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THE IMPACT OF TIKTOK ON STUDENTS' ACEDEMIC PERFORMANCE IN HANOI, VIETNAM: A STUDY ON SOCIAL MEDIA INFLUENCE

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ABSTRACT

This study examines the impact of TikTok on university students' academic performance in Hanoi, focusing on the roles of Perceived Usefulness (PU), Perceived Ease of Use (PE), and Content Richness (CR). Using a quantitative approach, data were collected from 329 students through a structured survey conducted between January 2024 and January 2025. The Technology Acceptance Model (TAM) framework guided the analysis, with multiple linear regression revealing that PU (β = 0.287), PE (β = 0.182), and CR (β = 0.384) significantly enhance learning performance, explaining 57.7% of the variance. Content Richness emerged as the most influential factor, highlighting the importance of diverse and engaging educational content on TikTok. The findings underscore TikTok's potential as a supplementary learning tool, though challenges such as distraction risks remain. Recommendations include developing curated educational content, enhancing platform usability, and fostering collaborations with academic institutions to improve content quality. This study contributes to the growing literature on social media in education, offering practical insights for optimizing TikTok's role in higher education while calling for further longitudinal research to explore its long-term effects.

KEYWORDS:- Tiktok, Learning performance, Social media in Education, Technology Acceptance Model.

1. INTRODUCTION

In the era of digital transformation, individuals have access to diverse and dynamic learning methods, expanding opportunities for knowledge acquisition. Social media has emerged as a crucial tool in facilitating information search and learning. Among these platforms, TikTok, despite being relatively new, has gained widespread popularity and has become an integral part of both entertainment and education, particularly among students. Its short-form video format, designed for rapid content consumption, not only influences entertainment trends but also shapes users' cognitive processes, learning habits, and knowledge acquisition behaviors (Anderson, 2022; Xiao et al., 2023). Recent studies indicate that educational content on TikTok is growing significantly, with educators, experts, and students utilizing the platform to share knowledge through concise, engaging videos, making information more accessible and easier to comprehend (Madsen & O'Mara, 2021). This shift underscores the potential of TikTok as a learning tool, complementing traditional education methods and reshaping how knowledge is disseminated in the digital age.

Research on the impact of social media on learning has highlighted both its benefits and drawbacks. In Vietnam, Dung (2023) identified 14 factors influencing the learning behavior of students studying Chinese, with negative effects, such as distraction, laziness, and anxiety outweighing positive ones like knowledge enhancement and increased confidence. Lan et al. (2023) explored Gen Z's perception of educational content on TikTok, emphasizing its authenticity and accessibility, though the study was limited in scope. Similarly, research at Van Lang University examined students' perceptions of using social media to learn English vocabulary, finding it beneficial but constrained by a small sample size (Pham, 2023). Internationally, Lamimi et al. (2024) applied the Technology Acceptance Model (TAM) to analyze students' intentions to use TikTok for learning, highlighting the importance of perceived usefulness in shaping attitudes and behavioral intentions. Meanwhile, Mosharrof Hosen et al. (2021) investigated the role of social media in knowledge sharing and learning performance, showing that while social media can enhance motivation and collaboration, it also poses risks of distraction.

While various studies have explored its educational impact, there is still a lack of in-depth research on TikTok's specific role in academic performance. Most existing studies focus on general social media platforms like Facebook and YouTube, overlooking TikTok's unique features such as short-form videos, visual learning, and personalized content recommendations. Additionally, current research primarily examines students' intentions to use social media for learning rather than its actual effects on comprehension, retention, and knowledge application. Studies also tend to rely on self-reported surveys rather than experimental evaluations, limiting their ability to assess TikTok's real impact. Furthermore, research samples often focus on small groups of Gen Z students or specific disciplines, making it difficult to generalize findings across diverse academic fields. To address these gaps, this study investigates how TikTok influences university and college students' learning performance in Hanoi, analyzing perceived usefulness, perceived ease of use, and content richness. By comparing TikTok-based learning with traditional methods, the study aims to provide insights into optimizing TikTok's role in higher education in Vietnam.

2. THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1 Theoretical background

Technology acceptance model – TAM

The Technology Acceptance Model (TAM) was developed by Fred Davis in 1989 to explain why a technology is accepted or rejected and to predict user behavior regarding its adoption (Davis, 1989).

This model focuses on understanding how individuals perceive and interact with technology, thereby explaining the transition from perception to actual usage behavior.

According to TAM, two key factors determine the acceptance of technology. First, Perceived Usefulness (PU) refers to the degree to which a user believes that adopting a particular technology will bring practical benefits, enhancing productivity or work efficiency. If users perceive that a technology can help them achieve their goals or complete tasks more easily, they are more likely to accept it (Davis, 1989). Second, Perceived Ease of Use (PEOU) describes users' perceptions of how effortless it is to learn and operate a technology. The easier a technology is to use and the fewer difficulties it presents, the higher the likelihood of user adoption. The interplay between these two factors not only influences users' evaluations of technology but also significantly impacts their attitudes toward its adoption. A positive attitude toward technology leads to an increased intention to use it, ultimately manifesting in actual usage behavior (Venkatesh et al., 2003). The model has been widely applied across various fields, including information technology, education, healthcare, and e-commerce, to analyze user behavior (Holden & Karsh, 2010).

The educational aspect of Tiktok

TikTok, initially known for entertainment content, has emerged as a valuable educational tool due to its fast, dynamic, and visually engaging format (Kumar & Nanda, 2021). The platform offers diverse educational content, from languages to science and soft skills, enabling personalized and flexible learning (Chugh & Ruhi, 2022).

A key advantage of TikTok in education is its ability to deliver concise content, allowing learners to absorb knowledge efficiently. Interactive features such as duet, stitch, and comments further enhance engagement and collaborative learning (Dinh & Nguyen, 2023). Additionally, TikTok's algorithm personalizes content recommendations, optimizing the learning experience (Montag et al., 2021).

Compared to YouTube's in-depth tutorials or Facebook's group discussions, TikTok excels in delivering brief, engaging lessons suited to visual learners (Tang & Hew, 2022). However, challenges remain, such as content quality control and the risk of distraction. Further research is needed to assess its impact on learning outcomes and best practices for educational integration (Zhong, 2021).

Students' Learning Performance

Students' learning performance reflects their acquisition of knowledge, skills, and attitudes during education. Bloom (1956) categorizes learning into cognitive, psychomotor, and affective domains, providing a framework for evaluation. Biggs and Tang (2011) highlight that learning outcomes extend beyond grades, emphasizing critical thinking and self-directed learning. Motivation significantly influences performance, with Deci and Ryan (1985) noting that intrinsic motivation enhances engagement. Zimmerman (2002) underscores the role of self-regulation, such as time management and goal-setting, in academic success. Mayer (2009) supports the use of multimedia to improve comprehension, while Tang and Hew (2022) demonstrate how digital tools like virtual reality enhance language skills, offering insights into technology's role in learning.

2.2 Hypothesis development

Perceived usefulness

Perceived Usefulness (PU) is a critical determinant of students' adoption of TikTok as a learning tool. According to Davis (1989), PU reflects the extent to which users believe a technology enhances their performance, significantly influencing its acceptance. In the context of education, students are more likely to engage with TikTok if they perceive it as an effective medium for knowledge acquisition compared to traditional methods. Mayer (2009) supports this by demonstrating that multimedia formats, such as short videos, improve comprehension and retention by integrating visual and auditory elements. Furthermore, Venkatesh and Davis (2000) highlight that PU directly impacts user motivation and engagement, which are essential for academic success. Sun and Zhang (2006) add that PU can foster proactive learning behaviors by increasing students' investment in digital learning environments. Similarly, Abdullah et al. (2016) found that when students perceive a system as useful, they dedicate more effort to their studies, particularly in online settings. Thus, the following hypothesis is proposed:

H1: Perceived Usefulness has a direct positive impact on students' learning performance.

Perceived ease of use

Perceived Ease of Use (PEOU) refers to the degree to which students find TikTok accessible and user-friendly for learning purposes. Davis (1989) posits that PEOU influences technology adoption by reducing barriers to usage, thereby enhancing user engagement. Venkatesh and Davis (2000) further argue that technologies perceived as easy to use encourage sustained interaction, as they require minimal effort to navigate. In the context of TikTok, its intuitive interface and personalized content recommendations enable students to access educational materials effortlessly, potentially improving their learning outcomes. Sun et al. (2008) confirm that ease of use in digital platforms correlates with higher learner satisfaction and performance, as it minimizes technical distractions and allows focus on content. Al-Maroof and Al-Emran (2018) also note that PEOU fosters positive attitudes toward technology, encouraging its integration into daily learning routines. Therefore, the following hypothesis is proposed:

H2: Perceived Ease of Use has a direct positive impact on students' learning performance.

Content richness

Content Richness (CR) is a pivotal factor in making TikTok an effective learning platform. Tang and Hew (2022) suggest that diverse and engaging content formats, such as short videos and interactive challenges, enhance knowledge absorption by catering to visual and interactive learning preferences. Sun et al. (2008) emphasize that rich content, incorporating multimedia elements like text, images, and videos, positively influences learner engagement and comprehension. Additionally, Huang et al. (2012) argue that varied and in-depth content stimulates critical thinking and improves retention, crucial for academic success. TikTok's ability to offer concise, visually appealing and up-to-date educational content can thus motivate students and facilitate active learning. Based on these insights, the following hypothesis is proposed:

H3: Content Richness has a direct positive impact on students' learning performance.

3. METHODOLOGY

3.1 Study design

This study adopts a quantitative research approach to test the proposed hypotheses, utilizing a structured survey as the primary data collection tool. The design of the survey instrument followed a systematic process to ensure reliability and validity. First, measurement scales for the research variables were developed by adapting established scales from prior studies. The independent variables: Perceived Usefulness (PU), Perceived Ease of Use (PE), and Content Richness (CR)were adapted from scales validated by Lamimi et al. (2024). The dependent variable, Learning Performance (LP), was measured using scales derived from Al-Rahmi et al. (2018) and Blasco-Arcas et al. (2013). To ensure cultural and contextual relevance for Vietnamese respondents, the scales underwent a rigorous translation process involving both forward and backward translation, followed by expert validation to refine the items.

A preliminary survey was conducted with a small group of participants to test the instrument's clarity and reliability. Feedback from this pilot phase was used to adjust the language, structure, and presentation of the questionnaire, ensuring its suitability for the target population. The final survey was administered to university students in Hanoi who actively use TikTok for learning purposes. A convenience sampling method, a non-probability sampling technique, was employed to recruit participants, focusing on those with experience in digital learning environments. The sample size was determined based on the recommendation by Hair et al. (2010), which suggests a minimum sample of 5–10 times the number of observed variables.

Data collection was conducted over a three-month period, from November 2024 to January 2025, using both online (via Google Forms and Microsoft Forms) and in-person survey methods at universities and training centers in Hanoi. The questionnaire comprised two main sections: (1) demographic information, including gender, academic year, major, and digital learning experience; and (2) items measuring the research constructs, assessed on a 5-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). A total of 413 responses were anticipated to ensure sufficient data for analysis.

3.2 Measures

After data collection, the dataset was cleaned and coded for analysis using SPSS 20. Reliability was assessed with Cronbach's Alpha (threshold ≥ 0.6, item-total correlation > 0.3) and Exploratory Factor Analysis (EFA) to confirm construct convergence (Nunnally & Bernstein, 1994). Multiple linear regression was then applied:

$$\mathbf{Y} = \boldsymbol{\beta}_1 \mathbf{X}_1 + \boldsymbol{\beta}_2 \mathbf{X}_2 + \boldsymbol{\beta}_3 \mathbf{X}_3 + \boldsymbol{\epsilon}$$

Where **Y** is Learning Performance, $\mathbf{X}_1$ is Perceived Usefulness, $\mathbf{X}_2$ is Perceived Ease of Use, $\mathbf{X}_3$ is Content Richness, and $\boldsymbol{\beta}_1$to $\boldsymbol{\beta}_3$ are regression coefficients. Model diagnostics included checking multicollinearity with Variance Inflation Factor (VIF < 10 acceptable, Henseler et al., 2009) and autocorrelation with the Durbin-Watson test (range 1.5–2.5 indicating no issue), ensuring robust results.

3.3 Sample characteristics

The survey was conducted from January 2024 to January 2025, yielding a total of 413 responses. Data were screened and cleaned prior to analysis, resulting in the exclusion of 84 invalid responses due to the following issues: (1) all answers marked in a single option (26 responses), (2) zigzag response patterns (34 responses), and (3) respondents confirming no TikTok usage (24 responses). After filtration, 329 valid responses were retained, representing 79.7% of the total collected. Descriptive statistical analysis was performed to examine the sample characteristics.

3.3.1 Tiktok Usage Frequency

Table 3.1 presents the frequency of TikTok usage among the 329 participants. The majority (45.9%, n = 151) used TikTok for 1–3 hours per day, indicating a moderate usage pattern. The second-largest group (23.7%, n = 78) spent 3–5 hours daily, reflecting a relatively high engagement level. Users spending less than 1 hour daily comprised 19.5% (n = 64), suggesting low frequency, possibly due to limited interest. The smallest group (10.9%, n = 36) used TikTok for over 5 hours daily, indicating frequent usage potentially for entertainment or content creation.

Table 1: Tiktok Usage Frequency Statistics

TikTok Usage (hours/day)	Frequency	Percentage (%)	Cumulative Percentage (%)
Less than 1 hour	64	19.5	19.5
1-3 hours	151	45.9	65.3
3-5 hours	78	23.7	89.1
More than 5 hours	36	10.9	100.0
Total	329	100.0	

(Source: results of the author group)

3.3.2 Demographic Characteristics

Table 2 summarizes the demographic profile of respondents based on gender, academic year, and major. Females dominated the sample (67.2%, n = 221), followed by males (31.3%, n = 103), with 1.5% (n = 5) identifying as other. Second-year students were the largest group (49.8%, n = 164), suggesting high interest in the study topic. Third-year students accounted for 18.8% (n = 62), while first-year (11.2%, n = 37), fourth-year (10.3%, n = 34), and other categories (9.7%, n = 32) were less represented. Regarding majors, Economics and Management led with 52.6% (n = 173), followed by other (12.8%, n = 42), Engineering-Technology (9.1%, n = 30), Social Sciences and Humanities (7.3%, n = 24), Education (7.0%, n = 23), Arts-Design (6.1%, n = 20), Medicine (2.7%, n = 9), and Natural Sciences (2.4%, n = 8).

Table 2: Demographic Characteristics of Respondents

Demographic Characteristic	Category	Frequency	Percentage (%)	Cumulative Percentage (%)
Gender	Male	103	31.3	31.3
	Female	221	67.2	98.5
	Other	5	1.5	100.0
	Total	**329**	**100.0**	

Academic Year	First Year	37	11.2	11.2
	Second Year	164	49.8	61.1
	Third Year	62	18.8	79.9
	Fourth Year	34	10.3	90.3
	Other	32	9.7	100.0
	Total	**329**	**100.0**	
Major	Other	42	12.8	12.8
	Economics-Management	173	52.6	65.3
	Engineering-Technology	30	9.1	74.5
	Arts-Design	20	6.1	80.5
	Education	23	7.0	87.5
	Natural Sciences	8	2.4	90.0
	Social Sciences-Humanities	24	7.3	97.3
	Medicine	9	2.7	100.0
	Total	**329**	**100.0**	

(Source: results of the author group)

The sample predominantly consists of female respondents (67.2%), second-year students (49.8%), and Economics-Management majors (52.6%), indicating their heightened interest in the study. In contrast, Medicine (2.7%), Natural Sciences (2.4%), and the "Other" gender category (1.5%) showed lower participation, reflecting limited engagement from these groups.

4. ANALYSIS AND RESULTS

4.1 Reliability Assessment

The reliability of the measurement scales was assessed using Cronbach's Alpha, with a minimum threshold of 0.6 deemed acceptable, consistent with guidelines for novel constructs (Nunnally & Bernstein, 1994). Item-total correlations below 0.3 led to exclusion, with content relevance considered.

Table 3: Cronbach's Alpha and Item-Total Correlation Range

Variable	**Cronbach's Alpha**	**Item-Total Correlation Range**
Perceived Usefulness (PU)	0.849	0.637–0.732
Perceived Ease of Use (PE)	0.832	0.521–0.695
Content Richness (CR)	0.840	0.636–0.695
Learning Performance (LP)	0.875	0.641–0.780

(Source: results of the author group)

All constructs demonstrated satisfactory reliability, with PU (4 items), PE (5 items), CR (4 items), and LP (5 items) exceeding the threshold, and no significant Alpha improvement upon item removal.

4.2 Exploratory Factor Analysis (EFA)

Principal Component Analysis (PCA) with Varimax rotation was initially applied to extract factors, validated by the Kaiser-Meyer-Olkin (KMO) measure (threshold ≥0.5) and Eigen values ≥1, with Total Variance Explained (TVE) targeted above 50% (Hair et al., 2010). The first iteration extracted only one factor (Eigen value = 7.024, explaining 54.032% of variance), indicating limited differentiation. Consequently, Principal Axis Factoring (PAF) was adopted with three pre-specified factors, guided by theoretical constructs (PU, PE, CR), to enhance model fit. Factor loadings >0.5 were considered significant.

Table 4: KMO and Barlett's Test (Second Iteration)

Measure	Value
KMO Measure of Sampling Adequacy	0.945
Bartlett's Test: Approx. Chi-Square	2344.289
Bartlett's Test: df	78
Bartlett's Test: Sig.	0.000

(Source: results of the author group)

Table 5: Total Variance Explained (Second Iteration)

Factor	Initial Eigenvalues: % of Variance	Cumulative %	Extraction Sums: % of Variance	Rotation Sums: % of Variance	Rotation Sums: Cumulative %
1	54.032	54.032	50.876	20.423	20.423
2	7.252	61.285	3.820	19.333	39.756
3	6.418	67.702	3.283	18.223	57.979

(Source: results of the author group)

The second iteration confirmed data suitability (KMO = 0.945, $p < 0.001$), with PAF extracting three factors explaining 57.979% of variance. The Rotated Factor Matrix grouped variables as follows: Factor 1 (CR1–CR4, loadings 0.541–0.707), Factor 2 (PE1, PE3–PE5, loadings 0.542–0.617), and Factor 3 (PU1–PU3, loadings 0.540–0.721). Items PE2 and PU4 were excluded due to low (<0.5) or cross-loadings.

Table 6: Rotated Factor Matric for Independent Variables

Variable	Factor 1	Factor 2	Factor 3
PU1			0.679
PU2			0.721
PU3			0.540
PE1		0.542	
PE3		0.615	
PE4		0.617	
PE5		0.584	
CR1	0.596		

CR2	0.673		
CR3	0.541		
CR4	0.707		

(Source: results of the author group)

For LP, EFA (KMO = 0.843, $p < 0.001$) extracted one factor with an Eigen value of 3.539, explaining 67.177% of variance, and loadings of 0.764–0.874, confirming scale validity.

Table 7: Rotated Factor Matrix Dependent Variable

Variable	Factor 1
LP1	0.791
LP2	0.874
LP3	0.764
LP4	0.819
LP5	0.846

(Source: results of the author group)

4.3 Regression Analysis and Hypothesis Testing

4.3.1 Correlation Analysis

Pearson correlation analysis revealed positive relationships between LP and PU ($r = 0.669$), PE ($r = 0.635$), and CR ($r = 0.702$), all significant at $p < 0.01$.

Table 8: Correlation Matrix

		PUtb	PEtb	CRtb	LPtb
PUtb	Pearson Correlation	1	.668**	.679**	.669**
	Sig. (2-tailed)		.000	.000	.000
PEtb	Pearson Correlation	.668**	1	.680*	.635**
	Sig. (2-tailed)	.000		.000	.000
CRtb	Pearson Correlation	.679**	.680**	1	.702**
	Sig. (2-tailed)	.000	.000		.000
LPtb	Pearson Correlation	.669**	.635**	.702**	1
	Sig. (2-tailed)	.000	.000	.000	

(Source: results of the author group)

4.3.2 Multiple Linear Regressions

The regression model, estimated via the Enter method in SPSS 20.0, is:

$$\mathbf{Y = 0.287\ X_1 + 0.182\ X_2 + 0.384\ X_3}$$

where **Y** is Learning Performance, $\mathbf{X_1}$ is PU, $\mathbf{X_2}$ is PE, and $\mathbf{X_3}$ is CR. All predictors were significant ($p < 0.05$), with standardized Beta coefficients of 0.287, 0.182, and 0.384, respectively, supporting H1, H2, and H3. Content Richness had the strongest effect.

Table 9: Coefficients[a]

Model		**Unstandardized Coefficients**		**Standardized Coefficients Beta**	**t**	**Sig.**	**Correlations**			**Collinearity Statistics**	
		B	**Std. Error**				**Zero-order**	**Partial**	**Part**	**ToleranceTolerance**	**VIF**
1	**(Constant)**	.618	.151		4.083	.000					
	PUtb	.275	.051	.287	5.390	.000	.669	.286	.194	.460	2.173
	PEtb	.172	.050	.182	3.414	.001	.635	.186	.123	.458	2.182
	CRtb	.381	.054	.384	7.113	.000	.702	.367	.257	.446	2.240

(Source: results of the author group)

4.3.3 Model Fit

The model explained 57.7% of variance in LP ($R^2 = 0.577$, Adjusted $R^2 = 0.573$). The ANOVA F-value of 147.759 ($p < 0.001$) confirmed model fit.

Table 10: Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.760[a]	.577	.573	.47447	.577	147.759	3	325	.000	2.072

a. *Predictors: (Constant), CRtb, PUtb, PEtb*
b. *Dependent Variable: LPtb*

(Source: results of the author group)

Table 11: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	99.791	3	33.264	147.759	.000[b]
	Residual	73.165	325	.225		
	Total	172.956	328			

a. *Dependent Variable: LPtb*

b. Predictors: (Constant), CRtb, PUtb, PEtb

(Source: results of the author group)

4.4 Model Diagnostics

4.4.1 Multicollinearity

VIF values (2.173–2.240) were below the threshold of 10 (Hair et al., 2010), indicating no multicollinearity.

4.4.2 Autocorrelation

The Durbin-Watson statistic of 2.072 (range 1.5–2.5) confirmed no autocorrelation, ensuring model robustness.

The regression model validated all hypotheses, with Content Richness showing the greatest impact on learning performance.

5. RECOMMENDATION AND CONCLUSION

5.1 Recommendation

The study's findings highlight the significant influence of Perceived Usefulness (PU), Perceived Ease of Use (PE), and Content Richness (CR) on students' learning performance in Hanoi. Based on these insights, the following recommendations are proposed to optimize TikTok's educational potential:

Enhancing Perceived Usefulness: Educational institutions and content creators should collaborate to develop high-quality, academically rigorous TikTok content. Implementing a "Learning Mode" feature, where students can access curated educational videos tailored to their majors, could enhance perceived value. Additionally, integrating expert-validated content with certification labels would boost credibility and encourage active learning (Tang & Hew, 2022).

Improving Perceived Ease of Use: TikTok should refine its interface with intuitive search tools and personalized recommendations prioritizing educational content. Offering short tutorials on effective hash tag use and content navigation, alongside a dedicated "Study Mode" to minimize distractions, would facilitate easier access and engagement (Chugh & Ruhi, 2022).

Enriching Content Richness: Diversifying content through interactive formats (e.g., live Q&A sessions, info graphics) and partnering with universities to produce verified educational series can enhance knowledge absorption. A moderated content library, with expert ratings, would ensure quality and relevance, fostering a dynamic learning community (Montag et al., 2021).These strategies aim to leverage TikTok's unique features to support academic success while mitigating potential distractions.

5.2 Conclusion

This study provides valuable insights into the impact of TikTok on students' learning performance in Hanoi, confirming that Perceived Usefulness, Perceived Ease of Use, and Content Richness positively influence outcomes, with Content Richness exhibiting the strongest effect ($\beta = 0.384$). The regression model explained 57.7% of variance, underscoring TikTok's potential as a supplementary educational tool. These findings align with prior research on social media's role in knowledge sharing and engagement (Mosharrof Hosen et al., 2021), while addressing gaps in TikTok-specific studies. The results suggest that students should adopt structured TikTok usage plans to maximize educational benefits and minimize time wastage. Educational institutions are encouraged to integrate TikTok into teaching strategies, creating credible content to enhance learning efficiency in the digital era. However, this study is an initial exploration, limited by its focus on Hanoi and reliance on self-reported data. Future research should employ longitudinal designs and experimental methods to assess long-term impacts and optimize TikTok's educational integration across diverse contexts.

REFERENCES

[1] Abdullah, F., Ward, R., & Ahmed, E. (2016). Investigating the influence of the most commonly used external variables of TAM on students' Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of e-portfolio. *Computers in Human Behavior*, 63, 75-90.

[2] Al-Maroof, R. S., & Al-Emran, M. (2018). Students' acceptance of Google Classroom: An exploratory study using PLS-SEM approach. *International Journal of Emerging Technologies in Learning (iJET)*, 13(6), 112-123.

[3] Al-Rahmi, W. M., Othman, M. S., & Yusuf, L. M. (2015). The role of social media for collaborative learning to improve academic performance of students and researchers in Malaysia higher education. *International Review of Research in Open and Distributed Learning*, 16(4), 177-204.

[4] Anderson, M. (2022). The role of short-form video platforms in shaping modern learning behaviors. *Journal of Digital Learning*, 45(3), 123-135.

[5] Biggs, J., & Tang, C. (2011). *Teaching for quality learning at university: What the student does* (4th ed.). McGraw-Hill Education.

[6] Blasco-Arcas, L., Buil, I., Hernández-Ortega, B., & Sese, F. J. (2013). Using clickers in class. The role of interactivity, active collaborative learning and engagement in learning performance. *Computers & Education*, 62, 102-110.

[7] Bloom, B. S. (1956). *Taxonomy of educational objectives: The classification of educational goals*. Longmans, Green.

[8] Chugh, R., & Ruhi, U. (2022). Social media in higher education: A literature review and research directions. *The Internet and Higher Education*, 53, 100841.

[9] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340.

[10] Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Plenum Press.

[11] Dinh, T. P., & Nguyen, T. H. (2023). Interactive features of TikTok and their impact on user engagement in educational contexts. *Asian Journal of Media Studies*, 12(2), 89-102.

[12] Dung, D. Q. (2023). The impact of social media on learning behavior of CSL learners. *International Journal of Social Science and Human Research*, 6(7), 4076–4084.

[13] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Prentice Hall.

[14] Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing*, 20, 277-319.

[15] Holden, R. J., & Karsh, B. T. (2010). The technology acceptance model: Its past and its future in health care. *Journal of Biomedical Informatics*, 43(1), 159-172.

[16] Huang, Y. M., Huang, T. C., & Hsieh, M. Y. (2012). Using annotation services in a ubiquitous Jigsaw cooperative learning environment. *Educational Technology & Society*, 15(2), 3-15.

[17] Kumar, A., & Nanda, P. (2021). TikTok as an educational tool: Opportunities and challenges. *Journal of Educational Technology Systems*, 50(1), 45-60.

[18] Lamimi, A., Smith, J., & Johnson, K. (2024). Applying the Technology Acceptance Model to analyze students' intentions to use TikTok for learning. *International Journal of Educational Technology*, 21(3), 78-92.

[19] Madsen, S., & O'Mara, J. (2021). Short-form video platforms and their role in modern education. *Educational Media International*, 58(2), 145-160.

[20] Mayer, R. E. (2009). *Multimedia learning*. Cambridge University Press.

[21] Montag, C., Yang, H., & Elhai, J. D. (2021). On the psychology of TikTok use: A first glimpse from empirical findings. *Frontiers in Public Health*, 9, 641673.

[22] Mosharrof Hosen, M., Ogbeibu, S., Giridharan, B., Cham, T. H., & Lim, W. M. (2021). Taking a leaf from social media: An empirical investigation of social media knowledge sharing and knowledge acquisition in higher education. *VINE Journal of Information and Knowledge Management Systems*, 51(4), 576-594.

[23] Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

[24] Pham, T. Q. (2023). Students' perceptions of using social media to learn English vocabulary: A case study at Van Lang University. *Vietnam Journal of Applied Linguistics*, 22(1), 67-82.

[25] Sun, P. C., & Zhang, J. X. (2006). The role of perceived usefulness in the acceptance of e-learning systems. *British Journal of Educational Technology*, 37(6), 875-890.

[26] Sun, P. C., Tsai, R. J., Finger, G., Chen, Y. Y., & Yeh, D. (2008). What drives a successful e-Learning? An empirical investigation of the critical factors influencing learner satisfaction. *Computers & Education*, 50(4), 1183-1202.

[27] Tang, Y., & Hew, K. F. (2022). Emoticon, emoji, and sticker use in computer-mediated communication: A review of theories and research findings. *International Journal of Communication*, 16, 3932-3963.

[28] Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, 46(2), 186-204.

[29] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478.

[30] Xiao, L., Zhang, Y., & Wang, H. (2023). Cognitive impacts of short-form video consumption on young adults. *Journal of Media Psychology*, 35(2), 89-102.

[31] Zhong, B. (2021). From smart phones to classroom: PowerPoint or TikTok? A comparative review of two learning modalities. *Educational Technology Research and Development*, 69(5), 2423-2440.

[32] Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice*, 41(2), 64-70.

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