Examining the Impact of Live Streaming Engagement on English Language Proficiency: a UTAUT Framework

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Abstract. This study examines the impact of live streaming engagement on English language proficiency using the Unified Theory of Acceptance and Use of Technology as a theoretical framework. Key UTAUT constructs, including effort expectancy, performance expectancy, and social influence, are explored in the context of technology-enhanced language learning. Recent studies indicate that effort expectancy and social influence significantly influence learner motivation and technology adoption in language MOOCs and live-streaming platforms. This study employs a quantitative research design using structured surveys to measure learner engagement, perceived usefulness, and language proficiency outcomes. Findings reveal that interactive features and engagement tools can positively impact language acquisition, with higher engagement correlating with improved language proficiency. The study offers valuable insights for educators, developers, and policymakers seeking to optimize digital language learning environments.

Keywords: Live streaming learning, English language performance, UTAUT, Tencent Live, behavioral intention, effort expectancy

1 Introduction

This study examines the impact of live streaming engagement on English language performance using the UTAUT framework [1]. Higher engagement on Tencent Live was linked to improved language proficiency, with effort and performance expectancy as key predictors [2]. Insights inform educators, developers, and policymakers on enhancing digital learning through effective technology adoption strategies [3].

2 Research Objectives

This study examines live streaming platforms in language education, highlighting their role in enhancing engagement and English performance through interactive tools

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like video presentations, polls, and quizzes. Active participation and real-time feedback improve language skills, supporting findings on engagement in online learning [4][5]. Using the UTAUT framework [1], it identifies effort expectancy, performance expectancy, social influence, and facilitating conditions as key factors influencing platform use, supported by studies on technological self-efficacy [3]. Recommendations include improving usability, technical support, and interactivity for better language education. Platforms like Tencent Live enable real-time interaction through video conferencing, live chat, and polls, fostering collaborative learning and flexible, inclusive education through blended learning modes.

3 Theoretical Framework

As depicted in Fig. 1, performance expectancy, effort expectancy, and social influence directly influence behavioral intentions, while facilitating conditions affect actual technology use, moderated by factors such as gender, age, experience, and voluntariness [1]. Recent studies have extended the UTAUT model in educational contexts. Abbad examined Moodle adoption, emphasizing performance and effort expectancy in Jordan [6]. Alyoussef highlighted perceived enjoyment and mobile self-efficacy in m-learning in higher education [7]. Lal et al. explored study-life quality in e-learning adoption in developing countries [3]. These findings emphasize the continued relevance and adaptability of the UTAUT model in understanding technology adoption in educational contexts across diverse regions and learning platforms.

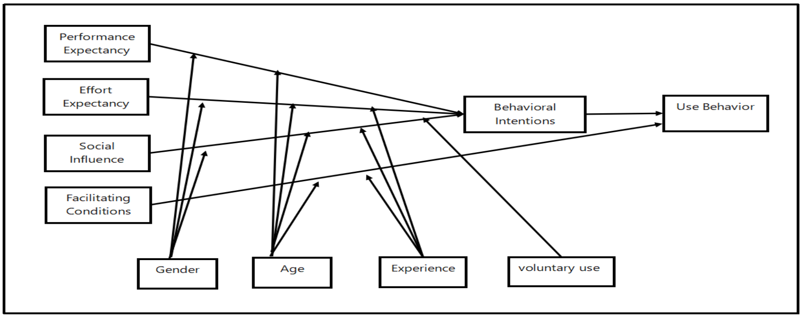

Fig. 1. UTAUT Model. Reprinted from Venkatesh

This study applied the UTAUT framework to examine students' acceptance of Tencent live courses at Sichuan Early Childhood Teacher Training College, focusing on performance expectancy, social influence, effort expectancy, and facilitating conditions. To address this, a modified UTAUT model with five confirmed hypotheses (H1-H5) was used, which is showing in following figure 2.

H1: Performance expectations significantly shape the intention to act.

H2: Effort expectations significantly impact the intention behind actions

H3: Social influence plays a key role in the formation of behavioral intention

H4: Facilitation has a significant effect on usage behavior

H5: Behavioral intention strongly influences usage behavior

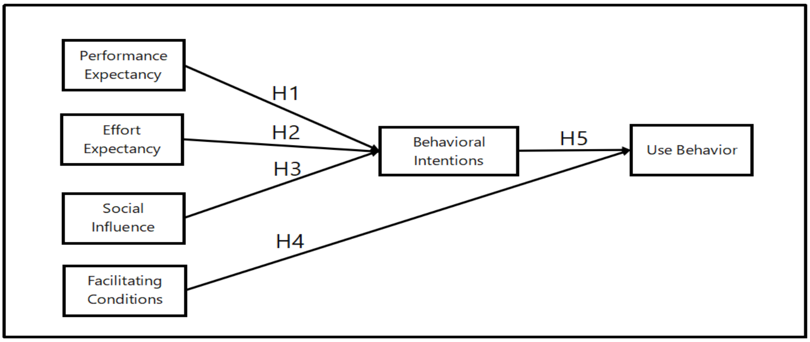

Fig. 2. Modified UTAUT

4 Research Methodology and Data Analysis

Data was collected from students at Sichuan Early Childhood Teacher Training College using convenience sampling via the Questionnaire Star platform. Of 462 distributed questionnaires, 437 responses were received, with 13 excluding for incompleteness, resulting in 424 valid responses. Hair recommends a minimum sample size of 100 to 150 for structural equation modeling (SEM) to ensure reliable and valid results. With 424 valid responses, this study exceeds the recommended minimum, providing a robust dataset for SEM analysis.

Table 1. Demographic characteristics of the sample

Variable	Number of Respondents	Percent (%)
Gender		
Male	181	41.3
Female	256	58.7
Age		
18-20 years	121	27.6
21-23 years	179	40.9
Above 23 years	137	31.4
Your Level		
Year one	93	21.2
Year two	257	58.8
Year three	87	19.9
College		
Education	128	29.2
IT	119	27.2
Management	87	19.9
Others	103	23.5

The sample consisted of undergraduate students from various colleges, including 33.6% in Education, 29.5% in IT, 24.4% in Management, and 12.4% in other fields.

The students were almost evenly distributed across year levels:1 year, 2 year, and 3 year (see Table 1).

5 Data analysis and Results

The study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to validate the research model and test hypotheses, following the two-step approach recommended by Anderson and Gerbing and further refined by assessing measurement model reliability and validity before testing structural relationships. According to Table 2, model fit was evaluated using CMIN/df (≤ 3.00), GFI (≥ 0.90), IFI (≥ 0.90), AGFI (≥ 0.80), CFI (≥ 0.90), and RMSEA (≤ 0.08), with most data meeting or closely aligning with these thresholds.

Table 2. CFA Statistics of Model Fit

Goodness-Fit Indexes	Recommended Value	Result Model
CMIN /df	≤ 3.00	1.362
Goodness-of-fit index (GFI)	≥ 0.90*	0.839
Incremental fit index (IFI)	≥ 0.90	0.957
Adjusted goodness-of-fit index (AGFI)	≥ 0.80	0.846
Comparative fit index (CFI)	≥ 0.90	0.953
Root mean square error of approximation (RMSEA)	≤ 0.08	0.046

6 Measurement Model

The study recommends conducting Confirmatory Factor Analysis (CFA), reviewing fit indices, and examining residual matrices for six core variables. Latent variables with CFA values above 3 should be excluded to ensure model validity [8],which is showing in table 3.

Table 3. Reliability and Convergent Validity Coefficients

Factor	Variables	Standard-ised Loadings (> 0.707)	Reliability (R^2) (> 0.5)	AVE (> 0.5)	Composite Reliability (CR) (> 0.7)	Cronbach's Alpha (> 0.7)
Performance Expectancy (PE)	PE1	0.736	0.533	0.618	0.851	0.801
	PE2	0.875	0.726			
	PE3	0.821	0.631			
Effort Expectancy (EE)	EE1	0.734	0.583	0.654	0.847	0.837
	EE2	0.871	0.714			

	EE3	0.894	0.662			
Social Influences (SI)	SI3	0.769	0.529	0.661	0.792	0.823
	SI4	0.853	0.638			
Facilitating Conditions (FC)	FC1	0.847	0.654	0.682	0.867	0.725
	FC2	0.827	0.651			
	FC3	0.831	0.662			
	BI1	0.827	0.649	0.681	0.883	0.818
Behavioural	BI2	0.862	0.732			
Intentions (IU)	BI3	0.869	0.772			
	BI4	0.726	0.562			
	UB2	0.713	0.521	0.563	0.771	0.764
Usage Behaviour (AU)	UB3	0.729	0.531			
	UB4	0.782	0.589			

Table 4. Factor Correlations

Factor	FC	SI	EE	PE	IU	AU
FC	1					
SI	0.263	1				
EE	0.714	0.274	1			
PE	0.559	0.437	0.574	1		
IU	0.462	0.362	0.351	0.517	1	
AU	0.339	0.293	0.582	0.733	0.594	1

According to Table 4, performance expectancy (PE) shows the strongest correlation with actual use (AU) at 0.733, emphasizing its key role in system adoption, while facilitating conditions (FC) and effort expectancy (EE) significantly influence engagement through ease of use and performance expectations.

7 Conclusion

This study examines live streaming engagement's impact on English proficiency using the UTAUT framework. Results show that performance expectancy, effort expectancy, facilitating conditions, and behavioral intention significantly influence technology adoption, while social influence is less relevant. Higher engagement improves proficiency, especially in speaking and listening, due to increased instructor interaction. Effort and performance expectancy drive platform use, with technological infrastructure playing a crucial role. However, challenges like limited resources and unstable internet hinder full utilization.

The study underscores the importance of engagement in language learning, highlighting how technological factors shape adoption and effectiveness. It emphasizes the role of live streaming in enhancing English proficiency and suggests future research on motivation and self-efficacy in learning outcomes. Addressing infrastructure limitations and resource constraints could further optimize the benefits of this approach.

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