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Modelling the Roles of Cewebrity Trust and Platform Trust in Consumers' Propensity of Live-Streaming: An Extended TAM Method

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Abstract: Live streaming is a booming industry in China, involving an increasing number of Internet users. Previous studies show that trust is a cornerstone to develop *e*-commerce. Trust in the streaming industry is different from that of other *e*-commerce areas. There are two major dimensions of trust in the live streaming context: platform trust and cewebrity trust, which are both important for customers to adopt and reuse a specific live streaming service. We collected questionnaire data from 520 participates who have used live streaming services in China. We model the collected data and identified factors that can influence users' propensity by an extended technology acceptance model (TAM) method. According to our analysis, both cewebrity trust and platform trust will greatly influence users' intention to reuse a certain platform. Moreover, results also indicate that cewebrity trust is far more important than platform trust. These findings can lead to several management strategies to improve the adherence of users to streaming platforms.

Keywords: Live streaming, extended TAM approach, consumers' propensity, cewebrity trust, platform trust.

1 Introduction

Live streaming refers to online streaming media simultaneously recorded and broadcast in real time to the viewer or streaming in short. The live streaming industry allows ordinary people to present their charisma and talent to a crowd of people in cyberspace and it has been flourishing in China in recent years. The content of live streaming is diverse, it can be the streaming of scheduled promotions and celebrity events as well as streaming between individuals, include video games, real-life activities and so on. Several Chinese live streaming platforms have brought up many cewebrities. A cewebrity is a web celebrity, who is mostly famous through their presence on the internet. Nowadays, being a cewebrity means a lot more than feeling the sense of pride. Particularly, the emerging streaming platforms have turned cewebrity into a well-paying

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career by converting fans to consumers. Platforms allow users to reward live presenters with virtual presents, which can then be sold off for cash, and this has created a billion-yuan market. According to the data from CINIC (China Internet Network Information Center), live streaming companies, such as “HuaJiao” and “DouYu” etc. have made an astonishing amount of profits from live interactions between cewebrities and fans. Therefore, it is of great important to improve the experience of interactions to cultivate a loyalty group of fans. Platforms need to improve the level interactive contents, increase users’ favorability.

In this paper, we explored key factors impacting consumers’ adoption and adherence to live-streaming platforms in China, which include trust, cost, emotion, convenience, etc. Specifically, we discussed the influence of trust factors including the platform trust and the cewebrity trust. We extended the Technology Acceptance Model (TAM) method to model the factors impacting customers’ propensity of technology adoption in a live streaming context. Data collected from 520 respondents (fans of live steaming platforms) were used to test the extended TAM model. Several managerial implications were derived from the analysis and further studies were suggested.

2 Literature survey

The technology acceptance model (TAM) is a theoretical model proposed by Davis based on Theory of Reasoned Action (TRA) [Ajzen and Fishbein (1980)]. TAM believes that the acceptance and utilization of a new technology by consumers are influenced by behavioral intentions, and behavioral intentions are influenced by customers’ attitude towards the targeted new technology, including perceived usefulness and perceived ease of use. In TAM, perceived usefulness refers to the extent to which individuals believe that a new technology can improve their performance; perceived ease of use refers to the extent to which individuals believe that the use of a new technology can require less effort. TAM has been widely used to explain and predict the acceptance and adoption of new things, such as medicine technology [Wu, Wang and Lin (2007)], information system [Chau and Hu (2001)], *e*-business [Pavlou (2003)], online shopping [Gefen, Karahanna and Straub (2003)], Internet banking [Zhang, Zhou, Wang et al. (2008)], mobile *e*-commerce [Wang and Li (2012)], on-line games [Hsu and Lu (2004)] and so on. Those studies have demonstrated that TAM is very effective in interpreting and predicting the acceptance of new things.

However, TAM has its inherent limitations. Firstly, it only considers the behavior of the cognitive subject, while ignoring personal emotions, personality traits and other intrinsic psychological factors as well as social norms, interpersonal effects and other external social factors impacting on the behavior [Davis (1992); Venkatesh and Davis (2004); Venkatesh (2003)]. The study of Legris et al. [Legris, Ingham and Collerette (2003)] shows that the original TAM can only explain 40% to 60% of consumer behavior intentions, and nearly half of the influencing factors are difficult to explain.

Therefore, we propose to extend TAM and use the extended method to explain and predict the behaviors of people on live streaming platforms.

3 Methods and results

3.1 Extension of the TAM method

This paper aims to extend the TAM model by introducing customer perceived value and consumer trust theory. Our idea is inspired by the unified model of trust in *e*-commerce relationship development by Zhang et al. [Zhang and Wang (2009)]. The foremost purpose of this paper is to capture factors that can impact user's intention to adopt and stick to a specific live streaming service. The extended TAM model is a more comprehensive model of technology acceptance, and it considers more impacting factors about the acceptance and retention of innovative interactive technology. Specially, we emphasize that trust plays an important role in behavior intention. And this research divides the trust into two separate dimensions: platform trust and cewebrity trust. Live streaming cewebrities can switch freely between platforms, but whether their fans will switch platforms synchronously is dependent on the acceptance of the new platform.

To predict users' behavioral intention, our model incorporates a few features. Firstly, we incorporate the impacts of the economic value, emotions, convenience and the community; we also investigate the roles of platform trust and cewebrity trust. Each of these factors corresponded to a hypothesis. Six hypotheses (H1-H6) are illustrated in Fig. 1.

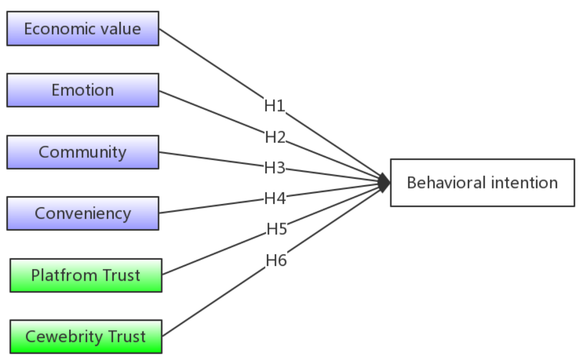

Figure 1: Features considered in our model

The first hypothesis (H1) is that both the buyer and the seller make economic gains because each obtains something useful. This is inspired by the study of Sinha [Sinha (1998)], in which it was pointed out that more benefits brought about by the products represents a higher perceived economic value.

Consumers who have had a hedonic experience with live streaming would be more likely to exhibit a positive attitude to stay with the current streaming platform [Zhang, Zhou and Lan (2010)]. H2 state that the emotional value, which refers to the emotional utility gained by the consumers from certain products or services, has an influence on the behavioral intention of users.

Chuan et al. [Chuan, Salniza, Salleh et al. (2015)] regarded network structures as a joint value creation source through access to new skills, new knowledge, new people, and new technologies by sharing risk and integrating complementary competencies Chuan et al. [Chuan, Salniza, Salleh et al. (2015)]. Therefore, customer communities in live streaming is a good potential driver of creating values together (H3).

Literature on service marketing shows that convenience depends on several factors, including time and effort. Here, convenience refers to the speed of completing a task quickly and easily [Anderson and Srinivasan (2003)]. Convenience value should have a strong impacting on adoption of innovative interactive technology, because customer is fond of instant convenient access to services (H4).

Hassan et al. [Hassan, Alexander and Collins (2003)] suggest that trust is a cornerstone to develop *e*-commerce. Dutot [Dutoto (2014)] believes that trust is a key factor to maintain the prosperity of social media. And Liu et al. [Liu, Marchewka, Lu et al. (2004)] insisted that trust is relevant in all kinds of high tech context. Long-term relationships with customers are critical to the success of the power business, and trust plays a central role in the adoption and retention of customers [Kim, Ferrin and Rao (2008)]. Thus, trust is important in maintaining relationships and providing customer value, although it is also considered difficult to manage [Bejou, Ennew and Palmer (1998)]. Of course, the security and reliability of the network is also important to ensure the user's communication privacy [Liu and Li (2018); Zhang, Cai, Liu et al. (2018); Sun, Cai, Li et al. (2018)], and a great quantity of research has been done in this area [Cai, Wang, Zheng et al. (2013); Xia, Cai and Xu (2018); Li, Cai and Xu (2018)]. This research divides the trust into two separate dimensions: platform trust and cewebrity trust because both live steaming platform and cewebrity are important for customer to adopt and reuse their live streaming servers (H5 and H6).

3.2 Data collection

In this study, we designed a questionnaire to collect data from streaming users. The questionnaire collects the background information of the respondents and it includes 32 questions on six aspects (economy, community, emotion, convenience, platform trust and cewebrity trust), which are listed on a 5-point Likert scale. Based on this questionnaire, we carried out a survey in China from January to March in 2017. In the end, a total number of 520 questionnaires were collected and 462 of them were valid.

Table 1: A profile of participants

Characteristics	**Indicators**	**# of participants**	**%**
Gender	Male	224	48.5%
	Female	238	51.5%
Age	<=18	30	6.5%
	19-22	226	48.9%
	23-30	166	35.9%
	31-40	14	3.0%
	>40	26	5.7%
Education level	Below junior high school	8	1.7%
	High school	36	7.8%
	University	342	74.0%
	Graduate or above	76	16.5%

Table 2: A profile of platform usage

Characteristics	Platform	# of participants	%
Streaming platform name	HUAJIAO	10	2.1%
	DOUY	106	23.0%
	INKE	20	4.3%
	PANDA	42	9.1%
	QQLIVE	188	40.7%
	Others	96	20.8%
Streaming program type	Games	174	37.7%
	Talk show	120	26.0%
	Travel	72	15.6%
	Concert	158	42.1%
	Celebrity	112	34.2%
	Education	60	5.6%
	Sports	108	13.0%
	Finance	46	10.0%
	Fashion	104	22.5%
	Outdoor lives	48	10.4%
	Others	24	5.2%

A profile of participants is listed in Tab. 1, which includes basic characteristics like gender, age and education level. Most streaming users are young people aged from 19-30 (over 80 percent) and most of them have received university education.

A profile of platform usage is listed in Tab. 2, which gives the top streaming platforms and top types of streaming content. It is evident that users use live streaming service mostly for entertainment, including games, talk shows, concerts, celebrities, etc.

3.3 Data analysis

We analyzed the data in two steps: firstly, we employed the measurement model to evaluate the convergent validity and discriminate validity; next, we utilized the structural model to evaluate and verify the assumptions. The data were analyzed using IBM SPSS AMOS 24. AMOS is powerful structural equation modeling software that supports research and theories by extending standard multivariate analysis methods, including regression, factor analysis, correlation, and analysis of variance. With SPSS AMOS you can build attitudinal and behavioral models that reflect complex relationships more accurately than with standard multivariate statistics techniques.

3.3.1 The measurement model

CFA (Confirmatory Factor Analysis) is used to determine how well the questions, which are treated as the latent variables indicators, can represent the whole model. We compared two different structures: a theoretical one and one created via data for testing hypotheses [Bryman and Cramer (2005)]. We conducted a confirmatory analysis via SL (Std. Loading), CR (Cronbach Alpha, a lower-bound estimate of the reliability of a psychometric test in statistics) and AVE (Average Variance Extracted, a measure of the amount of variance that is captured by a construct in relation to the amount of variance due to measurement error) to test the validity and reliability of our measures. Results are demonstrated in Tab. 3.

Table 3: Standardized (Std.) loading for sub-scales

C&S	Items	Details	SL
ECO	Eco2	Gift in live platform at a reasonable price.	0.755
	Eco3	Platform charges a small proportion of the cewebrity income.	0.712
	Eco4	The speed of the refund on the live platform is very fast.	0.702
EMO	Emo1	Watching live makes me feel cool.	0.817
	Emo2	Send gifts on live can be used to express my love.	0.809
	Emo3	Interaction with the cewebrity on live makes me pleasure.	0.858
COM	Com1	Live platform allows me to find the feeling of the organization.	0.863
	Com2	Live platform allows me to communicate with others.	0.927
	Com3	Live platform allows us to share knowledge with each other.	0.802
CON	Con1	The interface of the live platform is simple and convenient.	0.856
	Con2	It is convenient to present a gift on the live platform.	0.854
	Con3	Live communication mode is very convenient.	0.705
	Con4	Recharge fast on live platform.	0.775
	Con5	The information on the live platform is updated quickly.	0.793
PLT	Tru1	Trust the live platform brand.	0.960
	Tru2	Trust the live platform service.	0.965
	Tru3	Trust the privacy protection provide by live platform.	0.858
CWT	Cwt1	Trust the beauty of the cewebrity	0.685
	Cwt2	Trust the talent of the cewebrity	0.921
	Cwt3	Trust the personality of the cewebrity	0.842
BIN	Bin1	I would like to watch live video of the specific cewebrities	0.811
	Bin2	I would like to use the specific platforms	0.923
	Bin3	I am willing to continue to use live platform	0.716
	Bin4	I will recommend live platform to others	0.721
	Bin5	I think the live platform will be an indispensable part of life	0.713

Here, the constructs and sources (C&S) include the economic value (ECO), the emotion value (EMO), the community value (COM), the convenience value (CON), the platform trust (PLT), the cewebrity trust (CWT) and the behavioral intention (BIN). To note, CFA is not suitable for two manifest variables; model with 3 manifest variables is just identified, so it cannot detect the model fit metric.

Fit index values of CFA for sub-scales are presented in Tab. 4. Fit index values for sub-scales do not reach the desired range according to the boundary value listed in Tab. 5. Landis et al. [Landis, Edwards and Cortina (2009)] argued that the fit metric does not standard for the correlation between residuals when Standardized loading values are up to the recommended standard. Anderson et al. [Anderson and Gerbing (1988)] present recommendations for this state: (a) elimination of problematic items and (b) estimation of the structural model only. We can adjust the model according to the modification indices value (M.I.), deleting item CON4 and item BIN5 with the largest M.I. value. After adjusting the model, the fit indices value (see Tab. 4) reach an ideal range.

Table 4: Fit indices of confirmatory factor analysis for sub-scales

Fit indices	Community value		Behavioral intention	
	before	after	before	after
GFI	0.853	0.998	0.858	0.961
AGFI	0.560	0.991	0.288	0.902
SRMR	0.064	0.006	0.069	0.007
RMSEA	0.299	0.000	0.396	0.000
NNFI	0.719	1.000	0.569	1.000
CFI	0.860	1.000	0.856	1.000

Table 5: Fit indices for the structural model

Fit indices	Decision criteria (source)	Result
Chi-square/df	<3.00 [Bollen (1989)]	2.764
GFI	>0.9 [Schermelleh-Engel and Moosbrugger (2003)]	0.886
AGFI	>0.85 [Schermelleh-Engel and Moosbrugger (2003)]	0.782
SRMR	<0.08 [Hu and Bentler (1999)]	0.050
RMSEA	<0.10 [Tabachnik and Fidell (2007)]	0.088
NNFI	>0.80 [Hooper, Coughlan and Mullen (2008)]	0.900
CFI	>0.95 [Hu and Bentler (1999)]	0.956

In Tab. 5, GFI is 0.886 and AGFI is 0.782, therefore, they are not within acceptable limits. GFI and AGFI are largely affected by sample size [Fan and Sivo (2005)]; therefore, use of these fit indexes is not recommended [Sharma, Mukherjee, Kumar et al. (2005)]. Other value of fit indices is reasonable.

Table 6: Reliability and convergence validity analysis

Construct	Item	Parameter significance estimation				Composition reliability	Convergence validity
		Un Std.	S.E.	*Z*-value	P	CR	AVE
ECO	Eco2	1				0.751	0.502
	Eco3	0.932	0.123	7.566	***		
	Eco4	0.889	0.119	7.485	***		
EMO	Emo1	1				0.868	0.686
	Emo2	1.046	0.082	12.822	***		
	Emo3	0.979	0.074	13.23	***		
COM	Com1	1				0.899	0.749
	Con2	1.151	0.067	17.07	***		
	Com3	0.943	0.064	14.821	***		
CON	Con1	1				0.877	0.642
	Con2	0.994	0.066	15.038	***		
	Con3	0.818	0.071	11.436	***		
	Con5	0.91	0.066	13.765	***		
PLT	Plt1	1				0.950	0.863
	Plt2	1.005	0.031	32.523	***		
	Plt3	0.914	0.042	21.942	***		
CWT	Cwt1	1				0.860	0.675
	Cwt2	1.320	0.119	11.136	***		
	Cwt3	1.217	0.108	11.23	***		
BIN	Bin1	1				0.860	0.674
	Bin2	1.052	0.081	13.035	***		
	Bin3	0.760	0.066	11.541	***		
	Bin4	0.773	0.062	12.470	***		

*** p-value<0.001

In Tab. 6, all values of CR are higher than the threshold of 0.70 [Chin (1998)]. They are in the range of 0.751 and 0.950, indicating that the project internal consistency reached a high level. In addition, all AVE values exceed 0.50 (Tab. 6). AVE value of at least 0.50 indicates that the potential variable has an explanatory power of more than 50%. Thus, the measurement model achieves enough sum the convergence effect is satisfactory.

Fornell et al. [Fornell and Larcker (1981)] evaluated the effectiveness of the Fornell and Larcker evaluations. Each reflex structure should be more strongly related to its own indicators than others. Tab. 6 shows that the all correlations between constructs are less than the square root of AVE except for ECO & CON. The difference between ECO and CON does not reach the ideal state, but the numerical difference is very small (ECO=0.709; CON=0.779), so it is still within reasonable limits. Almost each reflex structure is more strongly related to its own indicators than others. So the validity of the judgment Construction measures has been established.

Table 7: Discriminant validity of constructs

Construct	Convergence validity	Discriminant validity						
	AVE	RES	ARC	CON	TRU	COM	EMO	ECO
BIN	0.674	**0.821**						
CWT	0.675	0.793	**0.822**					
CON	0.642	0.783	0.578	**0.801**				
TRU	0.863	0.745	0.783	0.606	**0.929**			
COM	0.749	0.650	0.723	0.579	0.771	**0.865**		
EMO	0.686	0.689	0.624	0.622	0.628	0.776	**0.828**	
ECO	0.502	0.528	0.528	0.779	0.515	0.518	0.663	**0.709**

3.3.2 The structural model

Recently, Gu et al. [Gu, Sun and Sheng (2017)] pointed out that the structural information is an effective way to represent prior knowledge and it can be vital for training classifiers in real-world problems. In the theoretical part of our study, we had an explicit set up of structural information, in which six latent variables were included: Economic value (ECO), Emotion value (EMO), Community value (COM), Convenient value (CON), Platform trust (PLT), Cewebrity trust (CWT). Hair et al. [Hair, Hult, Ringle et al. (2016)] recommended the coefficient of determination (R2) and corresponding *t*-values to evaluate the structural model and argued that R2 values of endogenous latent variables of 0.75, 0.50, or 0.25 can be described as highly, moderately or weakly, respectively. The R2 values for the endogenous construct are 0.874 for the behavioral intention (BIN), indicating a high level of the prediction accuracy. The estimated coefficient values close to zero are usually non-significant.

Table 8: Path co-efficient and *t*-values for structural model

Hypo-theses	Causality	Path coefficients	*T*-value
H1	The economic value has a positive effect on the behavioral intention to use the streaming platform.	0.440	3.363***
H2	The emotion value has a positive effect on the behavioral intention to use the streaming platform.	0.371	3.372***
H3	The community value has a positive effect on the behavioral intention to use the streaming platform.	0.270	2.347**
H4	The convenient value has a positive effect on the behavioral intention to use the streaming platform.	0.680	5.749***
H5	The platform trust has a positive effect on the behavioral intention to use the streaming platform.	0.175	1.843**
H6	The cewebrity trust has a positive effect on the behavioral intention to use the streaming platform.	0.458	4.629***

* p-value<0.05, ** p-value<0.01, *** p-value<0.001

In this step, we consider the existence of structural model relations and their correlation. Five hypotheses were tested based on the ECO, EMO, COM, CON, PLT, CWT and BIN. Using the calculated path coefficients, hypotheses were tested and relationships between latent variables were explained. Statistically meaningful relationships between latent variables were demonstrated by significant path coefficients. As shown in Tab. 8, Economic value (ECO) (β=0.440, p<0.05), Emotion value (EMO) (β=0.371, p<0.05), Community value (COM) (β=0.270, p<0.05), Convenient value (CON) (β=0.680, p <0.05), Platform trust (PLT) (β=0.175, p<0.05) and Cewebrity trust (CWT) (β=0.458, p <0.05) were positively related to Behavioral Intention. Thus, H1, H2, H3, H4, H5 and H6 are supported.

The estimated path coefficients show that the convenient value dimension has the strongest positive relationship with the behavioral intention of the consumer to use a certain streaming platform, followed by the cewebrity trust, economic value, the emotion value, the community value and the platform trust.

4 Conclusions

This study explores key factors impacting customer acceptance and retention of live steaming platforms. The study proposed six critical factors including convenient value, cewebrity trust, economic value, emotional value, community value, and platform trust and tested the relationship between those factors and customer behavior intention by using an extended TAM method. This study greatly improves TAM by increasing several important variables within the context of live streaming to explain technology acceptance behavior for current users. Our study concludes that the two kinds of trust play considerable roles in consumers' adoption of live streaming, and the cewebrity trust is more important than the platform trust. This has an important implication to practice. If the most important factors highlighted by our method such as convenience value, cewebrity trust and economic value are properly managed, it will lead to a potentially successful adoption and retention of the customer.

Therefore, by focusing on these key factors, the marketing strategy should be more effective [Deng, Lu, Wei et al. (2010)]. Live streaming platforms should simplify the interface, so that users can easily find the favorite content and cewebrities, while the service providers must maximize the users' perception of cost and effectiveness. A cewebrity wants to maintain a good relationship with his/her fans, and actively spread the positive energy, focusing on long-term benefits. Specially, it is important for a live streaming platform to treat cewebrities well, maintain stability of cewebrities, as customer trust cewebrities more than platforms. For future work, we will investigate how cewebrities can affect the streaming service provides as them are also users of technology; in addition, if we can collect enough data, we will be able to introduce more advanced methods like machine learning methods [Gurusamy and Subramaniam (2017)] and fuzzy approaches [Kaur and Kaur (2017); Wang, Jiang and Yang (2016)]. Currently, the data collection process of our study depends on questionnaires, a possible improvement in the future is to automatically collect data from live streaming platforms that are hosted on cloud systems, which are usually managed using a balanced scheduling method [Xu, Zhang, Khan et al. (2017)].

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