Understanding donation intention in live-streaming from dedication and constraint perspectives

Shih-Wei Chou
National Kaohsiung First University of Science and Technology, swchou@nkust.edu.tw

Trieu Nguyen
National Kaohsiung First University of Science and Technology, f110121116@nkust.edu.tw

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Understanding donation intention in live-streaming from dedication and constraint perspectives

(Work-in-Progress)

Shih-Wei Chou [1]
Trieu Nguyen [2,*]

*Corresponding author
[1] Department of Information Management, National Kaohsiung University of Science and Technology Kaohsiung, Taiwan, Professor, swchou@nkust.edu.tw
[2] College of Management, National Kaohsiung University of Science and Technology, Kaohsiung, Taiwan, Master Student, f110121116@nkust.edu.tw

ABSTRACT

The pervasiveness of live-streaming, especially in the period of Covid-19, has brought ample monetizing opportunities for content creators through viewers' donation. Given that donation is commonly driven by the gained benefits to the donors, voluntary donation in live-streaming is still unstable due to the lack of constraints. Drawing on the dedication-constraint framework, we examined how streamer-viewer interactions, motivational feedback and self-regulation deficiency affect viewers' donation intention in live-streaming. A survey was conducted among live-streaming users in Taiwan, and the collected data were analyzed by partial least squares. The findings show that the motivational feedback (dedication-based mechanism) has a stronger influence than self-regulation deficiency (constraint-based mechanism) in determining viewers' donation intention. Responsiveness is proven as the most important interaction-based antecedent of motivation feedback and self-regulation deficiency, beside personalization and entertainment. In sum, our empirical findings have significant implications for research and practice to deepen the understanding of donation, encourage viewers to donate and maintain the relationship with content creators in live-streaming communities.

Keywords: Donation, live-streaming, interaction, dedication, constraint.

INTRODUCTION

Live-streaming has been gaining in popularity, especially in the COVID-19 pandemic. The pandemic positively impacted the live-streaming market with a massive increase in the usage of live-streaming services and platforms among various industries. For example, music artists keep performing through live concerts while gamers increase their live game-streaming time to reach viewers who were experiencing their social-distancing period. The habit of watching live-streaming is still kept until now, and live-streaming has become a lucrative profession for content creators. This is because streamers can exploit various revenue affordances in live-streaming (e.g., Twitch, YouTube Live, Facebook Live and YY Live), such as advertisement, subscription and donation from viewers, in which donation has become more popular and important. Donation becomes more and more popular when YY Live (China) acquired $905.7 million from donations in the third quarter of 2019 (YYInc, 2019). However, drawing on the donation literature, donation has been largely studied as a charitable practice, not a way to show their appreciation (Wan et al., 2017), through which streamers and viewers can tighten the mutual relationship. Besides, existing donation-related studies have concentrated on the benefits to the self, such as seeking satisfaction or monetary aspirations (Ye et al., 2015). We argue that donation driven by benefits gained from streamers' service is inadequate, as viewers could find even-better benefits from other streamers (e.g., having more interesting content and greater streaming skills). Viewers bear no constraints to voluntarily donate and stick with the current streamers. Hence, present researchers' attention to the importance of constraint to donation outcomes is limited. Thereby, we opt to use the dedication-constraint framework to fully comprehend the formation of donating intention.

Prior work on live-streaming frequently relies on a social-technical viewpoint to investigate donation behaviors (Hou et al., 2021; Wan et al., 2017). However, there has not been much effort put into researching the unique aspect of live-streaming that is the streamer-viewer interaction in real-time, through which viewers experience the benefits and costs. There is a need to advance extant literature by developing and testing a model that includes the human-interaction approach to stimulate donation intention in live-streaming. Thereby, the following research questions will be addressed in this study:

RQ1. How do conceptualized dedication-constraint factors affect viewers' donation intention?
RQ2. How does streamer-viewer interaction affect dedication-based and constraint-based factors?

This study draws on dedication-constraint framework to enhance the understanding about donation outcome, and it makes the following key contributions. First, we broaden our present knowledge of donations to content creators. Specifically, beside the conceptualization of dedication (i.e., motivation feedback), we examine self-regulation deficiency as constraint-based reactions generated from a history of interacting with streamers. Second, this research responds to recent calls for increased use of dual-system models to completely characterize IS usage behavior in general and promote donation practices in live-streaming in specific. Third, we expand our understanding of the process of streamer-viewer interaction, from which content creators may build a coordinated plan to attract viewers, provide a good interacting experience, and direct viewers to donation with the aims of maintaining relationship with content creators, consequently fostering the development of the live-streaming community.

BACKGROUND

Live streaming, interaction and donation intention

Live streaming is a revolutionary method of recording and streaming in real time (Xue et al., 2020). Live-streaming provides more effective real-time interactivity and streamer-viewer connectivity than pre-recorded videos uploaded on YouTube. For example, the real-time interactivity allows streamers to instantly answer and explain viewers' doubts and questions, through which viewers may perceive the live-streaming interaction quality regarding personalization, responsiveness and entertainment (Xue et al., 2020). Moreover, live-streaming platforms provide donation-supported tools, including donation notification, donation link, top donors list, and importantly, ''top donor'' announcement can give streamers a strong sense of social status (Sjöblom et al., 2019). Besides, donation as a revenue stream can encourage streamers to create high-quality content to viewers (Hou et al., 2021) Therefore, donation is a critical engagement behavior leading to the success of live-streaming.

Previous research has investigated donation behavior using socio-psychological theory. This stream of work mainly bases on benefit-driven motivations from individual, live-streaming feature-related, social, cultural stimuli to identify viewers' voluntary donation. For instance, Wan et al. (2017) draws on emotional attachment theory that has significant motivational and behavioral implication, to understand the link between reactions to social-technical stimuli and readiness to donation. Although useful, motivational feedback approach may not fully explain the donation in live-streaming. In this study, we explore the impacts of streamer-viewer interactions on donation intention using the integrated view of motivational feedback (dedication-based) and self-regulation deficiency (constraint-based).

The conceptual dedication-constraint model

According to social exchange theory, dedication-constraint model includes two mechanisms that support the development of long-term relationships between customers and service providers (Bendapudi and Berry, 1997). Dedication is described as a person's desire to continue relationships in the prospect of gaining long-term mutual benefits (Kim and Son, 2009). Constraint mechanism refers to the economic, social, or psychological investments that keep people in their current relationships (Kim and Son, 2009). Unlike prior work, we conceptualize dedication-based mechanisms as motivational feedback (affective feedback and social feedback), and the constraint-based as self-regulation deficiency (cognitive preoccupation and behavioral compulsion). In terms of antecedents of the dedication-constraint model, when focusing on the uniqueness of live-streaming, we decide to examine three dimensions of real-time interactivity, including personalization, responsiveness and entertainment.

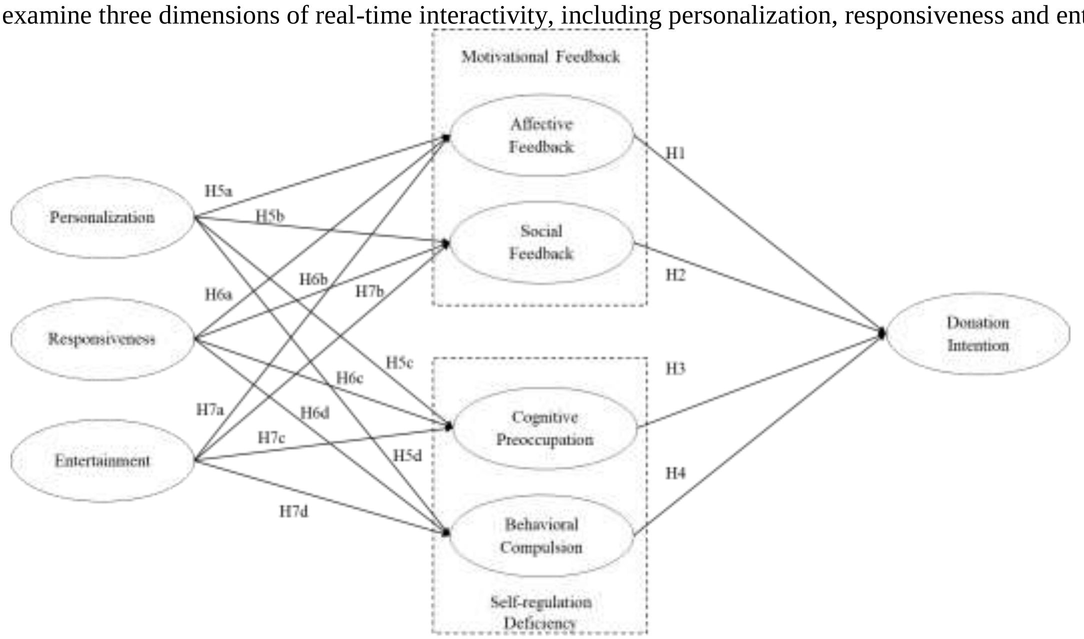

Figure 1: Research model

HYPOTHESIS DEVELOPMENT

Hypotheses between motivational feedback, self-regulation deficiency and donation intention

Motivation is used in this work as a conceptualization of dedication-based mechanism to analyze the donation intention, as motivation focuses on perceived benefits from favorable experience. Bendapudi and Berry (1997) indicated feedback to initial motivation generated from perceived benefits (based on one's consumption experience) will in turn drive one's decision-making to perform specific behaviors for the purpose of maintaining relationships with partners (e.g., through continued use or loyalty). In the live-streaming, when viewers perceive benefits (e.g., good personalized, responsive and entertaining experience) from the interactions with streamers, they will have motivational feedback towards donation intention to prolong the relationship with streamers. Otherwise, motivational feedback is represented by affective feedback and social feedback (Hassan et al., 2019).

H1: Affective feedback has a positive effect on viewers' donation intention.
H2: Social feedback has a positive effect on viewers' donation intention.

Prior research has recognized the importance of the constraint mechanism in studying post-adoption behaviors, and it has been referred to as switching costs (Kim and Son, 2009). We argue that the streamer's quality and performance are artificial switching costs that cannot transfer to other streamers, making it difficult for viewers to find the same-quality streamer in a short period of time and end up continuing the relationship. In the present research, we emphasize the role of self-regulation towards the costs. When the stimulus is enormously huge, no self-regulatory capacity can restrain it, implying the self-regulation deficiency against these constraints (Liu et al., 2020). In live-streaming context, viewers are preoccupied with these constraints (self-regulation deficiency) and do not want to discontinue their present live-streaming connections with streamers. They are more likely to perform particular actions (e.g., donations) to continue interacting and consuming high-quality content, leading to the impacts of two dimensions of self-regulation deficiency (cognitive preoccupation and behavioral compulsion) on donation intention.

H3: Cognitive preoccupation has a positive effect on viewers' donation intention.
H4: Behavioral compulsion has a positive effect on viewers' donation intention.

Hypotheses between interactions and dedication-constraint model representatives

Personalization measures how well the given material matches the preferences and needs of the users (Xue et al., 2020). Franke and Schreier (2010) claimed that the perceived preference fit from self-designed items promotes customer' delight. Personalized suggestions or one-of-a-kind offers in social commerce provide users a high sense of social support (Liang et al., 2011). Personalized content is simpler to recall, thus processing relevant information requires greater cognitive effort as the specificity of goals broadens (Tam and Ho, 2006). Moreover, since personalized content is more attentive than the irrelevant, it steers viewers around flow experience, leading to compulsive symptoms (Chen et al., 2017).

In the live-streaming context, personalization describes the streamers' ability of tailoring the content that fits viewers' preference and personal need. This definitely makes viewers enjoyable and feel connected to live-streaming communities, leading to H5a and H5b. On the other hand, the easy-to-recall personalized content is more likely to live in viewers' mind and make them addicted to even conduct compulsive behaviors- H6d.

H5a: Personalization has a positive effect on affective feedback.
H5b: Personalization has a positive effect on social feedback.
H5c: Personalization has a positive effect on cognitive preoccupation.
H5d: Personalization has a positive effect on behavioral compulsion.

The term "responsiveness" describes how quickly media platforms respond to users' query (Xue et al., 2020). Responsiveness in an online interaction shows a fairness in social exchange that makes users satisfied for the time spent and feel recognized (Xue et al., 2020). Besides, Wu (2019) and Speckens et al. (2007) found that interactive websites can make users more involved in communications and use cognitive efforts to process information, accidentally eliciting the mental imagery and obsessive compulsive symptoms.

In live- streaming, responsiveness refers to how fast and efficiently streamers offer response to viewers. In an effort of spending time in live-streaming and seeking answers, viewers might have positive emotional responses for responsive answers, and feel that their participation is recognized by other participants, leading to H6a, H6b. Otherwise, viewers may often recall the images of how responsively streamers interact with them and these overwhelming cognitive efforts will make viewer's minds preoccupied, and it is hard to restrain their urge to have more interactions with streamers, leading to H6c and H6d.
H6a: Responsiveness has a positive effect on affective feedback.

H6b: Responsiveness has a positive effect on social feedback.
H6c: Responsiveness has a positive effect on cognitive preoccupation.
H6d: Responsiveness has a positive effect on behavioral compulsion.

Entertainment is the pleasure one objectively has when engaging in a particular behavior or activity (Xue et al., 2020). Entertainment from interactions is proven as a facilitator of social ties, connectivity, and friendship (Hsieh and Tseng, 2017). However, these hedonic benefits are found to limit the ability to regulate time spent on those platforms, causing the maladaptive cognitions and compulsive behavior (Japutra and Song, 2020; Osatuyi and Turel, 2018).

In the live-streaming, viewers may feel pleasant, satisfied, and free to socialize with others through funny moments of interacting with streaming, leading to positive feedback both emotionally and socially- proposing H7a and H7b. The amusing moments are hard to completely erase, but constantly revolve in viewers' mind, causing the cognitive preoccupation and even drive the viewers' behavioral compulsion, urging more interactions– leading to H7c and H7d.

H7a: Entertainment has a positive effect on affective feedback.
H7b: Entertainment has a positive effect on social feedback.
H7c: Entertainment has a positive effect on cognitive preoccupation.
H7d: Entertainment has a positive effect on behavioral compulsion.

METHODOLOGY

Data was collected in Taiwan that has high proportions of live-streaming awareness and usage to test the research model. We distributed the questionnaire via online channels to reach the target respondents who are users of Twitch, YouTube Live and Facebook Live. Data-collecting procedure was conducted under the longitudinal approach. At stage I, we used the several items in the questionnaire to measure the interactivity-related antecedents and factors of dedication-constraint model factors. The stage II was implemented two weeks later to assess donation intention via the remaining items. There were 300 questionnaires sent out, and 208 samples used for official data analysis, in which 109 of them are males (52.4%) and the 18-25 age group account for the largest percentage of 58.1%.

The measurement items were evaluated adopting a seven-point Likert scale, ranging from 1 (completely disagree) to 7 (completely agree). Four items used to measure donation intention were adapted from Ye et al. (2015). Four items each measuring affective feedback social feedback were developed from Hassan et al. (2019). Four items each measuring cognitive preoccupation and behavioral compulsion were adapted from Haagsma et al. (2013). Personalization, responsiveness and entertainment (3 items each) was developed from Xue et al. (2020).

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used as the primary data analysis approach in this study. PLS-SEM was used because it is appropriate to examine the path coefficients between the latent variables of structural models (Hair Jr et al., 2021), and it does not require large sample sizes or assumptions about data distributions (Pavlou and Fygenson, 2006). We followed the two-step approach (Anderson and Gerbing, 1988) to examine both the measurement (outer) model and structural (inner) model. The SmartPLS software, version 3.3.3, was used for data analysis.

RESULT

Common method biases and Measurement model

Harman's single factor test was employed, and findings show that the first factor' variance constitutes only 39.26% of the total variance that is lower than the benchmark of 50% (Podsakoff et al., 2012). We assessed the measurement model via its reliability and validity (Henseler, 2017). The results shown in Table 1 and Table 2 confirm the good reliability, convergent and discriminant validity. Besides, multicollinearity is not a significant issue in our study that is evidenced by using variance inflation factor (VIF) values (1.381 to 2.545), lower than the cut-off value of 5.0 (Hair Jr et al., 2021).

Table 1: Results of reliability and AVE.

Constructs	Items	Cronbach's alpha	Composite Reliability	Average Variance Extracted
Personalization	PE	0.794	0.879	0.708
Responsiveness	RE	0.856	0.912	0.776
Entertainment	EN	0.874	0.922	0.798
Affective Feedback	AF	0.869	0.911	0.718
Social Feedback	SF	0.847	0.898	0.689
Cognitive Preoccupation	CP	0.899	0.929	0.767
Behavioral Compulsion	BC	0.862	0.906	0.707
Donation Intention	DI	0.879	0.917	0.733

Source: This study.

Table 2: Descriptive statistics and correlation among constructs.

	Mean	SD	PE	RE	EN	AF	SF	CP	BC	DI
PE	4.742	1.058	**0.842**							
RE	4.891	1.273	0.536	**0.881**						
EN	5.018	1.240	0.429	0.439	**0.893**					
AF	4.802	1.069	0.459	0.463	0.391	**0.847**				
SF	4.837	1.044	0.453	0.581	0.383	0.444	**0.830**			
CP	4.821	1.179	0.410	0.604	0.419	0.462	0.506	**0.876**		
BC	4.767	1.130	0.426	0.463	0.418	0.465	0.558	0.466	**0.841**	

DI	5.035	1.044	0.475	0.619	0.455	0.639	0.646	0.637	0.509	**0.856**

Note: The squares root of average variance extracted are displayed by the diagonal elements in bold.
Source: This study.

Structural model

We used the PLS-SEM and bootraping technique (5000 boostraping resamples at 95% confidence interval) to test the path coefficients and proposed hypotheses. The results are listed in Table 3 with 9 out of 12 supported hypotheses. Findings show R-square values for donation intention (64.7%), affective feedback (29.9%), social feedback (37.6%), cognitive preoccupation (39.7%), and behavioral compulsion (29.5%). Additionally, all control variables exert no significant impact on the dependent variable (donation intention).

Table 3: The path coefficients of research model.

		Coefficient	t-value	Result
H1	AF -> DI	0.331^{***}	5.231	Supported
H2	SF -> DI	0.319^{***}	5.037	Supported
H3	CP -> DI	0.289^{***}	5.136	Supported
H4	BC -> DI	$0.018^{N.S.}$	0.305	Not supported
H5a	PE -> AF	0.248^{**}	3.298	Supported
H5b	PE -> SF	0.167^{**}	2.638	Supported
H5c	PE -> CP	$0.074^{N.S.}$	1.199	Not supported
H5d	PE -> BC	0.190^{*}	2.396	Supported
H6a	RE -> AF	0.255^{**}	3.444	Supported
H6b	RE -> SF	0.439^{***}	6.030	Supported
H6c	RE -> CP	0.488^{***}	8.065	Supported
H6d	RE -> BC	0.264^{**}	3.272	Supported
H7a	EN -> AF	0.173^{*}	2.295	Supported
H7b	EN -> SF	$0.119^{N.S.}$	1.806	Not supported
H7c	EN -> CP	0.173^{*}	2.548	Supported
H7d	EN -> BC	0.220^{**}	2.921	Supported

Note: *p<0.05; **p<0.01; ***p<0.001; NS, non-significant
Source: This study.

CONCLUSION: DISCUSSION, IMPLICATIONS, FUTURE WORK

Our findings confirm that the characterization of motivational feedback (dedication-based) and self-regulation deficiency (constraint-based) as corresponding reactions for interaction-based stimuli properly analyzes the mechanisms of donation intention, demonstrating persuasive evidence to consolidate our theoretical arguments above. First, motivational feedback (i.e., dedication-based mechanism) plays a stronger predicting role than self-regulation deficiency (i.e., constraint-based mechanism) for viewers' subsequent donation intention. This implies that viewers are more likely to form their intention of donating to streamers by perceiving current values of interactions with streamers. Regarding the relationships between streamer-viewer interactions and representatives of dedication-constraint mechanisms, responsiveness is the most important, with all four supported hypotheses. This finding is pertinent, because responsiveness is the best demonstration of the live-streaming success (i.e., real-time interactivity).

Our study contributes to theory by combining the conceptualized dedication-constraint framework with the key of live-streaming (streamer- viewer interaction) and explaining the viewer's donation intention. This study fills a gap in the donation literature by exposing the shortcomings of the benefit-oriented approach only and providing insight into the powerful effects of the constraint-based. Furthermore, the application of the dedication-constraint model enriches the existing empirical study employing dual-systems to provide a comprehensive knowledge of IS behavior, including reflective-reflexive dual system (Gong et al., 2019), conscious and unconscious response (Nguyen et al., 2022), promotion-prevention approach (Ye et al., 2015). Besides, this study advances dedication-constraint literature by expanding the applicability to a totally new online context (live-streaming) but also its conceptualization and measurement, becoming a premise encouraging the innovative conceptualization and application.

Besides, our empirical study provides fresh insights into the live-streaming interaction antecedents of donation intention, emphasizing the importance of personalization, responsiveness and entertainment in practice. Streamers should proactively predict the viewers' preferred topics, then deliver content that responsively solves their personal needs and create entertaining moments. This encourages viewers to donate to content creators, motivating them to create more high-quality content, contributing to the streamer-viewer relationship and the development of live-streaming communities overall.

Our research has several limitations and future research. First, the follow-up study should be internationally conducted to reduce the cultural bias because live-streaming seems more popular in Eastern countries. Second, in order to avoid the limited conceptualization for a specific context, future studies should extend the dedication-constraint conceptualization to more insightfully explain donation intention in various online settings.

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