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
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-
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

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

![Proposed research model](image-url)
H1: Proactive personality positively predicts performance in online learning.
H2: Behavioral engagement mediates the relationship between proactive personality and online learning performance.
H3: Emotional engagement mediates the relationship between proactive personality and online learning performance.
H4: 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 (α=0.86) in the study by Shang and Gan (2009). In this study, this scale has also demonstrated a good reliability (α=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 (α=0.880), emotional engage-
ment ($\alpha=0.751$), and cognitive engagement ($\alpha=0.629$). Furthermore, Jung and Lee (2018) provided a satisfactory report of Cronbach’s alpha coefficients of behavioral engagement ($\alpha=0.84$), emotional engagement ($\alpha=0.92$), and cognitive engagement ($\alpha=0.86$) 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

| Construct | Measurement Items | Cronbach’s alpha | CR |
|-----------|-------------------|------------------|----|
| PP        | If I see someone in trouble, I will try my best to help s/he. 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. | 0.87 | 0.94 |
| SBE       | I follow the rules of the online class. 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. | 0.90 | 0.91 |
| SEE       | I like taking the online class. 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. | 0.92 | 0.88 |
| SCE       | I check my schoolwork for mistakes. 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 recorded session and learning again. I talk with people outside of school about what I am learning in the online class. | 0.79 | 0.89 |

PP proactive personality, SBE subjective measure of behavioral engagement, SEE subjective measure of emotional engagement, SCE subjective measure of cognitive engagement; CR composite reliability
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 Admiraaal (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).

### 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 |
| OEE        | 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 |
| OEE        | 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? |
| OCE        | 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... |
| OCE        | Integration | The learner constructs meaning from the information shared in exploration | According to the articles, these two aspects are contingent on each other |
| OCE        | 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. |

OEEOEE Objective measure of emotional engagement, OCE Objective measure of cognitive engagement
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 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
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 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

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  | 0.23** | 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|       |       |       |       |       |       |       |       |       |       |       |       |
| 13.OLP      |       |       |       |       |       |       |       |       |       |       |       | 0.24** |

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

*** p<0.001, ** p<0.01, * 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 learning 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,
0.050; \( \beta = 0.020, [0.002, 0.054] \)). However, the indirect effects via negative emotion (\( \beta = 0.018, [-0.051, 0.079] \)) and resolution (\( \beta = 0.011, [-0.018, 0.045] \)) 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
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.

| 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 | R² | F | β | t | LLCI | ULCI |
| Model O₁ (Objective measure of Behavioral Engagement as mediators) | | | | | | | |
| OBE | PP | 0.14 | 0.02 | 2.13 | 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 | | | | | | | (p=0.069) |
| Model O₂ (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 | | | | | | | |
| Negative | | | | | | | |
| Confused | | | | | | | |
| Model O₃ (Objective measures of Cognitive Engagement as mediators) | | | | | | | |
| Triggering | PP | 0.15 | 0.02 | 2.77* | 0.11 | 2.24* | 0.01 | 0.21 |
| Integration | 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 | | | | | | | |
| Integration | | | | | | | |
| Resolution | | | | | | | |

| 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 |
| O₁ | OBE | 0.012 | 0.009 | 0.001 | 0.037 |
| O₂ | 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 |
| O₃ | 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 |
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 learning 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.

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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.

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