Education and Information Technologies (2023) 28:4795–4817
https://doi.org/10.1007/s10639-022-11319-7

How proactive personality promotes online learning performance? Mediating role of multidimensional learning engagement

Huanyou Chai[1] · Tianhui Hu[2] · Gengfeng Niu[3]

Received: 14 May 2022 / Accepted: 31 August 2022 / Published online: 24 October 2022

Abstract
Research on online learning effectiveness has experienced a shift towards focusing on learner characteristics or differences. However, little attention has been paid to learners' personality traits, especially those that highly match with the environmental characteristics of online learning. Guided by recent active learning approach and Model of student differences for learning in online education, this study adopts proactive personality (a dispositional tendency to be active, goal-oriented, and not constrained by environmental forces) as a key predictor and examines whether its relationship with online learning performance is mediated by learning engagement as a multidimensional construct. Using a multi-method approach (including self-reports, log file analysis, and content analysis), this study collected both subjective and objective measures of learning engagement from a total of n = 322 undergraduates. Results showed that proactive personality was positively associated with online learning performance. In addition, this association was mediated by all subjective and certain objective measures of learning engagement. Findings contribute to understanding the impact of proactive personality on online learning performance and the interplay of learners' individual factors and learning engagement factors in online learning environments. This study recommends promoting learning engagement to realize learners' online success, especially for those with low levels of proactive personality.

Keywords Proactive personality · Learning performance · Subjective and objective measures · Learning engagement · Online learning

Extended author information available on the last page of the article

1 Introduction

The tremendous growth of Massive Open Online Courses (MOOCs) and information technology has sparked an increased interest in online learning for learners from various levels of education (Hofer et al., 2021). Especially during the rampant pandemic of COVID-19, nearly all students around the world are required to participate in online learning activities. Nowadays, online learning is considered as an indispensable and extremely important constituent of higher education (Kumar et al., 2019). Previous studies have mostly found that online learning could facilitate learner interactions, coordinate cognitive actions, and finally enhance learners' learning performance (see Sun & Chen, 2016). However, there are also some studies demonstrating the challenges faced by online learners, such as a less rigid schedule and design and the time-consuming nature (Tallent-Runnels et al., 2006). Therefore, it necessitates research into the factors impeding or facilitating the effectiveness of online learning and how they affect online learning effectiveness (i.e., the underlying mediating mechanisms).

According to Cidral et al.'s (2018) summary, research on what promotes online learning outcomes has experienced a shift from focusing on course contents, learners' attitudes, to learners' (individual) characteristics or differences. This shift echoes the proposition from two commentaries in PNAS (Proceedings of the National Academy of Sciences of the United States of America, Lubinski, 2020; Stoet & Geary, 2020), which highlight learner differences as potential influencing factors of online learning outcomes. As such, a great and recent interest lies in examining what affects online learning outcomes with performance in particular from the perspective of learner characteristics and proposing adaptive intervention schemes. Numerous factors, including demographic variables (e.g., gender and age), perceived behavior control, effort expectancies, and broad personality traits (Dikaya et al., 2021; Yu, 2021), have been identified in this emerging strand of literature (see Panigrahi et al., 2018). Despite valuable insights from extant studies, relatively little attention has been paid to learners' personality traits that highly match with the environmental characteristics of online learning.

This study adopts proactive personality (Bateman & Crant, 1993) as a well-matched predictor of online learning performance and further examines the mediating mechanism underlying their relationship. It contributes to unveiling how proactive personality promotes students' online learning performance and providing some valuable suggestions for improvement. Notably, proactive personality refers to a dispositional tendency to be active, goal-oriented, and not constrained by environmental forces (Crant, 1995, 1996). Inspired by recent active learning approach (e.g., Lamon et al., 2020; Theobald et al., 2020), many scholars have incorporated proactive personality as an important predictor into the research on academic success in traditional and online learning environments (Chen et al., 2021; Islam et al., 2018). Compared to traditional (face-to-face) classes where instructors dominate the learning processes, online classes are in more urgent need of learners' proactivity to advance their learning progression. In addition, according to trait activation theory (Tett & Guterman, 2000) and person-environment fit theory (Edwards et al., 1998) in work contexts, only when a learner's individual traits fit well with the environment s/he is learning, can s/he transform them into certain learning actions and further achieve academic success. Considering the challenging, autonomous, and asynchronous nature of online learning, most successful online learners are characterized by self-discipline, self-motivation, and goal-orientation (Gregory, 2016), which bear striking similarities to the dispositional nature of proactive personality rather than broad personality traits. Given the considerations above, it is of great importance to examine the effect of proactive personality on online learning performance and how this effect occurs.

Overall, this study aims to investigate the positive impact of proactive personality on students' online learning performance. Additionally, it examines the mediating role of learning engagement on this effect. This study is distinguished from other studies by exploring the relationship between proactive personality as a well-matched trait and online learning performance. Additionally, it is the first to simultaneously examine the subjective and objective measures of learning engagement as a mediator. Moreover, it addresses learning engagement a multidimensional construct rather a unidimensional one.

2 Literature Review

2.1 Theoretical framework

No research to date has specifically theoretically examined how proactive personality affects learning performance in the context of online learning. However, some existing studies have theorized about the mediating mechanism for linking learner differences to online learning outcomes. Initially, in a systems-based model coined by Lowe and Holton (2005) and later revised by Knowles et al. (2015), some external processes (e.g., technology-based design and delivery) are believed to affect the relationship between learner differences and online learning outcomes. Yet to a large extent, these kinds of processes seem to influence learning outcomes in an indirect rather than a direct manner. Recently, Money and Dean (2019) have proposed a theoretical framework of Model of Student Differences for Learning in Online Education (MSDLOE), which contends that learning engagement (a common proxy of student internal processes) comprise the mediating mechanism that directly link learner differences to learning outcomes of online delivery. Another framework was the conceptual framework proposed by Eynon and Malmberg (2021), who claimed that *structure* (similar to learner differences) precedes *agency* (e.g., learning engagement), which further leads to varying *outcomes* of learning via the Internet (e.g., online learning performance). Moreover, theory on traditional classes could also give some meaningful insights into how personality affects online learning performance. In Biggs's (1993) 3P (presage, process, and product) Model of Teaching and Learning, *process* (e.g., learning engagement) acts as a mediator in the relationship between *presage* (i.e., learner differences or teaching context) and *product* (e.g., learning performance). Goal-orientation theory is a socio-cognitive theory of motivation that hypothesizes the role of the academic motivation in linking proactive personality to academic success (Cook & Artino Jr., 2016). Self-determination theory (SDT) is another motiva-

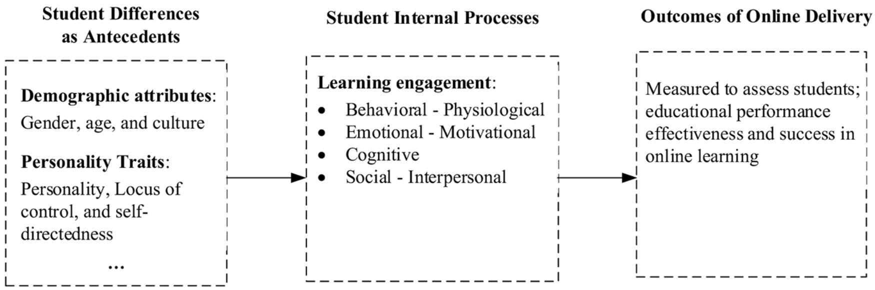

Fig. 1 MSDLOE (Taken from Money & Dean 2019)

tion theory that assumes the mediating role of three common and essential human needs: autonomy, competency, and relatedness (Deci & Ryan, 1985).

Guided by the theories discussed above, some empirical studies have examined the mediating mechanism underlying the relationship between learner differences (even proactive personality) and online learning outcomes. For example, Deng et al. (2020a) adopted 3P Model of Teaching and Learning to examine the relationships among learner factors, engagement patterns, and MOOC learning outcomes. They found that significant differences existed among the MOOC participants with different engagement patterns regarding learner factors (e.g., gender) and learning outcomes (course completion). Drawing on self-determination theory, Gao et al. (2015) identified the mediating role of the above-mentioned three needs in the relationship between proactive personality and online learning performance. In addition, a vast body of research has suggested the role of various aspects of learning engagement in linking student differences to online learning outcomes (e.g., Altanopoulou & Tselios, 2018; Diep et al., 2017; Zhu et al., 2019), lending strong support to MSDLOE.

To conclude, most of the aforementioned theories highlight learning engagement as a key mediator that links learner differences to online learning performance (Money & Dean, 2019). Thus, we grounded our research in MSDLOE, which provides a comprehensive and targeted picture of the role of learning engagement in online learning.

2.1.1 Definition and core concepts of MSDLOE

MSDLOE is an integrated model proposed by Money and Dean (2019). By systematically reviewing recent literature pertaining to populations of students engaged in online learning, the authors identified key antecedents and processes that determine various outcomes of online delivery (see Fig. 1). In MSDLOE, varying types of online learner differences are defined and identified as antecedent inputs, such as gender, age, and social economic status (SES) in the domain of demographic attributes, certain personality traits or types, locus of control, and self-directedness in the domain of personality traits, etc. Outcomes of online delivery consist of a wide variety of performance measures and achievement markers, such as quiz scores, pass rates for courses, final course grades, etc. Most importantly, learner internal processes act as an important mediator that links learner differences to outcomes of online delivery. According to the authors' summary, student internal processes could be reflected by various types of learning engagement, including behavioral (physiological), emotional (motivational), cognitive, and social (interpersonal) domains.

2.1.2 Definition and measurement of learning engagement in online learning

Given the prominent feature of separating students and teachers in time and space, online learning strongly calls for continuous learning engagement among learners (Lu & Cutumisu, 2022; Perez Alvarez et al., 2020). Despite much literature on learning engagement, there is a lack of consensus of its definition and conceptualization in the context of online learning. Most online learning researchers treat it as a unidimensional construct and equate it with participation in online learning activities, i.e., the behavioral aspect of learning engagement. For example, learning engagement is often represented and measured by the number of video lectures watched (Campbell et al., 2015; Xu et al., 2020), the number of contributions to the discussion forum (Xiong et al., 2015), video interactions (Li et al., 2015), the number of notes taken (Veletsianos et al., 2015), and the number of reflective diaries submitted (Zhang & Liu, 2019). Recently, an increasing number of literature has examined the multidimensional nature of learning engagement to acquire a comprehensive understanding of online learning processes and design targeted interventions. For example, Deng et al. (2020b) conceptualized learning engagement as a combination of the behavioral, social, emotional, and cognitive domains, while Sun and Rueda (2012) operationalized it as a three-dimensional construct consisting of behavioral, emotional, and cognitive engagement. Drawing on the most common approach in previous studies, this study divided learning engagement into three dimensions: behavioral, emotional, and cognitive aspects. Specifically, behavioral engagement could be conceptualized as participation in various academic activities in online learning. Emotional engagement refers to students' positive, negative, and confused emotions to their teachers, peer learners, and course contents. Cognitive engagement is defined as learners' investment in cognitive efforts to master course contents or related skills in online learning.

Regarding the measurement of learning engagement, it is initially measured by subjective data from self-report surveys, observations, and interviews (e.g., Jung & Lee, 2018; Sun & Rueda, 2012). For example, in the study of Jung and Lee (2018), a self-reports questionnaire was used to examine the relationship between learning engagement and persistence in MOOCs. In recent years, the growing availability and impact of information technology and learning analytics has sparked the interest of researchers and educators to collect learners' objective data of learning engagement in online learning platforms (e.g., Deng et al., 2020a; Liu et al., 2022; Zhang & Liu, 2019). In particular, as a core component of online learning platforms, the discussion forum is endowed with great opportunities to keep track of learners' various aspects of learning engagement data. As such, learners' digital traces in the discussion forum are often used to represent or reflect learning engagement in online learning (e.g., Galikyan & Admiraal, 2019; Liu et al., 2022). For behavioral engagement, it could be represented by the number of contributions to the discussion forum (e.g., Xiong et al., 2015; Xu et al., 2020). Emotional engagement could be measured by the numbers of information units of three aspects of positive, negative, and confused emotion embodied in the discussion discourse (Liu et al., 2022). Cognitive engagement is often evaluated by the numbers of varying types of cognitive events or levels, which are invested by learners in the discussion discourse and rated according to a well-established or recently developed coding scheme.

2.2 The relational model

2.2.1 Proactive personality and online learning performance

Proactive personality, defined as "the relatively stable tendency to effect environmental change", was initially proposed to examine the effect of dispositional factors on individuals' proactive behavior or proactivity (Bateman & Crant, 1993). Compared to individuals with low proactive personality, those with high are less likely to be subjective to the constraints of environment, but to alter the environment proactively (Crant, 1995, 1996). Besides, they do better in identifying opportunities and tend to take actions and persevere until reaching success (Bateman & Crant, 1993).

In educational settings, research on proactive personality systematically shows that learners with higher proactive personality tend to have more feelings of self-efficacy and higher motivation to learn (Major et al., 2006), which would in turn lead to better learning outcomes. Moreover, Gregory and Lampley (2016) pointed out that most of the successful online learners are characterized by self-discipline, self-motivation and responsibility, which correspond well to the core components of proactive personality. There are also some empirical studies that have found a significantly positive relation between proactive personality and learners' learning outcomes in traditional (Wang, Lei, & Wang, 2016) and online classes (Liu et al., 2019; Zhu et al., 2019).

2.2.2 Proactive personality and learning engagement

As suggested by its definition, proactive personality is characterized by the dispositional tendency to be active and goal-oriented (Crant, 1995, 1996). Therefore, individuals with higher proactive personality are more likely to take proactive actions to achieve career or academic success (Bateman & Crant, 1993). In educational settings, these proactive actions could be reflected in various aspects of learning engagement, such as more contributions to the discussion forum in behavioral aspect (Xu et al., 2020a), more emotional information in the discussion discourse in emotional aspect (Comer et al., 2015), and higher levels of cognitive events in cognitive aspect (Liu et al., 2022). In addition, existing studies on traditional classes have documented positive relationships between proactive personality and the behavioral and cognitive aspects of learning engagement (e.g., Islam et al., 2018; Major et al., 2006). There are also some studies that demonstrated positive associations between them in online learning environments (Gao et al., 2015; Kickul & Kickul, 2006; Zhu et al., 2019). However, little research has comprehensively investigated the relationship between proactive personality and learning engagement as a combination of multiple aspects.

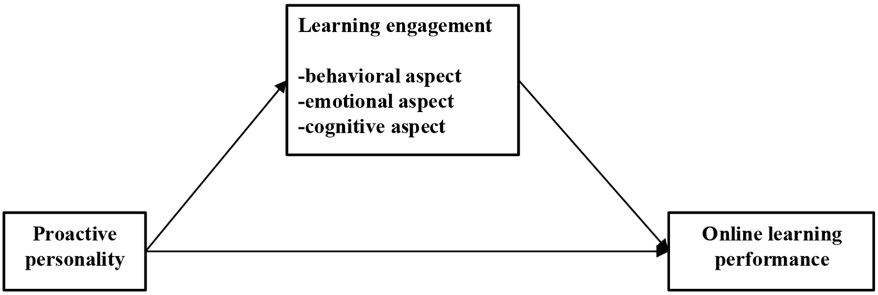

Fig. 2 Proposed research model

2.2.3 Learning engagement and online learning performance

A large number of empirical studies have examined the relationships between certain aspects of learning engagement and online learning performance. Regarding behavioral engagement, research has demonstrated its consistent positive relationship with learning performance across various samples, measures, and settings. For example, online learners with higher learning performance are more likely to have more video views (de Barba et al., 2016) and discussion posts (Morris et al., 2005). The association between emotional engagement and online learning performance has been examined in a few studies. For example, Liu et al. (2022) found that learners' emotional engagement in the MOOC forum could positively predict learning performance. Similar findings are also shown in the work of Liu et al. (2019).

Regarding cognitive engagement, however, studies contradict each other in their findings of whether and how it affects online learning performance. Some studies found that some behavioral measures of cognitive engagement (e.g., pausing and backward seeking events in video interaction) were positively associated with online learning performance (Sinha et al., 2014), while others reported negative associations (Giannakos et al., 2015). According to the summary of Li and Baker (2018), these controversial findings could be attributed to different or even opposite mechanisms underlying those behavioral measures of cognitive engagement. Instead, another strand of research is to leverage learners' cognitive engagement in the discussion forum, though not comprehensive, to predict online learning performance. In this vein, a large number of studies have consistently demonstrated positive relationships between certain measures of cognitive engagement and online learning performance (e.g., Galikyan & Admiraal, 2019; Liu et al., 2022).

2.3 The present study and its hypotheses

Given the analysis above, this study aims to test a mediation model in which the behavioral, emotional, and cognitive aspects of learning engagement mediate the relationship between proactive personality and online learning performance (see Fig. 2). Specifically, both subjective and objective measures of learning engagement are adopted to elucidate its role in linking proactive personality to online learning performance. Our research hypotheses are proposed as follows:

H_1: Proactive personality positively predicts performance in online learning.

H_2: Behavioral engagement mediates the relationship between proactive personality and online learning performance.

H_3: Emotional engagement mediates the relationship between proactive personality and online learning performance.

H_4: Cognitive engagement mediates the relationship between proactive personality and online learning performance.

3 Methods

3.1 Research context and participants

Participants were 322 students (mean age = 18.40, 136 males, 186 females) enrolled in an educational psychology course at a college in central China. This course is a general-knowledge and mandatory one for normal students. It lasted for 10 weeks and was delivered via StarC, one of the most widely used course management systems in China. Before class every week throughout the semester, students were first encouraged to preview the course materials including videos, slides, and additional texts. Then they were required to post questions and discuss the course contents on the course discussion forum. During the class, the instructor was responsible for providing answers to the problems encountered by students and elaborating the key points of the course.

3.2 Measures

3.2.1 Proactive personality

Students' proactive personality was measured by the Chinese version of Proactive Personality Scale revised by Shang and Gan (2009). This scale is composed of 11 items (see Table 1) belonging to a unidimensional construct. Each item was rated on a 5-point Likert scale, ranging from 1 (strongly disagree), 2 (partially disagree), 3 (not sure), 4 (partially agree), to 5 (strongly agree). Concerning the value of Cronbach's alpha coefficient in this scale, it reached a satisfactory level ($\alpha = 0.86$) in the study by Shang and Gan (2009). In this study, this scale has also demonstrated a good reliability ($\alpha = 0.87$). Its value of composite reliability was 0.94.

3.2.2 Learning engagement

Subjective measures of learning engagement were captured by Engagement Scale adapted by Sun and Rueda (2012). This scale consists of 19 items (see Table 1) and a three-dimensional construct, including *behavioral engagement* (five items), *emotional engagement* (six items), and *cognitive engagement* (eight items). Each item was rated on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Cronbach's alpha coefficients were reported acceptable by Sun and Rueda (2012) regarding the scales of *behavioral engagement* ($\alpha = 0.880$), *emotional engage-*

Table 1 Measurement items of proactive personality and subjective learning engagement

Construct	Measurement Items	Cronbach's alpha	CR
PP	If I see someone in trouble, I will try my best to help s/he.	0.87	0.94
	I'm good at turning problems into opportunities.		
	I've been looking for a better way to do things.		
	When I have a problem, I would face it directly.		
	I like to challenge the status quo.		
	If I believe in an idea, nothing can stop me from achieving it.		
	If I believe in something, I will do it regardless of the likelihood of success.		
	There's nothing more exciting than seeing my ideas come to life.		
	I'm always looking for new ways to make my life better.		
	I enjoy facing and overcoming obstacles to my ideas.		
	I always want to be special in a certain group.		
SBE	I follow the rules of the online class.	0.90	0.91
	I have trouble using the online class.		
	When I am in the online class, I just 'act' as if I am learning.		
	I am able to consistently pay attention when I am taking the online class.		
	I complete my homework on time.		
SEE	I like taking the online class.	0.92	0.88
	I feel excited by my work at the online class.		
	The online classroom is a fun place to be.		
	I am interested in the work at the online class.		
	I feel happy when taking online class.		
	I feel bored by the online class.		
SCE	I check my schoolwork for mistakes.	0.79	0.89
	I study at home even when I do not have a test.		
	I try to look for some course-related information on other resources such television, journal papers, magazines, etc.		
	When I read the course materials, I ask myself questions to make sure I understand what it is about.		
	I read extra materials to learn more about things we do in the online class		
	If I do not know about a concept when I am learning in the online class, I do something to figure it out.		
	If I do not understanding what I learn online, I go back to watch the re-corded session and learning again.		
	I talk with people outside of school about what I am learning in the online class.		

PP proactive personality, *SBE* subjective measure of behavioral engagement, *SEE* subjective measure of emotional engagement, *SCE* subjective measure of cognitive engagement; *CR* composite reliability

ment (α=0.751), and *cognitive engagement* (α=0.629). Furthermore, Jung and Lee (2018) provided a satisfactory report of Cronbach's alpha coefficients of *behavioral engagement* (α=0.84), *emotional engagement* (α=0.92), and *cognitive engagement* (α=0.86) in their study. In our study, the Cronbach's alpha coefficients of each dimension were 0.90, 0.92, and 0.79, respectively. The values of composite reliability were 0.91, 0.88, and 0.89, respectively.

Objective measures of learning engagement were captured by the behavioral, emotional, and cognitive aspects of learner-generated digital contents in the log-file

Table 2 The coding scheme of objective measures of emotional and cognitive engagement

Engagement	Measure	Definition	Examples
OEE	Positive	The learner expresses positive emotions such as surprise, curiosity, enjoyment, pride, hope, and serenity	*Haha, I cannot agree with you more about this viewpoint*
	Negative	The learner expresses negative emotions, such as anxiety, frustration, boredom, anger, hopelessness, and shame	*I feel it is difficult to understand the brain mechanisms underlying emotional regulation*
	Confused	The learner experiences confused emotions, such as query, doubt, conjecture, and bewilderment	*How to explain the subconscious? I don't know*
OCE	Triggering event	The learner posts a question/problem observed or experienced to which he/she can relate from his/her own experience or previous studies	*How can we understand the relationship between language and cognitive development?*
	Exploration	The learner shares this/her understanding of the essence of the question/problem and searches for relevant information and explanations	*I think the development of language determines cognitive development as…*
	Integration	The learner constructs meaning from the information shared in exploration	*According to the articles, these two aspects are contingent on each other*
	Resolution	The learner resolves the question/problem through direct or mental modeling of solutions	*Recently I have used this method to alleviate my negative feelings. It did work well.*

OEE Objective measure of emotional engagement, O*CE* Objective measure of cognitive engagement

data. Regarding *behavioral engagement*, we followed the practice of Xu et al. (2020) who calculated it using the number of each student's contributions to the discussion forum. Regarding *emotional engagement*, it was represented by the numbers of thematic units of *positive*, *negative*, and *confused emotion* of each student in the discussion forum, as done by Liu et al. (2022). Regarding *cognitive engagement*, this study divided it into four kinds of cognitive events in online discussions, i.e., *triggering event*, *exploration*, *integration*, and *resolution*, as described in Galikyan and Admiraal (2019) and Galikyan et al. (2021).

Noticeably, we adopted the method of content analysis to analyze the latter two aspects of learning engagement in this study. The analysis unit of *emotional* and *cognitive engagement* were thematic units or units of meaning, but not the specific messages. According to Rourke et al. (2001) and Tirado et al. (2016), a unit of meaning could be defined as a thought, idea, or opinion. Depending on the semantic or affective sense used, each message could contain one or more units of meaning. Furthermore, we developed a coding scheme to analyze *emotional* and *cognitive engagement* in the discussion forum (Table 2). This scheme of *emotional engagement* was derived from Liu et al.'s (2022) work, while that of *cognitive engagement* was revised from the PIM framework developed by Garrison and Anderson (2003).

3.2.3 Online learning performance

This variable was measured by students' final course grade. It comprised weighted scores from online participation in discussions (5%), video viewing (5%), and a final course exam (90%). Notably, all students' final grade was converted to differentiated scores ranging from 0 to 100.

3.3 Data collection and analysis

Ethical approval s for participant recruitment and their consent to use online data were gained from the hosting institution. Participants' demographic information (including student ID, gender, grade, etc.) and their online learning information were collected from the log-file in StarC, i.e., login time, postings, video viewing, etc. Student ID was used to connect and organize the questionnaire and subjective and objective data of learning engagement. All students' names were pseudonyms.

Questionnaires concerning *Proactive Personality* and subjective measures of *learning engagement* were distributed through the Internet (https://www.wjx.cn/). In addition, as described above, the objective measures of *Behavioral Engagement* were represented as the number of contributions to the discussion forum. The quantitative statistics of objective measures of *emotional* and *cognitive Engagement* was conducted over three stages. In the first stage, two experienced coders were invited to code a sample of randomly selected 100 units of analysis independently. After discussing and analyzing the inconsistent results in the sample, they revised the coding scheme. For an analysis unit with multiple subcategories of *emotional* or *cognitive engagement*, we followed the practice of Wang et al. (2015) who selected the category with the longest emotional text length or the highest cognitive level. Secondly, the two coders were asked to jointly code 500 units of analysis in another sample and verified the reliability of the coding scheme. Two statistical values of 0.81 (Cohen's Kappa of *emotional engagement*) and 0.79 (Cohen's Kappa of *cognitive engagement*) were reached by both coders. Thirdly, the two coders coded the remaining units of analysis separately.

SPSS 22.0, as well as the Process plug-in written by Hayes (http://www.afhayes.com), was adopted for data statistical analysis. First, the mean value, standard deviation, range, skewness, and kurtosis of each variable in the research, as well as discriminant validity of each latent construct, were calculated and stored for subsequent correlation analysis and regression analysis. Second, two multiple collinearity tests were conducted among the subjective and objective measures of behavioral, emotional, and cognitive aspects of *learning engagement*, respectively. There existed varying degrees of multi-collinearity problem in both subjective and objective measures of *learning engagement* because the variance expansion factor of each measure was more than 1 (Hair et al., 2006). Therefore, we entered measures of one aspect of *learning engagement* at a time in the mediation effect tests to avoid serious threats to the validity of our findings. Third, we tested the mediation effect of subjective measures of *learning engagement* in the relationship between *proactive personality* and *online learning performance*. Noticeably, gender and age were included as two covariates in the mediation models, and data normalizations were performed prior to

Table 3 Descriptive statistics of the observed variables

Variables	Min	Max	Mean	SD	Skewness	Kurtosis
PP	2.64	5.00	3.95	0.48	0.23	0.17
SBE	2.00	5.00	3.95	0.60	-0.41	1.06
SEE	2.00	5.00	3.91	0.62	-0.47	0.81
SCE	2.25	5.00	3.59	0.55	0.15	0.29
OBE	4	32	17.29	6.02	0.44	-0.53
Positive	0	47	19.95	9.27	0.26	-0.36
Negative	0	22	9.27	5.82	0.29	-0.99
Confused	0	33	13.30	7.03	0.49	-0.36
Triggering	1	18	12.79	3.64	-0.98	-0.01
Exploration	1	36	15.23	8.77	0.03	-0.98
Integration	1	37	16.32	8.26	0.70	1.11
Resolution	0	13	4.09	3.96	0.81	-0.66
OLP	60	98	76.23	8.00	0.31	0.60

Min minimum, *Max* maximum, *SD* standard deviation; *OBE* objective measure of behavioral engagement; *Triggering* triggering event, *OLP* online learning performance

mediation effect tests. Fourth, we tested whether this relationship was mediated by objective measures of *learning engagement*. This step was aimed to supplement the results of subjective measures of *learning engagement* by incorporating its objective measures into analysis.

4 Results

4.1 Results of descriptive statistics

Table 3 shows the descriptive statistics of all variables in this study. First, the values of *proactive personality* and subjective measures of *learning engagement* were all above 3.90, indicating that students in this study tend to be dispositionally proactive and academically-engaged in the selected course. Second, there were varying ranges in the objective measures of *learning engagement*. For example, the measure of *positive emotion* ranged from 0 to 47, while the *resolution* measure ranged from 0 to 13. Third, the skewness and kurtosis values of all variables were all less than 1 and 1.5, demonstrating that all variables were approximately subordinate to normal distribution. Also, this finding was further verified by tests of normality plots.

Table 4 shows the validity of and bivariate Pearson correlations among *proactive personality*, subjective and objective measures of *learning engagement*, and *online learning performance*, as well as their validity evidence. First, *proactive personality* was positively correlated with *online learning performance* ($r=0.53$, $p<0.001$), and all subjective (r ranged from 0.14 to 0.53) and objective measures (r ranged from 0.12 to 0.52) of *learning engagement* except for *Exploration* ($r=0.03$, $p>0.05$). Second, *online learning performance* was positively correlated with all subjective (r ranged from 0.61 to 0.63) and objective (r ranged from 0.16 to 0.47) measures of *learning engagement* except for *exploration* ($r=0.09$, $p>0.05$). Overall, these results serve as the foundations for the following mediation model tests. Besides, the square

Table 4 Validity and bivariate correlations

Variables	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1.PP (0.76)	0.58^{**}	0.53^{**}	0.48^{**}	0.14^{*}	0.52^{**}	0.44^{**}	0.50^{**}	0.12^{*}	0.03	0.18^{**}	0.30^{**}	0.53^{**}
2.SBE (0.81)		0.84^{**}	0.68^{**}	0.04	0.39^{**}	0.26^{**}	0.26^{**}	0.17^{**}	0.02	0.08	0.12^{*}	0.61^{**}
3.SEE (0.75)			0.69^{**}	0.06	0.33^{**}	0.26^{**}	0.23^{**}	0.13^{*}	0.04	0.08	0.13^{*}	0.62^{**}
4.SCE (0.71)				0.09	0.35^{**}	0.33^{**}	0.28^{**}	0.19^{**}	0.02	0.20^{**}	0.15^{**}	0.63^{**}
5.OBE					0.19^{**}	0.21^{**}	0.16^{**}	-0.18^{**}	0.83^{**}	0.72^{**}	0.67^{**}	0.16^{**}
6.Positive						0.48^{**}	0.52^{**}	0.22^{**}	0.09	0.22^{**}	0.37^{**}	0.47^{**}
7.Negative							0.53^{**}	0.25^{**}	0.02	0.29^{**}	0.35^{**}	0.39^{**}
8.Confused								0.45^{**}	-0.04	0.48^{**}	0.57^{**}	0.43^{**}
9.Triggering									0.01	0.07	0.08	0.25^{**}
10.Exploration										0.34^{**}	0.41^{**}	0.09
11.Integration											0.47^{**}	0.23^{**}
12.Resolution												0.24^{**}
13.OLP												

The number in the parenthesis after each variable represent its square roots of average variance extracted (AVE);

$^{***}p<0.001$, $^{**}p<01$, $^{*}p<0.05$, two-tailed Pearson correlation roots of the average variance extracted (AVE) of each latent construct (in the parenthesis after each variable) were higher than the correlations among the constructs themselves except the correlation between subjective measures of *behavioral* and *emotional engagement* ($r = 0.84$). As a whole, this finding suggested acceptable discriminant validity.

4.2 Results of the mediation model tests

Before testing our proposed research model, we analyzed the overall effect of *proactive personality* on *online learning performance*. Results showed that proactive personality could positively predict *online learning performance* ($\beta = 0.54$, $p < 0.001$), which supported H1 and laid the foundation for subsequent mediation model tests.

Table 5 shows the main results of testing the mediation effects of subjective measures of l*earning engagement* in the relationship between *proactive personality* and *online learning performance*. First, *proactive personality* positively predicted subjective measure of *behavioral engagement* ($\beta = 0.42$, $p < 0.001$), which in turn positively predicted *online learning performance* ($\beta = 0.25$, $p < 0.01$). Second, *proactive personality* positively predicted subjective measure of *emotional engagement* ($\beta = 0.38$, $p < 0.001$), which in turn positively predicted *online learning performance* ($\beta = 0.25$, $p < 0.001$). Third, *proactive personality* positively predicted subjective measure of *cognitive engagement* ($\beta = 0.49$, $p < 0.001$), which in turn positively predicted *online learning performance* ($\beta = 0.49$, $p < 0.001$). Further tests of indirect effects (see Table 6) showed significant indirect effects of *proactive personality* on *online learning performance* via all subjective measures of *learning engagement* ($\beta = 0.107$, [0.040, 0.190]; $\beta = 0.099$, [0.035, 0.184]; $\beta = 0.237$, [0.171, 0.309]). Therefore, subjective measures of *Behavioral*, *Emotional*, and *Cognitive Engagement* mediated the relationship between *proactive personality* and *online learning performance*. Fig. 3 plotted the standardized coefficients of the mediation models.

Table 7 shows the main results of testing the mediation effects of objective measures of *learning engagement* in the relationship between *proactive personality* and *online learning performance*. First, *proactive personality* positively predicted the objective measure of *behavioral engagement* ($\beta = 0.14$, $p < 0.05$), which in turn positively and marginally predicted *online learning performance* ($\beta = 0.08$, $p = 0.069$). Second, *proactive personality* positively predicted subjective measure of *positive* ($\beta = 0.52$, $p < 0.001$), *negative* ($\beta = 0.49$, $p < 0.001$), and *confused* ($\beta = 0.44$, $p < 0.001$) *emotion* in *emotional engagement*, all of which positively predict *online learning performance* ($\beta = 0.20$, $p < 0.01$; $\beta = 0.17$, $p < 0.01$) except for *negative emotion* ($\beta = 0.04$, $p > 0.05$). Third, *proactive personality* positively predicted subjective measure of *triggering event* ($\beta = 0.11$, $p < 0.05$), *integration* ($\beta = 0.18$, $p < 0.01$), and *resolution* ($\beta = 0.30$, $p < 0.001$) in *cognitive engagement*, all of which positively predicted *online learning performance* ($\beta = 0.19$, $p < 0.001$; $\beta = 0.11$, $p < 0.05$) except for *resolution* ($\beta = 0.04$, $p > 0.05$). Further tests of indirect effects (see Table 8) showed significant indirect effects of *proactive personality* on *online learning performance* via the objective measure of ($\beta = 0.012$, [0.001, 0.037]), *positive* and confused *emotion* in *emotional engagement* ($\beta = 0.101$, [0.043, 0.168]; $\beta = 0.074$, [0.025, 0.137]), and *triggering event* and *integration* in *cognitive engagement* ($\beta = 0.022$, [0.005,

Table 5 Regressions testing subjective measures of learning engagement in the association between proactive personality and online learning performance

Regression equation		Fitting index			Significance of coefficients			
outcome	predictors	R	R^2	F	β	t	LLCI	ULCI
Model S_1 (Subjective measure of *Behavioral Engagement* as mediator)								
SBE	PP	0.45	0.21	15.83^{***}	0.42	6.50^{***}	0.29	0.55
OLP	PP	0.58	0.34	37.94^{***}	0.44	6.68^{***}	0.31	0.56
	SBE				0.25	3.26^{**}	0.10	0.41
Model S_2 (Subjective measure of *Emotional Engagement* as mediator)								
SEE	PP	0.42	0.18	12.78^{***}	0.38	5.62^{***}	0.25	0.52
OLP	PP	0.59	0.34	39.96^{***}	0.44	6.52^{***}	0.31	0.58
	SEE				0.25	3.36^{***}	0.11	0.41
Model S_3 (Subjective measure of *Cognitive Engagement* as mediator)								
SCE	PP	0.48	0.23	28.17^{***}	0.49	9.16^{***}	0.38	0.59
OLP	PP	0.69	0.47	64.91^{***}	0.31	6.71^{***}	0.22	0.40
	SCE				0.49	10.54^{***}	0.40	0.58

Note. LL=lower limit, CI=confidence interval, UL=upper limit

Table 6 Tests of indirect effects of proactive personality on online learning performance via subjective measures of learning engagement

Model	Mediator	Effect size	Boot SE	Boot LLCI	Boot ULCI
S_1	BE	0.107	0.037	0.040	0.190
S_2	EE	0.099	0.039	0.035	0.184
S_3	CE	0.237	0.044	0.171	0.309

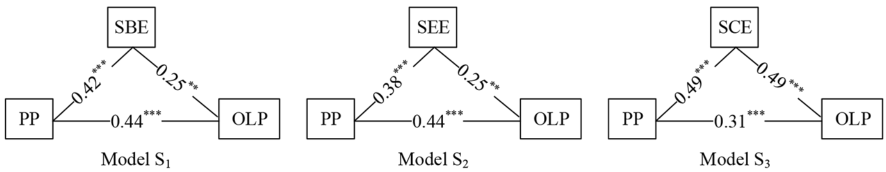

Fig. 3 Path diagram of the mediation models of subjective measure of Learning Engagement

0.050]; β=0.020, [0.002, 0.054]). However, the indirect effects via *negative emotion* (β=0.018, [-0.051, 0.079]) and *resolution* (β=0.011, [-0.018, 0.045]) were non-significant. Therefore, it gained partial support that objective measures of *behavioral*, *emotional*, and *cognitive engagement* mediated the relationship between *proactive personality* and *online learning performance*. Fig. 4 plotted the standardized coefficients of the mediation models.

5 Discussion

This study was aimed to investigate the relationship between proactive personality and online learning performance, and further test whether learning engagement mediates this relationship. Despite the vast body of literature on the relationship

Table 7 Regressions testing objective measures of Learning Engagement in the association between *Proactive Personality* use and *Online Learning Performance*

Regression equation		Fitting index			Significance of coefficients			
outcome	predictors	R	R^2	F	β	t	LLCI	ULCI
Model O_1 (Objective measure of *Behavioral Engagement* as mediators)								
OBE	PP	0.14	0.02	2.13 (p=0.097)	0.14	2.40^{*}	0.03	0.25
OLP	PP	0.54	0.30	28.81^{***}	0.53	10.23^{***}	0.43	0.63
	OBE				0.08	1.82 (p=0.069)	-0.007	0.17
Model O_2 (Objective measures of *Emotional Engagement* as mediators)								
Positive	PP	0.52	0.27	54.59^{***}	0.52	12.41^{***}	0.44	0.60
Negative	PP	0.51	0.26	51.14^{***}	0.49	11.65^{***}	0.41	0.57
Confused	PP	0.44	0.20	35.95^{***}	0.44	10.27^{***}	0.36	0.52
OLP	PP	0.60	0.37	23.68^{***}	0.35	5.87^{***}	0.23	0.47
	Positive				0.20	3.19^{**}	0.07	0.32
	Negative				0.04	0.55	-0.09	0.17
	Confused				0.17	2.74^{**}	0.05	0.29
Model O_3 (Objective measures of *Cognitive Engagement* as mediators)								
Triggering	PP	0.15	0.02	2.77^{*}	0.11	2.24^{*}	0.01	0.21
Ingetration	PP	0.19	0.04	3.45^{*}	0.18	3.06^{**}	0.07	0.30
Resolution	PP	0.31	0.09	10.26^{***}	0.30	5.15^{***}	0.18	0.41
OLP	PP	0.59	0.34	24.09^{***}	0.49	8.60^{***}	0.38	0.60
	Triggering				0.19	3.75^{***}	0.09	0.29
	Integration				0.11	2.08^{*}	0.01	0.21
	Resolution				0.04	0.72	-0.06	0.14

Table 8 Tests of indirect effects of *Proactive Personality* on *Online Learning Performance* via objective measures of *Learning Engagement*

Model	Mediator	Effect size	Boot SE	Boot LLCI	Boot ULCI
O_1	OBE	0.012	0.009	0.001	0.037
O_2	Positive	0.101	0.031	0.043	0.168
	Negative	0.018	0.032	-0.051	0.079
	Confused	0.074	0.027	0.025	0.137
O_3	Triggering	0.022	0.011	0.005	0.050
	Integration	0.020	0.013	0.002	0.054
	Resolution	0.011	0.016	-0.018	0.045

between learner characteristics and online learning performance, most of them focus on demographic variables (e.g., Ghaleb et al., 2021; Ruipérez-Valiente et al., 2022; Yu, 2021), broad personality traits (e.g., Abe, 2020; Yu, 2021), etc. This study contributes to the literature by investigating the role of a narrow descriptor of personality that highly matches with the environments of online learning. In addition, it further explores the mediating role of learning engagement as a multidimensional construct that could explain how proactive personality promotes online learning performance. Moreover, this study innovatively used both subjective and objective data of learning engagement collected from self-reports and learners' digital traces in the online discussion forum.

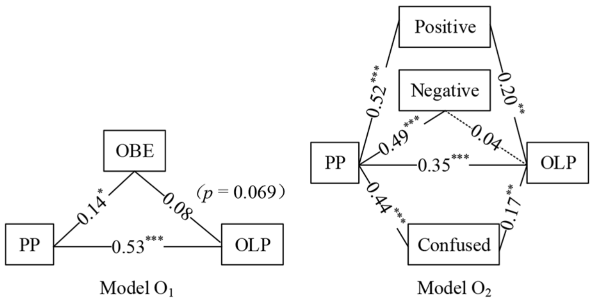

Fig. 4 Path diagram of the mediation models of objective measure of Learning Engagement

First, the overall effect of proactive personality on online learning performance was found to be significantly positive, indicating that proactive personality is a valid predictor of online learning performance. As such, Research Hypothesis 1 was supported. This finding was consistent with previous studies documenting the direct link between proactive personality and online learning performance (Kickul & Kickul, 2006; Zhu et al., 2019). On the one hand, it echoes the recent active learning approach (e.g., Lamon et al., 2020; Theobald et al., 2020) highlighting the important role of proactivity for motivating academic success. On the other hand, it coincides with the stipulation of trait activation theory (Tett & Guterman, 2000) and person-environment fit theory (Edwards et al., 1998) that whether learner differences match the learning environments determines their learning performance. During online learning, learners are separated from their teachers physically and located in an environment full of challenging, autonomous, and asynchronous nature. Compared to traditional classes, learners in online classes should be more self-disciplined, self-motivated, and goal-orientated in order to have equivalent learning gains (Gregory, 2016). Therefore, learners with high proactive personality are more likely to have better online learning performance than those with low.

Second, this study further found significantly positive mediating effects of almost all aspects of learning engagement, be it measured by subjective and objective data, in the relationship between proactive personality and online learning performance. Thus, Research Hypotheses 2–4 were generally supported, though not statistically validated by all measures of learning engagement. These findings indicated that learning engagement could act as a mediator in the relationship between proactive personality and online learning performance. In line with the MSDLOE (Money & Dean, 2019) and 3P Model of Teaching and Learning (Biggs, 1993), these findings support the proposition that learning engagement act as a key mediator that links learner differences to learning performance in traditional or online classes. In addition, for the first stage of the mediation process (i.e., the association between proactive personality and learning engagement), our results coincide with the characteristics of proactive personality suggesting that learners high in this personality trait tend to take more proactive actions in various environments (Bateman & Crant, 1993). In online learning environments, these proactive actions could reflect in more contributions to the discussion forum, and more emotional and cognitive events in the discussion discourse. For the second stage of the mediation process (i.e., the association between learning engagement and online learning performance), our results are compatible with previous studies illustrating the link between certain aspects of learning engagement and online learning performance (e.g., Barba et al., 2016; Morris et al., 2005). The more learners engage in online learning in the behavioral, emotional, and cognitive aspects, the better learning performance they could gain.

Finally, it should be noted that the mediating effects of '*negative emotion'* and '*resolution*' measures of learning engagement were not supported by the analysis results. This may be attributed to the problem of varying degrees of multi-collinearity in both objective emotional and cognitive engagement (Hair et al., 2006). According to the statistical characteristic of multi-collinearity, it is likely that some other measures (e.g., '*positive emotion*', '*triggering event*', etc.) in objective learning engagement may overshadow those two measures' mediating effects. Given that our research goal was only to unveil the mediating role of overall level of both emotional and cognitive engagement, it is therefore not necessary to further determine the independent role of their every sub measures.

6 Conclusion

This study examines the relationship between proactive personality and online learning performance and whether this relationship is mediated by learning engagement. Our results show that proactive personality could positively promote online learning performance through the mediating role of learning engagement. In other words, proactive personality exerts its positive effect on online learning performance via the intermediary benefits of learning engagement. Hence, it is only through learning engagement that students' proactive personality could positively influence online learning performance.

6.1 Educational implications

6.1.1 Theoretical implications

First, this study extends trait activation theory and person-environment fit theory from the traditional work contexts to online learning by examining proactive personality as a predictor of online learning performance. Second, this study empirically tests the validity of MSDLOE and extends 3P Model of Teaching and Learning from traditional face-to-face classes to online classes by incorporating learning engagement as a mediator into the relationship between proactive personality and online learning performance. By doing so, we could gain valuable insights about the effect of proactive personality on online leaning performance and its underlying mediating mechanism. When exploring the effects of learner differences on online learning performance, previous studies generally focused on demographic variables and broad personality traits, and rarely examined the underlying mechanism. Findings of this study help fill in these gaps by adding proactive personality as a key predictor and learning engagement as a mediator in jointly predicting online learning performance.

6.1.2 Methodological implications

Methodologically, previous studies on learning engagement in online learning either adopted self-reported instruments (i.e., questionnaires or validated tests) to collect subjective data, or applied learning analytics methods to analyze objective data in the log file to measure engagement. On the one hand, self-reported measures are sensitive to higher measurement errors. On the other hand, objective measures are limited to the behavioral and cognitive aspects of engagement. This study combined self-reports and learning analytics methods to analyze both subjective and objective data of learning engagement from the behavioral, emotional, and cognitive aspects. Specifically, we collected the objective data of learning engagement exclusively from the discussion forum as it is the primary space for learners to show their various aspects of engagement in online learning. Thus, these two methods of data analysis could supplement for each other and provide a comprehensive understanding of the role of learning engagement. In addition, to eliminate the adverse effect of multi-collinearity, we only incorporated measure(s) of one aspect of learning engagement each time into the mediation model tests.

6.1.3 Practical implications

First, given the positive association between proactive personality and online learning performance, it is important to pay special attention to learners who have low levels of proactive personality. When these learners are found to be in need of help, timely and effective assistance is highly recommended to support their online learning success. Second, the finding regarding the mediating effect of learning engagement in the relationship between proactive personality and online learning performance indicates the need to effectively promote learning engagement in online learning. Specifically, course instructors could develop some online collaborative activities or tasks (Dumford & Miller, 2018), provide high-quality feedback (Chiu, 2022), and conduct active learning activities (Gray & DiLoreto, 2016) to facilitate learners' various aspects of learning engagement. Third, given the robust relationship between learning engagement in the discussion forum and online learning performance, course instructors should devote more efforts to encourage learners' engagement especially in this learning space, such as the adoption of topic analysis instant feedback system (Chen et al., 2020), the implementation of online collective reflection (Lord et al., 2017), etc.

6.2 Limitations

First, participants were recruited from a single online course in a university using a convenience sampling method, so they were highly homogeneous. Further research will be implemented among diverse learner populations (i.e., learners from different courses and universities) to obtain stronger statistical power in different types of teaching modes. Second, the present study only included gender and age as the covariates in the proposed research models. Other factors such as major, prior knowledge, and online learning attitude may also potentially influence the hypothesized associations. One avenue of future research may be to collect more other factors to alleviate the extraneous effect of covariates. Third, this study only selected proactive personality as the representative of learners' personality traits and analyzed learners' objective measures of learning engagement extracted solely from the log files on the discussion forum. Future research is needed to examine the role of the other personality traits and extract objective data of learning engagement from other spaces in specific online learning platform.

Acknowledgements Not applicable.

Author contribution All the authors had the same role in Conceptualization, Methodology, Formal analysis and investigation, writing- Original draft preparation, etc.

Funding This work was supported by the Postdoctoral Science Foundation Funded Project of China under Grant [2021M700463]. No competing financial interests existed.

Data Availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no competing interests.

References

Abe, J. A. A. (2020). Big five, linguistic styles, and successful online learning. *The Internet and Higher Education*, *45*, 100724

Altanopoulou, P., & Tselios, N. (2018). Big Five personality traits and academic learning in wiki-mediated collaborative activities: Evidence from four case studies. *International Journal of Distance Education Technologies (IJDET)*, *16*(3), 81–92

Bateman, T. S., & Crant, J. M. (1993). The proactive component of organizational behavior: A measure and correlates. *Journal of Organizational Behavior*, *14*, 103–118

Biggs, J. B. (1993). From theory to practice: A cognitive systems approach. *Higher Education Research & Development*, *12*(1), 73–85

Campbell, J., Gibbs, A. L., Najafi, H., & Severinski, C. (2015). A comparison of learner intent and behaviour in live and archived MOOCs. *International Review of Research in Open and Distance Learning*, *15*(5), 235–262

Chen, P., Bao, C., & Gao, Q. (2021). Proactive personality and academic engagement: The mediating effects of teacher-student relationships and academic self-Efficacy. *Frontiers in Psychology*, *12*, 652994.

Chen, C., Li, M., Chang, W., & Chen, X. (2020). Developing a topic analysis instant feedback system to facilitate asynchronous online discussion effectiveness. *Computers & Education*, *163*, 104095

Chiu, T. K. F. (2022). Applying the self-determination theory (SDT) to explain student engagement in online learning during the COVID-19 pandemic. *Journal of Research on Technology in Education*, *54*(1), 14–30

Cidral, W. A., Oliveira, T., Di Felice, M., & Aparicio, M. (2018). E-learning success determinants: Brazilian empirical study. *Computers & Education*, *122*, 273–290

Comer, D. K., Baker, R., & Wang, Y. (2015). Negativity in massive online open courses: Impacts on learning and teaching and how instructional teams may be able to address it. *InSight: A Journal of Scholarly Teaching*, *10*, 92–113

Cook, D. A., & Artino, A. R. Jr. (2016). Motivation to learn: An overview of contemporary theories. *Medical Education*, *50*(10), 997–1014
Crant, J. M. (1995). The proactive personality scale and objective job performance among real estate agents. *Journal of Applied Psychology*, *80*, 532–537
Crant, J. M. (1996). The proactive personality scale as a predictor of entrepreneurial intentions. *Journal of Small Business Management*, *34*(3), 62–74
der Barba, P. G., Kennedy, G. E., & Ainley, M. D. (2016). The role of students' motivation and participation in predicting performance in a MOOC: Motivation and participation in MOOCs. *Journal of Computer Assisted Learning*, *32*(3), 218–231
Deci, E. L., & Ryan, R. M. (1985). The general causality orientations scale: Self-determination in personality. *Journal of Research in Personality*, *19*(2), 109–134
Deng, R., Benckendorff, P., & Gannaway, D. (2020a). Linking learner factors, teaching context, and engagement patterns with MOOC learning outcomes. *Journal of Computer Assisted Learning*, *36*(5), 688–708
Deng, R., Benckendorff, P., & Gannaway, D. (2020b). Learner engagement in MOOCs: Scale development and validation. *British Journal of Educational Technology*, *51*(1), 245–262
Diep, N. A., Cocquyt, C., Zhu, C., Vanwing, T., & de Greef, M. (2017). Effects of core self-evaluation and online interaction quality on adults' learning performance and bonding and bridging social capital. *The Internet and Higher Education*, *34*, 41–55
Dikaya, L. A., Avanesian, G., Dikiy, I. S., Kirik, V. A., & Egorova, V. A. (2021). How personality traits are related to the attitudes toward forced remote learning during COVID-19: Predictive analysis using Generalized Additive Modeling. *Frontiers in Education*, *6*, 629213
Dumford, A. D., & Miller, A. L. (2018). Online learning in higher education: Exploring advantages and disadvantages for engagement. *Journal of Computing in Higher Education*, *30*(3), 452–465
Edwards, J. R., Caplan, R. D., & Harrison, V. R. (1998). Person-environment fit theory: Conceptual foundations, empirical evidence, and directions for future research. In C. L. Cooper (Ed.), *Theories of organizational stress*. Oxford: Oxford University Press
Eynon, R., & Malmberg, L. E. (2021). Lifelong learning and the Internet: Who benefits most from learning online? *British Journal of Educational Technology*, *52*(2), 569–583
Galikyan, I., & Admiraal, W. (2019). Students' engagement in asynchronous online discussion: The relationship between cognitive presence, learner prominence, and academic performance. *The Internet and Higher Education*, *43*, 1–9
Galikyan, I., Admiraal, W., & Kester, L. (2021). MOOC discussion forums: The interplay of the cognitive and the social. *Computers & Education*, *165*, 104133
Gao, J., Li, M., & Zhang, W. (2015). The relationship between proactive personality and E-learning engagement: A perspective of self-determination theory of motivation. *E-Education Research*, *8*, 18–29
Ghaleb, A., El Refae, G., Kaba, A., & Eletter, S. (2021). The impact of demographic characteristics on academic performance: Face-to-face learning versus distance learning implemented to prevent the spread of COVID-19. *International Review of Research in Open and Distance Learning*, *22*(1), 91–110
Giannakos, M. N., Chorianopoulos, K., & Chrisochoides, N. (2015). Making sense of video analytics: Lessons learned from clickstream interactions, attitudes, and learning outcome in a video-assisted course. *International Review of Research in Open and Distance Learning*, *16*(1), 260–283
Gray, J. A., & DiLoreto, M. (2016). The effects of student engagement, student satisfaction, and perceived learning in online learning environments. *International Journal of Educational Leadership Preparation*, *11*(1), 1–20
Gregory, C. B., & Lampley, J. H. (2016). Community college student success in online versus equivalent face-to-face courses. *Journal of Learning in Higher Education*, *12*(2), 63–72
Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (2006). *Multivariate data analysis* (6th ed.). Upper Saddle River, NJ: Prentice Hall
Hofer, S. I., Nistor, N., & Scheibenzuber, C. (2021). Online teaching and learning in higher education: Lessons learned in crisis situations. *Computers in Human Behavior*, *121*, 106789
Islam, S., Permzadian, V., Choudhury, R. J., Johnston, M., & Anderson, M. (2018). Proactive personality and the expanded criterion domain of performance: Predicting academic citizenship and counterproductive behaviors. *Learning and Individual Differences*, *65*, 41–49
Jung, Y., & Lee, J. (2018). Learning engagement and persistence in Massive Open Online Courses (MOOCS). *Computers & Education*, *122*, 9–22

Kickul, G., & Kickul, J. (2006). Closing the gap: Impact of student proactivity and learning goal orientation on e-learning outcomes. *International Journal on E-learning*, *5*(3), 361–372

Knowles, M. S., Holton, E. F., & Swanson, R. A. (2015). *The adult learner: The definitive classic in adult education and human resource development* (8th ed.).). New York, NY: Routledge

Kumar, P., Kumar, A., Palvia, S., & Verma, S. (2019). Online business education research: Systematic analysis and a conceptual model. *The International Journal of Management Education*, *17*(1), 26–35

Lamon, S., Knowles, O., Hendy, A., Story, I., & Currey, J. (2020). Active learning to improve student learning experiences in an online postgraduate course. *Frontiers in Education*, *5*, 598560

Li, N., Kidzinski, L., Jermann, P., & Dillenbourg, P. (2015). How do in-video interactions reflect perceived video difficulty? Paper presented at the *European MOOC Stakeholder Summit 2015*, Mons, Belgium

Li, Q., & Baker, R. (2018). The different relationships between engagement and outcomes across participant subgroups in Massive Open Online Courses. *Computers & Education*, *127*, 41–65

Liu, S., Liu, S., Liu, Z., Peng, X., & Yang, Z. (2022). Automated detection of emotional and cognitive engagement in MOOC discussions to predict learning achievement. *Computers & Education*, *181*, 104461

Liu, S., Peng, X., Cheng, H. N. H., Liu, Z., Sun, J., & Yang, C. (2019). Unfolding sentimental and behavioral tendencies of learners' concerned topics from course reviews in a MOOC. *Journal of Educational Computing Research*, *57*(3), 670–696

Lord, A. Y. Z., Chen, M., Cheng, Y., Tai, K., & Pan, W. (2017). Enhancing nutrition-majored students' reflective judgment through online collective reflection. *Computers & Education*, *114*, 298–308

Lowe, J. S., & Holton, E. F. (2005). A theory of effective computer-based instruction for adults. *Human Resource Development Review*, *4*(2), 159–188

Lu, C., & Cutumisu, M. (2022). Online engagement and performance on formative assessments mediate the relationship between attendance and course performance. *International Journal of Educational Technology in Higher Education*, *19*(1), 1–23

Lubinski, D. (2020). Understanding educational, occupational, and creative outcomes requires assessing intraindividual differences in abilities and interests. *Proceedings of the National Academy of Sciences, 117*(29), 16720–16722

Major, D. A., Turner, J. E., & Fletcher, T. D. (2006). Linking proactive personality and the Big Five to motivation to learn and development activity. *Journal of Applied Psychology*, *91*(4), 927–935

Money, W. H., & Dean, B. P. (2019). Incorporating student population differences for effective online education: A content-based review and integrative model. *Computers & Education*, *138*, 57–82

Morris, L. V., Finnegan, C., & Wu, S. (2005). Tracking student behavior, persistence, and achievement in online courses. *The Internet and Higher Education*, *8*(3), 221–231

Panigrahi, R., Srivastava, P. R., & Sharma, D. (2018). Online learning: Adoption, continuance, and learning outcome—A review of literature. *International Journal of Information Management*, *43*, 1–14

Perez Alvarez, R. A., Maldonado, J., Sharma, K., Sapunar, D., & Perez-Sanagustin, M. (2020). Characterizing learners' engagement in MOOCs: An observational case study using the NoteMyProgress tool for supporting self-regulation. *IEEE Transactions on Learning Technologies*, *13*(4), 676–688

Rourke, L., Anderson, T., Archer, W., & Garrison, D. R. (2001). Assessing social presence in asynchronous, text based computer conferences. *Journal of Distance Education, 14*, 51–70

Ruipérez-Valiente, J. A., Staubitz, T., Jenner, M., Halawa, S., Zhang, J., Despujol, I., et al. (2022). Large scale analytics of global and regional MOOC providers: Differences in learners' demographics, preferences, and perceptions. *Computers & Education*, *180*, 104426

Shang, J., & Gan, Y. (2009). Analysis of the effects of the proactive personality on graduates' career decision making self-efficacy. *Acta Scientiarum Naturalium Universitatis Pekinensis*, *45*(3), 548–554

Sinha, T., Jermann, P., Li, N., & Dillenbourg, P. (2014). Your click decides your fate: Inferring information processing and attrition behavior from MOOC video clickstream interactions. *2014 empirical methods in natural Language processing workshop on modeling large scale social interaction in massively open online courses*

Stoet, G., & Geary, D. C. (2020). Gender differences in the pathways to higher education. *Proceedings of the National Academy of Sciences, 117*(25), 14073–14076

Sun, A., & Chen, X. (2016). Online education and its effective practice: A research review. *Journal of Information Technology Education*, *15*, 157–190

Sun, J. C., & Rueda, R. (2012). Situational interest, computer self-efficacy and self-regulation: Their impact on student engagement in distance education. *British Journal of Educational Technology*, *43*(2), 191–204

Tallent-Runnels, M. K., Thomas, J. A., Lan, W. Y., & Cooper, S. (2006). Teaching courses online: A review of the research. *Review of Educational Research*, *76*(1), 93–135

Tett, R. P., & Guterman, H. A. (2000). Situation trait relevance, trait expression, and cross-situational consistency: Testing a principle of trait activation. *Journal of Research in Personality*, *34*(4), 397–423

Theobald, E. J., Hill, M. J., Tran, E., Agrawal, S., Arroyo, E. N., Behling, S., et al. (2020). Active learning narrows achievement gaps for underrepresented students in undergraduate science, technology, engineering, and math. *Proceedings of the National Academy of Sciences, 117*(12), 6476–6483

Tirado Morueta, R., Maraver López, P., Gómez, H., & Harris, Á., V. W (2016). Exploring social and cognitive presences in communities of inquiry to perform higher cognitive tasks. *The Internet and Higher Education*, *31*, 122–131

Veletsianos, G., Collier, A., & Schneider, E. (2015). Digging deeper into learners' experiences in MOOCs: Participation in social networks outside of MOOCs, notetaking and contexts surrounding content consumption. *British Journal of Educational Technology*, *46*(3), 570–587

Xiong, Y., Li, H., Kornhaber, M. L., Suen, H. K., Pursel, B., & Goins, D. D. (2015). Examining the relations among student motivation, engagement, and retention in a MOOC: A structural equation modeling approach. *Global Education Review*, *2*(3), 23–33

Xu, B., Chen, N., & Chen, G. (2020). Effects of teacher role on student engagement in WeChat-Based online discussion learning. *Computers & Education*, *157*, 103956

Yu, Z. (2021). The effects of gender, educational level, and personality on online learning outcomes during the COVID – 19 pandemic. *International Journal of Educational Technology in Higher Education*, *18*(14), 1–17

Zhang, S., & Liu, Q. (2019). Investigating the relationships among teachers' motivational beliefs, motivational regulation, and their learning engagement in online professional learning communities. *Computers & Education*, *134*, 145–155

Zhu, C., Chai, H., Zhou, X., & Sun, X. (2019). The relationship among proactive personality, interpersonal interactions, and learning performance in blended learning environments. *Distance Education in China*, *8*, 68–78

Authors and Affiliations

Huanyou Chai[1] · Tianhui Hu[2] · Gengfeng Niu[3]

✉ Huanyou Chai
hychai@bnu.edu.cn

Tianhui Hu
huayuan2963291362@mails.ccnu.edu.cn

Gengfeng Niu
niugfpsy@ccnu.edu.cn

[1] Research Center of Distance Education, Beijing Normal University, Beijing, China

[2] Faculty of Artificial Intelligence in Education, Central China Normal University, Wuhan, China

[3] School of Psychology, Central China Normal University, Wuhan, China