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Predicting Students' Online Learning—Character Strengths, Online Self-Regulated Learning, and Learning Satisfaction

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Abstract: Online learning provides numerous benefits to students. However, it remains unclear how psychological and learning-related factors affect a student's performance in online learning environments. In this paper, we examined various psychological and learning-related factors (e.g., character strengths, online self-regulated learning, self-efficacy, learning satisfaction) that may predict learning performance in online environments. Results indicated that after controlling gender, disciplinary background and proportion of online or hybrid courses, self-efficacy in online learning was a significant positive predictor of learning performance. A possible explanation is that self-efficacy pushes students to persist in achieving their academic goals. In contrast, humanity (a character strength) and time management (a subconstruct of online self-regulated learning) were negatively associated with learning performance. Other predictors were not statistically significant. The results suggest that when one focuses more on nurturing relations with others, exhibiting humanity strengths, they may have less energy for their academic work; when one has good time management for online modules, they may neglect their face-to-face modules and do not perform well overall. Future research should investigate the underlying mechanisms of how humanity and time management impact students' learning performance in online learning environments.

Keywords: Online learning, character strengths, self-regulated learning, self-efficacy

1. Introduction

During the COVID-19 pandemic, modules were forced to shift online, and even in the post-pandemic era, online and blended learning is still widely implemented (Jamilah & Fahyuni, 2022). Online learning refers to experiencing education via technological tools and having connection to the internet (Moore et al., 2011). It also encompasses mobile learning, whereby students can use their mobile phones to access digital learning management systems like Google Classrooms or communication platforms like Teams to learn online. Online learning offers advantages like accessibility, flexibility, and opportunities for learners to collaborate, access resources, and study conveniently (Waschull, 2001). Despite these benefits, some students may have poor academic performance or poor course persistence when learning online, making it critical to study predictors that may influence how they perform to help improve the quality of online courses (Xu & Jaggers, 2013).

In online settings, many factors can influence how well a student performs academically. For example, character strengths like being persistent or having love for learning are associated with student enjoyment and achievement (Wagner et al., 2020). As students mostly learn independently in an online setting, self-regulation was crucial for them to succeed (Wijekumar et al., 2006). Satisfaction with online courses is essential as it is associated with achievement of course learning outcomes (Vikas & Mathur, 2022). Students also need to have self-efficacy in handling and planning online learning behaviors (Zimmerman, 2008).

According to Peterson and Seligman (2004), character strengths are identifiable pathways to demonstrate virtues, which are valuable characteristics that are universal and classified into— wisdom (cognitive traits); courage (emotional traits); humanity (relational traits); justice (strong community life); temperance (protective traits); and transcendence (associations to the universe and purpose). Character strengths relate to educational outcomes— love of learning (wisdom) and perseverance (courage) are associated with achievement; prudence (temperance) is strongly related to overall school achievement; and social intelligence (humanity) is associated with self-rated group achievement (Wagner et al., 2020).

Online self-regulated learning (OSRL) includes setting goals, environment structuring, adopting task strategies, managing time, seeking help, and evaluating oneself (Barnard et al., 2008). There is a positive relationship between OSRL and Grade Point Average (GPA) (Barnard et al., 2008). In an online environment, there are multiple formats of complex digital content (Zimmerman, 2008), making self-regulation critical for students to coordinate and integrate content into workable cognitive representations (Azevedo et al., 2004).

Satisfaction with online learning (SOL), as well as online learning perception, is associated with achievement of course learning outcomes (Vikas & Mathur, 2022). Self-efficacy in online learning refers to how much students believe that they can utilize technology or online tools competently, and complete online learning work effectively; increase in self-efficacy in online learning contributes to students' better grades and academic achievement (Won et al., 2024). It could be possible that self-efficacy in online learning benefits online learning engagement (Kuo et al., 2021), which may translate to good performance. Academic satisfaction, the degree one enjoys their study experience (Lent et al., 2005), predicts achievement (Kumar & Dileep, 2006).

The studies mentioned above have shown that various factors influence learning. However, there are limited studies on how these factors predict students' learning performance in online settings, especially during the post-pandemic period. There is also a lack of research on predictors such as character strengths, OSRL, SOL or self-efficacy. To tackle these research gaps, this paper aims to study the different predictors of learning performance in online learning environments. This study is one of the first exploring the relationship between character strengths, OSRL, SOL and performance in higher education. Specifically, this study is guided by the research question: When gender, disciplinary background and proportion of online learning modules are controlled, how do different factors (character strengths, OSRL, SOL, self-efficacy in online learning, academic satisfaction) influence individual learning performance?

2. Methods

2.1 Participants and Instruments

829 responses were collected from a university in Singapore. After removing the duplicated and incomplete responses, there were 695 students. After filtering outliers and careless responses, 542 students remained in our final sample.

Participants' mean age was 25.32 years, with more females (n = 359). 72.14% were undergraduates, 25.65% were postgraduates, and 2.21% declared their program as "Others", as they were in special programs like "Postgraduate Diploma in Education". Participants were from— business (n = 147), engineering/ computer science (n = 126), science (n = 55), education (n = 108), humanities/ language (n = 44), medicine (n = 41), design/ communication (n = 23), or social sciences (n = 62). One could belong to multiple faculties. Most participants (n = 237) had less than 20% courses in online/hybrid format; 137 had 30% to 40% and 78 had

50%. Few (n = 48) had 60% to 80% and even fewer (n = 42) had more than 80% of courses in online/hybrid format.

Data was collected through an online self-reported survey between October 2023 and March 2024. Based on the Value in Action (VIA) Classification system (Peterson & Seligman, 2004), the 24-item Character Strengths-Semantic Differential Scale was used (CS-SDS, Chan et al., 2007). Participants rated descriptions on a 7-point continuum (e.g., Conforming-Creative). In our study, internal consistency is acceptable– α (wisdom)= 0.60; α (courage)= 0.60; α (humanity)= 0.59; α (temperance)= 0.55; α (transcendence)= 0.60. As the internal consistency for justice was low (α = 0.31), justice-related items were removed, after which the overall internal consistency is good (α = 0.86).

For OSRL, the Online Self-regulated Learning Questionnaire (OSLQ, Barnard et al., 2008) was used. The 24-item questionnaire measures— goal setting (α= 0.79), environment structuring (α= 0.77), task strategies (α= 0.67), time management (α= 0.71), help seeking (α= 0.67), and self-evaluation (α= 0.79). Overall internal consistency is good (α= 0.89).

SOL was measured using a 4-item scale developed by Lin (2005) (α= 0.90). Self-efficacy in online learning was measured using the Motivated Strategies for Learning Questionnaire (MSLQ, Pintrich et al., 1993). Using a 7-point Likert scale, students rated 8 statements (α= 0.93). Academic satisfaction was measured using a 7-item measure by Lent et al. (2005), using a 5-point Likert scale (α= 0.89). Participants were also asked to report their proportion of modules that were in online or hybrid format and their GPA category, used as a measure of online learning performance (out of 5)— < 2.0, 2.0 to 3.0, 3.0 to 4.0, or > 4.0.

2.2 Data Analysis

Firstly, 91 outliers were detected using "mahalanobis" function in the R stats package (R Core Team, 2025), with a *p*-value of 0.001 as a cutoff. Next, the careless R package (Yentes & Wilhelm, 2023) was applied to identify careless responses. We calculated the longstring index, then removed data points that exceeded 1.5 times the interquartile range above the third quartile of average longstring index, using "identify outliers" function in rstatix package (Kassambara, 2023). 63 careless responses were identified, with 1 case flagged as both outlier and careless. In total, 153 responses were removed, leaving us a final sample of 542. Lastly, as GPA category was ordinal, multiple ordinal logistic regression was done via "clm" function in the ordinal package (Christensen, 2023). Controlling gender, faculty, proportion of online/hybrid courses, these predictors were entered: subconstructs of character strengths and OSRL, SOL, self-efficacy in online learning, and academic satisfaction.

3. Results

Table 1 shows the results of the ordinal logistic regression. The model was statistically significant, $\chi^2(24) = 124.73$, $p < .001$, indicating that the predictors significantly distinguished outcome groups. The model explained between 21% (Cox & Snell R^2) and 25% (Nagelkerke R^2) of variance, with McFadden's $R^2 = 0.13$. For control variables, being female is associated with 39% lower odds of being in a higher GPA category. Business (2.43 times), humanities/language (3.06 times), and social science students (3.37 times) are more likely to be in a higher GPA category than their respective counterparts. Humanity ($\beta = -0.28$, Odds Ratio = 0.76, $p = .02 < 0.05$) and time management ($\beta = -0.56$, Odds Ratio = 0.57, $p < .001$) were negatively associated with GPA category. In contrast, self-efficacy in online learning ($\beta = 0.79$, Odds Ratio = 2.20, $p < .001$) was a significant positive predictor of GPA category. Other predictors were not statistically significant.

Table 1. *Ordinal logistic regression to predict students' individual learning performance*

Predictor	Estimate	Standard Error	Z	*p*	Odds

Gender (Female)	-0.50	0.21	-2.40	0.02*	0.61
Business	0.89	0.35	2.54	0.01*	2.43
Engineering/ Computer Science	0.21	0.35	0.58	0.56	1.23
Science	0.28	0.40	0.70	0.48	1.32
Education	-0.15	0.37	-0.42	0.68	0.86
Humanities/Language	1.12	0.41	2.73	0.01**	3.06
Medicine	-0.67	0.47	-1.42	0.15	0.51
Design/ Communication	0.76	0.55	1.38	0.17	2.13
Social Science	1.21	0.41	2.99	0.00**	3.37
Proportion of online/hybrid courses	0.04	0.08	0.45	0.65	1.04
Wisdom	0.01	0.17	0.04	0.97	1.01
Courage	0.09	0.18	0.49	0.62	1.09
Humanity	-0.28	0.12	-2.28	0.02*	0.76
Temperance	0.16	0.14	1.19	0.24	1.18
Transcendence	-0.27	0.17	-1.55	0.12	0.76
Goal Setting	0.27	0.19	1.42	0.15	1.31
Environment Structuring	-0.10	0.17	-0.58	0.56	0.91
Task Strategies	-0.18	0.15	-1.14	0.25	0.84
Time Management	-0.56	0.15	-3.81	<.001***	0.57
Help Seeking	0.07	0.17	0.44	0.66	1.08
Self-Evaluation	0.19	0.16	1.13	0.26	1.20
SOL	-0.03	0.10	-0.26	0.80	0.97
Self-Efficacy in Online Learning	0.79	0.12	6.66	<.001***	2.20
Academic Satisfaction	-0.09	0.21	-0.45	0.65	0.91

Notes: *$p < .05$; **$p < .010$; ***$p < .001$

4. Discussion and Conclusion

This study examines how various factors, such as character strengths or learning-related factors, influence how well a student performs in online settings. The result shows that each unit of increase in humanity is associated with 24% lower odds of being in a higher GPA category. We posit that an overemphasis on relational traits might detract participants from academic focus. Our finding is consistent with Azizi et al. (2019), who found a significant negative association between use of social networks and academic performance. A potential explanation is that if students spend too much time on social networking, they might compromise their academic performance in online learning, where they have more flexibility dividing their time between learning and socialization. Another explanation is if giving kindness is overdone and not reciprocal, it may be negatively associated with institutional identity and stress reduction, and the person giving kindness may not persist academically (Hosoda & Estrada, 2024).

Surprisingly, each unit increase in online time management is associated with 43% lower odds of a higher GPA. This finding contradicts with West and Sadoski (2011), who found that time management predicts academic performance, as those with good time management were less likely to delay content revision. This inconsistency may be related to how time management is defined and measured. For West and Sadoski (2011), good time management refers to managing time well for medical school/ practical courses. In our study, good time management refers to fixing a schedule to study for online/ hybrid courses, and allocating extra studying time for them. Furthermore, as online learners could be flexible and arrange time in an unstructured way (Zheng et al., 2018), they may have compensated for the lack of in-person interaction by allocating more time for online/ hybrid modules. This may backfire if they neglect face-to-face modules, which still comprise the majority of modules.

Higher self-efficacy is associated with 2.20 times the odds of achieving higher GPA categories. This could be related to learners' confidence and belief that they will succeed academically. Our findings echo Won and colleagues (2024), who found that academic self-efficacy in online learning predicted students' grades. The belief that one can complete an academic task successfully increases achievement likelihood (Won et al., 2024). With higher self-efficacy, students tend to have better online learning engagement (Kuo et al., 2021) that may transform into academic achievement.

There are some limitations: (1) our participants were from a university in Singapore, making our findings not generalizable to a wider population; (2) GPA was used as a measure of learning performance, which involves academic outcomes for all modules, instead of only online modules. Future studies can explore how to isolate the outcomes of online and hybrid learning from overall outcomes to better understand how various factors influence online learning performance, to inform the design of online learning strategies.

In conclusion, this paper contributes to the literature regarding online learning and informs educators to pay attention to the specific attributes of humanity, time management, and self-efficacy of students when delivering online learning classes. To improve online learning, educators could: (1) remind students to not be excessively relational or over focus on social networking; (2) remind students to have balanced time management across all modules, instead of allocating too much time resources for online/ hybrid modules only; and (3) help students build self-efficacy, for example, by creating scaffolded tasks, enabling them to have opportunities to feel academically self-efficacious (Won et al., 2024).

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