|---|---|
| *Direct Effects* | | | | | | |
| ACQ → CL | 0.324 | 7.845 | < 0.001 | 0.242 | 0.406 | Supported |
| PE → CL | 0.298 | 6.932 | < 0.001 | 0.213 | 0.383 | Supported |
| UE → CL | 0.287 | 6.548 | < 0.001 | 0.201 | 0.373 | Supported |
| *Mediating Effects* | | | | | | |
| ACQ → UE | 0.342 | 7.234 | < 0.001 | 0.249 | 0.435 | Supported |
| PE → UE | 0.315 | 6.876 | < 0.001 | 0.224 | 0.406 | Supported |
| *Moderating Effects* | | | | | | |
| CA × ACQ → CL | 0.187 | 4.823 | < 0.001 | 0.112 | 0.262 | Supported |
| CA × PE → CL | 0.165 | 4.256 | < 0.001 | 0.089 | 0.241 | Supported |

Note: CI = Confidence Interval; LL = Lower Limit; UL = Upper Limit

ACQ = Algorithmic Curation Quality; PE = Personalization Effectiveness;

UE = User Engagement; CL = Consumer Loyalty; CA = Cultural Adaptation

**Table 6. Structural Model Assessment Criteria**

| Endogenous Construct | $R^2$ | $R^2$ Adjusted | $Q^2$ | Interpretation |
|---|---|---|---|---|
| User Engagement | 0.534 | 0.531 | 0.412 | Substantial |
| Consumer Loyalty | 0.623 | 0.619 | 0.498 | Substantial |

Note: $R^2$ values: 0.25 (weak), 0.50 (moderate), 0.75 (substantial); $Q^2$ values > 0 indicate predictive relevance

**Table 7. Effect Sizes ($f^2$) and Predictive Relevance ($q^2$)**

| Relationship | $f^2$ Value | Effect Size | $q^2$ Value | Predictive Relevance |
|---|---|---|---|---|
| ACQ → CL | 0.285 | Medium | 0.234 | Medium |
| PE → CL | 0.246 | Medium | 0.198 | Medium |
| UE → CL | 0.312 | Medium | 0.256 | Medium |
| CA × ACQ → CL | 0.198 | Medium | 0.167 | Medium |
| CA × PE → CL | 0.176 | Medium | 0.145 | Medium |

Note: $f^2$ values: 0.02 (small), 0.15 (medium), 0.35 (large); $q^2$ values: 0.02 (small), 0.15 (medium), 0.35 (large)

**Table 8. Total Effects Analysis**

| Path | Direct Effect | Indirect Effect | Total Effect | VAF |
|---|---|---|---|---|
| ACQ → CL | 0.324 | 0.098 | 0.422 | 23.2% |
| PE → CL | 0.298 | 0.090 | 0.388 | 23.3% |
| UE → CL | 0.287 | - | 0.287 | - |
| CA × ACQ → CL | 0.187 | - | 0.187 | - |
| CA × PE → CL | 0.165 | - | 0.165 | - |

Note: VAF = Variance Accounted For; VAF > 80% = full mediation; 20% ≤ VAF ≤ 80% = partial mediation; VAF < 20% = no mediation

The structural model demonstrated robust predictive power and significant relationships across all hypothesized paths. The $R^2$ values for both endogenous constructs exceeded 0.50, indicating substantial explanatory power. The $Q^2$ values were well above zero, confirming the model's predictive relevance. All path coefficients were significant at $p < 0.001$, with moderate to strong effect sizes. The moderating effects of Cultural Adaptation showed significant enhancement of the relationships between algorithmic factors and Consumer Loyalty.

***4.3 Fuzzy-set Qualitative Comparative Analysis (fsQCA)***

This study complemented the PLS-SEM analysis with fsQCA to identify complex configurations leading to high Consumer Loyalty. The fsQCA was conducted using fsQCA 3.0 software, following calibration procedures recommended by Ragin (2008).

**Table 9. Calibration Criteria for fsQCA**

| Construct | Full Membership (0.95) | Crossover Point (0.5) | Full Non-membership (0.05) |
|---|---|---|---|
| ACQ | 6.5 | 4.5 | 2.5 |
| PE | 6.5 | 4.5 | 2.5 |
| UE | 6.5 | 4.5 | 2.5 |
| CL | 6.5 | 4.5 | 2.5 |
| CA | 6.5 | 4.5 | 2.5 |

Note: Values based on 7-point Likert scale measurements

**Table 10. Analysis of Necessary Conditions**

| Condition | Consistency | Coverage |
|---|---|---|
| ACQ | 0.892 | 0.845 |
| ~ACQ | 0.284 | 0.312 |
| PE | 0.885 | 0.838 |
| ~PE | 0.292 | 0.324 |
| UE | 0.878 | 0.832 |
| ~UE | 0.298 | 0.335 |
| CA | 0.856 | 0.812 |
| ~CA | 0.315 | 0.346 |

Note: ~ indicates absence of the condition
Consistency threshold = 0.90; Coverage threshold = 0.80

**Table 11. Configurations for High Consumer Loyalty**

| Configuration | Conditions | | | | Coverage | Consistency |
|---|---|---|---|---|---|---|
| | ACQ | PE | UE | CA | | |
| 1 | ● | ● | ● | ● | 0.452 | 0.923 |
| 2 | ● | ● | ● | ○ | 0.385 | 0.895 |
| 3 | ● | ● | ○ | ● | 0.342 | 0.887 |
| 4 | ● | ○ | ● | ● | 0.328 | 0.882 |

Note: ● = presence of condition; ○ = absence of condition
Solution coverage: 0.782; Solution consistency: 0.898

**Table 12. Alternative Pathways to High Consumer Loyalty**

| Path Description | Raw Coverage | Unique Coverage | Consistency |
|---|---|---|---|
| ACQ*PE*UE*CA | 0.452 | 0.156 | 0.923 |
| ACQ*PE*UE*~CA | 0.385 | 0.124 | 0.895 |
| ACQ*PE*~UE*CA | 0.342 | 0.098 | 0.887 |
| ACQ*~PE*UE*CA | 0.328 | 0.087 | 0.882 |

Note: * indicates AND condition; ~ indicates absence of condition

The fsQCA results revealed four main configurations leading to high Consumer Loyalty. The most empirically relevant configuration (raw coverage = 0.452, consistency = 0.923) indicated that the combination of high levels of all conditions (ACQ, PE, UE, and CA) was sufficient for achieving high Consumer Loyalty. The overall solution demonstrated good coverage (0.782) and consistency (0.898), suggesting that these configurations explain a substantial portion of cases with high Consumer Loyalty.

The analysis of necessary conditions showed that no single condition reached the consistency threshold of 0.90, indicating that high Consumer Loyalty requires combinations of conditions rather than single factors. However, Algorithmic Curation Quality (consistency = 0.892) and Personalization Effectiveness (consistency = 0.885) came closest to being necessary conditions.

These findings complement the SEM results by revealing the complex combinatorial nature of factors leading to Consumer Loyalty in digital streaming platforms. The fsQCA results particularly highlight the importance of considering multiple pathways to achieving high Consumer Loyalty, rather than focusing on individual causal relationships.

## 5. DISCUSSION OF RESEARCH RESULTS AND CONCLUSIONS

The empirical findings of this study offer several significant insights into the mechanisms driving consumer loyalty in digital streaming platforms. The results substantiate and extend existing theoretical frameworks while providing novel perspectives on the interplay between algorithmic factors and user behavior.

First, the strong direct effects of Algorithmic Curation Quality ($\beta = 0.324$) and Personalization Effectiveness ($\beta = 0.298$) on Consumer Loyalty align with previous findings in digital service research. This supports Zhang et al.'s (2015) assertion that recommendation system quality significantly influences user retention in streaming services. The results also reinforce Chen and Wang's (2016) findings regarding the critical role of personalization in fostering customer loyalty in digital platforms.

The mediating role of User Engagement revealed through both SEM and fsQCA analyses presents a more nuanced understanding of how algorithmic features translate into loyalty. The partial mediation effects (VAF = 23.2% for ACQ and 23.3% for PE) suggest that while algorithmic factors directly influence loyalty, a significant portion of their impact operates through enhanced user engagement. This finding extends Davidson and Kim's (2015) work on engagement mechanisms in digital platforms by demonstrating the specific pathways through which algorithmic features enhance user participation and subsequent loyalty.

A particularly novel contribution emerges from the analysis of Cultural Adaptation's moderating effects. The significant interaction terms ($\beta = 0.187$ for CA×ACQ and $\beta = 0.165$ for CA×PE) support Park et al.'s (2017) theoretical framework on cultural customization in digital services. However, the fsQCA results reveal a more complex picture, showing that Cultural Adaptation's influence varies across different configurational pathways to loyalty. This finding suggests that cultural considerations in algorithmic design may be more context-dependent than previously theorized.

The complementary use of PLS-SEM and fsQCA methodologies has revealed important asymmetric relationships that traditional variance-based approaches might have missed. The identification of four distinct configurational paths to high Consumer Loyalty, with the most empirically relevant configuration showing a consistency of 0.923, suggests that multiple strategic approaches can be effective in building customer loyalty. This aligns with Thompson et al.'s (2016) observations about the equifinality of loyalty-building strategies in digital services.

From a theoretical perspective, this study contributes to the literature by integrating algorithmic quality measures with user engagement theory in a culturally conscious framework. The findings extend beyond simple direct relationships to reveal complex interactions and multiple pathways to loyalty, addressing a gap in existing digital service research identified by Nguyen and Le (2017).

From a practical standpoint, the results suggest that platform managers should focus on both technical excellence in algorithmic curation and cultural adaptation of their services. The significant mediating role of user engagement indicates that platforms should design their algorithmic features not just for accuracy, but also to encourage active user participation and interaction.

The study's limitations include its cross-sectional nature and focus on the Vietnamese market context. Future research could benefit from longitudinal studies examining how these relationships evolve over time and comparative studies across different cultural contexts. Additionally, investigating the role of emerging technologies and changing user preferences could provide valuable insights for theory and practice.

In conclusion, this research advances our understanding of how algorithmic factors influence consumer loyalty in digital streaming platforms, while highlighting the crucial roles of user engagement and cultural adaptation. The findings provide both theoretical insights for academics and practical guidelines for platform managers in designing and implementing effective recommendation systems that drive user loyalty across different cultural contexts.

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