Academic success online: The mediating role of self-efficacy on personality and academic performance

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Research Article

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Abstract

Academic success in any context is dependent upon a student's belief in their ability to succeed. While learning online, a students' self-efficacy is affected by their confidence in their ability to interact within the online environment. With the proliferation of personalized learning and the growth of Massive Open Online Courses, this growing trend is a shift in focus from the centralized brick-and-mortar locus of control, to one of enabling student choice and agency for how, when, and where they learn. In the pre-pandemic setting, this research study examined the personality types of students enrolled in eight sections of four online courses in educational technology, and the role self-efficacy for learning online played in their academic performance. Key findings reveal that personality affects learners' academic achievement is moderately significant, self-efficacy for online learning affects learners' academic achievement in a small but significant way, and student conscientiousness and academic performance were significantly and fully mediated by self-efficacy for learning online while controlling for gender and English language proficiency. There were no mediation effects with the other personality traits. A discussion around learning design strategies is provided. The authors recommend that institutions adopt more flexible learning options for teaching and learning that include both online and blended learning options that provide student's choice and agency over the learning experience but also enable the institution to be better equipped for what the uncertain future of education holds.

Introduction

Academic success is dependent upon a student's belief in their ability to succeed in any context (Bandura, 1997). While learning online a students' belief – or self-efficacy – to achieve is affected by their confidence and ability to interact within the online environment (Shen et al., 2013). Technology and online learning enable student choice and agency for how, when, and where they learn shifting the focus away from faculty-centered brick-and-mortar learning environments (Code, 2020). Some studies suggest that increased student agency is associated with higher levels of involvement and improved learning outcomes (Taub et al, 2020; Sawyer et al., 2017; Rowe et al., 2011; Snow et al., 2015). Research in online learning to date has focused mainly on the difference between the academic performance of online students compared to students in more traditional face-to-face environments; with many studies findings no significant difference between online and traditional methods of delivery (Arbaugh et al., 2009; Means et al., 2013). In a recent meta-analysis, Means et al. (2013) examined the effectiveness of online learning compared with that of face to face and blended learning. The overall finding is that online learning on average produces stronger student learning outcomes than learning solely through face-to-face instruction, although the effect size was small ($g = 0.20, p < .001$). Blended learning when contrasted with face-to-face instruction revealed a moderate effect size ($g = .35, p < .001$). What remains less clear, is how student choice and agency – represented most often by self-efficacy – factored into this effect.

Learner agency refers to the degree of freedom and control one has over the learning environment. Student agency over the learning environment (Code, 2020) is akin to human agency as conceptualized by Bandura (1997; 2001) that is characterized by intentionality, forethought, self-reactiveness, and self-

reflectiveness. Agency is most influenced by self-efficacy as “such beliefs influence whether people think pessimistically or optimistically and in ways that are self-enhancing or self-hindering” (Bandura, 2001, p.10). It is well established in the literature that academic self-efficacy is predictive of academic performance and effort regulation (Zimmerman, 2000); deep processing strategies and goal orientations further mediate this relationship (Alqurashi, 2016; Honicke & Broadbent, 2016; Johnson, 2017; Tsai, Chuang, Liang, & Tsai, 2011). Logically, it follows that when learners have high computer self-efficacy, it is more likely that they have a more successful online learning experience (Moos & Azevedo, 2009; Tsai & Tsai, 2003). Despite this strong evidence, there is a paucity of research investigating the kind of effect self-efficacy has on individual differences such as personality and to what extents this impacts the academic performance of students in the online learning context. The current study aims to address this gap.

Theoretical Framework

The present study is grounded in the theoretical model of Bandura’s (1997) social-cognitive framework that emphasizes the causal – and mediating – role of self-efficacy in human behavior and performance. Bandura’s social cognitive framework (1997) is formed on the premise that human functioning is determined by the reciprocal relations among personal (e.g., beliefs, personality), behavioral (e.g., self-regulation, academic achievement), and environmental (e.g., social interaction) factors, and that students’ behaviors and beliefs emerge and develop within specific contexts (e.g., classrooms, online learning). In essence, self-efficacy is an essential motive to learn (Zimmerman, 2000).

Self-efficacy

Self-efficacy is a self-reflective belief in one’s capability to succeed and is an essential condition of human functioning (Bandura, 1997). Self-efficacy beliefs contribute to a student’s sustained interest, motivation, and performance in school. These “beliefs act as determinants of behaviour by influencing the choices that [students] make, the effort they expend, the perseverance they exert in the face of difficulties, and the thought patterns and emotional reactions they experience” (Pajares, 1996). The “metacognitive capability to reflect upon oneself and the adequacy of one’s thoughts and actions is the most distinctly human core property of agency” (Bandura, 2006, p. 165). A student’s beliefs about their ability to achieve determines their level of motivation and is ultimately reflected in the amount of effort exerted and whether they persist through a difficult situation (Bandura, 2001). For example, students who enter college with the goal of obtaining a science degree ultimately switch majors or leave higher education (US Department of Education, 2013). In a longitudinal study, Robnett, Chemers and Zurbriggen (2015) examined the associations among research experience, science self-efficacy, and identity as a scientist. They found that undergraduate students’ involvement in research predicted the extent to which they identified as a scientist nearly 2 years later and suggest that science self-efficacy mediated this relationship. Similarly, Kardash (2000) found that after a summer research experience, undergraduates

displayed greater efficacy in domains such as interpreting data and orally communicating findings. These findings lead one to question whether a student's self-efficacy beliefs, and confidence in their ability to achieve, are specific to a particular task or, if this confidence can translate to other aspects of their lives.

Task specific, domain-specific and general self-efficacy beliefs

Task-specific, domain-specific and general self-efficacy beliefs are three forms of self-efficacy beliefs are described in the literature (Grether, Sowislo & Wiese, 2018). Bandura's (1997) work focuses predominantly on task and situation specific self-efficacy as he regards self-efficacy to be contextualized with the potential that, once established, it may potentially generalize beyond a certain situation. Generalization, Bandura stipulates is restricted to situations that are most similar to the one in which those self-efficacy beliefs have been developed (Bandura, 1986; Grether, Sowislo & Wiese, 2018). Nevertheless, scholars have put forth a conceptualization of general self-efficacy that considers "individuals' perceptions of their ability to perform across a variety of situations" (Judge, Erez, & Bono, 1998, p. 170). General self-efficacy is regarded as a stable competency belief independent of the situation (Chen, Gully, & Eden, 2001; Scherbaum, Cohen-Charash, & Kern, 2006). For example, Grether and colleagues (2018) examined the prospective relations between general self-efficacy and different types of domain-specific self-efficacy beliefs: Occupational and academic self-efficacy beliefs as well as self-efficacy beliefs regarding the compatibility of work and family life. Their research findings suggest that general self-efficacy plays a more dominant role when demands are still new and bottom-up effects become more important when the situation is more familiar (Grether, Sowislo & Wiese, 2018). It would be reasonable then, to consider that academic success when learning online is reliant on a student's confidence and ability to function in the general online environment.

Self-efficacy for online learning

Research on self-efficacy began long before the advent of online learning. Until the last decade, much of the research in self-efficacy and online learning has revolved around computer self-efficacy, Internet and information seeking self-efficacy, and self-efficacy for learning management system (LMS) use (Alqurashi, 2016). As the rate of online learning has increased, research has shown that many students are not as successful in this context (Gregori et al., 2018; Lee & Choi, 2011; Yukselturk et al., 2014) and self-efficacy predicts critical factors such as retention (Yukselturk et al., 2014), perceived learning (Alqurashi, 2016), and course satisfaction (Cho & Heron, 2015; Jan, 2015). Shen, Moon-Heum, Tsai, and Marra (2013) reviewed several key factors in the research that impact academic performance in learning online: A students' prior experience with online learning environments, the role gender plays in self-efficacy, students' academic status and self-efficacy, and students' overall learning experience satisfaction. As a result, Shen and colleagues (2013) went on to develop and validate the Self-Efficacy Questionnaire for Online Learning (SeQoL). In validating their instrument, they found that online learners with higher online learning self-efficacy have higher learning satisfaction and expect better grades (Tsai

et al, 2020). The research reported in this study aims to examine whether, and in what way, personality dimensions and a students' self-efficacy for online learning predict academic achievement.

Personality

Personality and social cognition each have an influential role in human behavior (Stajkovic et al. 2018). Understanding the relationship between personality and academic motivation is essential to developing more effective teaching strategies (Komarraju & Karau, 2005). The Big Five or the five-factor model (FFM) of personality developed in the 1980's (Digman, 1990) remains the dominant personality theory today and is defined by the following factors: Openness, Extraversion, Conscientiousness, Agreeableness, and Emotional Stability or Neuroticism. Personality traits are known to change over time, and contemporary models of personality recognize that trait development occurs across the life span (Sutin, Luchetti, Stephan, Robins, & Terracciano, 2017). Research has found that people who score higher in the Big Five traits of Conscientiousness, Extraversion, Agreeableness, and Emotional Stability tend to do better in school, achieve more in their careers, and have healthier interpersonal relationships (Schwaba, Robins, Grijalva, & Bleidorn, 2019). Analyzing the effects of cognition and personality on grades, achievement tests and a variety of important life outcomes, reveals that personality significantly predicts academic performance (Borghans et al., 2016).

Despite personality being a powerful predictor for most life outcomes (Borghans et al., 2016), achievement and grades are widely used as indicators of cognition (Nisbett, 2012). Further, studies that use achievement and grades as proxies for intelligence, conflate the effects of intelligence with the effects of personality (Borghans et al., 2016), conflation that has resulted in vague theoretical development. Measures of personality, have ultimately been shown to independently predict achievement scores and grades above and beyond intelligence (Hakimi, Hejazi & Lavasani, 2011). Mmeta-analyses of the five-factor model of personality found that academic performance was significantly correlated with Agreeableness, Conscientiousness, and Openness (Poropat, 2009; Vedel, 2014). To date, the role individual differences in personality and self-efficacy play in students' success in learning online has had limited exploration in the literature. The research presented in this article aims to contribute to this body of edvidence, by further examining the mediating effect of personality and self-efficacy on a students' academic performance while learning online.

Research Questions

This exploratory research study examines students' personality types and whether self-efficacy – particularly self-efficacy for learning online – mediates the impact of personality on overall academic performance in this context. The research questions explored in this study are:

1. To what extent do individual differences in personality affect learners' academic achievement in online learning environments?

2. To what extent do individual differences in self-efficacy for online learning affect learners' academic achievement in online learning environments?
3. Does self-efficacy for online learning mediate the effects of personality on academic achievement?

Research Design & Methodology

Participants

Participants in this study were multidisciplinary undergraduate students ($N = 370$) enrolled in eight sections of four online courses in educational technology at a western Canadian university. Students who chose to participate were given a 1% bonus grade for their involvement in a survey administered during the first 2 weeks of class. Response rate was 67% ($n = 240$) and 226 (94.2%) indicated they were undergraduate students with 155 (64.6%) aged 18-22, and 71 (29.6%) aged 23-26. Among them, 165 (68.8%) identified as Women, and 75 (31.3%) identified as Men. The majority, 157 (65.4%), identified as English Foreign Language learners (EFL) while 83 (34.6%) identified as Native English Speakers (NES).

Learning Design

The online courses involved in this research include: *Learning Design, Interactive and Multimedia Learning, Social Media and Personalized Learning*, and *Distributed and Open Learning*. Course descriptions, goals and learning outcomes are listed in Appendix A. All courses shared a similar learning design and were taught either by authors Code or Zap. Courses were all aligned to program outcomes and learning objectives with minimal subject-content overlap and could be taken in any order. Courses were designed around a weekly modular structure, where students would generally complete up to 6 tasks for each module (Figure 1). The manner in which the discussion posts and replies were set-up, and the types of module activities varied depending upon the learning objectives of the module. All courses were hosted and delivered on a university installation of the Moodle Learning Management System (Moodle, 2017).

Measures

Demographics

Demographic information collected from each student included: Age, gender, number of online courses taken, and whether they were undergraduate or graduate students. In addition to this demographic information, the authors also wanted to take into account whether English was a learners' native language as they noticed that there was a disproportionate amount of English as Foreign Language (EFL) students frequently taking these courses on offer in this program and we wanted to take this into account. Further, we wanted to determine the effect of EFL status on student success in learning in the

online context. Cultural and language issues in online participation are not well understood (Ruthotto et al., 2020) and by collecting and examining this demographic information, this research will add to the literature in this area.

Academic Achievement

For the purposes of this research, academic achievement is indicated by the student's final percent Grade in the course.

Personality

Student's personality dimensions were assessed using the 50-item International Personality Item Pool (IPIP) public domain personality scale (Goldberg et al., 2006; McCrae & John, 1992). The IPIP measures aspects of an individual's personality along dimensions of Neuroticism (Emotional Stability), Agreeableness, Openness, Extraversion and Conscientiousness. Students indicated the accuracy towards a statement that describes their Emotional Stability ("have frequent mood swings"), Agreeableness ("believe that others have good intentions"), Openness ("enjoy hearing new ideas"), Extraversion ("am skilled in handling social situations"), and Conscientiousness ("pay attention to details"). Students rated the accuracy of each item using a 5-point Likert scale ranging from 1 = *very inaccurate*, 2 = *moderately inaccurate*, 3 = *neither accurate nor inaccurate*, 4 = *moderately accurate*, to 5 = *extremely accurate*. Previously reported reliability of this scale is $\alpha = 0.89$, $CI95 = .88, .90$.

Self-Efficacy for Online Learning

Student's self-efficacy was assessed using the a 30-item Self-Efficacy Questionnaire for Online Learning (SeQoL; Shen et al., 2013). The SeQoL is conceptualized across five domains of self-efficacy related to the online learning environment: task completion ("keep up with course schedule"), socializing with classmates ("initiate social interaction with classmates"), interacting with their instructor ("clearly ask my instructor questions"), handling a course-management system ("submit assignments"), and interacting with classmates ("Actively participate in online discussions"). Students rated their confidence levels on each item using a 5-point Likert scale ranging from 1 = *not at all confident*, 2 = *slightly confident*, 3 = *moderately confident*, 4 = *mostly confident*, to 5 = *extremely confident*. Reported reliability of this scale in the literature is $\alpha = 0.89$, $CI95 = .88, .90$ (Shen et al, 2013; Tsai et al, 2020).

Data Collection

The instruments utilized in this research were delivered via a web-based survey method of data collection using a local installation of LimeSurvey (<https://www.limesurvey.org>) an open-source web-survey management platform. Data was then exported to SPSS (IBM Corp, 2020) for analysis.

Results

Demographics

Participants in this study were multidisciplinary undergraduate students ($N = 370$) enrolled in eight sections of four online courses in educational technology at a western Canadian university. Response rate was 67% ($n = 240$) and students were given a 1% bonus grade for their participation in a survey administered during the first 2 weeks of class. Of the students who consented to participate in the study, 226 (94.2%) were undergraduate students with 155 (64.6%) aged 18-22, and 71 (29.6%) aged 23-26. Among them, 165 (68.8%) identified as women, and 75 (31.3%) identified as men. The majority, 157 (65.4%), were English foreign language (EFL) learners while 83 (34.6%) were native English speakers (NES).

Table 1 presents a summary of the descriptive statistics. All variables with the exception of age were normally distributed based on skewness and kurtosis values. As age has a kurtosis of $K = 14.4$, based on standardized Z -scores 6 participants were identified as outside the acceptable range ($Z \pm 2.58$) and were removed from further analysis. Similarly, grade had a skewness of $S = -5.14$, and upon further review one subject had a Z -score outside of the acceptable range and was removed from further analysis. Data analysis for this research was conducted using SPSS (IBM Corp, 2020).

Table 1

Summary of Descriptive Statistics

	<i>M</i>	<i>SD</i>	<i>S</i>	<i>K</i>
Age	1.51	.95	3.28	14.4
Gender	1.69	.47	-.81	-1.36
Engl	1.65	.48	-.65	-1.59
Online	1.72	1.05	1.22	.08
Grade	80.22	12.4	-5.1	.01

Note: CI = confidence interval.

Reliability Analysis

Internal reliability of the International Personality Item Pool (Goldberg et al., 2006; McCrae & John, 1992) subscales of Emotional Stability (Neuroticism), Extraversion, Agreeableness, Conscientiousness and Openness, and the Self-Efficacy for Online Learning scale (Shen et al., 2013) was investigated using Cronbach's alpha (Cronbach, 1951). Results indicated that the alphas for the scales were between $\alpha = .73$ and $\alpha = .97$ with all but the subscale for Openness above $\alpha = .83$. The reliabilities of the instruments with

this population, are all above the acceptable level of $\alpha = .70$ (Tabachnick & Fidell, 2019). See Table 2 for a summary of the scale reliabilities. The correlation matrix is in Appendix B.

Table 2

Summary of Reliability of Measures of Personality and Self-Efficacy for Online Learning

	<i>M</i>	<i>SD</i>	<i>S</i>	<i>K</i>	α	95% CI
Neuro	22.50	5.69	.01	-.45	.83	[.80, .88]
Extra	33.36	6.25	.06	.11	.85	[.82, .88]
Agree	39.08	5.38	-.14	-.38	.84	[.80, .87]
Consc	35.49	6.25	.26	-.49	.87	[.84, .89]
Open	36.26	5.18	.336	-.45	.73	[.67, .78]
SEOL	120.3	17.4	-.44	-.20	.97	[.96, .97]

Note: CI = confidence interval. Neuro: Neuroticism/Emotional Stability, Extra: Extraversion, Agree: Agreeableness, Consc: Conscientiousness, Open: Openness, SEOL: Self-Efficacy for Online Learning

Gender and Group Differences

A series of *t*-tests were used to examine gender and group differences. Results reveal a significant difference in Grades between males and females, $t(219) = -2.76, p < .01, d = -.373$. Using Cohen's *d* (1988) to help determine the magnitude of this difference, we use the following rule-of-thumb established by Whitehead et al (2015): Extra small ($d \leq 0.1$), small ($d = 0.2$), medium ($d = 0.5$) or large ($d = 0.8$), respectively. There was a small to moderate effect size of $d = -.373$ for Gender, with men receiving higher grades on average than their women counterparts. In addition, there was a small to moderate effect for Gender on Agreeableness, $t(184) = -2.51, p < .01, d = -.370$, with men receiving lower scores on average than women. In short, these results suggest that there was a small to moderate difference based on Gender with men achieving higher grades while scoring lower on Agreeableness. Further analysis is necessary before any claims can be made and will be taken into consideration in the following sections.

An examination of group differences between Native English Speakers (NES) and English Foreign Language (EFL) learners, reported in Table 3, reveals a significant difference in Grades – with NES students receiving higher grades on average over EFL students, $t(219) = 6.26, p < .01, d = .846$. Further, EFL students appear to be at a significant disadvantage when it comes to their academic achievement in these courses with a large effect size of $d = .846$. Without further analysis, one would likely assume that this difference was a result of the primary language of instruction being in English. However, the analysis revealed additional differences. There were significant group differences in Online Learning Experience, $t(125) = 3.28, p < .01$, with EFL students having more experience learning online than their NES counterparts with an effect of $d = .589$. Despite having more experience learning online, EFL learners, on average, attain lower grades in these courses.

As personality dimensions also play a strong, and potentially predictive role in learning and achievement (Schwaba, Robins, Grijalva, & Bleidorn, 2019), the next phase of this group analysis reveals that with this population of students, there were significant, and large between group effects in personality. The group differences between NES and EFL students revealed a small but significant effect for decreased Emotional Stability (Neuroticism) $t(238) = -2.60, p < .01, d = -.337$, indicating that EFL students tended to be on average less emotionally stable. Results show that NES students were moderately more Extraverted, $t(139) = 3.09, p < .01, d = .519$, and Open, $t(238) = 5.03, p < .01, d = .652$, than their EFL counterparts. Of particular note, with this population there was a large effect size on Conscientiousness, $t(238) = 6.02, p < .01, d = .780$, indicating that the NES students who took these courses were much more conscientious. Finally, with respect to SEOL, NES were moderately more confident in their ability to learn online than their ELL counterparts, $t(238) = 3.29, p < .01, d = .427$.

The univariate analysis presented here reveals an interconnected relationship between NES, EFL and Gender across all of the personality and self-efficacy dimensions studied. To help clarify the relationship between these constructs, and in order for to determine if there is an interaction between all of the various factors studied in this research, we conducted a two-way multiple analysis of variance (MANOVA). Before we conduct the MANOVA, we first need to do a post-hoc power analysis to determine if, and whether any of the effects we find really are true differences in the constructs being studied and not due to error.

Table 3
Summary of Differences Between Native English Speakers (NES) and English Foreign Language Learners (EFL)

	NES (1)		EFL (2)		t^d	p	df	F	p	d^c
	M	SD	M	SD						
Gender	1.75	.44	1.66	.48	1.49	.14	180 ^a	2.56	.11	
Online	2.05	1.26	1.54	.87	3.28	.00**	125 ^a	15.37	.00**	.589
Grade	86.70	12.77	76.56	10.77	6.26	.00**	219 ^b	44.68	.00**	.846
Neuro	21.23	6.24	23.12	5.27	-2.60	.01**	238	6.23	.01**	-.337
Extra	53.11	7.02	32.38	5.61	3.06	.00**	139 ^a	9.70	.00**	.519
Agree	39.31	5.32	38.71	6.02	.69	.49	184 ^b	.32	.57	
Consc	38.58	6.16	33.75	5.78	6.02	.00**	238	34.73	.00**	.780
Open	38.43	5.11	35.01	4.96	5.03	.00**	238	20.01	.00**	.652
SEOL	125.46	16.57	117.78	17.52	3.29	.00**	238	11.96	.00**	.427

^a Violated Levene's test, reported values with equal variances not assumed; ^b Difference in degrees of freedom due to variation in data collection; ^c Cohen's d (effect size); * $p < .05$ level, two-tailed; ** $p < .01$ level, two-tailed. Neuro: Neuroticism/Emotional Stability, Extra: Extraversion, Agree: Agreeableness, Consc: Conscientiousness, Open: Openness, SEOL: Self-Efficacy for Online Learning

Post-hoc Power Analysis

A post hoc power analysis was conducted using the statistical software package, G*Power (Faul et al., 2007), to ensure that we have enough power to avoid Type II error. Our sample size of $n = 213$ was used along with a 2 x 2 MANOVA special effects and interactions as a baseline. The recommended effect sizes used for this assessment were as follows: small ($f_2 = .02$), medium ($f_2 = .15$), and large ($f_2 = .35$) (see Cohen, 1988; Cohen, 1992). The alpha level used for this analysis was $p < .05$. Post hoc analyses revealed the statistical power for this study was .32 for detecting a small effect and 1.00 for the detection of a moderate to large effect size. Thus, there was more than adequate power (i.e., power $\geq .80$) at the moderate to large effect size level, but less than adequate statistical power at the small effect size level. Put simply, the probability of concluding that there is no effect when there is one, is increased at smaller effect sizes. Therefore, all effect sizes approaching $p < .05$ will be reported as these findings would likely have a stronger level of significance given more statistical power (a larger sample size).

Multivariate Analysis of Variance (MANOVA)

Prior to conducting the MANOVA, a series of Pearson correlations were performed between all of the dependent variables in order to test the MANOVA assumption that the dependent variables would be correlated with each other in the moderate range (i.e., .20 – .60; Meyers, Gamst, & Guarino, 2006). A meaningful pattern of correlations was observed amongst most of the dependent variables (Appendix A), suggesting that a MANOVA is appropriate in this case. Note that for the purposes of the remaining analyses, the self-reported status of English as a foreign language will be used as an indirect self-reported grouping of English Language Proficiency (ELP).

A two-way MANOVA was conducted to test the hypothesis that there would be one or more mean differences between Gender and self-reported ELP. A two-way MANOVA has generally one primary aim: To understand whether the effect of one independent variable (e.g., gender) on the dependent variables (collectively) is dependent on the value of the other independent variable (e.g., ELP). Each personality dimension was used as dependent variables to examine whether the effects of gender and ELP are dependent on each other (an interaction effect). Results of the complete MANOVA analysis using standard scores are in Table 4.

Table 4

Univariate and Multivariate Effect Sizes and F-Statistics Associated with English Language Proficiency, Gender, and Self-Reported English Language Proficiency *Gender on Personality*

	ELP				Gender			ELP	Gender
		<i>F</i>	<i>p</i>		<i>F</i>	<i>p</i>		<i>F</i>	<i>p</i>
Neuro	.020	3.513	.063	.008	1.342	.248	.001	.225	.635
Extra	.031*	5.715	.018	.001	.165	.685	.006	1.098	.296
Agree	.000	.010	.920	.040*	7.251	.008	.000	.019	.890
Consc	.063**	11.847	.001	.018	3.164	.077	.004	.677	.412
Open	.076**	14.578	.000	.006	1.069	.303	.005	.866	.353
SEOL	.029*	5.164	.024	.007	1.252	.265	.000	.008	.931
Multivariate									
Pillai's Trace	.208**	4.396	.000	.177**	3.595	.000	.058	1.031	.420
<i>df</i>		(10,167)			(10,167)			(10,167)	

Note: * $p < .05$; ** $p < .001$

Note: Box's M value of 276.51 was associated with a p value of .001, which was interpreted as *significant* based on Huberty and Petoskey's (2000) guideline (i.e., $p < .005$), thus covariance matrices between the groups were *not* assumed to be equal therefore Pillai's Trace is reported as opposed to Wilks' Lambda.

Neuro: Neuroticism/Emotional Stability, Extra: Extraversion, Agree: Agreeableness, Consc: Conscientiousness, Open: Openness, SEOL: Self-Efficacy for Online Learning

A significant MANOVA effect on Gender was obtained, $F(10,167) = 3.60$, $p < .001$, Pillai's Trace = .18, accounting for almost 18% of the variance. A significant MANOVA effect on ELP was also obtained, $F(10,167) = 4.40$, $p < .001$, Pillai's Trace = .21, accounting for almost 21% of the variance. However, there was a *non-significant* interaction effect between Gender and ELP on the combined dependent variables $F(10,167) = 1.03$, $p = .42$, Pillai's Trace = .06, thus there is no *multivariate interaction* between gender and ELP. Simply put, both Gender and ELP have a significant effect on personality dimensions and self-efficacy on their own, but they are *not dependent* on each other – they have no interaction effect.

A series of one-way ANOVA's on each of the dependent variables was conducted as follow-up tests to the MANOVA. As can be seen in Table 4, statistically significant ANOVA's on Gender were found on Agreeableness, with a small effect size (partial η^2) of .04 (Agree). Further, statistically significant ANOVA's for ELP were found on Extraversion, Conscientiousness, Openness, and Self-Efficacy for Online Learning, with small to moderate effect sizes (partial η^2) ranging from a low of .029 (SEOL) to a high of .076 (Open). As Gender and ELP were found to play a significant but independent role in academic achievement (Grade) the remaining analyses will control for Gender and ELP, as we consider the potential causal nature of this relationship.

Hierarchical Multiple Linear Regression

To test the hypothesis that a student's level of achievement is a function of both personality and SEOL while controlling for Gender and ELP, a hierarchical multiple linear regression was performed. Results of

the regression analysis (Table 5) provided partial confirmation for the research hypothesis as follows.

Beta coefficients for the two predictors were Conscientiousness, $\beta = .34$, $t(239) = 2.88$, $p < .001$; SEOL, $\beta = .16$, $t(239) = 3.97$, $p < .001$. Meaning, that for every 1-point increase in Conscientiousness, there is a .34-point increase in the standard deviation of academic achievement. Similarly, for SEOL, for every 1-point increase in self-efficacy there is a .16-point increase in the standard deviation of academic achievement. As evidence from the literature indicates that self-efficacy is both theoretically and empirically linked as a mediating factor in predicting academic achievement (e.g. Alghamdi et al., 2020; Code, 2020; Zimmerman, 2001), our next, and final stage of analysis will focus on examining this mediating relationship.

Table 5

Summary of Hierarchical Regression Analysis for Variables Predicting Academic Achievement Controlling for Gender and English Language Proficiency

Predictor	<i>B</i>	<i>SE B</i>	β	<i>t</i>	<i>p</i>	R^2	ΔR^2	ΔF	<i>p</i> ΔF	pr^2
Neuro	-.10	.13	-.05	-.74	.46	.23	.00	.55	.46	
Extra	.03	.12	.02	.29	.77	.23	.00	.09	.77	
Agree	.23	.15	.11	1.57	.12	.27	.01	2.46	.12	
Consc	.34	.12	.19	2.88	.00**	.23	.03	8.32	.00**	.04
Open	.28	.15	.12	1.88	.06	.23	.01	3.54	.06	.02
SEOL	.16	.04	.24	3.97	.00**	.23	.05	15.78	.00**	.07

Note: Hierarchical regression variables entered in two blocks with the first block in each model containing Gender and English language proficiency (ELP) as a control; pr^2 = squared partial correlation as an indicator of effect size; * $p < .05$; ** $p < .01$.

Neuro: Neuroticism/Emotional Stability, Extra: Extraversion, Agree: Agreeableness, Consc: Conscientiousness, Open: Openness, SEOL: Self-Efficacy for Online Learning

Mediation Analysis

A mediation analysis revealed that the relationship between Conscientiousness (X) and Grades (Y) **was** mediated by SEOL (M) while controlling for Gender and ELP. As Figure 2 illustrates, the standardized regression coefficient between Conscientiousness and SEOL was statistically significant $F(3,209) = 28.38$, $p < .01$, $R^2 = .29$; $\beta = 1.43$, $t(209) = 8.29$, $p < .01$, as was the standardized regression coefficient between SEOL and academic achievement $F(4,208) = 20.61$, $p < .01$, $R^2 = .28$; $\beta = .14$, $t(208) = 2.90$, $p < .01$.

.01. The standardized indirect effect was $\beta = (1.43)(.14) = .20$. We tested the significance of this indirect effect using bootstrapping procedures. Unstandardized indirect effects were computed for 5,000 bootstrapped samples, and the 95% confidence interval was computed by determining the indirect effects at the 2.5th and 97.5th percentiles. The bootstrapped unstandardized indirect effect was $\beta = .19$ and the 95% confidence interval ranged from .06, .35 and the Sobel test (normal theory test) was $Z = 2.81, p < .01$. Thus, the indirect effect was statistically significant. What this model tells us is that SEOL *fully mediates* the effect of Conscientiousness on academic achievement ($p < .01$).

Discussion

To what extent do individual differences in personality affect learners' academic achievement in online learning environments?

The extent that individual differences in personality affects learners' academic achievement is moderate but significant in this population of students. The regression analysis revealed that conscientiousness was the only trait that was a significant predictor of academic achievement with a beta weight of $\beta = .34, t(239) = 2.88, p < .001$ while controlling for gender and English language proficiency. Meaning, that for every 1-point increase in conscientiousness, there is a .34-point increase in standard deviation of academic achievement which equals a 4.34% increase in overall final grade. This finding is consistent with the literature that depicts conscientiousness as a significant predictor of academic achievement (Dumfart & Neubauer, 2016; Morris & Fritz, 2015; Poropat, 2009). While this finding is not surprising, it adds to the literature that explores students' personality in the online learning context (e.g., Abe, 2020; Alkis & Temizel, 2018).

To what extent do individual differences in self-efficacy for online learning affect learners' academic achievement in online learning environments?

The extent that individual differences in self-efficacy for online learning affects learners' academic achievement is small but significant in this population of students. The regression analysis revealed that self-efficacy for online learning had a beta weight of $\beta = .16, t(239) = 3.97, p < .001$ while controlling for gender and English language proficiency. Meaning, that for every 1-point increase in self-efficacy for online learning there is a .16-point increase in the standard deviation of academic achievement which equals a 1.98% increase in overall final grade. This finding is also consistent with the literature that depicts self-efficacy as a significant predictor of academic achievement (Pajares, 1996; Komarraju & Nadler, 2013). This finding adds to the literature that examines the effects of students' self-efficacy for learning in the online context (e.g., Bradley, Browne, & Kelley, 2017; Ng, 2017).

Does self-efficacy for online learning mediate the effects of personality on academic achievement?

Self-efficacy for learning online was found to completely mediate the effects of conscientiousness on academic achievement with this population (Figure 2). There were no mediation effects with the other personality traits. The regression coefficient between conscientiousness and self-efficacy for online learning was statistically significant $\beta = 1.43$, $t(209) = 8.29$, $p < .01$, as was the regression coefficient between self-efficacy for online learning and academic achievement $\beta = .14$, $t(208) = 2.90$, $p < .01$. The overall indirect effect of this model is $\beta = .20$. However, the direct effect of conscientiousness on academic achievement becomes insignificant when self-efficacy for online learning is taken into account. Thus, what this model tells us is that self-efficacy for online learning *fully mediates* the effect of conscientiousness on academic achievement ($p < .01$).

The predictive effect of self-efficacy on academic achievement is well known and forms the basis of Bandura's theory of agency (1997; 2001). Over the past 20 years, self-efficacy research has expanded across disparate disciplines (e.g., Klassen & Klassen, 2018; Tiwari, Bhat, & Tikoria, 2017; Vishnumolakala et al., 2017;) has added to this body of evidence. However, an empirical examination of the mediating relationship of self-efficacy within various learning contexts is a recent development (e.g., Cattellino, et al., 2019; Honicke & Broadbent, & Fuller-Tyszkiewicz, 2020). The findings of this research add to the literature on how self-efficacy *completely* mediates the impact of personality traits on academic achievement. This work is adding novel insight as it specifically considers this mediating relationship within the online learning context which, is particularly salient as learning online has become so ubiquitous.

Learning Design Strategies

From a learning design perspective, the results of this study indicate that it would be worthwhile to consider what supports could be incorporated for students who might *not* have high levels of conscientiousness or may score higher in neuropathy (lower emotional stability). Further, as self-efficacy was found to significantly predict academic achievement, and mediate conscientiousness, strategies to support the development of student self-efficacy for online learning are critically important. For example, student agency and self-efficacy can be improved through learning design by considering:

1. A direct and careful overview of the course so expectations are clear.
2. Additional background material especially in the form of multimedia. Multimedia is particularly effective in supporting students whose mother tongue is not in the language of instruction.
3. Wherever possible make connections to past learning experiences and knowledge. For example, if you know the likely background or area of study students are coming into a course with, one can incorporate examples and readings (or media) from that area of study.
4. A variety of opportunities for and methods of assessment. For example, allow students to complete weekly discussion posts using audio, video, and text. Most modern LMS's have these options, so if

how the discussion happens is not a learning outcome, then allowing students to respond using a variety of media would support a variety of learner preferences and provide additional choice.

5. Clear instructions on how to access support in the form of: Instructional in terms of access to a teaching assistant and instructor; technical such as a help desk; language, writing and communication support such as those often available at Library Writing Centers; and tutoring and study support.
6. Providing access to or facilitating ways for students to interact informally or socially. One of the best ways to support students in their learning is to encourage social interaction. Learning is known to be a social process, so if students feel isolated their opportunities to learn through co-regulation and feedback are hampered.

Study Limitations

There were several limitations to this study that could have impacted the results. The first relates to the sample size and the relative power of .32 as a result. Put simply, the probability of concluding that there is *no effect* when there is one *is increased at smaller effect sizes*. The authors therefore reported all effect sizes approaching $p < .05$ to indicate that if the sample size had been larger there *would likely* be an effect. For example, the MANOVA revealed that decreased Emotional Stability (Neuropathy) had an effect size $d = -.337$, $p < .06$ which was found to have a small yet increased prevalence with our English as a foreign language learner. One may posit that decreased emotional stability could be a result of a number of factors for example: Increased anxiety as a result of learning in a different language other than your mother tongue. Since a detailed study of Emotional Stability was not a part of our study, this would likely be a fruitful line of future research. In addition, our findings suggest that with a larger sample size, our Emotional Stability would likely have a stronger level of significance and more statistical power so a replication or a continuation of this research is warranted. A quick search of the literature reveals it is a rich area of exploration (See Sanchez-Ruiz et al, 2013; Serebryakova et al., 2016; Wehner & Schils, 2019).

Another limitation is the potential of a self-selection bias. Anecdotally, the course instructors (Code, Zap) described several possible motivations they have observed as to why students take these particular classes over the several years of teaching these courses. At the time this research was conducted, the university had relatively few online and flexible learning options for students. The fact that these courses were online made them attractive to some students, not necessarily because of the curriculum but because of the delivery modality – especially if they were confident in their ability to learn online, which our empirical results clearly reveal. Another impetus the instructors observed, was that students required senior level electives for their degree programs. Thus, the majority of students in these courses were senior level undergraduates taking these courses to fill degree requirements – sometimes at the very end of their programs right before graduation. All of these motivations would potentially contribute to a self-selection bias.

Future research or a follow up study should include more information about the number of flexible learning options at the institution, and the likelihood that students would choose alternative delivery options if they were available. It should also be noted that this study was completed in the pre-pandemic setting so there will likely be differences in motivations and populations of online learners in the future. In addition, data on which undergraduate program or major the study participants came from was unavailable. This additional information about the demographic would provide important insight into whether there was a self-selection bias if the courses were listed as electives for students in a particular area of study.

Implications and Future Research

Understanding how various students react to learning online is crucial in improving the design, delivery, evaluation of online courses and programs (Keller & Karau, 2013; Richardson et al., 2012). Earlier research in online education focused mainly on comparing the academic performance of students learning online to students in face-to-face environments (e.g. Means et al., 2013). As discussed, meta-analyses examined the effectiveness of online learning compared with that of face to face and blended learning and identified *which pedagogical practices were associated with positive outcomes* (Means et al., 2013). A follow up meta-analysis by Vo et al. (2017) supports this finding however adds that this result seems to be more pronounced in STEM-related fields. Given the state of higher education at the time of this article, it should be noted that the courses upon which Means et al. (2013) and Vo et al. (2017) conducted their meta-analysis, were specifically designed for online or blended learning delivery, unlike many of the courses that had to 'pivot' in response to Emergency Remote Teaching (ERT; Hodges, et al., 2020). The impact of the pandemic on higher education, and teaching and learning generally, has been and will likely continue to be considerable.

On March 11, 2020, the WHO Director-General declared SARS-CoV-19, the novel coronavirus that causes the COVID-19 infection (WHO, 2020) a global pandemic. This declaration pitched the higher education community into disarray leaving administrators with the difficult decision on what to do about active courses, and what to do about the coming months. Ultimately, many institutions made the choice to 'switch' or 'pivot' to alternative delivery formats with only days' notice (e.g., UBC, 2020). Initially there was confusion around what was expected of faculty and teaching support teams that included that limited the ability around how and what they were to develop to support teaching and learning with relatively few courses and programs designed specifically for online learning. What actually ended up occurring is what is now referred to as emergency remote teaching (ERT; Hodges et al. 2020). ERT "temporary shift of instructional delivery to an alternate delivery format due to crisis circumstances" (Hodges et al., 2020).

Hodges and colleagues (2020) were quick to argue that ERT pedagogy must not be conflated with what has been done for 'traditional' online learning, as with ERT there was very little lead up time, and thus little to no time to properly design online learning experiences for students. In essence what we were left with is a pandemic transformed pedagogy (Code, Ralph & Forde, 2020). The authors would further postulate that since choice of both teaching and learning methodology was a choice largely removed from both

faculty and students, agency was inhibited, and the result is a likely decline in self-efficacy for teaching and self-efficacy for learning online (Code, Forde & Ralph, 2020). The authors are concerned, as is the higher education community at large that with the switch to ERT, quality instruction has plummeted and the student experience has suffered (Hodges et al, 2020).

The research reported in this article examined the personality types of students attracted to online courses and the role that self-efficacy for learning online plays in academic performance. This work adds several important key findings to the literature including that conscientiousness significantly affects learners' academic achievement, self-efficacy for online learning significantly affects learners' academic achievement, but that conscientiousness and academic performance are both *significantly* and *fully mediated* by self-efficacy for learning online (while controlling for gender and English language proficiency). At the time of the writing of this article, the COVID-19 global pandemic changed the course of teaching and learning in higher education and as a result inhibited choice and agency for educators and their students (Code, Ralph & Forde, 2020). With a return to campuses around the world, the authors recommend that institutions adopt more flexible learning options for teaching and learning that include both online and blended learning modalities. Doing so will not only provide student's choice and agency over learning experience, but will enable the institution to be better equipped for what the uncertain future of education holds.

Declarations

Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Ethical approval

All procedures performed in the studies involving human participants were in accordance with the ethical standards of the University of British Columbia's BREB (approval H20-01103) and are in accordance with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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Figures

Course Format

All students are expected to complete up to 6 tasks every two weeks:

1. Watch introduction video (~5mins)
2. Watch theory lecture (~10-20mins)
3. Read/Watch assigned readings and videos
4. Complete module topic challenges (Forum or Badge)
5. Post feedback to your peers (on Forum Challenges)
6. Complete module quizzes on the readings, other course badge activities (Ongoing)

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Intro Video						
Theory Lecture						
Readings/Videos						
			Original Post		Peer Feedback	
Module Quizzes, Challenge Badge Activities, Other Course Badges						

Figure 1

Example learning design format for each of the courses included in the study.

Figure 2

Standardized regression coefficients for the relationship between conscientiousness (CONSC) and academic achievement (GRADES) as mediated by self-efficacy for online learning (SEFONL) while controlling for gender and English language proficiency. The standardized regression coefficient between conscientiousness and academic achievement, controlling for self-efficacy for online learning, is in parentheses. ** $p < .01$

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Appendix.docx](#)