CONTINUANCE INTENTION IN DOUYIN LIVE-STREAMING E-COMMERCE: A UTAUT2 PERSPECTIVE

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Abstract

Purpose: This study explores what keeps consumers using DouYin live streaming for shopping in China. Using the UTAUT2 framework, media richness theory, and social presence theory, the study examines how seven factors—performance expectancy, effort expectancy, social influence, support conditions, hedonic motivation, price value, and habit—predict whether active users intend to continue using DouYin as a shopping channel.

Study Design/Methodology/Approach: The study used an online survey of 230 active DouYin shoppers across four major Chinese cities (Beijing, Shanghai, Guangzhou, and Shenzhen), conducted from October to November 2024, employing non-probability purposive sampling. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to test how each UTAUT2 factor predicts continuance intention. All constructs showed acceptable to good reliability (α = 0.74-0.85). Common method bias was checked using Harman's single-factor test (first-factor variance = 31.2%).

Findings: All seven UTAUT2 factors significantly predicted continuance intention. Social influence (β = 0.214, $p < .001$) and price value (β = 0.214, $p < .001$) were virtually tied as the strongest drivers, followed in descending order by habit (β = 0.196, $p < .001$), effort expectancy (β = 0.172, $p < .01$), support conditions (β = 0.125, $p < .05$), hedonic motivation (β = 0.113, $p < .05$), and performance expectancy (β = 0.102, $p < .05$), the weakest though still significant predictor. The model explained 54.5% of the variance in continuance intention (R^2 = 0.545; adjusted R^2 = 0.531).

Originality/Value: This study offers one of the first full-model UTAUT2 examinations of DouYin live-streaming e-commerce continuance, using all seven constructs and a validated survey instrument. It uses media richness theory to explain the ranking of factors, proposes the seller-substitution mechanism as a conjecture for future testing, and provides modality-specific strategic guidance for live commerce platform operators and brands.

Keywords: Live Streaming E-commerce, Douyin, UTAUT2, Social Influence, Media Richness

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Introduction

Live-streaming e-commerce has become one of the most important developments in digital retail in recent years. In China, DouYin—ByteDance's domestic app, separate from its international version, TikTok—has become one of the leading live shopping platforms. By mid-2023, 526 million Chinese internet users (48.8% of all netizens) had shopped via livestreaming e-commerce (China Internet Network Information Center [CNNIC], 2023), and DouYin's e-commerce division reported 80% year-on-year GMV growth in 2022 (TechNode, 2023), making it one of the largest synchronous commerce platforms in the world's largest e-commerce market. This growth shows a real change in how Chinese consumers shop: instead of browsing alone, they now participate in live, social shopping events alongside sellers, streamers, and other viewers.

DouYin differs from traditional e-commerce in the type of shopping experience it creates. Users watch live product demos, ask questions in real-time chat, see other viewers buying, and make purchases during countdown deals and flash sales. Media richness theory (Daft & Lengel, 1986) characterizes this as a high-richness channel that provides immediate feedback, multiple cues simultaneously, and a personal touch, all influencing how consumers assess products. Social presence theory (Short et al., 1976) also predicts that the high level of social interaction in live streaming, including seeing other viewers, being addressed directly by the streamer, and forming personal connections, changes how people experience and evaluate the shopping encounter.

Despite DouYin's size, researchers still do not fully understand what keeps consumers coming back to shop on it. Previous studies have looked at specific aspects such as social presence and interactivity (Xu et al., 2020), trust and parasocial relationships (Wongkitrungrueng & Assarut, 2020), platform affordances (Kozinets et al., 2021), and impulse buying, but each study only looks at one piece of the picture. Platform managers need a complete view: not just which factors matter, but how important each one is compared to the others. Understanding continuance is arguably more consequential than understanding initial adoption for platform operators since sustained usage, not first-time trial, is what drives the recurring transaction volume, advertising inventory, and creator-economy engagement that live-commerce platforms depend on.

This study fills that gap by applying UTAUT2 (Venkatesh et al., 2012) to understand why active DouYin users continue to use the platform for shopping. UTAUT2 encompasses seven dimensions of technology adoption: functional, enjoyment-based, social, economic, habitual, and infrastructure-related aspects, which align well with DouYin's combination of functional, social, and entertainment features. Two key points should be highlighted. First, this study assesses continuance intention, whether active users intend to continue using DouYin for shopping, not whether new users will try it for the first time. Second, some theoretical explanations offered for specific results are post-hoc interpretations based on theory, not findings directly tested in this study. Since eligibility depended on recent, active shopping engagement rather than demographic representation, the sample tends to be younger and more female.

This pattern aligns with China's disclosed live-commerce user base (CNNIC, 2023) and is further explained as a scope condition in the Methodology and Limitations sections.

This study focuses on three key research questions. RQ1 investigates which UTAUT2 factors significantly influence continuance intention among active DouYin shoppers and compares their relative importance. RQ2 explores how media richness theory and social presence theory explain the observed ranking of these factors. RQ3 considers what these results mean for DouYin operators, brands, and content creators in prioritizing their platform features and content investments.

Objectives

1. To identify which UTAUT2 factors significantly predict continuance intention among active DouYin shoppers, and to compare how important each factor is relative to the others.
2. To explain the observed factor ranking using media richness theory and social presence theory, providing theoretically grounded reasons for why certain factors matter more than others.
3. To turn the findings into practical, evidence-based recommendations for DouYin operators, brands, and content creators.

Literature Review

DouYin Live Streaming E-commerce as a Synchronous Service Encounter

Live streaming e-commerce can be defined as a convergence of product demo, entertainment, real-time social interaction, and purchasing in one live stream (Wu & Huang, 2023). DouYin excels in this, with a few reinforcing features. A natural short-video algorithm pulls users from entertainment to live video shopping broadcasts, making it easy to get into a live stream. It's a buy button integrated with payment that removes friction when buying. With its network of Key Opinion Leaders (KOLs), brand studios, and micro-influencers, it establishes personal links between streamers and viewers, making commercial interactions appear more like a trusted recommendation (Wongkitrungrueng & Assarut, 2020; Lo et al., 2022). There's no doubt that live streaming offers a completely different shopping experience. Interactivity and feeling part of a community are the main factors that influence purchase intention, not necessarily the product information itself, as demonstrated by Xu et al. (2020). Consumers' trust in live streamers differs from the institutional trust measured in e-commerce studies (McKnight et al., 2002), which relies on formal guarantees and certifications, because it is based on consistency, responsiveness, and interpersonal trust that consumers experience with streamers. Unlike traditional platforms, consumers' trust in live streamers is based on consistency and responsiveness as well as interpersonal trust, rather than on formal guarantees or certifications (Wongkitrungrueng & Assarut, 2020). According to Lo et al. (2022), the emotional excitement produced by live broadcasts causes a feeling of impulse purchase, which is driven by social influence and entertainment value. Dubbed a commercial environment (Bitner, 1992; Hopkins et al., 2009), DouYin is saturated with fascinating cues: viewer counters and scrolling chat show

social activity, countdown timers and lack-of-stock cues foster urgency, and streamers talk directly to the audience in a warm and personal way. As a whole, these attributes form a shopping experience that is quite different from the discrete browsing that occurs in a typical e-commerce setting: more like Pine and Gilmore (1998) conception of shopping as a staged experience than of a mere exchange transaction. It is not only useful to stay on DouYin, but there are also many reasons to feel a sense of belonging, value, entertainment, and habit. This picture is further confirmed by more recent work: Ko and Ho (2024) report the role of expectation confirmation and existing trust to maintain continued purchase intention in live streaming shopping, while Imanuddin and Handayani (2025) report that the Stimulus-Organism-Response mechanisms are not only related to functional utility but are also significant in affecting continued purchase intention in social commerce livestreaming, which represents a separate area of study that deserves more attention: continuance intention.

Theoretical Foundations

Media Richness Theory

Media richness theory (Daft & Lengel, 1986) ranks communication channels by their ability to reduce misunderstanding and ambiguity through four qualities: immediate feedback; multiple cues at once (words, images, voice, and body language); natural conversational language; and personal focus. High-richness channels work best for complex or emotional communication; low-richness channels work best for clear, factual information. The theory predicts that a channel works best when its richness matches the type of task being done. DouYin live streaming is one of the richest digital shopping channels available: sellers talk, demonstrate, use facial expressions and gestures, and respond to comments—all at the same time. Viewers get instant responses, can see what other viewers are buying, and experience the stream as a lively social event rather than a product page. This richness matters for adoption. First, sellers can explain value and respond to price concerns in real time, making price value a stronger driver. Second, because the seller performs much of the work the platform would normally handle, platform-level functional quality (performance expectancy) becomes less critical. Third, live social activity, including other viewers commenting and buying, creates ongoing social proof throughout the session.

Social Presence Theory

Social presence theory (Short et al., 1976) says that different media create different feelings of being with other people. High-social-presence media create warmth, emotional connection, and trust. Low-social-presence media lead to more detached, information-based decisions. In e-commerce, Gefen and Straub (2004) show that social presence builds trust, and Hassanein and Head (2007) show that it increases enjoyment and purchase intention. Both findings apply to DouYin continuance: users who feel a genuine social connection during DouYin streams are more likely to keep coming back than those who use it only as a functional shopping tool. DouYin builds high social presence through several layers at once: the streamer talks directly to the audience on camera; scrolling comments and reaction emojis show other viewers participating; real-time purchase alerts show that people around you are buying; and regular

viewers form a personal connection—a parasocial relationship—with streamers they follow (Horton & Wohl, 1956; Wongkitrungrueng & Assarut, 2020; Lo et al., 2022). Together, these features do not feel like add-ons. They are what make the DouYin shopping experience feel different from any other channel. Social presence theory also predicts that DouYin's high social presence should make social influence a stronger driver of continuance than on traditional platforms, because social activity is visible and occurs in real time rather than being stored as reviews and ratings. It also helps explain habit: the ongoing relationship viewers have with their favorite streamers, and the sense of belonging to a community, give users a reason to return regularly, which does not exist on purely transactional, asynchronous platforms.

UTAUT2 and the Case for Full-Model Application

UTAUT2 was developed by Venkatesh et al. (2012) by extending the original UTAUT model (Venkatesh et al., 2003) with hedonic motivation, price value, and habit to better model the behavior of ordinary consumers adopting technology. The instrument has been extensively validated in various fields such as mobile payment (Morosan & DeFranco, 2016), social media commerce (Alalwan et al., 2017), digital health (Dwivedi et al., 2019), and digital content services (Oyedele & Simpson, 2018). Previous research on live streaming has included only a few UTAUT2 variables, where Xu et al. (2020) excluded the price value, and Wongkitrungrueng and Assarut (2020) focused only on trust and engagement. This research combines all seven constructs and tests all of them simultaneously, rather than testing each construct individually.

This study defines the seven UTAUT2 constructs as follows for the DouYin context: 1) Performance Expectancy (PE)—whether DouYin helps users shop more effectively; 2) Effort Expectancy (EE)—how easy DouYin feels to use for shopping; 3) Social Influence (SI)—whether important people in the user's life think they should use DouYin; 4) Support Conditions (SC)—whether the user has the devices and internet connection needed to use DouYin well; 5) Hedonic Motivation (HM)—how enjoyable and entertaining DouYin is; 6) Price Value (PV)—whether DouYin offers good value for money; and 7) Habit (HB)—whether using DouYin for shopping has become automatic. These seven dimensions capture the key reasons people continue to use any technology, making UTAUT2 the most suitable framework for this study.

Hypothesis Development

Seven hypotheses are proposed, one for each UTAUT2 construct. Each hypothesis is supported by the theories reviewed above and by prior research on live streaming. All hypotheses predict a positive effect on continuance intention within the same sample; no comparisons between groups are made.

Performance Expectancy (PE)

PE measures how well DouYin works as a shopping tool. In a live streaming context, this includes the quality of product demonstrations, how clearly sellers explain products, how quickly sellers answer questions, and how reliably the purchase process works. Users who feel that DouYin genuinely helps them find and buy the right products are expected to keep using it. This is one of the most consistently

supported factors in UTAUT2 research (Venkatesh et al., 2012), and it is expected to hold for DouYin even though sellers handle some of the work that the platform itself would normally do.

H1: Performance expectancy positively influences continuance intention to use DouYin.

Effort Expectancy (EE)

EE measures how easy DouYin feels to use for shopping. DouYin is designed to be simple: its algorithm automatically surfaces content to users, purchases can be made with one tap, and payment is built in. However, shopping on a live stream still requires more effort than browsing a static page: users need to watch the broadcast, read the chat, evaluate deals quickly, and buy within time limits. Users who find all of this manageable are expected to continue using DouYin (Davis, 1989; Venkatesh et al., 2012).

H2: Effort expectancy positively influences continuance intention to use DouYin.

Social Influence (SI)

SI in UTAUT2 measures subjective norm—how much the people around you think you should use the platform. It is important to be clear about what this construct covers: the SI survey items measure only peer normative pressure. They do not measure the social proof visible inside a live broadcast (such as other viewers commenting and buying), or the personal connection viewers feel with streamers. Those are different kinds of social influence that this study does not directly measure, and they are important areas for future research. Within the scope of peer normative pressure, social presence theory predicts that DouYin's highly social nature strengthens how much peer endorsements matter: when you can see that your friends and colleagues actively use DouYin for shopping, the pressure to join in is reinforced by direct evidence. Research consistently confirms social influence as a key driver of live streaming adoption (Wongkitrungrueng & Assarut, 2020; Xu et al., 2020; Alalwan et al., 2017).

H3: Social influence (as subjective norm) positively influences continuance intention to use DouYin.

Price Value (PV)

PV measures whether DouYin offers good value for money. Live streaming has developed a unique pricing model: exclusive deals available only during broadcasts, countdown flash sales, KOL-negotiated prices, and bundle offers. Sellers actively build up the sense of value in real time by explaining quality, showing features, emphasizing savings, and creating urgency through time limits and low stock. Media richness theory explains why this works so well: in a high-richness synchronous channel, sellers can directly shape how consumers weigh the benefits against the cost (Zeithaml, 1988), rather than leaving shoppers to decide quietly on their own.

H4: Price value positively influences continuance intention to use DouYin.

Hedonic Motivation (HM)

HM measures how fun and enjoyable DouYin is to use. The broadcast format itself, streamer personality, live game features (virtual gifts and lucky draws), and the spectacle of seeing many other viewers participate all make DouYin inherently entertaining (Kozinets et al., 2021; Holbrook & Hirschman, 1982). Social presence theory also predicts that the warmth and emotional engagement of

a high-social-presence platform add to enjoyment. Users who find DouYin genuinely fun are expected to keep using it for reasons beyond just getting a good deal.

H5: Hedonic motivation positively influences continuance intention to use DouYin.

Habit (HB)

HB measures how automatic and routine DouYin use has become. Because DouYin is both an entertainment app and a shopping platform, users who habitually scroll through short videos are naturally exposed to live commerce without actively switching apps or deciding to shop. Limayem et al. (2007) show that as users spend more time on a platform, habit becomes one of the strongest predictors of continued use because habitual actions occur partly without conscious decision-making. Since all respondents in this study are active users, strong habit effects are expected.

H6: Habit positively influences continuance intention to use DouYin.

Support Conditions (SC)

SC measures whether users have the devices and internet connection needed to use DouYin effectively. Watching live streams demands more technical skills than browsing a product page: users need a stable, fast internet connection, a compatible device, and smooth video playback. Users who feel well-equipped are expected to continue using DouYin more. Those who face regular technical problems—slow connections, buffering video, incompatible devices—face real barriers that reduce their willingness to engage (Parasuraman, 2000; Venkatesh et al., 2012). This is consistent with perceived-risk research showing that functional and performance-related risk reduce technology engagement more broadly (Featherman & Pavlou, 2003).

H7: Support conditions positively influence continuance intention to use DouYin.

Building on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2; Venkatesh et al., 2012), this study introduces a conceptual framework where seven independent constructs collectively predict the intention to continue using DouYin for live streaming e-commerce. These constructs are expected to positively influence continuance intention, creating an integrated framework (Figure 1) that highlights the functional, social, hedonic, and structural factors driving ongoing engagement with live streaming e-commerce.

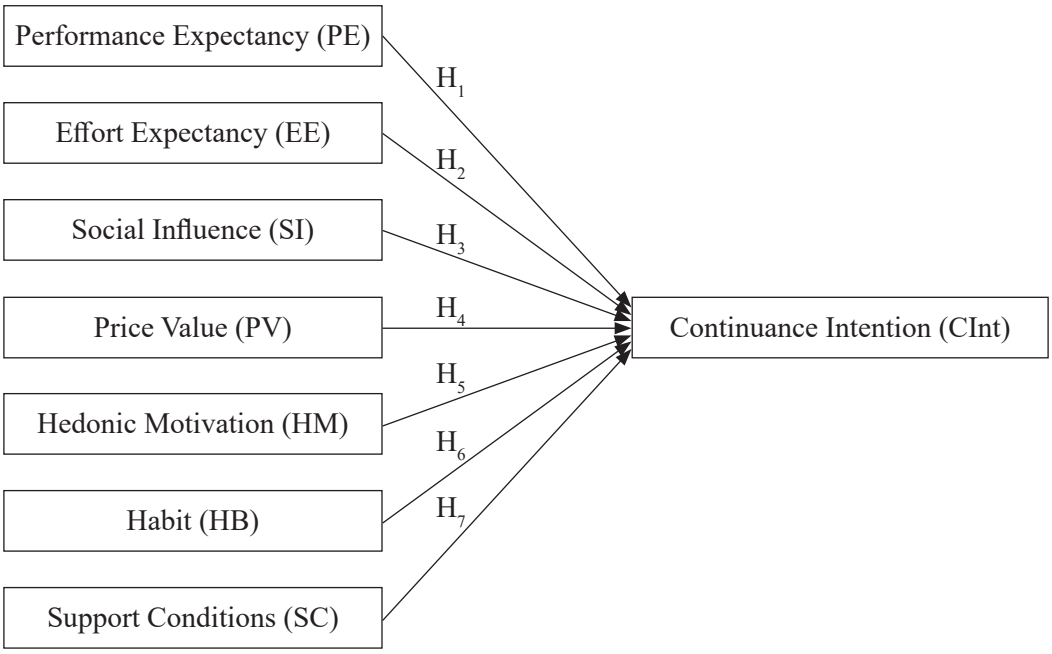


Figure 1 Proposed Research Framework adapted from UTAUT & UTAUT2

Methodology

This study used a quantitative cross-sectional survey design. The proposed model was estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is well suited to prediction-oriented models with reflective latent constructs and does not require multivariate normality (Hair et al., 2019). Based on the research question, this study used purposive sampling and selected the specific population of active DouYin shoppers. The survey link was sent to the WeChat groups of shoppers and DouYin content creators in October–November 2024 on Wenuanxing (SurveyStar). Eligibility screening was done at the entry point: Only individuals who were 1) 20 years old or older, 2) lived in Beijing, Shanghai, Guangzhou, or Shenzhen, and 3) had shopped on DouYin at least once a month in the last three months were allowed to continue. A total of 247 responses were received, of which 17 were removed because they failed built-in attention checks, leaving n = 230 responses (which is more than the suggested 15:1 ratio of 105 cases for seven predictors in a regression; Hair et al., 2010).

The items were all measured with validated scales, which were adapted from Venkatesh et al. (2012) with slight wording changes for the DouYin context. Three items on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree) were used for each construct. The items were selected from validated UTAUT2 scales and reviewed by three academics for content validity, and the items were translated into Chinese by a professional translator with back-translation verification, finally, the items were tested with 30 active users of DouYin by using the pilot test method, and the Cronbach's alpha (α) value is in the range from 0.68 to 0.86 for all constructs, indicating acceptable to good reliability at the pilot stage. The full-sample alpha values (α) are in the range from 0.74 to 0.85, showing good to acceptable reliability in the main study and are presented in Table 5. The operationalization of the UTAUT2 constructs is shown in Table 1.

Table 1 UTAUT2 Construct Operationalization

Construct	Items	Sample Item	Theoretical Grounding	Source
PE	3	Using DouYin improves my shopping effectiveness.	Task effectiveness; outcome quality (Brady & Cronin, 2001)	Venkatesh et al. (2012)
EE	3	I find DouYin easy to use for shopping.	Perceived ease of use (Davis, 1989)	
SI	3	People important to me think I should use DouYin.	Subjective norm; peer normative pressure (Venkatesh et al., 2012)	
SC	3	I have the resources necessary to use DouYin for shopping.	Facilitating infrastructure; technology readiness (Parasuraman, 2000)	
HM	3	Using DouYin for shopping is fun and enjoyable.	Experiential value; hedonic consumption (Holbrook & Hirschman, 1982)	
PV	3	DouYin offers good value for money on purchases.	Perceived value; benefits-sacrifice tradeoff (Zeithaml, 1988)	
HB	3	Using DouYin for shopping has become a habit for me.	Automaticity; continuance habit (Limayem et al., 2007)	
CInt	3	I intend to continue using DouYin for shopping in the future.	Continuance intention (Limayem et al., 2007; Ajzen, 1991)	

Remarks: CInt = Continuance Intention. SI captures only subjective norm; in-broadcast social proof and parasocial relationship constructs are not measured by these items.

Partial Least Squares Structural Equation Modeling (PLS-SEM)

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to estimate the proposed model structure. This is a structural model that directly estimates the scores of latent variables from their indicators instead of relying on summated scales (Wold, 1982; Lohmöller, 1989). Each of the seven exogenous constructs (PE, EE, SI, PV, HM, HB, and SC) was modeled as a reflective (Mode A) latent variable predicting continuance intention (CInt), also reflective, through the path weighting approach for estimating inner-model parameters, consistent with their conceptualization as multi-item reflective scales in the UTAUT2 literature (Venkatesh et al., 2012). The model was estimated in R using the seminr package (Ray et al., 2021), a package that has been continually benchmarked and compared with other packages such as SmartPLS, ADANCO, semPLS, and matrixpls, and therefore provided a defensible alternative when SmartPLS was not available in the analysis environment. Path significance was evaluated using 5,000 resampled data from a nonparametric bootstrapping procedure. These were evaluated by means of the Heterotrait-Monotrait ratio of correlations (HTMT; Henseler et al., 2015), effect sizes by means of Cohen's f^2 (f Squared function), and predictive relevance (Q^2 computed using 10-fold cross-validated PLSpredict; Shmueli et al., 2016; Hair et al., 2019).

Results

A number of critical checks were carried out in preliminary analyses. All three measures of reliability–Cronbach's alpha, rhoA and composite reliability (rhoC)–were used to evaluate reliability,

and a criterion of 0.70 was used for all three (Nunnally & Bernstein, 1994; Hair et al., 2019). Convergent validity was assessed by measuring the item-to-construct loadings and Average Variance Extracted (AVE) values with 0.50 as the minimum threshold (Hair et al., 2019). Finally, discriminant validity was verified using the Fornell-Larcker criterion (Fornell & Larcker, 1981) and the Heterotrait-Monotrait ratio of correlations (HTMT) (Henseler et al., 2015), which was under 0.85 for all the correlations. Common Method Bias (CMB) was assessed using two complementary checks, since Harman's single-factor test alone is a necessary but not sufficient safeguard. First, Harman's single-factor test showed the first factor accounted for 31.2% of variance, below the 40% threshold of concern. Second, a full collinearity test (Kock, 2015) was conducted by regressing each construct's composite score on all other constructs as presented in Table 2. The resulting variance inflation factors ranged from 1.27 to 2.14, well below the conservative 3.3 threshold, providing convergent evidence that Common Method Bias is not a serious concern in this dataset. Procedural remedies were also applied at the design stage, including anonymized responses and built-in attention-check items to screen out inattentive respondents. Path coefficients were evaluated using nonparametric bootstrapping, and significant values and 95% confidence intervals were reported for each predictor.

Table 2 Common Method Bias: Full Collinearity Test (VIF)

Construct	VIF
PE	1.321
EE	1.481
SI	1.268
PV	1.490
HM	1.286
HB	1.481
SC	1.412
BI	2.144

Sources or Remarks: Author's Calculation. VIF = variance inflation factor from a full collinearity test (Kock, 2015), computed by regressing each construct's composite score on all other constructs; all values fall below the conservative 3.3 threshold, indicating common method bias is not a serious concern. This corroborates Harman's single-factor test, which showed the first factor accounted for 31.2% of variance (below the 40% threshold of concern).

Table 3 Convergent and Discriminant Validity

Construct	AVE	√AVE	PE	EE	SI	PV	HM	HB	SC	CI
PE	.712	.844	-	.419	.294	.379	.327	.460	.468	.506
EE	.705	.840	.333	-	.335	.535	.350	.509	.461	.613
SI	.701	.837	.232	.264	-	.305	.351	.340	.351	.540
PV	.705	.840	.300	.424	.241	-	.455	.437	.453	.626
HM	.660	.812	.252	.268	.267	.348	-	.429	.393	.521
HB	.674	.821	.358	.393	.262	.339	.321	-	.492	.636
SC	.696	.834	.369	.360	.272	.354	.298	.378	-	.564
CI	.769	.877	.416	.503	.443	.515	.413	.511	.459	-

Sources or Remarks: Author's Calculation. Bold diagonal values (√AVE) exceed all inter-construct correlations in their row and column, confirming the Fornell-Larcker criterion (Fornell & Larcker, 1981). Values above the diagonal are Heterotrait-Monotrait ratios (HTMT); all values fall below the 0.85 threshold (Henseler et al., 2015), corroborating discriminant validity established by the Fornell-Larcker criterion.

Inter-construct correlations were low to moderate (r = 0.232-0.535), consistent with the seven UTAUT2 constructs capturing meaningfully distinct dimensions of continuance intention, and discriminant validity was confirmed because the square root of each construct's AVE exceeded its highest inter-construct correlation in all cases (Fornell & Larcker, 1981); this was further corroborated by HTMT values well below the conservative 0.85 threshold as shown in Table 3.

Table 4 presents the sample profile. Most respondents were female (53.9%), middle-income (67.0% earning CNY 5,001-10,000 per month), educated (62.6% bachelor's degree; 29.6% postgraduate), and aged 20-40 (67.0%)—consistent with DouYin's known demographics in tier-one Chinese cities (CNNIC, 2023). Users aged 51-70 made up 21.8% of the sample, confirming DouYin's expansion beyond younger demographics. Shopping frequency was high: 44.8% shop on DouYin at least several times per week.

Table 4 Sample Demographic Profile and DouYin Usage (n = 230)

Characteristic	n	%	Characteristic	n	%
Gender			**Usage frequency (shopping)**		
Male	106	46.1	Daily	32	13.9
Female	124	53.9	Several times/week	71	30.9
Age group			Weekly	67	29.1
20-30 years	86	37.4	Monthly	60	26.1
31-40 years	68	29.6	**Education**		
41-50 years	26	11.2	Diploma or below	18	7.8
51-60 years	34	14.8	Bachelor's degree	144	62.6
61-70 years	16	7.0	Master's degree or above	68	29.6
			Monthly income (CNY)		
			1,000-5,000	41	17.8
			5,001-10,000	154	67.0
			>10,000	35	15.2

Sources: Sample of active DouYin shoppers from four tier-one Chinese cities.

Table 5 displays the reliability and descriptive statistics. All Cronbach's alpha (α), rhoA, and rhoC values are above 0.70 (α ranges from 0.74 to 0.85; rhoA from 0.749 to 0.850; rhoC from 0.853 to 0.909), and all AVE values surpass 0.50 (ranging from 0.660 to 0.769), indicating convergent validity and reliability (Hair et al., 2019). Item loadings all range from 0.780 to 0.882, as shown in Figure 2; all values exceed the 0.70 minimum recommended by Hair et al. (2019).

Table 5 Reliability and Descriptive Statistics

Construct	α	rhoA	rhoC	Mean	SD	Skew	Kurt
Performance Expectancy (PE)	0.80	0.799	0.881	2.87	0.84	0.25	0.04
Effort Expectancy (EE)	0.79	0.802	0.877	2.82	0.83	-0.02	-0.06
Social Influence (SI)	0.79	0.814	0.873	2.82	0.85	0.20	0.02
Price Value (PV)	0.79	0.818	0.876	2.77	0.81	0.29	0.15
Hedonic Motivation (HM)	0.74	0.749	0.853	2.73	0.74	-0.01	0.07
Habit (HB)	0.76	0.767	0.860	2.72	0.74	-0.17	-0.29
Support Conditions (SC)	0.78	0.799	0.872	2.83	0.81	0.01	-0.27
Continuance Intention	0.85	0.850	0.909	3.35	1.12	-0.18	-1.08

Sources: Authors' calculation

Table 6 presents the PLS-SEM structural model results together with the corresponding hypothesis test outcomes, integrating path coefficients, bootstrapped standard errors, t-values, significance levels, and effect sizes (f^2) for all seven hypothesized relationships. All seven paths (H1-H7) were statistically significant and supported, with standardized path coefficients from $\beta = 0.102$ (performance expectancy) to $\beta = 0.214$ (social influence and price value). The model showed strong explanatory and predictive power ($R^2 = 0.545$, Adjusted $R^2 = 0.531$). Figure 2 presents the corresponding path diagram, mapping these coefficients onto the full structural model alongside the outer loadings linking each construct to its retained items.

Table 6 PLS-SEM Structural Model and Hypothesis Testing Results (n = 230)

H	Path	SE	*β*	t	*p*	f^2	Result
H3	SI → CInt (+)	0.047	0.214	4.595	<.001**	0.086	Supported
H4	PV → CInt (+)	0.049	0.214	4.369	<.001**	0.071	Supported
H6	HB → CInt (+)	0.050	0.196	3.903	<.001**	0.060	Supported
H2	EE → CInt (+)	0.050	0.172	3.415	.001**	0.045	Supported
H7	SC → CInt (+)	0.049	0.125	2.558	.011*	0.025	Supported
H5	HM → CInt (+)	0.048	0.113	2.349	.017*	0.022	Supported
H1	PE → CInt (+)	0.045	0.102	2.260	.025*	0.017	Supported

Sources or Remarks: Author's calculation. $R^2 = 0.545$; Adjusted $R^2 = 0.531$; $Q^2 = 0.397$ (10-fold cross-validated redundancy); GoF = 0.618; maximum HTMT = 0.636 (all construct pairs below the 0.85 threshold); bootstrap based on 5,000 resamples. CInt = continuance intention. Predictors are listed in descending order of β. *$p < .05$; **$p < .01$.

Figure 2 visually depicts the full PLS-SEM model, integrating both the measurement and structural components in a single diagram. The seven hypothesized structural paths (H1-H7) are labeled with their standardized path coefficients (β) and significance level. The endogenous construct, continuance intention (CInt), also reports its coefficient of determination ($R^2 = .545$), reflecting the proportion of variance explained by the seven UTAUT2 predictors.

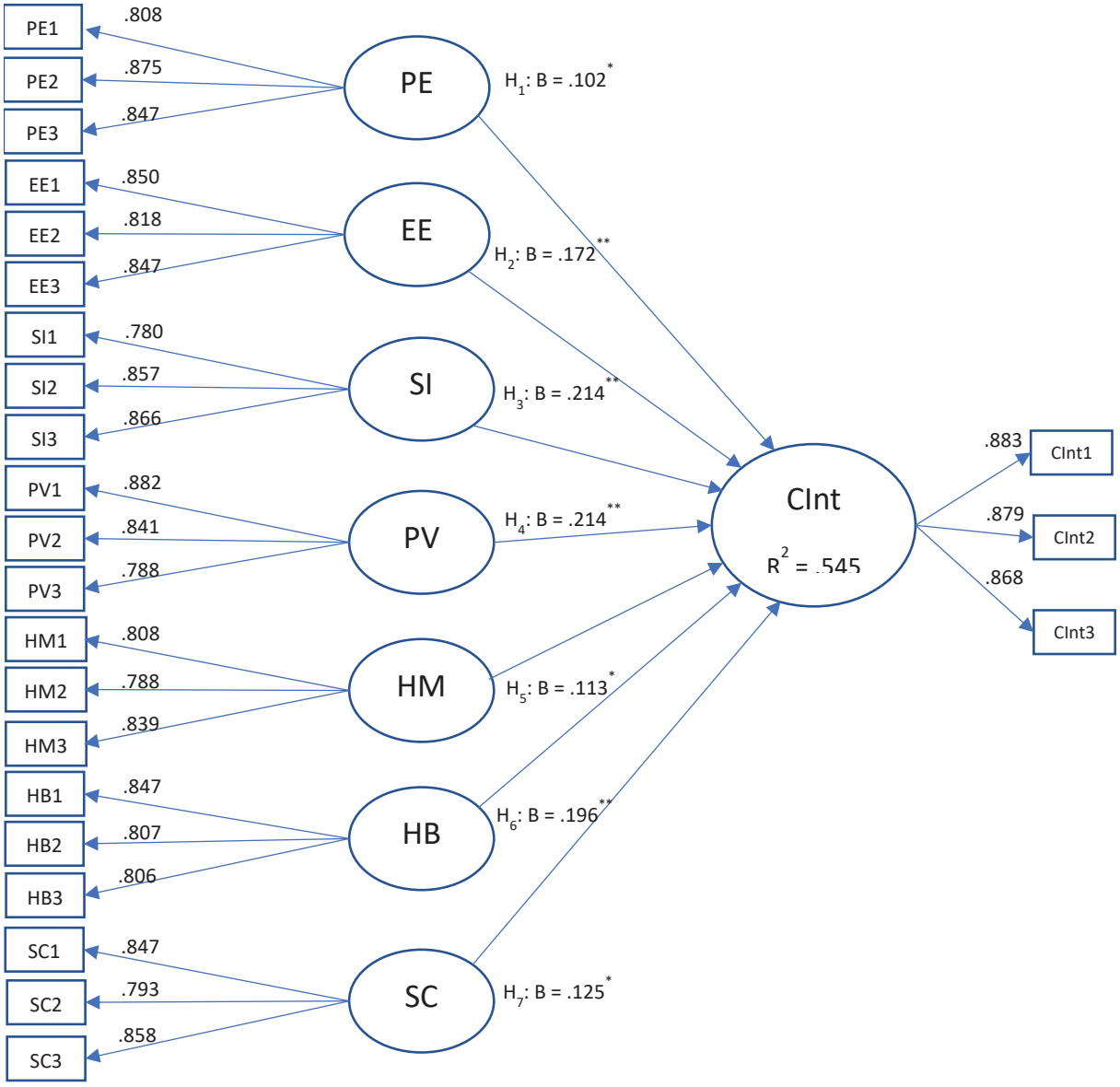


Figure 2 PLS-SEM Structural Model with Standardized Path Coefficients (n = 230)

Remarks: Author's calculation; *$p < .05$; **$p < .01$ (standardized path coefficients β, bootstrap n = 5,000)

Discussion

Together, social influence ($\beta = 0.214$, $p < .001$) and price value ($\beta = 0.214$, $p < .001$) are the two strongest drivers for continuance intention, with habit ($\beta = 0.196$, $p < .001$) not far behind. Theories of media richness and social presence provide a theoretical interpretation of social influence's strong position. In this study, we use the subjective norm (how much people around you think you should use DouYin for shopping) as the measure of social influence. Social presence theory suggests that in high-presence platforms there are stronger and continuous peer endorsements (Gefen & Straub, 2004; Wongkitrungrueng & Assarut, 2020; Alalwan et al., 2017). The UTAUT2 SI items measure only peer normative pressure and not in-broadcast parasocial relationships or streams. This is most likely because these are unmeasured mechanisms and cannot be disaggregated in this data set to explain the SI coefficient. The result is

consistent with Wongkitrungrueng and Assarut (2020), who found that social influence is one of the most important factors influencing the adoption of live commerce, and Alalwan et al. (2017), who revealed that social influence is one of the most important factors influencing the adoption of mobile commerce. Both previous studies, however, went beyond subjective norm and measured a wider range of social influence measures, such as in-platform social cues, whereas our SI items only measured subjective norm, meaning that the full effect of social influence in DouYin may be larger than our coefficient suggests.

The price value stands out as the co-equal robust predictor due to DouYin's unique value offering in real time. Sellers actively build perceived value in broadcasts by comparing quality, offering countdowns, selling at Key Opinion Leader (KOL) prices, and creating social proof of purchase decisions. This is active value construction, which is particularly effective in high-richness synchronous channels (Zeithaml, 1988). Additionally, the loss aversion effect demonstrated in time-limited pricing (Tversky & Kahneman, 1981) can be seen as further enhancing the perceived value in the limited time frames of DouYin broadcasts during promotions. This result corroborates previous studies by Morosan and DeFranco (2016), where they identified price value as significant for the adoption of NFC mobile payment, and also extends Zeithaml (1988) value framework to a real-time synchronous context. However, the seller-dominated value construction in live streaming, such as countdown sales, KOL pricing, and social proof of sales, is a more dynamic value mechanism than the more static price comparisons found in previous UTAUT2 research in traditional e-commerce settings.

The significant association with habit ($\beta = 0.196, p < .001$) indicates that DouYin's role in combining entertainment and commerce has made it easier for users to perform live commerce activities as a habit. This matches the findings of Limayem et al. (2007), who show that habit can become the most influential factor driving continued use over time, and of Venkatesh et al. (2012), who validate habit as an important predictor in a variety of consumer technology settings. In contrast to the previous UTAUT2 model, where the construct of habit usually comes after functional and social factors, its strong ranking in this model implies that DouYin's entertainment-commerce business model makes it easier to build a habit than the entertainment-commerce business model.

The effort expectancy ($\beta = 0.172, p < .01$) is a concept in the middle of the list between the strongest drivers and the weaker ones. This is in line with Davis (1989) and Venkatesh et al. (2012), who have always identified perceived ease of use as a key adoption determinant. Its position indicates that the ability to make purchases in one tap has reduced the "barrier to action" for active users without removing it as a differentiator for continuance altogether. Support conditions ($\beta = 0.125, p < .05$) are among the weaker, but still statistically significant, predictors. This indicates that among a well-equipped tier-one sample, the technical requirements of streaming place only a secondary demand on continued video engagement, and that, as Venkatesh et al. (2012) discover, the facilitating conditions of the context are a significant but comparatively minor adoption driver across contexts. Its weaker performance in this area could suggest that support conditions play more of a threshold role (required but not necessarily distinguishing

within a relatively well-equipped sample) than a perpetuating role in continuance, which it seems will be significant in lower-tier markets where DouYin is growing.

Hedonic motivation ($\beta = 0.113$, $p < .05$) and performance expectancy ($\beta = 0.102$, $p < .05$) are the weakest, though still significant, predictors. The small impact of hedonic motivation contrasts starkly with Chen et al. (2024), who found that entertainment is among one of the most important predictors of live streaming purchase intention and we explain this contrast as a result of the threshold condition. For most active users, the live broadcast format produces entertainment as a structural aspect, meaning that the differences in continuation are not large enough to be attributed to a difference in hedonic motivation. The performance expectancy is ranked last, unlike the findings of Venkatesh et al. (2012) and Xu et al. (2020), who found that PE is among the top predictors of technology adoption and live streaming engagement, respectively. This is explained by a post-hoc conjecture on seller substitution. Streamer interaction can replace some of the functionality of a platform in synchronous encounters. The two explanations are speculative inferences that would need to be tested through empirical studies in the future.

These findings also align with recent live-streaming commerce literature. Ko and Ho (2024) similarly found that ongoing trust and expectation confirmation, rather than initial ease of use, drive continued purchase intention in live-streaming shopping, consistent with effort expectancy's comparatively modest role in this study. Imanuddin and Handayani (2025), applying a Stimulus-Organism-Response framework to social commerce livestreaming, likewise identify social and hedonic stimuli as key organismic drivers of continuance, reinforcing the strong roles found here for social influence and habit. Together, these recent studies suggest that the relative importance of trust-and-confirmation mechanisms versus baseline ease-of-use may be converging across live-streaming commerce platforms more broadly, rather than being unique to DouYin.

Conclusions

This study examined the factors that drive active DouYin users to continue shopping on the platform, using a sample of 230 users from four major Chinese cities. All seven UTAUT2 factors were significant predictors, and the model explained 54.5% of the variance in continuance intention ($R^2 = 0.545$; Adjusted $R^2 = 0.531$), estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM). Social influence and price value emerged as the strongest, virtually tied, drivers of continuance intention, followed in descending order by habit, effort expectancy, support conditions, hedonic motivation, and performance expectancy, the weakest though still significant predictor. Discriminant validity (HTMT), effect sizes (f^2), and predictive relevance (Q^2) all confirmed the robustness of the model.

The findings directly address three gaps identified in the introduction. First, prior studies on live streaming adoption have tested only partial sets of UTAUT2 constructs (Xu et al., 2020; Wongkitrungrueng & Assarut, 2020), leaving the relative importance of all seven factors unknown. Second, existing research has focused predominantly on initial purchase intention rather than continuance among active users. Third,

this study benchmarks the relative importance of all seven predictors using standardized coefficients reported as a continuous ranking by effect size, rather than a single-point ranking or discrete groupings, clarifying which differences in predictive strength are well-supported versus descriptive. This study addresses all three gaps simultaneously.

Theoretical Contributions

Academically, this study provides the first full-model UTAUT2 examination of DouYin live streaming e-commerce continuance intention, applying all seven constructs simultaneously to an active-user sample. Reporting predictors as a continuous ranking by standardized effect size, rather than imposing discrete significance-based groupings, avoids overstating the precision of fine-grained distinctions between closely spaced coefficients. This approach is replicable across other platforms and technology adoption contexts.

Theoretically, media richness theory is used to explain why the factor hierarchy looks the way it does—specifically, why price value ranks as the top driver (sellers can actively construct value in real time in a high-richness channel) and why performance expectancy ranks last (streamer interaction substitutes for platform-level functional quality in synchronous encounters). Social presence theory explains why social influence and habit are amplified in DouYin's synchronous, entertainment-integrated environment relative to asynchronous platforms. Two post-hoc interpretations—the seller-substitution mechanism for PE and the threshold-condition explanation for HM—are introduced as clearly labeled conjectures for future empirical testing. Together, these theoretical contributions offer a richer account of technology continuance in synchronous commerce contexts than UTAUT2 alone provides.

Managerial/Practical Implications

In practice, the findings offer modality-specific guidance for three audiences. For platform operators, the leading role of price value, social influence, and habit suggests that investment in exclusive live-pricing infrastructure, social proof mechanisms—visible viewer counts, real-time purchase alerts, peer sharing features—and habit-forming design (e.g., recurring streaming schedules integrated into the short-video feed) will yield the highest continuance returns. For brands and content creators, effort expectancy's moderate role indicates that keeping the purchase path frictionless remains worthwhile, even though it is no longer a top differentiator of continuance. For market expansion teams, the comparatively weaker but still significant role of support conditions even in a well-equipped tier-one sample signals that device compatibility and connection quality will be considerably more important barriers in lower-tier Chinese cities and international markets where DouYin is expanding. The seller-substitution pattern identified for performance expectancy also has a direct design implication. Because streamer interaction appears to compensate for gaps in platform-level functional quality, operators should calibrate investment in AI-driven interface automation (e.g., automated recommendations, chatbot-assisted checkout) against continued investment in live streamer training and support, since over-automating the interface risks displacing the human interaction that currently substitutes for functional shortcomings, particularly for less tech-savvy or lower-expectancy user segments.

Limitations and Future Research Direction

Four main limitations should be acknowledged. First, the cross-sectional design captures a single point in time. Longitudinal research would clarify how the factor hierarchy evolves as DouYin matures. Second, the four-city tier-one sample limits generalizability to lower-tier Chinese cities and international markets. Third, while PLS-SEM corrects for the measurement-error attenuation inherent in summated-scale approaches, the structural model remains inherently linear, and non-linear or threshold relationships between predictors and continuance intention cannot be detected without additional nonlinear PLS extensions. Fourth, respondents were recruited through WeChat groups oriented around DouYin shopping and content creation, which likely selected for users who were already engaged, habitual, and socially embedded in the platform; this sampling approach may inflate estimates of habit, hedonic motivation, and social influence relative to the broader population of occasional or lapsed DouYin shoppers, and should be considered when interpreting the relative strength of these predictors.

Four future research directions are recommended: 1) disaggregate the social influence construct into peer normative pressure, in-broadcast social proof, and parasocial streamer influence; 2) test the seller-substitution mechanism by adding streamer interaction quality as a moderator of PE-continuance; 3) test whether the relative ordering of predictors by effect size holds within specific product categories; and 4) validate self-reported intentions against actual platform usage data.

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Ethics Considerations

All procedures performed in this study were in accordance with accepted ethical standards for minimal-risk behavioral research. Data were collected anonymously. No personally identifiable information was collected, and participation was voluntary. Respondents were informed about the purpose of the study and were free to withdraw at any time. All responses were used exclusively for academic research purposes, and informed consent was implied through voluntary participation.

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