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Why Learners Fail in MOOCs? Investigating the Interplay of Online Academic Hardiness and Learning Engagement among MOOCs Learners

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Abstract: Although the proliferation of Massive Open Online Courses (MOOCs) has created highly interactive learning environment for higher education, the low completion rate (or high dropout rate) deteriorates the development of MOOC courses. This study explores why learners are not highly engaged in MOOCs from the perspective of academic hardiness and learning engagement. The interplay of online academic hardiness and online learning engagement is mapped through both structural equation model and predictive model. Our explanatory and predictive analysis found that commitment is the most important factor of online academic hardiness, significantly influencing learning engagement. Moreover, the role of challenge contributes much to cognitive and emotional engagement. Other interesting findings and instructional implication will be discussed in the paper.

Keywords: MOOCs, online academic hardiness, online learning engagement, learning analytics

1. Introduction

Even though the advancement of MOOCs was considered as disruptive innovative technologies that transform the landscape of postsecondary teaching and learning (Christensen & Weise, 2014), the massive enrollment lead to low completion rate (or high dropout rate) in MOOCs which deteriorates the development of MOOCs (Freitas, Morgan, & Gibson, 2015; Hew & Cheung, 2014; Jordan, 2014; Perna et. al, 2014). In view of low engagement of MOOCs, several researchers and practitioners are dedicated to investigating why learners are not engaged in MOOCs learning environment, such as student factors, course/program factors, and environmental factors (Carnoy et. al, 2012; Hart, 2012; Hew & Cheung, 2014; Lee & Choi, 2011).

Although many works have been devoted to student factors, we found that academic hardiness, an important psychological concept in the learning process, are missing in the current literature. The relationship between the academic hardiness and learners' online learning engagement are unclear in the MOOCs context. Considering that taking an online course requires a great amount of self-regulation and efforts, we argue that academic hardiness could be an important construct in open online environment.

1.1 Academic Hardiness

Derived from Kobasa (1979)'s hardiness theory, academic hardiness is a useful framework to understand why certain people are more willing to engage in challenging work and cope with stressful jobs (Kobasa, 1979). Previous studies found that academic hardiness plays an important role in learning process, such as anxiety, self-efficacy, and academic performance (Benishek & Lopez, 2001; Wang & Tsai, 2016).

The academic hardiness is composed of three distinct cognitive processes: *Commitment, Control*, and *Challenge* (Benishek & Lopez, 2001; Benishek et al., 2005). *Commitment* refers to the dedication of student's reported willingness on specific goals or context to make sense of the meaning of purpose in life. *Control* is defined as learners' belief that they possess to achieve personal desirable educational goals through efforts and effective emotional self-regulation. *Challenge* is the students' purposeful efforts that students believe to be important to achieve higher levels of goals in terms of more demanding tasks or experiences.

1.2 Learning Engagement

Students' learning engagement refers to the quality of effort students make to perform well and achieve desired outcomes, including *behavioral, emotional* and *cognitive engagement* (Henrie, Halverson, & Graham, 2015; Sun & Rueda, 2012; Vaughan, 2010). *Behavioral engagement* refers to the observable behaviors necessary to academic success, such as attendance, participation, and homework completion in class. *Emotional engagement* includes both feelings learners possess about their learning experiences, such as interest, enthusiasm, interest, enjoyment, vitality, frustration, or boredom, and their social connection with others at school. *Cognitive engagement* is the concentrated effort learners give to effectively understand what is being taught, including self-regulation and metacognitive behaviors (Fredricks et al., 2004; Skinner, Furrer, Marchand, & Kinderman, 2008).

Even though online learning engagement in MOOCs courses are widely explored, most measures of learning engagement in MOOCs employed behavioral engagement (such as count data) out of convenience purpose, ignoring the important role of motivational factors such as emotional and cognitive engagement. Moreover, learning engagement accounts a great amount of learning performance in MOOCs, by analyzing factors that led to high/low engagement depicts a better picture for MOOCs stakeholders, such as researchers, practitioners, and platform designers. In view of the indispensable role of learning engagement in MOOCs, the current study aims to understand how online academic hardiness influences learning engagement.

1.3 Purposes of the Study

This study explores why some learners are more engaged in MOOCs courses while some are not from the perspective of academic hardiness and learning engagement. In particular, from the structural relationship perspective, we would like to investigate the interplay of online academic hardiness and learning engagement in MOOCs environment in Taiwan. From the predictive perspective, we also examine significant factors that contributed much to online learning engagement through building predictive model using data mining techniques (Shmueli & Koppius, 2011). To distinguish explanatory and predictive goals, the following questions drive the study.

1. What is the relationship of online academic hardiness and learning engagement?
2. What are significant predictive variables for online learning engagement? How does the predictive model perform?

2. Method

2.1 Participants and Context of the Study

Previous studies on MOOCs take advantages of log data, interviews, surveys and web content analysis. However, to better understand the leaners' psychological attributes, this study employs validate survey questionnaire to conduct the study. We partnered with one of the popular MOOCs platform in Taiwan and distributed the survey at the platform at the end of the courses in 2017 March and April. Each participant taking one of the courses would take less than ten minutes to carry out the survey.

To better represent the context of the MOOCs, six courses were selected from different disciplines including life science (Eco-system and Global Changes; Systems Neuroscience), computer science (Introduction to Data Structure; Introduction to IoT), and business and management (Topics on Investment; Understanding & Rethinking Media). The courses have been run on a yearly basis and the course designs are similar in nature. All the courses are video-based learning MOOCs (xMOOCs), namely instructional videos are the main content of the MOOCs to identify important concepts. The supported learning activities including discussion board, weekly quizzes, and assignments are to help student better understand the course content. The midterm/final examinations are to evaluate the effectiveness of the studies.

Of all the 1266 online survey distributed, 665 respondents successfully completed the survey (completion rate 52.52%). To detect anomalies data of the survey questionnaires, we used Rasch fit statistics from Item Response Theory (Chien et al., 2007) and finally excluded 57 responses of which outfit and infit values are above 2. In total, 608 observations constituted the study. Among the 608 observations, male learners represented 46.7%, female learners represented 53.0%, and other gender represented 0.3%. The average age was 23.93 [standard deviation (SD) = 5.78], which indicate that most leaners were undergraduate or graduate students. Most of the participants obtained a bachelor degree (74.4%), while 21.4% reported a master degree, 3.5% received high school degree and 0.8 % obtained doctoral degree respectively. Of all the learners, more than half students (43.25%) had experiences of online courses and had completed 1-2 courses, 12.5% of the respondents had completed at least three online courses, 29.44% of the respondents had experiences of online course but failed to complete, and 14.8% of the respondents took the online course the first time.

2.2 Data collection and Analysis

The data used in this study were obtained mainly from convenience samplings from online survey website in Chinese. The instruments of the study were adopted from existing validated scales. Both scales used 5-point Likert rating (5 = *strongly agree*, 4 = *agree*, 3 = *neither agree nor disagree*, 2 = *disagree* and 1 = *strongly disagree*). The online academic hardiness scale (OAH) was adopted from Creed, Conlon, & Dhaliwal (2013) and Wang & Tsai (2016) while the learning engagement scale (LE) was adopted and modified from Sun & Rueda (2012).

To gain the expert validity, the questionnaire was first drafted and sent to two academic professors and five students for internal interview. Based on their comments and suggestion, we revised the wording and items to improve the scale quality. All the data were transformed and coded using RStudio software (Version 1.0.136). The R packages included *psych, corrplot, lavaan, semPlot, TAM, sirt, randomForest,* and *caret*. We used *TAM* and *sirt* packages to formulate the Rasch model for detecting anomaly data; *psych* and *corrplot* packages are to calculate the reliability and correlation matrix; *lavaa* and *semPlot* packages are used for modeling structural equation modeling (SEM).

3. Results

3.1 Test of the Research Model

We used *lavaan* and *semPlot* packages to calculate the overall fit and explanatory power of the SEM model in order to conform that relationship among constructs as expected in research model. Based on Hu & Bentle (1999)'s criteria, the chi-square (χ^2=236) statistic is 955.3 ($p<0.001$), the comparative fit index (CFI) is 0.9 (should $\geq$ 0.9), the Tucker-Lewis Index (TLI) is 0.9, the root-mean-square error of approximation (RMSEA) is 0.07 (should $\leq$ 0.06), and the standardized root-mean-square residual (SRMR) is 0.07 (should $\leq$ 0.8). The above statistics suggests that our research model provide good model fit.

The results show that most of the hypothesis are supported. *Commitment* is found to be most important construct for online learning engagement, indicating that learners with higher commitment would be more engaged in the online learning environment. *Challenge* is also found to be an important variable to emotional and cognitive engagement. The path coefficients depict that *challenge* significantly contributes to emotional and cognitive engagement, implying that in order to increase leaners' *emotional* and *cognitive engagement*, creating a challenging environment might be a good way. Contrary to our hypothesis, *control* is found to have a little impact on *behavioral* and *cognitive* engagement and only possess a slight impact (path coefficient = 0.09, p<0.05).

3.2 Analysis of Predictive Model

In order to evaluate the predictive accuracy and predictive power, random forest data mining algorithm was used to build the model. The online learning engagement was transformed into binary category in terms of high and low engagement based on average engagement. We randomly partitioned data into training set (426 observations) and validation set (176 observations). Moreover, we used mean decrease accuracy (MDA) to better understand important predictors of the three models. Table 1 lists the top five predictors that contribute the most to the model.

Consistent with relationship modeling, we found that *commitment* the most significant factor to the three models. In the behavioral engagement model, learners' *online learning experiences* play an important role in the model, while *cognitive engagement, challenge*, and *emotional engagement* are also important variables. As for emotional engagement model, cognitive engagement, behavioral engagement and challenge are important variables; interestingly, leaners' education to our surprise has a great impact on the emotional engagement model, indicating that leaners with higher education would be more emotionally engaged in the online courses. In cognitive engagement model, learners' age could be considered significant factors that improve learning. This finding is reasonable because leaners' cognitive ability might be highly related to their age.

Table 1: Important variables of three predictive model using mean decrease accuracy.

Mean Decrease Accuracy	Behavioral engagement	Emotional engagement	Cognitive engagement
Rank 1	COM (32.17)	COM (61.93)	COM (27.47)
Rank 2	CE (15.31)	CE (60.10)	EE (23.47)
Rank 3	CHA (11.62)	BE (21.28)	BE (12.77)
Rank 4	OCE (9.55)	CHA (20.06)	CHA (10.35)
Rank 5	EE (8.12)	EDU (16.02)	AGE (10.08)

Note: COM = commitment; CHA = challenge; CON= control; BE = behavioral engagement; EE = emotional engagement; CE = cognitive engagement; OCE = online course experiences; EDU = education; AGE = age of the leaner

4. Instructional Implications and Conclusion

The present study investigates the relationship between online academic hardiness and online learning engagement through both structural equation model and predictive model. Based on the previous findings (Fredricks et al., 2004; Sun & Rueda, 2012; Wang & Tsai, 2016), our study improves the understanding of the impact of online academic hardiness on online learning engagement (see table 2 for the summary of the research model). Our data and analysis indicate that:

- *Commitment* is the most significant factor to learning engagement either in explanatory or predictive model, meaning that increasing leaners' commitment in online learning environment may improve leaners' overall engagement. Based on this finding, we suggest that online instructors and teaching assistants on MOOCs should pay attention to leaners' online leaning commitment by implementing strategies that encourage learning commitment. For example, instructors could perform their hardiness and efforts in instructional videos to trigger learners' commitment (Wang & Tsai, 2016). Additionally, platform designers, psychologists, and learning scientists could work together to brainstorm plausible ways to improve students' commitment through the design of the platform and activities. By emphasis on peer-to-peer interaction and deliberate practice for commitment, leaners would be more engaged in online learning environment.
- *Challenge* plays an important role in emotional and cognitive engagement, which implies that creating a challenging learning environment makes learners cognitive and emotional more involved in MOOCs learning process. Instructors should avoid over-simplifying the learning content for improving understanding in MOOCs; rather, they should design problems or activities to arouse cognitive conflicts for better cognitive learning. In designing such activity, conflict map could be used to design problems that foster scientific learning (Tsai, 2000; Tsai & Chang, 2005). Moreover, asking challenging problems before the instructional video as driving questions may arouse students' thinking and attention. We suggest MOOCs content designers evaluate the level

of learning tasks based on target audience's proficiency to increase emotional and cognitive engagement.

- Our predictive analytics found that learners' prior online learning experiences are also important to behavioral engagement, which reflects the constructivism view of learning. Valuing learners' prior knowledge and design appropriate learning content is of great importance in online learning environment (Tsai, 1998). Even though leaners on MOOCs are claimed from diverse variety, we suggest MOOCs instructors analyze leaners' prior knowledge in advance for better design of engagement and effectiveness. For instance, content designers could encourage learners to (1) share prior experiences that links to the learning content in discussion board or (2) reflect their personal experiences as reflective journals to make more connection between knowledge and experiences.

Table 2: Summary and path estimate of the study.

	Behavioral engagement	Emotional engagement	Cognitive engagement
Commitment	0.59 *** (+)	0.32*** (+)	0.33*** (+)
Challenge	N.S.	0.85*** (+)	0.85*** (+)
Control	N.S.	0.09* (+)	N.S.

Note: $^{***}p < 0.00$, $^{**}p < 0.01$, $^{*}p < 0.05$; N.S.= not significant

Our study presents the interplay of online learning hardiness and online learning engagement in a more holistic way to better understand why some learners might fail in MOOCs. However, three limitations should be stated for further improvement. First, we used convenience sampling in the current study, the data may not be able to reflect all the phenomenon in MOOCs. Future studies could employ more rigorous techniques of MOOCs data collection, such as stratified sampling or experiment to improve the data quality. Second, the predictive model of the validation set might be overfitting in predicting future engagement. More robustness testing or data mining techniques could be considered in building future engagement predictive models. Third, the current study takes advantages of self-reported data to map the relationship of academic hardiness and engagement. Future studies could focus on more authentic data sources, such as eye-tracking, brainwave or Galvanic skin response (GSR) to measure learners' engagement. We sincerely hope that the current study benefits both academia and practitioners by incorporating path analysis and data mining techniques and there would be more studies on online academic hardiness and learning engagement.

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