Explore the Relationship Between Procedural Score Feedback and Subsequent Time Allocation and Learning Outcomes of Learners in a Massive Open Online Course (MOOC)

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Abstract. Procedural feedback is considered to be one of the most powerful educational interventions. Procedural feedback attempts to help learners improve their future performance by providing information about past performance. However, little is known about the impact of processual feedback on learners' subsequent performance. This study aims to uncover the relationship between procedural score feedback, time allocation, and learning outcome, for which a conceptual model was constructed. The model was validated by collecting clickstream data from 7924 MOOC learners in a Chinese MOOC. Partial least squares structural equation modeling (PLS-SEM) was used to test the various hypotheses of the model above. The results found that: (1) procedural score feedback has a significant positive effect on learning outcomes. (2) time allocation for evaluative tasks partially mediates the relationship between procedural score feedback and learning outcome. (3) time allocation for non-evaluative tasks does not mediate the relationship between procedural score feedback and learning outcome. The study suggests some potentially effective measures for MOOC teachers and developers to provide learners with procedural support and to ensure that they achieve good learning outcomes. It also hopes to inspire future research and advance the theory and practice of online education.

Keywords: MOOC · Procedural Score Feedback · Study Time Allocation · Learning Process Analysis · Behavioral Analysis

1 Introduction

Feedback is the transmission of information about the 'outcome' of learning behavior (Tanes et al. 2011). In contrast to final feedback, procedural feedback is an opportunity to provide feedback early in the learning process, before the teacher formally assesses and provides feedback on the outcome (i.e. teacher intervention) (Sedrakyan 2016). Procedural feedback is prominent in supporting learners' behavioral performance in learning. Sedrakyan et al. argue that it is important for course instruction to know whether low

R. Hou et al. (Eds.): BDTA 2021/2022, LNICST 480, pp. 149–168, 2023.
https://doi.org/10.1007/978-3-031-33614-0_11

performance is influenced by misunderstandings of questions, tasks, or concepts or by procedural aspects of learning (e.g., not putting enough effort into validating a solution) to distinguish whether cognitive or behavioral types of feedback are needed (Sedrakyan and Snoeck 2017; Sedrakyan 2016). Therefore, procedural feedback becomes a necessary part of supporting learners' problem inquiry, goal focus, and continuity, and it should receive extra attention from course instructors and administrators.

The application of a new generation of information technology in the field of education has triggered huge changes in educational concepts, teaching and learning styles, and management mechanisms. Currently, open learning spaces express a break from convention and routine through a school-less form, and MOOCs are rapidly emerging worldwide as a form of self-help online learning source. MOOCs are regrouping teaching conditions and learning elements, and are promoting changes in teaching content, model of instruction, and management mechanisms, bringing new opportunities to the reform and development of teaching and learning. However, as a weakly supervised form and self-regulation, MOOCs tend to induce psychological and behavioral problems such as anxiety, procrastination, disorientation, and attention deficit in some learners. Actually, technology-enhanced procedural feedback offers a number of possibilities for addressing these issues, such as providing motivation, engaging participation, and improving retention. However, it has also been found that providing appropriate feedback through digital teaching and learning is not easy, due to the fact that much digital feedback still lacks the support of educational theory and has to be adapted to learners' reading levels to recognize the feedback.

Additionally, procedural feedback is considered to be one of the most powerful educational interventions. Procedural feedback attempts to help learners improve their future performance by providing information about previous performance. Score feedback provides a very effective learning strategy for distributed exercises in MOOCs (Dunlosky et al. 2013). If tests are done well, feedback can be given to students to help them identify areas and key signals that they should focus on (Smith and Lipnevich 2018; Bjork et al. 2010). Generally, when feedback is delivered appropriately and students are able to use it, it can improve teaching and learning (Lipnevich and Smith 2008; Smith and Lipnevich 2018). Slavin explored the value of feedback through the reward structure, arguing that the frequency, size, and sensitivity with which learners receive rewards affect their performance, and there is a correlation between improved performance and increased rewards (Slavin 1980). This illustrates that learner behavior is reinforced by positive outcomes and that rewards provide positive feedback and reinforcement of individual outcomes (Eisenberger and Rhoades 2001). The score feedback provides learners with the information they need to guide their subsequent decisions. Firstly, it provides an informative guide for learners to evaluate their experience, certain extent, and the effectiveness of the endeavor. Moreover, it also provides a controlled guide for learners to engage in self-regulation. However, fewer studies have examined the impact of procedural feedback on adult learners who take informal online courses and have never been face-to-face. This study attempts to fill this gap by focusing on the relationship between procedural score feedback and subsequent time allocation and final outcomes in a MOOC.

2 Theoretical Foundation

2.1 Feedback and Score Feedback

Much research has focused on the design and application of instructional feedback to test its effectiveness. Researchers have been interested in the impact of feedback on students' outcomes and how to provide appropriate feedback in a way that inspires students to regulate, arguing that procedural tests have the value of encouraging distributed exercises, identifying areas of expertise, identifying points of focus, and are effective learning strategies to help learners enhance their self-concept and self-direction (Dunlosky et al. 2013; Smith and Lipnevich 2018; Bjork et al. 2010). The effects of score feedback on memory and learning outcomes have been explored. For example, Beckman investigated the effects of pretesting in a sample of undergraduate students taking a science course, and students reported that pretesting motivated them to monitor their own learning (Beckman 2008). Janelli and Lipnevich conducted an experimental study of 399 students enrolled in the American Museum of Natural History's (AMNH) Climate Change MOOC course and found no effect of pre-test and feedback on learning outcomes among all students. Nevertheless, there was evidence that successful recall of information made students more likely to successfully recall the same information in the future (Janelli and Lipnevich 2021).

MOOCs have currently built mechanisms for publishing academic results through the development of system features and assessment modules such as unit tests, forums, and tasks, resulting in visual feedback in the form of learning dashboards and lists (van Den Hurk 2006; Misra and McKean 2000). MOOC unit tests are a non-face-to-face basic means of testing students' knowledge acquisition in an interactive context (van Den Hurk 2006; Misra and Mckean 2000). In order to answer a question or manipulation, the quiz or exam forces students to generate information through knowledge coding and then reuse these coding processes when the test is administered again. And in the view of Bjork et al. (2010), the use and reuse of coding processes have the potential to provide advantages in future examination attempts.

2.2 Study Time Allocation

Study time allocation is a typical decision-making behavior of learners who make item choices under metacognitive monitoring (Slavin 2012), and learners allocate their attention and subjective effort in a way that reflects their understanding of the task and their ability to selectively engage (Misra and McKean 2000; Eilam and Aharon 2003). Thus, learners' perceptions of reward structures cannot directly influence learning outcomes but are subject to metacognitive modulation.

Current research on the thesis has focused on the factors that influence it and its relationship to the various elements of teaching and learning. In terms of factors influencing study time allocation, Bloom characterizes study time allocation in terms of time spent on work, arguing that time spent on work varies with students' cognitive characteristics, affective characteristics, and quality of instruction (Bloom 1976). Vroom's expectancy theory provides a perspective on time allocation research, arguing that the amount of time individuals actively devote to learning is influenced by a combination of goal validity and expectancy (Vroom 2019).

In terms of the utility of time allocation on learning outcomes, an experimental study by Koriat et al. found that time allocation for learning reflects the fluency with which learners encode learning items and predicts the outcome of learners' recall of learning items (Koriat et al. 2005). van Den Hurk's study showed that students with good time management skills not only scored higher on cognitive. Carroll has used the practical time to evaluate learning output, arguing that learning effectiveness is a function of the amount of time students actually put in divided by the amount of necessary time they should put in (Carroll 1963). Misra and Mckean argue that time management is an effective strategy for reducing academic stress and anxiety and that effective time management can improve learning performance (Misra and Mckean 2000).

In terms of the relationship between study time allocation and behavior, Koriat argues that time management, the allocation of content phases, and behavioral sequences during activities are temporal dimensions of learners' metacognitive control (Koriat et al. 2006). Studies by Hristova and Kim et al. confirm that the number of times learners gaze at a learning item or the duration of gaze can reflect learners' attentional bias (Hristova and Grinberg 2009; Kimet al. 2012).

In addition, according to Self-Determination Theory (SDT), factors such as guidance, rules, feedback, evaluation, and rewards in the social environment influence the satisfaction of individual psychological needs. What's more, learners tend to construct agendas for study time allocation based on elements such as task difficulty, reward structure, and time constraints in the learning situation, directed by learning goals, in conjunction with individual characteristics such as achievement motivation, domain knowledge, and self-efficacy, and perform the agendas under the monitoring of a central executive system for study time allocation (Ariel et al. 2009). It is thus evident that study time allocation provides a pathway for the influence of learners' metacognitive monitoring on their engagement and outcomes.

2.3 Learned Industriousness Theory

Eisenberger's Learned Industriousness Theory (LIT) suggests that individual behavior is reinforced by positive outcomes and that individuals whose effort experiences are characterized by secondary rewards will tend to have the most rewarding responses (high effort operations) in their subsequent behavior; rewards provide positive feedback and reinforcement mechanisms for individual behavior, making them willing to invest more effort (e.g., time and frequency) in learning and acquiring the skills necessary to solve the challenges encountered during the task, and to generalize this learning to new tasks (Eisenberger et al. 1999). It follows that learning is a process in which effort and reinforcement interact, and that diligence is an integral response to engagement and self-efficacy regulation (Eisenberger and Rhoades 2001).

Moreover, it has been shown that learners' commitment to learning can be predicted by perceived task value, competence beliefs, motivational regulation, and perceived teacher support (Zhang and Liu 2019; Korlat et al. 2021). In addition to learning according to the rhythm of the course (instructional design, task requirements, etc.), learners also draw on perceptions of reward structure to fulfill learning commitments and increase engagement (Slavin 2012). Reward strategies can be used as an element of motivation for student progress and achievement, encouraging them to track their learning and performance (Codish and Ravid 2014).

In the context of the new generation of learning management systems, MOOC has developed a clear reward structure based on value-based rewards, supplemented by honor-based rewards, which are informative and controlled in terms of learning criteria (e.g., instructions, achievement requirements, etc.) that can guide and regulate the learner's process, thus influencing their study time allocation (Mazzoni and Cornoldi 1993).

3 Hypotheses Development

3.1 Procedural Score Feedback (PSF) and Learning Outcomes (LO)

Learners usually follow the pacing and task requirements of the course design and regulate their pace in MOOCs, driven by internal motivation, and learning experience, to continuously meet the outcome and performance expectations (Slavin 1980). In the MOOC context, feedback following learning inputs, such as grades, points, and badges, constitute procedural score feedback (PSF), which provides learners with important material to perceive their status and outcomes. In fact, when exploring the dynamics of learning outcomes, studies have found a correlation between outcome rewards and learners' fulfillment of commitment and retention of engagement as one of the factors influencing collaborative learning outcomes (Slavin 2012). As a result, the following hypothesis was therefore proposed.

H1: There is a positive effect of procedural score feedback on the final learning outcome.

3.2 Study Time Allocation (STA) and Learning Outcomes (LO)

Study time allocation is a process of cognitive engagement and regulation of the learning process and learning sources by MOOC learners. In order to adapt to the semi-supervised, self-regulated context of the MOOC, learners need to monitor and regulate their cognitive sources, motivational goals, and emotional states in a timely manner, with the necessary social support, in order to achieve their learning goals. There are two main types of objects that MOOC learners engage in, namely evaluative tasks such as quizzes, exams, and non-evaluative tasks such as viewing courseware and notifications. Thus, the corresponding study time allocation (STA) dimensions are time allocation for evaluative tasks (TAET) and time allocation for non-evaluative tasks (TANET). Therefore, this study proposes the hypothesis as follows.

H2: There is a positive effect of time allocation for evaluation tasks on learning outcomes.
H3: There is a positive effect of time allocation for non-evaluation tasks on learning outcomes.

3.3 Procedural Score Feedback (PSF) and Study Time Allocation (STA)

Procedural score feedback provides a scaffold for learners to understand their personal decisions and learning outcomes. In line with previous studies, Learners plan their time allocation based on the perceived value of the task and the perceived value of the reward. The informative and controlled nature of procedural score feedback can provide cues to guide and optimize the learning process and influence the learner's subsequent time allocation (Mazzoni and Cornoldi 1993). Furthermore, recent research has found that teachers' perceived task value positively predicts their online learning engagement in online professional learning communities and that teachers' motivational moderation partially mediates the ability of perceived task value to predict learning engagement (Zhang and Liu 2019). Therefore, both hypotheses are proposed.

H4: There is a positive effect of procedural score feedback on time allocated for evaluation tasks.
H5: There is a positive effect of procedural score feedback on time allocation for non-evaluation tasks.

As mentioned above, the research model constructed in this paper is shown in Fig. 1. It is hypothesized that the learning outcomes (LO) of MOOC learners are influenced by the time allocation of evaluative tasks (TAET), time allocation of non-evaluative tasks (TANET), and procedural score feedback (RSP). Likewise, the two types of study time allocation variables mediate the process by which procedural score feedback influences learning outcomes.

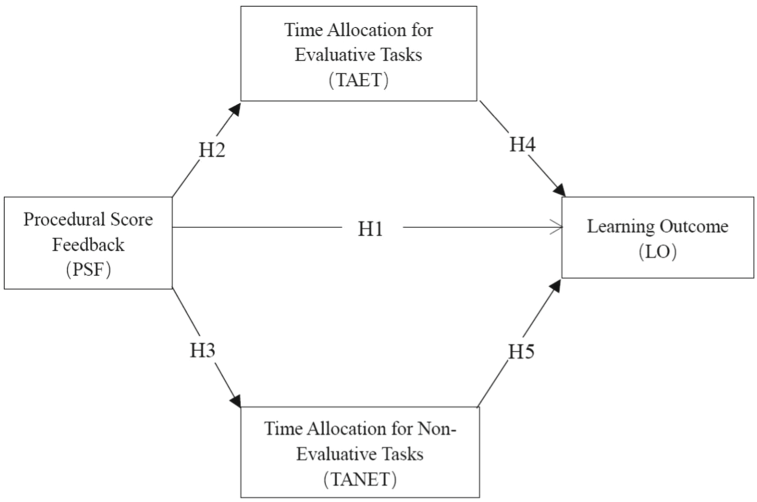

Fig. 1. Research model

4 Methodology

4.1 Research Context and Participants

In this study, 7924 learners' clickstream data in the course "How Teachers Do Research" on the Chinese university MOOC platform (https://www.icourse163.org) were collected. Due to the content of the course, the learners were mostly educational researchers and teacher-training students. Considering score as a classification criterion, 4,197 failures (<60), 595 passers (60–69), 949 moderators (70–79), and 2,183 excellenters (80–100). The data for the study were collected from 4 March 2016 to 29 January 2018, and the clickstream data extracted were mainly the record fields of information browsing, resource interaction, and evaluation participation generated by the learners. Besides, data pre-processing, cleaning, and integration were performed prior to data analysis.

4.2 Research Design

The research design consists of three segments. Session 1: Analyse the distribution of the variables through descriptive statistics of the independent and dependent variables to provide a basis for selecting an effective evaluation method for the research model; Session 2: Conduct an in-depth analysis of the research question with the structural equation modeling (SEM), mainly completing measurement model evaluation, structural model evaluation, and mediation analysis; Session 3: On the basis of quantitative analysis, generalize the strategies for MOOC procedural evaluation and feedback design.

In Session 2, along with the results of the statistical test, it was found that many of the variables had large skewness or kurtosis, indicating that the latent variables were mostly non-normally distributed. Therefore, using the maximum likelihood method that emphasizes the multivariate normal distribution of the variables would yield biased misinterpretations, and thus this study chooses to use a partial least squares (PLS) based method for the parameter estimation method.

4.3 Coding Scheme

Four latent variables were used in the study: procedural score feedback (PSF), time allocation for evaluative tasks (TAET), time allocation for non-evaluative tasks (TANET), and learning outcomes (LO). Firstly, three indicators were used to measure the procedural score feedback: assignment score, unit quiz score, and forum score, which are full of information about the effectiveness of the learner's engagement and potential guidance, and thus may convey developmental incentives or 'remedial' warnings. Secondly, five variables were used to measure learners' time allocation for tasks: time spent on participation in forums, completion of assignments, participation in quizzes, viewing quiz lists, and viewing exam lists. The time allocation for non-evaluative tasks was measured by three indicators: time spent on viewing announcements, watching micro-videos, and viewing assessment instructions. Furthermore, in order to observe learners' behavior under the influence of procedural score feedback, learners' time allocation was used to quantify the indicators above. Learning outcomes are measured by final exam scores. The coding scheme is shown in Table 1.

Table 1. Coding scheme

Latent variables	Observed variables	Coding	Explanation
Time allocation for non-evaluative tasks (TANET)	Time spent browsing course announcements	tanet1	The time allotted for learners to view information such as course announcements and bulletins
	Time spent on viewing videos and courseware	tanet2	The time allotted for learners to view the course videos and the accompanying courseware
	Time spent browsing assessment information	tanet3	Time allocation for learners to browse the course assessment information
Time allocation for evaluative tasks (TAET)	Time spent on checking examination lists	taet1	The time allocated for learners to browse information such as exam lists
	Time spent on participating forums	taet2	The time allocated for learners to participate in the forums
	Time spent on completing the assignments	taet3	Learners view assignment requirements and time allocation for assignments
	Time spent on the quizzes	taet4	The time allocated for learners to participate in the unit quizzes
	Time spent on checking the unit-quiz list	taet5	Time allocation for learners to browse the list of unit quizzes
Procedural Score Feedback (PSF)	Quiz scores	psf1	The learner's score on the unit quizzes
	Assignment scores	psf2	The learner's score on the assignments
	Forum scores	psf3	The learner's score on forum participation
Learning Outcome (LO)	Final score	lo1	The learner's score on final exam

5 Data Analysis and Results

5.1 Sample

Before starting the study, it was confirmed whether the sample of individuals followed a distribution within the parameters of normality. The values of kurtosis and Skewness were found for the selected indicators. With kurtosis and skewness, values lower than |3.00| indicate a normal distribution (Kline 2010, cited in Wu and Cheng 2019). In this study, KS values were found within an interval of |0.81| to |76.36| and SK values between |0.01| and |6.56|, which suggests that there is no serious deviation, from normality in the distributions (see Table 2). Therefore, the study needs to consider using statistical methods for analysis that is not limited by the distribution of variables to reduce bias in the study results.

Table 2. Descriptive statistical analysis of variables (N = 7924)

Variable	Min	Max	M	SD	KS	SK
tanet1	0.00	13354.63	753.08	1224.40	10.89	2.84
tanet2	0.00	198332.28	17618.53	21381.40	4.53	1.77
tanet3	0.00	46231.41	2140.29	3627.81	17.63	3.40
taet1	0.00	7299.72	513.36	956.93	5.92	2.31
taet2	0.00	68298.70	1009.80	2805.12	76.36	6.56
taet3	0.00	20778.59	933.70	1665.28	14.07	2.96
taet4	0.00	38889.42	3562.42	4309.12	4.50	1.75
taet5	0.00	18165.41	1078.87	1752.31	10.62	2.73
psf1	0.00	50.00	27.10	18.24	−1.69	−0.22
psf2	0.00	15.00	5.71	6.51	−1.81	0.33
psf3	0.00	100.00	31.33	37.01	−0.81	0.85
lo1	0.00	20.00	8.60	8.16	−1.83	0.01

Min, minimum value; Max, maximum value; M, Mean; SD, Standard Deviation; KS, Kurtosis Statistic; SK, Skewness Statistic.

5.2 Measurement Model Evaluation

In this paper, measurement models and structural models are assessed using partial least squares (PLS), which does not require consideration of the distribution of the variables. Reliability, two tests were applied (Hair et al. 2019): Cronbach's Alpha (α) and composite reliability (CR). Cronbach's alpha (α) is a popular measure of internal consistency, which is generally considered to be good when the value is greater than 0.7, and fair when it is between 0.5 and 0.7 (Jum and Ira 1978). All constructs included in the proposed model satisfied these conditions and thus all possess reliable internal consistency as Cronbach's alpha values ranged from 0.766 (TANET) to 1 (LO) and CR values ranged from 0.851 (TAET) to 1 (LO), as displayed in Table 3.

Table 3. Reliability and validity tests

Variable	PSF	TAET	TANET	LO	α	CR	AVE
tanet1			0.803		0.766	0.865	0.681
tanet2			0.870				
tanet3			0.800				
taet1		0.663			0.781	0.851	0.537
taet2		0.575					
taet3		0.761					
taet4		0.833					
taet5		0.663					
psf1	0.918				0.876	0.924	0.801
psf2	0.904						
psf3	0.862						
lo1				1.00	1.00	1.00	1.00

The validity of the measurement model includes two items: convergent validity and discriminant validity. Firstly, convergent validity is assessed using factor loading (FL), composite reliability (CR), and average variance extracted (AVE) (Werts et al. 1974). In this study, the factor loadings of all variables were greater than 0.5 (recommended value greater than 0.5), CR was greater than 0.850 (recommended value greater than 0.7) and AVE was greater than 0.536 (recommended value greater than 0.5), indicating that the measurement model has good convergent validity. Moreover, the discriminant validity of the measurement model is assessed by AVE, cross-loading, and related indicators. (Chin 1998). As shown in Tables 3 and 4, the factor loadings of each indicator on the corresponding latent variables are all greater than 0.7 (recommended value is greater than 0.7), and the factor loadings of the same variable are higher than those of other variables; the square root of the AVE of each latent variable is higher than the correlation coefficient with other latent variables, indicating that the measurement model has good discriminant validity.

Table 4. Discriminant validity test (Fornell and Larcher criterion)

	AVE	PSF	TAET	TANET	LO
PSF	0.801	0.895			
TAET	0.681	0.640	0.733		
TANET	0.537	0.557	0.731	0.825	
LO	1.000	0.865	0.584	0.497	1.000

Note: The values on the diagonal line in the table represent the square root of the corresponding dimension AVE

Given the high correlation between the independent variables, various problems may arise in interpreting the fitness results of the regression model (Meloun et al. 2002). Therefore, it is also necessary to check for the presence of multi-collinearity. The variance inflation factor (VIF) was assessed to identify the presence of multi-collinearity (Hair et al. 2019). The presence of more severe multi-collinearity was demonstrated when the VIF coefficients of the respective variables in the study model exceeded 5. The results in Table 5 show that the VIF values of all independent variables are less than 5, indicating that there is no multi-collinearity between the independent variables.

Table 5. Multi-collinearity test

Independent variable	Dependent variable	VIF value
LO	PSF	1.723
	TAET	2.928
	TANET	2.508

5.3 Model Fit Indices

Before evaluating the structural model, it is essential to assess the performance of the studied model using the fit metrics. As shown in Table 6, all the fit metrics satisfy the acceptable values advocated by Henseler et al. (2016), indicating that the proposed model is able to adequately fit the dataset.

Table 6. Model fit indices

Fit index	Recommended value/condition	Actual values
SRMR (Standardized Root Mean Square Residual)	<0.08	0.069
NFI (Normed Fit Index)	>0.9	0.883
d_ULS (Unweighted Least Squares)	"d_ULS < bootstrapped HI 95% of d _ULS and d_G < bootstrapped HI 95% of d_G"	0.373
d_G (Geodesic Discrepancies)		0.206
GoF (Goodness of Fit)	<0.1 (small) 0.25 (medium) >0.36 (large)	0.608
rms Theta	<0.12	0.109

Note: GoF = sqrt(average(AVE)* average(R^2))

5.4 Structural Model Evaluation

In this stage, the significance of the path coefficients (β values) of the relationships (proposed hypotheses) among constructs was evaluated. Accordingly, the bootstrapping procedure (with 5000 bootstrap resampling) was applied. Both T-statistics and p-values were employed to determine the Both T-statistics and p-value were employed to determine the significance of path coefficients (β); specifically, a significance level of 5% (p value < 0.05) and a t value higher than 1.96. The PLS-SEM analysis indicates the estimation and evaluation of proposed hypotheses, as presented in Fig. 2. The results demonstrate that four out of the five hypotheses are These are H1 (PSF->LO), H2 (PSF->TAET), H3 (PSF->TANET) and H4 (TAET->LO). This implies that PSF and TAET have significant and direct positive effects on LO, with PSF acts as the strongest predictor (($\beta = 0.833$, p-value < 0.001). Further, H2 (PSF->TAET) is also supported as PSF ($\beta = 0.640$, p-value $= 0.000 < 0.001$) has a significant positive influence on TAET, H3 (PSF->TANET) is also supported as PSF ($\beta = 0.557$, p-value $= 0.000 < 0.001$) has a significant positive influence on TANET.

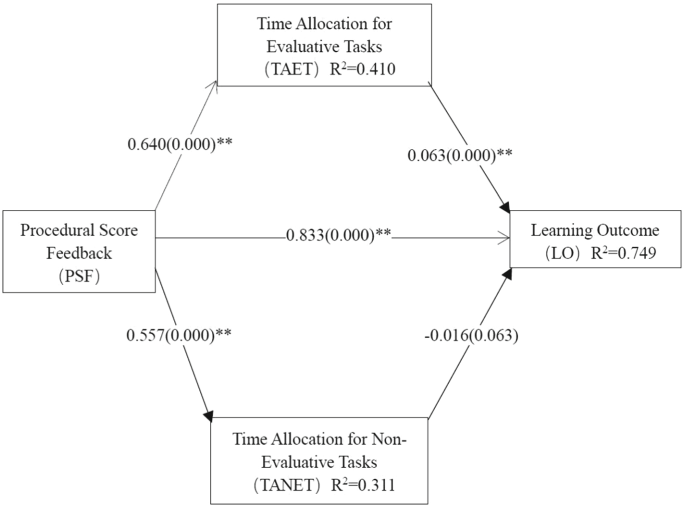

Fig. 2. Structural model analysis. Note: Numbers between brackets represent p value. **p value < 0.01, *p value < 0.05

Also, during this stage additional measures were evaluated, namely the determination coefficient (R^2), effect size (f^2), and predictive relevance (Q^2) (Hair et al. 2019). R^2 measures the predictive power of the research model by assessing the degree to which the independent variables explain the variance among the results in Table 7 indicate that the value of R^2 for LO (the key target construct) is 0.749, demonstrating that PSF, TAET, and TANET explain 74.9% of the variance among the dependent variables. Such predictive power is considered substantial (>0.67) (Chin 1998). TAET also explains 41% ($R^2 = 0.41$) of the variance in PSF. Additionally, TANET explains 31.1% ($R^2 = 0.311$) of the variance in PSF, indicating moderate TAET also explains 41% ($R^2 = 0.41$) of the variance in PSF.

Q^2 measures (only calculated for dependent variables) were obtained by running the blindfolding procedure (applying the omission distance of $D = 7$). All values of Q^2 (see Table 7) are above zero (Geisser 1975), indicating that the research model possesses high predictive relevance (Cohen 1988). Finally, the effect size (f^2) values for PSF, TAET and TANET on LO, and for PSF on TAET and TANET are displayed in Table 7. Based on Cohen (1988), the results suggest that the effect sizes for PSF, TAET, and TANET on LO are large, and PSF on TAET and TANET are large too.

Table 7. Results of R^2, f^2 and Q^2

Variables	R^2	f^2	Q^2
TAET	0.410	0.694	0.203
TANET	0.311	0.451	0.196
LO	0.749	0.537	0.728
Recommended value /condition	>0.67 (High) 0.33 (Medium) <0.19 (Low)	>0.35 (Strong) 0.15–0.35 (Medium) 0.02–0.15 (Weak)	0–1

5.5 Mediation Analysis

MacKinnon et al. suggest a 95% confidence value for the BI (BC Confidence Level) when performing Bootstrapping, and if the confidence interval does not include 0, the mediating effect is present; if the confidence interval includes 0, the mediating effect is not present (MacKinnon et al. 2007). If the confidence interval does not include 0, a mediating effect exists; if the confidence interval includes 0, a mediating effect does not exist (MacKinnon et al. 2007). The results of the study are shown in the Table 8. 95% confidence intervals for the indirect effect of procedural score feedback (PSF) via time allocation for evaluation tasks (TAET) on learning outcomes (LO) were [0.043,0.083], with confidence intervals excluding 0 indicating a significant mediating effect, corresponding to an indirect effect value of 0.04. However, the indirect effect of procedural score feedback (PSF) via time allocation for non-evaluation tasks (TANET) of time allocation (TANET) had a 95% confidence interval of [−0.031, 0.001] for the indirect effect of influencing learning outcomes (LO), with confidence intervals including 0, indicating a non-significant mediating effect.

Table 8. Intermediary Effect

Path	2.5%	97.5%	Results	Value
RSP->AST-PET->LO	0.043	0.083	Significant	0.04
RSP->AST-PNET->LO	−0.032	0.001	Not Significant	-

6 Discussion

The role of task value and academic emotion on learning engagement has been widely recognized by academics (Artino 2008), but the impact of procedural score feedback on learning time allocation has rarely been discussed in previous research. This study uses an empirical approach to analyze the mechanisms by which procedural feedback affects the allocation of learning time. The results show that procedural score feedback (PSF) significantly affects learners' subsequent allocation of learning time and has a stronger effect on the allocation of time to evaluative tasks (TAET) than to non-evaluative tasks (TANET). This result is consistent with previous research (Lei et al. 2017). Procedural score feedback (PSF) as a motivational mechanism for the course with embedded cues, and task value tendencies can help learners to form and adjust their personal learning pace. When learners experience learning gains and task values from learning, they can evaluate the effectiveness of their own learning inputs based on the gap between their effort state and expectations, and thus adjust the time allocation of learning tasks and learning resources. Those behavioral inputs that have met learning expectations will be reinforced and transferred, otherwise, they will be adjusted, eventually forming habitual learning behaviors and relatively reasonable time allocation. Thus, the results of procedural score feedback will lead to differences in learners' time allocation.The role of course-cued information on learning outcomes has received academic attention (Lamb et al. 2018), but there have been no consistent research findings. The present study shows that procedural score feedback (PSF) positively predicts learning outcomes (LO). This finding is similar to Webb and Johnson's research (Webb 1982; Jonassen et al. 2008), which validates the behavioral school's basic view of the utility of rewards, that extrinsic motivation is an enabler of intrinsic motivation, helping to guide individuals to enhance their self-competence around task goals or reward criteria, which in turn enhances the self-efficacy required to complete the task and psychological motivation.

According to the MOOC context, procedural score feedback provides a quantifiable and perceptible developmental scaffolding of learning for the learner's stage-by-stage commitment to learning. This is very similar to the reward structure of a course. Deci et al. argue that the informational nature of course rewards activates individual competency needs (Deci et al. 1999), provides cues and monitors learners' behavior, and can provide pacing guidance and process regulation for learners. Specifically, the types and modules in the reward structure of a catechism can guide learners to plan their own cognitive resources, make flexible pacing changes to reduce cognitive load, and enhance the sense of presence in online learning; the frequency and acceptability of rewards can facilitate learners' metacognitive monitoring and thus adjust paths to keep learners in an effective learning state.

Besides, Learning engagement levels can represent learner diligence, and this study examines the role of two types of learning time allocation on learning outcomes. The results indicate that time allocation to evaluative tasks (TAET) positively predicted learning outcome (LO) and it also had a mediating effect on the path of procedural score feedback (PSF) affecting learning outcome (LO), however, time allocation to engage in non-evaluative tasks (TANET) was weaker in predicting learning outcome (LO). This finding is in line with previous research findings (Broadbent 2017; van Den Hurk 2006). Study time allocation is a component of metacognitive control, where learners focus first on the way learning as whole proceeds and then on the allocation of time to individual items (Thiede and Dunlosky 1999). The allocation of learning time during learning reflects how well learners follow explicit or implicit learning rules (Kovanovic 2016), and there is a wide variation in learners' time commitment to task engagement and resource preferences. The metacognitive monitoring of learners in MOOC learning enables learners to focus more on tasks related to the evaluation of the course phase, and to allocate more time to this, often leading to good learning outcomes.

7 Implications for Theory and Practice

The above findings have some reference significance for MOOC feedback design and platform development. On the one hand, teachers can optimize the reward structure of the MOOC based on procedural score feedback and establish a clear and perfect reward mechanism to guide learners to increase their learning commitment. The main work includes two aspects: firstly, teachers should optimize the reward design and build a scientific and reasonable reward structure. In terms of reward types, in addition to increasing the number of points for resource access and behavioral participation, additional forms of honors such as ranking segments and points can be added to improve the single reward and comprehensive honor mechanisms; in terms of reward targets, reward mechanisms for learning groups can be designed in line with the needs of collaborative learning tasks to enhance learners' enthusiasm and sense of efficacy in collaborative learning; in terms of reward frequencies, they should be combined with course attributes and task In terms of the frequency of rewards, they should be planned in accordance with the attributes of the course and the characteristics of the tasks, and a reasonable frequency can motivate learners' progress; in terms of the acceptability of rewards, the design of direct and indirect rewards should be balanced, so as to play a comprehensive role of direct motivation and potential spur. Secondly, teachers and developers need to strengthen evaluation feedback mechanisms and build fully functional reward information push and visualization platforms. It has been shown that the behavior of learners to check the course progress and evaluation results in a timely manner can facilitate learners to adjust their learning pace (Gašević et al. 2016). Therefore, it is recommended that catechism platforms should be designed to provide vivid and real-time feedback on rewards, so that learners can clearly identify their progress and learning outputs, and receive 'external motivation' and learning references from the performance of their peers so that they can adjust and optimize their learning pace.

On the other hand, course teams and platform developers should guide learners' behavioral paths in conjunction with instructional design to help them allocate their learning time appropriately. This can be achieved through three tasks. First of all, teachers need to direct learners to devote more cognitive resources to more valuable learning activities. Given that procedural score feedback contains clear information about the value of the task, process management should focus on guiding learners' behavioral pathways by setting up reference learning times, progress dashboards, and resource indices to guide learners in planning their learning time allocation and carrying out in-depth learning. Moreover, the interaction between the pace of learning and the pace of teaching is facilitated through pedagogical activities. Research has shown that the allocation of learning time under the influence of groups of learners leads to a greater degree of structure in unstructured learning environments (online open environments) (Elvers et al. 2003). Along with the learning in a MOOC, the reward structure, the layout of resources, and the allocation of tasks are all reflections of the teaching rhythm, while the learning behavior and its time allocation are reflections of the learning rhythm. The course team can use the interaction between learning and teaching rhythms to assess the effectiveness of the design and inform the construction of the course. In addition, the course team can use this to personalize teaching and learning, guiding struggling learners to learn at the pace of their peers, adapt to the pace of teaching, and master the focus of their learning.

Furthermore, protocols should be signed between teachers and students to reduce the frequency of learners' 'disengagement' from the platform. Due to the learning environment, MOOC learners are prone to browse irrelevant websites and operate desktop software and other non-authentic learning states, which seriously interfere with learners' attention and learning continuity. Therefore, it is recommended that the course team should guide learners to actively commit to the learning behavior protocol by means of information prompts or access restrictions, blocking irrelevant websites, and restricting desktop software operations so that learners can focus on their tasks and thus improve their learning outcomes.

8 Conclusion and Future Work

The main aim of this study was to explore the latent relationship between procedural score feedback and study time allocation and learning outcomes. The empirical results indicate that the positive impact of procedural score feedback and time allocation for evaluative tasks on learning outcomes is mainly due to the fact that the reward structure of the MOOC acts as a 'vane' for learners' behavioral inputs and time allocation, which can provide an external value reference for their cognitive behavior, and that behavioral results and experiences trigger learners' learning motivation and behavioral rhythm regulation, thus facilitating the emergence of good learning outcomes for them.

The current study has a number of limitations that need to be addressed in future research. For example, the study was conducted through learners' feedback data and performance data over 8 weeks, which is considered cross-sectional data analysis, without phased data collection and validation, which may make it difficult to reflect the precise relationship between variables. Therefore, the subsequent study needs to conduct a comparison under multiple division results to test the validity of the research model in this paper. In addition, the data collected for this study only includes students from a MOOC in China, which limits the generalizability of the findings. Hence, further research is recommended to validate the research model using a larger sample size that includes students from a variety of MOOCs.

Acknowledgements. Thanks to the course team and MOOC platform (https://www.icourse163.org) for providing the data for this study.This work is funded by Shandong Province Higher Educational Research Program of China [Grant No. J18RA144], Shandong Social Science Planning Project of China[Grant No. 22CJYJ32], and Research Project of Shandong Youth University of Political Science[Grant No. XXPY20035].

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