Perception of Massive Open Online Courses and Its Relationship With Students' Learning Strategies

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ABSTRACT

The aim of the present paper is to explore students' perceptions of MOOCs in relation to their learning strategies. Drawing upon cognitive appraisal theory and learning strategies framework, the study examines the perception of MOOCs as threats or challenges and assesses students' learning approaches through the prism of deep and surface learning strategies. Survey data from 389 students enrolled in a MOOC form the empirical basis of the study. Analysis revealed that cognitive appraisal of MOOCs as a challenge is strongly related to the adoption of deep learning strategies. Conversely, perceiving MOOCs as a threat is associated with the use of surface learning strategies, although such strategies display a weaker yet significant relationship with perceiving MOOCs as a challenge. The implications of this research shed light on enhancing the quality of learning experiences and implementing learning strategies in MOOCs. Implementing these strategies can contribute to the improvement of MOOC design and instructional practices, ultimately fostering positive learning outcomes for students.

KEYWORDS

Cognitive Appraisal, Learning Strategies, MOOC, Online-Learning

INTRODUCTION

The perception of massive open online courses (MOOCs) and their relationship with students' learning strategies is highly relevant in contemporary education. MOOCs have disrupted traditional higher education models by offering an accessible, cost-free platform for knowledge acquisition and lifelong learning (Zermeño, 2020). Their openness and participatory nature provide a novel perspective on education, emphasizing connective learning and network-based knowledge construction (Haniya & Paquette, 2020). However, despite their accessibility and benefits, researchers continue to highlight the issue of high dropout rates among MOOC participants (Wang et al., 2023). This challenge becomes even more significant when MOOCs serve as integral components of university curricula, either as mandatory courses or as supplements to core disciplines.

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This study aims to examine students' perceptions and attitudes toward MOOCs in relation to their learning strategies, as these strategies are crucial in shaping knowledge acquisition and comprehension (Hattie & Donoghue, 2016). Moreover, engaging with MOOCs necessitates direct interaction with information technology, which research indicates can induce stress in some students, potentially affecting their course performance (Sharma & Gupta, 2022). Investigating the cognitive appraisal process provides deeper insight into factors influencing students' decision-making, self-regulation, and overall learning outcomes in MOOCs. These insights may inform pedagogical strategies and enhance the effectiveness of online learning in higher education.

The conceptual framework of this study is grounded in cognitive appraisal theory, which posits that students classify online courses as either a threat or a challenge (Lazarus, 1991). Examining these cognitive appraisals offers valuable insights into the motivations and beliefs shaping students' engagement and learning approaches. This study also draws on learning strategies theory, which defines a learning strategy as a systematic approach to organizing and applying skills to enhance learning efficiency and effectiveness in academic and non-academic contexts (Boudah & O'Neill, 1999).

THEORETICAL FRAMEWORK

Cognitive Appraisal and MOOCs

Cognitive appraisal is defined as "the process of categorizing an encounter and its various facets, with respect to its significance for well-being" (Lazarus & Folkman, 1984, p. 31). It is not merely the cognitive processing of situational information but an evaluation of its relevance to an individual's well-being, influenced by both internal and external factors. Internal factors include personal values, beliefs, goals, and motives, while external factors encompass situational demands and available resources (Biggs et al., 2017).

Lazarus and Folkman (1980) identified two forms of cognitive appraisal: primary and secondary. Primary appraisal involves assessing the situation's significance for well-being, whereas secondary appraisal pertains to evaluating the internal and external resources available to manage the situation. Notably, Lazarus and Folkman (1984) cautioned against viewing primary appraisal as more important or necessarily preceding secondary appraisal. Both are equally integral to evaluating experiences, as they inform individuals about potential impacts on well-being and guide coping strategies for stress.

Primary appraisal can be further categorized into three forms: irrelevant, benign-positive, and stressful. Irrelevant appraisal occurs when an individual perceives a situation as inconsequential to well-being, while benign-positive appraisal reflects a recognition of potential benefits. In contrast, stressful appraisal involves perceiving the situation as posing harm/loss, threat, or challenge (Lazarus & Folkman, 1980). Unlike the first two, stressful appraisal often provokes significant emotional and cognitive responses, making it a focal point in research.

A harm/loss appraisal arises when an individual evaluates a situation as having already inflicted damage on well-being. Conversely, a challenge appraisal reflects a belief that the demands of a stressful situation can be overcome, with potential for personal growth and achievement (Lazarus et al., 1980; Park & Folkman, 1997). Individuals with a challenge appraisal anticipate success, social rewards, mastery, and learning (Lazarus, 1991; Lazarus & Folkman, 1984). Associated emotions include joy, excitement, and happiness (Lazarus, 1991). In contrast, a threat appraisal emerges when individuals perceive insufficient resources to meet situational demands, posing risks to self-esteem and well-being (Lazarus, 1991; Lazarus & Folkman, 1984).

Threat and challenge appraisals are not necessarily mutually exclusive. According to Lazarus and Folkman (1984), both can coexist when a situation offers growth opportunities but also presents significant risks. For instance, a job promotion may be viewed as a challenge due to professional advancement and financial benefits but simultaneously as a threat due to increased responsibilities and the risk of failure.

Cognitive appraisals play a role in education, as academic tasks require resources, elicit emotional responses, and influence students' goals and values (Boekaerts & Niemivirta, 2000). Boekaerts and Niemivirta (2000) developed the model of adaptable learning, emphasizing the role of cognitive appraisal in self-regulated learning (SRL). They argued that domain-specific knowledge, skills, and self-beliefs shape cognitive appraisal, which in turn influences goal-setting, effort, and strategy selection. The appraisal process thus connects cognitive evaluation with learning actions.

Positive appraisals (challenges) occur when students perceive academic tasks as opportunities for mastery and skill development. This fosters effective learning strategies, deeper engagement, and reduced stress (Gomes et al., 2022). Conversely, negative appraisals (threats) arise when students lack motivation or prior knowledge, leading to disengagement or reliance on surface learning strategies. Given its practical implications, understanding how students appraise and cope with academic stress is critical. Our study specifically examines threat and challenge appraisals in MOOCs, excluding harm/loss appraisal due to its limited relevance in shaping students' MOOC experiences.

MOOCs require greater autonomy and provide less direct interaction with instructors and peers, often leaving students to navigate challenges independently. This can induce stress and activate coping mechanisms based on individual appraisals. Research indicates that a challenge state enhances performance, while a threat state impairs it (Mendes et al., 2007; Seery et al., 2010). In information science, higher perceived challenges have been linked to increased adoption of e-books (Aharony, 2014a) and Web 2.0 technologies (Aharony, 2009). Furthermore, studies on technology-related stress highlight that challenge appraisals correlate with positive coping strategies, leading to more productive technology use (Zhao et al., 2020).

Cognitive appraisal also relates to motivational orientation. Blascovich (2008) argued that threat appraisal aligns with avoidance motivation, while challenge appraisal fosters approach motivation. Individuals who perceive a situation as threatening tend to avoid negative consequences rather than seek solutions. Conversely, those who perceive a challenge adopt proactive strategies aimed at achieving positive outcomes.

In the context of this study, these motivational tendencies provide insight into the relationship between cognitive appraisal and learning strategies. A challenge appraisal, associated with approach motivation, likely promotes deep learning strategies, encouraging students to engage with content for mastery. Conversely, a threat appraisal may drive students toward surface learning strategies, where the focus shifts from knowledge acquisition to merely securing satisfactory grades.

Although motivation plays a role in linking cognitive appraisal to learning strategies, it is primarily associated with secondary appraisal, which involves selecting coping mechanisms in response to stress. However, our study focuses on primary appraisal—specifically, how students perceive and evaluate MOOCs as stressful situations.

Deep and Surface Learning Strategies and MOOCs

Learning strategies are defined as "an individual's way of organizing and using a particular set of skills to learn content or accomplish other tasks more effectively and efficiently in school as well as in non-academic settings" (Boudah & O'Neill, 1999, p. 2). Hattie and Donoghue (2016) identified over 400 learning strategies that enhance students' learning by helping them anticipate actions, set objectives, monitor progress, adjust approaches, and assess both the learning process and outcomes.

Research differentiates between deep and surface learning strategies (Dolmans et al., 2015). Deep learning strategies foster comprehensive and meaningful understanding, while surface strategies focus on memorization and superficial comprehension (You, 2019). Biggs (1987) originally introduced the concept of approaches to learning (AL), categorizing them into the deep, surface, and achieving approaches. The achieving approach involves maximizing results with minimal effort and resources (Hattie & Donoghue, 2016). This study is framed within this model, emphasizing the role of educational context, student perceptions, and individual characteristics in shaping learning approaches.

Deep learning strategies are generally linked to better learning outcomes, whereas surface strategies primarily facilitate rote memorization and assessment performance (Dinsmore & Alexander, 2012). However, students' learning approaches are not fixed; they vary depending on contextual and individual factors (Dolmans et al., 2016). Given that students' motives and perceptions shape their learning behaviors, their appraisal of MOOCs may influence their preferred learning strategies. Understanding the relationship between cognitive appraisal of MOOCs and learning strategies is therefore essential. Several studies have explored this relationship. Lee et al. (2020) examined the links between self-efficacy, task value, and SRL strategies in MOOC learners, finding that higher self-efficacy and greater task value positively correlated with the use of SRL strategies. This suggests that students who believe in their abilities and recognize the value of MOOC tasks are more likely to adopt effective learning strategies. Similarly, Abdelghani (2022) investigated learning strategies in a MOOC on algorithms and programming, revealing that students employed cognitive strategies such as connecting new information to prior knowledge and using flowcharts to understand abstract concepts. This indicates that students recognize and apply effective strategies when learning complex subjects in MOOCs.

Pham et al. (2021) analyzed factors influencing students' intention to use MOOCs, highlighting the role of learning strategies in shaping attitudes. Their findings showed that deep learning strategies positively correlated with motivation to engage with Web 2.0 environments, while surface strategies negatively affected MOOC enrollment intentions. MOOC platform design and course content also influence learning strategy selection (You, 2019). Features that offer flexibility and accommodate diverse learning experiences can enhance student engagement and satisfaction.

Thus, deep learning strategies in MOOCs are associated with higher self-efficacy, task value, and motivation. Students who apply cognitive strategies and establish meaningful connections with course content tend to have a positive cognitive appraisal of MOOCs. In contrast, reliance on surface learning strategies and memorization may discourage engagement with MOOCs and limit their educational benefits.

Current Study

Dinsmore and Alexander (2012) emphasize the need for a clear framework in research on deep and surface processing, considering contextual factors and employing valid measurement tools. This study follows these recommendations by adopting Biggs' AL within the MOOC context and utilizing a validated learning strategies questionnaire (Aharony, 2009, 2016). Integrating these frameworks allows for the formulation of two hypotheses regarding the cognitive appraisal of MOOCs and students' learning strategies:

- **Hypothesis 1 (H1):** Students who appraise MOOCs as a challenge are more likely to employ deep learning strategies.
- **Hypothesis (H2):** Students who appraise MOOCs as a threat are inclined to adopt surface learning strategies.

The novelty of this research lies in its focus on primary appraisal, specifically the perception and evaluation of stressful situations. While motivation falls under secondary appraisal, which involves coping strategies in response to stress, it is beyond the scope of this study. The expected findings suggest that the relationship between the two primary forms of cognitive appraisal in MOOCs and learning strategies is both differential and complementary, reflecting the distinct cognitive and motivational processes associated with each form of appraisal.

METHODS

Participants

The empirical foundation of this study is based on survey data from 389 students enrolled in MOOCs as part of their academic curriculum at United Arab Emirates University. The MOOC was an xMOOC format integrated into their coursework. The sample comprised 358 female and 31 male students, with the majority specializing in Education and Social Science. Descriptive statistics are presented in Table 1.

Table 1. Characteristics of participants

Variable	*N = 389*	%
Gender		
Female	358	92
Male	31	8
Major		
Education	119	30.7
Humanities and Social Sciences	86	21.9
Business	50	12.9
Medicine	38	9.8
Science, technology, engineering, and mathematics	95	24.5

Measurement and Procedure

To assess the cognitive appraisal of MOOCs, a validated questionnaire was employed (Aharony, 2009, 2016). This questionnaire measured students' perceptions of threat versus challenge when completing MOOCs. It comprised nine statements rated on a 5-point Likert scale (1 = strongest disagreement; 5 = strongest agreement). Three statements assessed MOOCs as a challenge (Table A.1), while the remaining six measured MOOCs as a threat (Table A.2). The mean inter-item correlation coefficients indicated a moderate positive association among items, while Cronbach's α demonstrated high internal consistency reliability. Students learning strategies were assessed using another validated questionnaire, which measured AL through 14 statements rated on a 5-point Likert scale (1 = strongest disagreement; 5 = strongest agreement) (Aharony, 2009, 2014b). This questionnaire comprised two factors: deep and surface learning strategies, each represented by seven items (Tables A.3 and 4). The mean inter-item correlation coefficients revealed a moderate positive correlation among items, while Cronbach's α indicated strong internal consistency reliability.

Data Analysis

This study employed structural equation modeling (SEM) analysis (Ullman & Bentler, 2012) using R Studio. The analysis was conducted with the "lavaan" package (version 0.6.16), utilizing the maximum likelihood estimator and the nonlinear minimization subject to box constraints optimization method. SEM enables the examination of complex relationships between observed variables and latent constructs related to cognitive appraisal and learning strategies, offering a comprehensive evaluation of the theoretical framework.

RESULTS

Preliminary Analysis

Descriptive statistics and scale reliability are presented in Table 2. Cronbach's α was used to assess the reliability of the cognitive appraisal and learning strategies scales. All scales demonstrated high reliability, with Cronbach's α values ranging from 0.774 to 0.892.

Table 2. Descriptive statistics of the scales

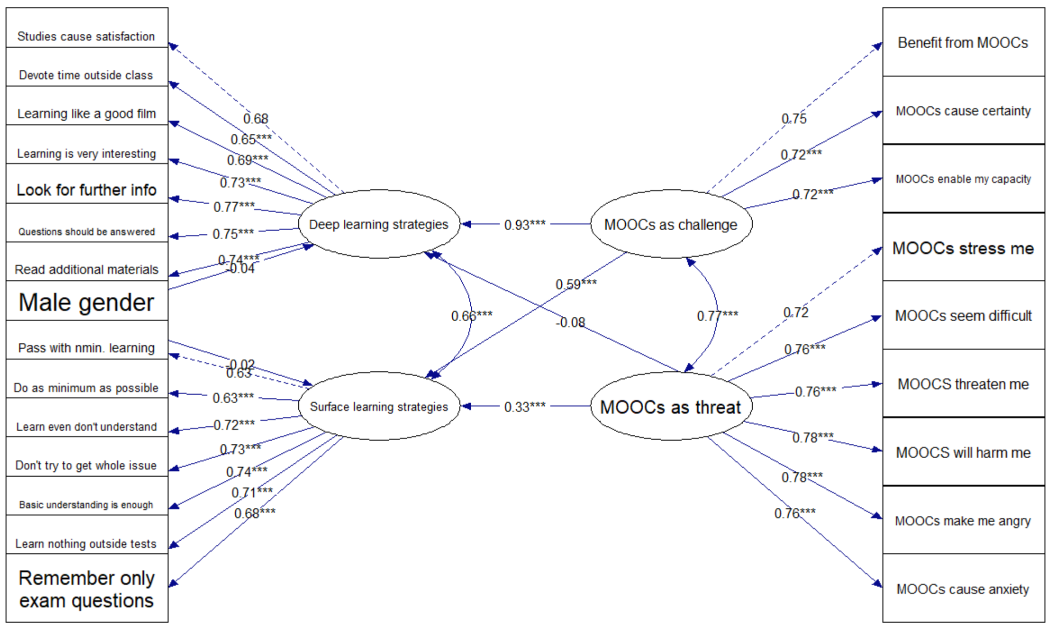
	Surface learning strategies	Deep learning strategies	Cognitive appraisal: A treat	Cognitive appraisal: A challenge
N	389	389	389	389
Missing	0	0	0	0
Mean	22.9	23.8	18.9	9.98
Standard deviation	6.20	6.16	5.53	2.78
Variance	38.4	38.0	30.6	7.74
Cronbach's α	0.866	0.881	0.892	0.774

Structural Equation Modelling

The results of the SEM analysis provide insights into the relationship between the primary cognitive appraisal of MOOCs and students' learning strategies. The significant relationships observed between latent variables and their respective items, as well as between the latent variables themselves, underscore the interconnectivity of these constructs (Figure 1). The appraisal of MOOCs as a challenge exhibited a strong positive relationship with deep learning strategies (standardized coefficient = 0.93, $p < 0.000$). Its association with surface learning strategies was weaker but still positive (standardized coefficient = 0.59, $p < 0.006$). Conversely, students who perceived MOOCs as a threat were more inclined to adopt surface learning strategies (standardized coefficient = 0.33, $p < 0.000$).

Additionally, a statistically significant positive relationship was found between the two types of cognitive appraisal (standardized coefficient = 0.77, $p < 0.000$) and learning strategies (standardized coefficient = 0.66, $p < 0.000$). However, gender did not show a statistically significant relationship with MOOCs' cognitive appraisal or learning strategies. The findings support H2, while evidence for H1 remains mixed.

Figure 1. The relationship between MOOCs cognitive appraisal and students' learning strategies



DISCUSSION

The findings of this study support H2, demonstrating a significant positive relationship between the cognitive appraisal of MOOCs as a threat and the adoption of surface learning strategies. However, the results for H1 provide mixed evidence. While perceiving MOOCs as a challenge is strongly associated with deep learning strategies, it also exhibits a weaker yet significant positive correlation with surface learning strategies.

The differential relationships between the two primary forms of cognitive appraisal of MOOCs and students' learning strategies can be attributed to the cognitive and motivational processes underlying each appraisal. Perceiving MOOCs as a challenge is positively associated with deep learning strategies, likely because students view MOOCs as beneficial, making their efforts worthwhile in improving outcomes (You, 2019). This perspective fosters intrinsic motivation and a mastery-oriented approach, encouraging deeper cognitive engagement and critical thinking (approach motivation). Conversely, perceiving MOOCs as a threat is linked to surface learning strategies, characterized by a focus on superficial comprehension and memorization. This appraisal induces anxiety and fear of failure, leading students to prioritize avoiding negative outcomes rather than seeking a deeper understanding (avoidance motivation). These findings align with Blascovich's (2008) research on threat and challenge appraisals and their connection to motivational orientations, as well as with Pham et al. (2021), who emphasized the role of learning strategies in shaping students' motivation to engage with MOOCs. However, the results also indicate that even students who perceive MOOCs as a challenge may still adopt surface learning strategies, albeit with a weaker correlation. This outcome may be explained by the influence of motivation, which is linked to secondary cognitive appraisal—the assessment of internal and external resources available for effectively managing a given situation.

Overall, the findings of this study partially support the biopsychosocial (BPS) model of challenge and threat, proposed by Blascovich (e.g., Blascovich, 1992; Blascovich & Tomaka, 1996; Tomaka et al., 1993). This model reconceptualizes challenge and threat appraisals as a bipolar measure, contrasting with earlier frameworks that considered them distinct and independent constructs (Lazarus & Folkman, 1984). However, the results align more closely with later research suggesting that challenge and threat appraisals can occur in parallel and independently, enabling the simultaneous processing of positive and negative information in the brain (Man et al., 2017; Uphill et al., 2019). This supports the idea that individuals can perceive a situation as both an opportunity for gain and a risk for loss, with challenge and threat appraisals either independently activated or co-occurring (Sirsch, 2003). Furthermore, dual models of attention propose that multiple stimulus features can be processed simultaneously, reinforcing the independent nature of challenge and threat appraisals (de Gelder & Vroomen, 2000). This perspective may help explain the positive relationship observed in our model.

Consequently, the phenomenon of students perceiving MOOCs as a challenge while still adopting a surface learning strategy, albeit with a weaker correlation, can be explained by the influence of motivation and the complex interplay between challenge and threat appraisals within the BPS model. These findings contribute to the BPS theoretical framework, offering insights into how cognitive appraisals interact in shaping learning behaviors.

In the context of MOOC learning and completion, our findings align with the SRL model proposed by Boekaerts, which emphasizes the role of cognitive appraisal, motivation, and goals in students' selection of learning strategies (Boekaerts & Niemivirta, 2000). Panadero (2017), in reviewing this model, highlights that when students perceive a potential threat to their well-being or self-concept (threat appraisal), they are more likely to follow the "well-being pathway", prioritizing self-protection over deep learning. Conversely, when tasks align with students' expectations and perceived capabilities (challenge appraisal), they are more inclined to adopt a "mastery/growth pathway", focusing on achieving high-quality learning outcomes.

It is important to note that initially chosen learning strategies are not fixed and may change over time. This aligns with research indicating that learning strategies are dynamic rather than stable (Dolmans et al., 2016). For example, students who initially follow the "mastery/growth pathway" may shift to the "well-being pathway" if tasks become more challenging than expected. Conversely, students may transition from the "well-being pathway" to the "mastery/growth pathway", increasing their focus on deep learning (Panadero, 2017). These shifts can be influenced by external factors (e.g., peer support) or internal factors (e.g., evolving goals or motivation). The interplay between these learning strategies may explain the positive correlation observed in our model.

Our findings suggest that MOOC learning exemplifies SRL due to the high level of autonomy required, along with the need for self-assessment and self-regulation. By examining the correlation between cognitive appraisals and learning strategies, this study extends Boekaerts' model by integrating insights specific to online learning environments.

The significance of our findings lies in identifying and exploring the distinct relationships between primary cognitive appraisals of MOOCs and students' learning strategies. This research contributes to a deeper understanding of the cognitive and motivational processes that shape individuals' perceptions of online courses and, consequently, the learning strategies they adopt. By uncovering these relationships, our study provides valuable insights for educators and instructional designers in enhancing online learning experiences. For instance, fostering a challenge-oriented mindset in students engaging with MOOCs can promote professional development. This study demonstrates that enhancing positive cognitive appraisals (challenge) can help students manage negative emotions, which, in turn, can motivate learning (Huang & Yang, 2023).

Instructional designers should prioritize promoting positive cognitive appraisals and integrating SRL strategies to enhance MOOC learners' experiences. Framing courses as opportunities for growth and professional development can encourage students to perceive challenges as beneficial, fostering deeper cognitive engagement. To reinforce this challenge-oriented mindset, designers can incorporate motivational prompts, highlight success stories, and emphasize long-term benefits. Additionally, embedding SRL strategies—such as goal-setting activities, reflective prompts, and progress-tracking tools—can empower learners to self-regulate their learning paths more effectively.

Providing flexibility and resources for strategy switching enables learners to adapt to increasing task complexity, ensuring they remain engaged and motivated even when challenges arise. By fostering positive cognitive appraisals and supporting SRL, instructional design can help students navigate MOOCs with resilience and a mastery-oriented approach, ultimately leading to more meaningful and sustained learning outcomes.

Future research could explore the factors influencing individuals' cognitive appraisals of MOOCs, including motivation, prior knowledge, self-efficacy, and learning goals. Additionally, examining the impact of cognitive appraisals on learning outcomes, such as knowledge acquisition and skill development, would provide a more comprehensive understanding of the complex relationship between cognitive appraisals and learning strategies in online education.

CONCLUSION

This study examines the relationship between students' perceptions of MOOCs and their learning strategies, which are essential for knowledge acquisition. It explores the cognitive appraisal process to identify factors influencing decision-making, self-regulation, and learning outcomes in MOOCs. The findings indicate that students who perceive MOOCs as a challenge are more likely to adopt deep learning strategies, whereas those who perceive them as a threat tend to rely on surface learning strategies. This study enhances the understanding of how cognitive appraisals shape learning approaches in MOOCs, offering valuable insights for educators and instructional designers to promote effective online learning experiences.

LIMITATIONS

This study has several limitations that should be acknowledged. First, its cross-sectional design restricts the ability to establish causal relationships between the variables. Additionally, the sample was drawn from a specific MOOC student population, limiting the generalizability of the findings to other educational contexts or learner groups. Another limitation is the reliance on self-report measures, which are susceptible to biases such as social desirability and response style effects. Finally, the study does not analyze the impact of cognitive appraisal and learning strategies on actual learning outcomes. Future research should address these limitations by refining research design, considering longitudinal approaches, and examining additional environmental and personal factors that influence students' adoption of more sophisticated learning strategies to enhance learning outcomes.

Despite these limitations, this study offers valuable insights into the relationship between cognitive appraisal and learning strategies in the MOOC context. The findings contribute to the existing literature on online learning and have implications for instructional design and pedagogical practices aimed at fostering deep learning approaches among MOOC students.

COMPETING INTERESTS STATEMENT

The authors have no competing interests to declare

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APPENDICES

Appendix A: Descriptive Statistics of Questionnaire Statements

Table A1. The statements for the appraisal of MOOCs as a challenge

Row	Missing (%)	Mean	SD	Skew	Item Difficulty	Item Discrimination	α if deleted
When you think of MOOC: You think you can benefit from this situation	0.00	0.45	1.12	-0.58	0.23	0.66	0.64
When you think of MOOC: This situation causes certainty	0.00	0.22	1.1	-0.34	0.11	0.56	0.75
When you think of MOOC: The situation enables me to show my capacity	0.00	0.3	1.14	-0.5	0.15	0.62	0.69

Mean inter-item-correlation = 0.533, Cronbach's α = 0.774

Table A2. The statements for the appraisal of MOOCs as a threat

Row	Missing (%)	Mean	SD	Skew	Item Difficulty	Item Discrimination	α if deleted
When you think of MOOC: The situation stresses me	0.00	0.17	1.1	-0.25	0.08	0.67	0.88
When you think of MOOC: The situation seems difficult to me	0.00	0.21	1.1	-0.28	0.11	0.71	0.87
When you think of MOOC: The situation threatens me	0.00	0.12	1.17	-0.15	0.06	0.70	0.87
When you think of MOOC: The situation will harm me	0.00	0.09	1.17	-0.18	0.04	0.75	0.87
When you think of MOOC: The situation makes me angry	0.00	0.12	1.19	-0.16	0.06	0.73	0.87
When you think of MOOC: This situation causes anxiety	0.00%	0.2	1.14	-0.23	0.10	0.71	0.87

Mean inter-item-correlation = 0.578, Cronbach's α = 0.892

Table A3. The statements for the deep learning strategy

Row	Missing (%)	Mean	SD	Skew	Item Difficulty	Item Discrimination	α if deleted
I find that studies cause me a great satisfaction	0.00	0.38	1.18	-0.62	0.19	0.64	0.87
I find that most of the learning subjects are interesting and I am ready to devote a lot of time outside class to enrich my knowledge	0.00	0.46	1.14	-0.61	0.23	0.63	0.87

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Table A3. Continued

Row	Missing (%)	Mean	SD	Skew	Item Difficulty	Item Discrimination	α if deleted
I compare the learning process to listening to a good concert or to enjoying a good film	0.00	0.32	1.21	-0.46	0.16	0.61	0.87
I devote a lot of time to learning because I find it very interesting	0.00	0.49	1.14	-0.68	0.25	0.69	0.86
In my leisure time I look for further information in reference books	0.00	0.36	1.15	-0.52	0.18	0.73	0.86
I usually come to class with some questions, and I expect they will be answered at the end of the lecture	0.00	0.42	1.13	-0.51	0.21	0.69	0.86
I read all the additional materials suggested by the lecturer	0.00	0.38	1.12	-0.52	0.19	0.68	0.86

Mean inter-item-correlation = 0.514, Cronbach's α = 0.881

Table A4. The statements for the surface learning strategy

Row	Missing (%)	Mean	SD	Skew	Item Difficulty	Item Discrimination	α if deleted
I would like to pass the course with minimal learning	0.00	0.2	1.16	-0.37	0.10	0.57	0.85
I don't find any course interesting, thus I do the minimum I can	0.00	0.1	1.23	-0.22	0.05	0.60	0.85
I learn things by heart, even if I do not understand them	0.00	0.32	1.21	-0.46	0.16	0.70	0.84
I find it easier to learn by heart and not to try to understand the whole issue	0.00	0.22	1.23	-0.38	0.11	0.69	0.84
I think it is enough to have minimal basic understandings in the material	0.00	0.25	1.2	-0.49	0.13	0.69	0.84
I think lecturers should understand that students will not learn material which is not going to be included in tests	0.00	0.34	1.14	-0.46	0.17	0.64	0.85
I think the best way to pass the exam is to remember questions that will probably appear in the exam	0.00	0.44	1.16	-0.58	0.22	0.59	0.85

Mean inter-item-correlation = 0.479, Cronbach's α = 0.866