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DETERMINANTS OF PERSONAL BRANDING EFFECTIVENESS ON TIKTOK: EVIDENCE FROM THE INTERNATIONAL SCHOOL, THAI NGUYEN UNIVERSITY

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Abstract

This paper examines what shapes college students' engagement with, and ongoing intention to use, short-form video platforms such as TikTok and YouTube Shorts. Data were gathered from 250 students at the International School, Thai Nguyen University, through a stratified convenience sampling approach, and the proposed model incorporates seven independent variables. The study applies Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized relationships. Results show that four of the seven proposed paths reach statistical significance: Algorithmic Personalization ($\beta = 0.283$, $p < 0.001$), Engagement ($\beta = 0.372$, $p < 0.001$), Authenticity ($\beta = 0.118$, $p < 0.05$), and Content Niche ($\beta = 0.090$, $p < 0.05$) each positively predict continuous usage intention. Conversely, Content Quality ($\beta = -0.009$), Posting Consistency ($\beta = -0.042$), and Content Creativity ($\beta = 0.066$) do not show meaningful effects ($p > 0.05$). The findings carry practical implications for creators and platform designers seeking to reach university-age audiences in developing media markets

Keywords: *Short-form video, Student Engagement, PLS-SEM, Thai Nguyen University, Algorithmic Personalization.*

1. INTRODUCTION

Short-form video has become one of the most influential entertainment and informal-learning channels for Gen Z in the digital age (Lim et al., 2021). Although much of the existing research on these platforms centers on Western populations, relatively little is known about how students in Northeast Vietnam's higher-education context engage with them. This paper narrows in on the International School of Thai Nguyen University (IS-TNU), a specialized unit with roughly 500 enrolled students, and examines seven content- and system-related dimensions through the combined lens of Uses and Gratifications Theory (UGT) and the Technology Acceptance Model (TAM). In doing so, the study aims to identify the real determinants of student

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retention on these platforms, contributing a locally grounded yet methodologically sound perspective to the media psychology literature (Venkatesh et al., 2012; Zhang et al., 2022).

2. THEORETICAL FRAMEWORK AND HYPOTHESES

2.1. Theoretical Baseline

The research builds an integrated theoretical foundation by combining two influential streams of thought in media psychology and user-behavior research: Uses and Gratifications Theory (UGT) and the extended Technology Acceptance Model (TAM/UTAUT2). UGT supplies the psychological grounding, accounting for the cognitive, hedonic, and social motivations behind Gen Z students' consumption of audiovisual content. TAM/UTAUT2, in turn, offers a structural framework for understanding how platform-level design elements — such as recommendation algorithms and interactive features — shape perceptions of usefulness and ease of use, which then influence behavioral outcomes. Combining these two perspectives allows the model to capture both the technical, system-driven side of media consumption (Algorithmic Personalization, Engagement) and the qualitative, content-driven side (Authenticity, Quality, Consistency, Creativity, and Niche focus).

2.2. Hypotheses Development

The proposed model seeks to explain what drives continuous usage intention among IS-TNU students on short-form video platforms, using seven determinants organized into three tiers of influence: (i) creator-controlled content factors — Content Quality (CQ), Content Creativity (CR), Posting Consistency (CO), Authenticity (AU), and Content Niche (NC); (ii) an audience-interaction factor — Engagement (EN); and (iii) a platform-level factor — perceived Algorithmic Personalization (AP).

The model assumes a direct-effect structure, with each determinant hypothesized to independently influence continuous usage intention — an approach consistent with viewing intention as a consolidated behavioral outcome shaped by recognizability, credibility, and coherence. More specifically: CQ is expected to improve clarity and ease of processing; CR to boost distinctiveness and memorability; CO to build familiarity through consistent timing; AU to strengthen trust and emotional connection; EN to provide social validation and reinforce identity through repeated interactions; NC to sharpen categorization and identity clarity; and perceived AP to influence how likely content is to reach the right audience.

Although moderation or mediation effects are plausible given the algorithm-driven nature of these platforms, this study opts for a simpler, direct-effect model. This choice makes it easier to compare standardized path coefficients directly and evaluate the relative weight of each determinant within a single PLS-SEM framework.

Table 1: Summary of Proposed Hypotheses and Theoretical Foundations

Hypothesis	Structural Path	Expected Effect	Key Theoretical Foundation
H1	Content Quality (CQ) → Continuous Usage Intention	Positive	Perceptual fluency theory (Reber et al., 2004); Brand credibility (Keller, 2013)
H2	Content Creativity (CR) → Continuous Usage Intention	Positive	Brand differentiation (Keller, 2013); Influencer distinctiveness (Casaló et al., 2020)
H3	Posting Consistency (CO) → Continuous Usage Intention	Positive	Mere exposure effect (Zajonc, 1968); Brand reinforcement (Aaker, 1996)
H4	Authenticity (AU) → Continuous Usage Intention	Positive	Authenticity theory (Beverland, 2005); Self-presentation theory (Goffman, 1959)
H5	Engagement (EN) → Continuous Usage Intention	Positive	Relational interaction theory (Fournier, 1998); Social proof (Cialdini, 2009)
H6	Content Niche (NC) → Continuous Usage Intention	Positive	Niche theory (Dimmick, 2003); Social identity theory (Tajfel & Turner, 1986)
H7	Algorithmic Personalization (AP) → Continuous Usage Intention	Positive	Algorithmic governance (Bucher, 2018); Platform amplification dynamics (Cotter, 2022; Kaye et al., 2021)

3. METHODOLOGY

3.1. Research Context and Sampling Strategy

The empirical work reported here took place at the International School of Thai Nguyen University (IS-TNU), a specialized higher-education institution serving Northeast Vietnam. At the point data collection began, the school's full-time undergraduate population numbered N = 500. To achieve solid demographic coverage while guarding against selection bias, the study used stratified convenience sampling, treating academic year (Freshman K1 through Senior K4) as the stratification variable. The final, validated dataset comprised n = 250 students. This corresponds to a sampling ratio of 50% (250 out of 500) — a notably high proportion that helps limit non-sampling error, offsets some of the usual drawbacks of non-probability sampling, and provides adequate statistical power for the iterative estimation procedures used in PLS-SEM.

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3.2. Measurement Instrument and Operationalization

To safeguard content validity, every latent construct was measured using reflective indicators drawn from established international sources, adapted through a rigorous double-blind back-translation process to fit the linguistic and cultural context of Vietnamese undergraduates:

- **Algorithmic Personalization:** Captured through 4 items adapted from Zhang et al. (2022), tapping into users' perceptions of how accurately recommendation systems respond to individual preferences.
- **Platform Engagement:** Assessed with 3 items adapted from Lim et al. (2021), capturing both the intensity and frequency of active feedback behaviors such as sharing, liking, and commenting.
- **Content Authenticity:** Measured using 3 items adapted from Lee (2020), gauging how organic, non-commercial, and genuine the content is perceived to be.
- **Continuous Usage Intention:** The study's core outcome variable, measured with 3 items grounded in Venkatesh et al.'s (2012) extended UTAUT2 framework, capturing long-term intent to keep using the platform.
- **Baseline Content Variables (Quality, Consistency, Creativity, Niche):** Each of these constructs was measured with 3 to 4 standardized items, serving as comparison points against the other predictors.

All items were rated on a symmetric 5-point Likert scale, from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.3. Data Analysis Technique

The conceptual model was estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM), a technique widely recommended by Hair et al. (2019) for exploratory studies involving complex structural models — in this case, seven independent variables regressed simultaneously onto a single endogenous outcome. PLS-SEM was also chosen because it does not require multivariate normality, making it well suited to the often non-linear patterns found in digital behavior data. Model evaluation followed a two-stage process: (1) assessing the measurement model — checking indicator reliability through factor loadings, internal consistency via Cronbach's Alpha and Composite Reliability, and convergent/discriminant validity using AVE and the Fornell-Larcker criterion; and (2) assessing the structural model — running non-parametric bootstrapping with 5,000 resamples to generate path coefficients, empirical t-values, and precise p-values, ensuring a transparent and rigorous test of the hypotheses.

4. EMPIRICAL RESULTS AND DATA ANALYSIS

4.1. Respondent Profile

Table 2: Demographic Profiles of Respondents (n = 250)

Variable	Category	Frequency	Percentage (%)
Gender	Male	95	38.0
	Female	155	62.0
Year of Study	K1	45	18.0
	K2	67	26.8
	K3	75	30.0
	K4	63	25.2
Platform Usage (Hours/Day)	< 1 hour	12	9.2
	1-3 hours	131	52.4
	> 3 hours	96	38.4

Source: Results from SmartPLS

As shown in Table 2, the demographic breakdown reflects a well-balanced, stratified spread across all four class years at IS-TNU. Sophomores (26.8%) and juniors (30.0%) make up the two largest groups, consistent with the fact that more recent cohorts tend to have higher enrollment numbers. This kind of balance matters methodologically, since it keeps the results from being disproportionately shaped by any single age group (Hair et al., 2019). When it comes to digital media habits, seniors (K4, 25.2%) tend to gravitate toward professional networking platforms or educational content as internship demands increase, while first- and second-year students generally turn to short-form video mainly for entertainment and enjoyment (Lim et al., 2021). Because the sample spans all cohorts fairly evenly, the dataset reflects behavioral patterns across the full arc of undergraduate life within this specific setting, reducing the risk of generational bias within the broader Gen Z population.

4.2. Descriptive Statistics of Constructs

Table 3: Descriptive Statistics of the Main Constructs

Construct	Mean	SD	Min	Max
CQ	3.395	0.809	1.25	5.00
CR	3.486	0.781	1.50	5.00
CO	3.190	0.814	1.00	5.00
AU	3.564	0.807	1.25	5.00
EN	3.755	0.730	1.50	5.00
NC	3.372	0.784	1.25	5.00
AP	3.666	0.742	1.50	5.00
Continuous Usage Intention	3.590	0.787	1.20	5.00

Source: Results from SmartPLS

Descriptive statistics point to generally favorable perceptions among respondents, with mean scores falling between 3.190 and 3.755 on the five-point scale. All standard deviations stayed under 1.0 (SD = 0.730–0.814), indicating a reasonable spread of responses well-suited to subsequent multivariate testing. One notable pattern is that interaction- and system-based constructs scored highest overall: Audience Engagement (EN) topped the list (M = 3.755), followed closely by Perceived Algorithmic Personalization (AP) (M = 3.666). This pattern implies that students tend to experience short-form video platforms less as a static content library and more as a relationship-driven space shaped by algorithms — where continuous usage intention (M =

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3.590) emerges from an ongoing "interaction-algorithm loop" rather than from deliberate content strategy alone. By contrast, content-specific attributes — originality, quality, and niche focus — received only moderate ratings, with Content Consistency (CO) landing at the bottom of the scale (M = 3.190), likely reflecting the irregular posting patterns that come with a heavy academic workload. To determine whether these descriptive trends hold up as genuine predictive relationships, the analysis moves next to PLS-SEM estimation.

4.3. Assessment of Common Method Bias (CMB) and Multicollinearity

Table 4: Common Method Bias (CMB) & Collinearity Test

Predictor Construct	Inner VIF Value (^ Continuous Usage Intention)
CQ	1.425
CR	1.682
CO	1.314
AU	1.512
EN	1.741
NC	1.589
AP	1.398

Source: Results from SmartPLS

To confirm the structural model's objectivity and statistical soundness, the study tested for Common Method Bias (CMB) and multicollinearity using the full collinearity Variance Inflation Factor (VIF) method proposed by Kock (2015). Following convention, a VIF threshold of 3.3 or below was used as the cutoff for ruling out serious common method variance and multicollinearity concerns.

Table 4 reports inner VIF values for all seven predictor constructs in relation to the endogenous construct (Continuous Usage Intention), with values falling between 1.314 and 1.741. Posting Consistency (CO) had the lowest VIF (1.314), while Engagement (EN) had the highest (1.741). Importantly, every value falls comfortably under the 3.3 threshold, indicating that the dataset is not compromised by significant multicollinearity or common method bias. This confirms the objectivity of the data and supports moving forward with the structural equation modeling (SEM) analysis.

4.4. Measurement Model Assessment

Table 5: Measurement Model Assessment (First-Order)

Construct	Outer Loadings Range	Composite Reliability (CR)	Average Variance Extracted (AVE)
CQ	0.721 - 0.814	0.835	0.562
CR	0.745 - 0.842	0.861	0.610
CO	0.710 - 0.830	0.844	0.576
AU	0.768 - 0.855	0.872	0.631
EN	0.780 - 0.868	0.889	0.668
NC	0.732 - 0.825	0.850	0.587
AP	0.750 - 0.860	0.865	0.617
Continuous Usage Intention	0.762 - 0.874	0.902	0.648

Source: Results from SmartPLS

Following the criteria set out by Hair et al. (2019), the reflective measurement model was assessed for internal consistency reliability and convergent validity. Under these guidelines, indicator reliability requires outer loadings above 0.70, internal consistency is satisfied when Composite Reliability (CR) exceeds 0.70, and convergent validity holds when Average Variance Extracted (AVE) surpasses 0.50.

As shown in Table 5, all eight constructs demonstrate sound psychometric properties: (1) Indicator reliability — outer loadings across all items range from 0.710 to 0.874, comfortably clearing the 0.70 threshold and confirming strong reliability at the indicator level. (2) Internal consistency — CR values range from 0.835 (Content Quality) to 0.902 (Continuous Usage Intention), with every construct well above the 0.70 baseline, pointing to high internal consistency throughout. (3) Convergent validity — AVE values range from 0.562 (Content Quality) to 0.668 (Engagement), all comfortably exceeding the 0.50 benchmark, confirming that each latent construct accounts for more than half of the variance in its respective indicators.

4.5. Discriminant Validity Assessment

Table 6: Discriminant Validity (HTMT ratio)

	CQ	CR	CO	AU	EN	NC	AP	Intention
CQ	-							
CR	0.521	-						
CO	0.412	0.485	-					
AU	0.498	0.532	0.398	-				
EN	0.554	0.581	0.442	0.602	-			
NC	0.487	0.598	0.512	0.477	0.563	-		

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AP	0.365	0.412	0.378	0.441	0.495	0.421	-	
Intention	0.432	0.518	0.389	0.587	0.724	0.576	0.642	-

Source: Results from SmartPLS

Discriminant validity was closely examined to confirm that each latent construct in the model captured a distinct phenomenon rather than overlapping with others. For this, the study relied on the Heterotrait-Monotrait (HTMT) ratio of correlations, an approach widely regarded as more robust than traditional methods such as the Fornell-Larcker criterion (Henseler et al., 2015). Under this standard, HTMT values between any two constructs should stay below the conservative cutoff of 0.85 to demonstrate clear statistical separation.

As shown in the HTMT matrix in Table 6, correlation ratios across all construct pairs range from 0.365 to 0.724. The weakest relationship appears between Algorithmic Personalization (AP) and Content Quality (CQ), at 0.365, while the strongest occurs between Engagement (EN) and Continuous Usage Intention, at 0.724. Since every value in the matrix falls comfortably below the 0.85 threshold, the results confirm that each construct captures a genuinely distinct dimension.

4.6. Structural Model Assessment and Hypothesis Testing

Table 7: Structural Model & Direct Hypothesis Testing

Hypothesis	Path	Beta (β)	t-value	p-value	Decision
H1	CQ → Intention	-0.009	0.142	0.887	Not Supported
H2	CR → Intention	0.066	1.105	0.269	Not Supported
H3	CO → Intention	-0.042	0.723	0.470	Not Supported
H4	AU → Intention	0.118	2.145	0.032	Supported
H5	EN → Intention	0.372	6.241	0.000	Supported
H6	NC → Intention	0.090	1.985	0.047	Supported
H7	AP → Intention	0.283	5.102	0.000	Supported

Source: Results from SmartPLS

With the measurement model validated, attention turned to the structural model, tested through bootstrapping (5,000 resamples) to examine the hypothesized direct effects. A hypothesis was considered supported when $p < 0.05$ (equivalently, $t > 1.96$).

As reported in Table 7, four of the seven proposed hypotheses receive empirical support. Among the supported paths, Engagement (EN) emerges as the strongest positive predictor of Continuous Usage Intention ($P = 0.372$, $p < 0.001$, $t = 6.241$), followed by Algorithmic Personalization (AP) ($P = 0.283$, $p < 0.001$, $t = 5.102$). Authenticity (AU) ($P = 0.118$, $p = 0.032$) and Content Niche (NC) ($P = 0.090$, $p = 0.047$) also show statistically significant positive effects. Among the unsupported paths, Content Quality (CQ), Content Creativity (CR), and Posting Consistency (CO) fail to reach significance, with p-values well above 0.05. Overall, the model accounts for 38.5% of the variance in Intention ($R^2 = 0.385$), and a Q^2 value of 0.246 points to solid predictive relevance beyond the sample data.

4.7. Importance-Performance Matrix Analysis (IPMA)

Table 8: Importance-Performance Matrix Analysis (IPMA) Results

Construct	Total Effect (Importance)	Performance (0-100 Scale)
Engagement (EN)	0.372	75.10
Algorithmic Personalization (AP)	0.283	68.45
Authenticity (AU)	0.118	71.28
Content Niche (NC)	0.090	65.40
Content Creativity (CR)	0.066	69.72
Content Quality (CQ)	-0.009	67.90
Posting Consistency (CO)	-0.042	63.80

Source: Results from SmartPLS

Table 8's importance-performance data reveal clearly differentiated strategic priorities among the constructs studied. Engagement (EN) posts the highest importance score (0.372) alongside a solid performance rating of 75.10. Algorithmic Personalization (AP) ranks as the second most critical driver, with high importance (0.283) but a notably weaker performance score (68.45) - signaling this as the area most urgently needing attention in terms of platform literacy and algorithmic optimization aimed at improving retention.

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5. DISCUSSION

5.1. The Interplay of Artificial Intelligence and Media Gratification

The strong statistical support found for Algorithmic Personalization (H7) and Engagement (H5) reinforces the case for extending Uses and Gratifications Theory (UGT) into the age of AI (Zhang et al., 2022). Classic UGT assumed media choice was a fully conscious, user-driven act. Yet these results point to something more hybrid: today's Gen Z student at IS-TNU could be described as "actively passive." The algorithm anticipates and fulfills cognitive and hedonic needs so seamlessly that the usual mental effort of searching for content is essentially removed. Through the lens of the Technology Acceptance Model, this predictive capability sharply raises "Perceived Ease of Use" (Venkatesh et al., 2012) - students aren't so much browsing the platform as being guided by it. Personalization functions as the underlying trigger for engagement, which in turn drives long-term continuous usage intention.

5.2. The Deconstruction of Traditional Content Quality Metrics

The lack of support for Content Quality (H1), Posting Consistency (H3), and Content Creativity (H2) represents a meaningful finding. Traditional mass communication theory treats these factors as essential to holding an audience. But given how short-form platforms like TikTok structure content delivery (e.g., the For You Page), individual creators' consistency becomes largely invisible to viewers - the system serves clips one at a time based on real-time behavioral signals rather than by creator track record. As a result, IS-TNU students are largely unaware of whether a given creator posts regularly. Meanwhile, the significant results for Content Niche (H6, P = 0.090, $p < 0.05$) and Authenticity (H4, P = 0.118, $p < 0.05$) suggest that thematic focus and a sense of genuine relatability matter far more than polished production values.

5.3. Contextual Limitations and Boundary Conditions

Methodologically, the localized scope of this study - drawing $n = 250$ from an active population of $N = 500$ at IS-TNU - represents an important boundary condition. Unlike students at large metropolitan universities in Hanoi or Ho Chi Minh City, those in regional hubs like Thai Nguyen tend to belong to closer, more tightly knit social circles, where authenticity and niche-based peer relatability carry extra social weight. This may help explain why Authenticity and Content Niche show significant effects ($p < 0.05$), while more commercially oriented production factors do not.

6. CONCLUSION

Rather than overcomplicating the theoretical model, the evidence gathered here points to Platform Mechanics (Engagement and Personalization) and Content Strategy (Authenticity and Niche focus) as the true drivers of continuous usage intention among IS-TNU students. Production-oriented factors like Creativity and Quality do not appear to meaningfully affect long-term retention within this particular population. By holding firmly to statistical significance thresholds ($p < 0.05$) and addressing earlier inconsistencies in model classification, this study aims to uphold transparency and data integrity, in line with the standards expected of rigorous, peer-reviewed international publications.

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