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Emergency Online Learning: The Effects of Interactional, Motivational, Self-Regulatory, and Situational Factors on Learning Outcomes and Continuation Intentions

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Abstract

This study investigated the effects of interactional, motivational, self-regulatory, and situational factors on university students' online learning outcomes and continuation intentions during the COVID-19 pandemic. Data were collected from 255 students taking a business course at a university in southern China. Hierarchical multiple regression analyses revealed that while family financial hardship caused by COVID-19 was a marginally significant negative predictor of students' learning outcomes, learner–content interaction; instructors' provision of e-resources, course planning, and organisation; and students' intrinsic goal orientation and meta-cognitive self-regulation were significant positive predictors with the latter two sets of predictors mediating the effects of learner–instructor and learner–learner interactions, respectively. Multinominal logistic regression analyses showed that learner–instructor interaction, learner–content interaction, and private learning space were significant positive predictors of students' intentions to continue with online learning, but learner–learner interaction was a significant negative predictor. These findings point to the differential effects of various types of interactional and situational factors on learning outcomes and continuation intentions, and the instructor- and learner-level factors that mediate the effects of learner–instructor and learner–learner interactions on learning outcomes. They contribute to our understandings of emergency online learning and provide implications for facilitating it.

Keywords: emergency online learning, motivation, self-regulation, learning outcomes, continuation intention

Introduction

The spread of COVID-19 plunged the world into a health crisis and has had profound impacts on almost every sector. The higher education sector, for example, responded to the crisis by transitioning to online learning (Greenhow & Lewin, 2021). This transition has fostered the continuation of learning during the pandemic. However, emergency online learning tends to feature inadequate instructional design and insufficient institutional support, which may pose grave challenges to students and instructors transitioning to online learning (Rehm et al., 2021; Wang et al., 2021). Aguilera-Hermida (2020), for instance, has identified three types of COVID-19-related challenges: situational, online educational, and emotional. While the situational and the online educational challenges refer to “distractors and financial hardship” and “students’ lack of access to supporting resources and lack of prior online learning experience,” respectively, the emotional challenges include mainly “a lack of motivation and negative emotions” (p. 5). These purported challenges notwithstanding, how they may influence students’ learning outcomes, and intentions to continue online learning remains largely unknown. Moreover, while a large body of research has examined online learning and its influencing factors in higher education, previous research has focused primarily on “the technology dimension and individuals’ experience” and has paid less attention to social and affective factors (Li et al., 2021, p. 3). Thus, this study investigates the effects of interactional, motivational, self-regulatory, and situational factors related to the COVID-19 on students’ perceived online learning outcomes and continuation intentions. The findings of this study contribute to our understanding of the differential effects of different types of interactional and situational factors on learning outcomes and continuation intentions in emergency online learning settings, as well as the instructor- and learner-level factors that mediate the effects of learner–instructor and learner–learner interactions on learning outcomes.

Interaction in Online Learning

Wagner (1994, p. 8) defines interaction as “reciprocal events that require at least two objects and two actions.” According to Moore (1989), three types of interaction come into play within distance or online learning, namely, learner–instructor, learner–learner, and learner–content. The literature has long acknowledged “the critical role of interaction in supporting and even defining education,” including enhancing the effectiveness of and continuation intentions for online learning (Anderson, 2003, p. 2; see also Juwah, 2006). In a meta-analysis of the three types of interactions in distance education, Bernard et al. (2009) find the interactions to have a positive effect on achievement outcomes.

Learner–instructor interaction refers to “interaction between the learner and the expert who prepared the subject material, or some other expert acting as instructor” (Moore, 1989, p. 2). As an integral part of both face-to-face and online education, learner–instructor interaction can provide learners with feedback, stimulate their interest, and enhance their engagement with learning (Anderson, 2003; Moore, 1989). Research has shown that learner–instructor interaction tends to impinge on students’ perceived learning (Arbaugh, 2000; Marks et al., 2005). Marks et al. (2005), for example, found a significant effect of learner–instructor interaction on perceived learning in graduate online courses. Moreover, research has shown that learner–instructor interaction is positively associated with learners’ satisfaction with and continuation intentions for online learning (Huang et al. 2017; Lin et al., 2017a). For example, in a study of students’ intentions to revisit massive open online courses (MOOCs), Huang et al. (2017) found that the degree of learner–instructor interactions had a positive influence on students' intentions to revisit MOOCs.

Learner–learner interaction refers to interaction "between one learner and other learners, alone or in group settings, with or without the real-time presence of an instructor" (Moore, 1989, p. 4). The literature has reported various benefits of leaner–learner interaction in online learning, including, among others, boosting motivation (Wagner, 1994), fostering the learning process (Anderson, 2003), tackling learners' loneliness (Weiner, 2003), and reducing dropout rates (Johnston et al., 2014). However, in synthesizing research on the effects of different types of interaction, Miyazoe and Anderson (2010) have found that although all three types of interactions had moderate effects on achievement outcomes, learner–instructor and learner–content interactions had greater effects than learner–learner interaction, despite learners' more positive attitudes towards the latter. Similarly, in a study of predictors for student satisfaction in online learning, Kuo, Walker, Schroder et al. (2014) have found that while both learner–instructor and learner–content interactions were significant predictors of student satisfaction, learner–learner interaction was a nonsignificant predictor. They concluded that "learner–learner interaction may be negligible in online course settings" (p. 35).

Finally, as "a defining characteristic of education," learner–content interaction refers to "interaction between the learner and the content or subject of study" (Moore, 1989, p. 3). Learner–content interaction has been found to have a positive effect on student perceived progress (Kuo, Walker, Schroder et al. 2014; Lin et al., 2017a). In a study on the relationship between interactions and learning outcomes in online language courses, for example, Lin et al. (2017a) find that only learner–content interaction significantly predicts students' perceived progress. However, the effect of learner–content interaction on student satisfaction and continuation intentions has been ambivalent. In Lin et al.'s (2017a) study, for example, both learner–instructor and learner–content interactions are found to be significant predictors of student satisfaction, with the latter being the stronger predictor. In contrast, Luo et al. (2017) have examined the effects of different types of interactions on students' sense of community and continuation intentions for e-learning, finding that only learner–learner and learner–instructor interactions had significant effects on learners' satisfaction and "stickness with the e-learning platform" (p. 153).

Motivation and Self-Regulation in Online Learning

Motivation and self-regulation are crucial for online learning success (Aguilera-Hermida, 2020; Wagner, 1994). According to the social-cognitive model of motivation, there are three general motivational constructs, namely, expectancy, value, and affect (Pintrich & De Groot, 1990, Pintrich et al., 1993). The value components deal with students' rationales for engaging in a learning task, including intrinsic goal orientation, extrinsic goal orientation, and task value beliefs. In particular, intrinsic goal orientation or intrinsic motivation focusing on learning and mastery has been found to significantly contribute to learning in both traditional and online learning settings (Eom & Ashill, 2016; Zhou, 2016). Cho and Shen (2013) examine the effect of goal orientation on academic achievement in online learning and find students' intrinsic goal orientation to be a significant predictor of students' academic achievement. In addition, research (e.g., Ifinedo, 2017; Park et al., 2012) has shown that intrinsic motivation (e.g., enjoyment) is a significant factor influencing students' continuation intentions to learn online. For instance, Abdullatif and Velázquez-Iturbide (2020) explore the relationship between motivations, personality traits, and intentions to continue MOOCs, finding a significant positive relationship between intrinsic motivation and intentions to continue MOOCs.

Self-regulation refers to “self-generated thoughts, feelings, and actions that are planned and cyclically adapted to the attainment of personal goals” (Zimmerman, 2000, p. 14). Research has long identified self-regulation as a significant contributor to academic success in traditional contexts (Pintrich & De Groot, 1990; Zimmerman, 1989, 2000). Given the nature of online learning, it is even more crucial (Kuo et al., 2013). In a meta-analysis of the relationship between self-regulated learning strategies and academic achievement in online higher education contexts, Broadbent and Poon (2015) have found a significant association between meta-cognition, time management, effort regulation, and critical thinking, on the one hand, and academic achievement on the other. In particular, Lin et al. (2017b) find self-regulated learning (SRL) strategies to have a significant positive effect on student learning outcomes, including student satisfaction, perceived progress, and final grades.

Moreover, research (e.g., Puzziferro, 2008; Kuo et al., 2013; Kuo, Walker, Schroder, et al., 2014; Zhu et al., 2020) has also found self-regulation, particularly meta-cognitive self-regulation, to be significantly and positively correlated with student satisfaction with and continuation intentions for online learning. For example, in examining the effects of technological self-efficacy and SRL strategies on student performance and satisfaction in online undergraduate courses, Kuo, Walker, Schroder, et al. (2014) found SRL to be a moderate predictor of student satisfaction with online learning. Furthermore, in a study of the effects of university students’ SRL capability, online interactions, and attitudes on online learning intention in a blended learning context, Zhu et al. (2020) concludes that “students with a higher level of self-management skills tended to consider online peer interaction to be less important for them” (p. 17).

Situational Factors in Online Learning

Apart from interaction, motivation, and self-regulation, situational factors also have a role to play in online learning, especially in emergency online learning. As noted, Aguilera-Hermida (2020) has identified three types of challenges related to COVID-19, including situational, online educational, and emotional challenges. Meeting these challenges requires careful instructional design and institutional support (Aguilera-Hermida, 2020; Hodges et al., 2020). However, the design and support needed for effective online teaching and learning may not be available during emergency online education caused by crises. For example, while accessibility to the instructor, other learners, and technologies is directly related to social and cognitive engagement (Aguilera-Hermida, 2020) and learning outcomes and continuation intentions (Luo et al., 2017), it may prove difficult to guarantee in emergency online learning. In addition, students may also encounter difficulties accessing private learning space and adequate e-resources due to the constraints caused by emergencies. Some of these factors have been examined in previous studies. For example, research has shown that that prior online learning experience is positively associated with learner satisfaction with online learning outcomes (Tallent-Runnels et al., 2006) and intentions to continue online learning (Tsai et al., 2018). However, other contextual factors have received little attention, such as distractors, financial hardship, and a lack of access to supporting resources.

In summary, the literature shows that a multitude of factors may influence students’ online learning outcomes and continuation intentions. It also indicates that some issues need further investigation.

First, while there seems to be consensus in the literature on the effects of interaction on learning outcomes, research on the effects of interaction on continuation intentions has yielded mixed findings. Second, the literature has paid relatively little attention to the effects of social, affective, and contextual factors on (emergency) online learning (Aguilera-Hermida, 2020; Li et al., 2021). To address these issues, this study focused on the effects of interactional, motivational, self-regulatory, and situational factors on students' learning outcomes and intentions to continue online learning during the COVID-19 pandemic and sought to answer the following two research questions:

RQ1. To what extent do interactional, motivational, self-regulatory, and situational factors predict students' perceived learning outcomes?

RQ2. What factors may predict students' intentions to continue online learning compared with traditional and blended learning?

Methodology

Participants

Participants of this study included undergraduate students taking the Intermediate Accounting course at a university in southern China. A total of 440 students from 11 classes took the course. Four instructors each taught two classes, and one instructor taught three classes. All classes adopted the same course materials, assignments, and assessment methods. More than half of the students (n = 255) participated in the study. As shown in Table 1, there were 49 male and 206 female participants, which was largely proportional to the gender distribution of students taking the course. The great majority of the respondents were between 19 and 20 years of age. They came from three majors, with 188 in business administration, 37 in accounting, and 30 in financial management. Due to the COVID-19 pandemic, all lectures were delivered online synchronously using Tencent Class, an online education platform by the Chinese tech company Tencent Holdings Ltd. About 60% of the students reported having had online learning experience before the COVID-19 outbreak.

Table 1

Participants' Demographics

Characteristic	Frequency	%
Gender		
Male	206	80.78
Female	49	19.22
Age (years)		
18	20	7.94
19	151	59.92
20	79	31.35
> 20	2	0.79
Major		
Business administration	188	73.73
Accounting (international)	37	14.51
Financial management	30	11.76
Prior online learning experience		
Yes	154	60.39
No	101	39.61

Measures

The measures used in this study included two outcome scales, seven predictor variables, and three demographic variables. The learning outcomes scale, adapted from Liu (2012), consisted of four items and assessed students' perceived learning outcomes for the course. The continuation intentions outcome variable gauged students' intentions to continue online learning and comprised three categories: continuing online learning, switching to traditional learning, and switching to blended learning.

The interactions scale was adopted from Kuo, Walker, Schroder, et al. (2014) and consisted of three subscales: the learner–instructor subscale, the learner–learner subscale, and the learner–content subscale. Both the intrinsic goal orientation and the meta-cognitive self-regulation scales were derived from Pintrich et al. (1991). The intrinsic goal orientation scale assessed the extent to which students conceived of their participation in a task for intrinsic reasons, such as curiosity, mastery, or challenge. The meta-cognitive self-regulation scale measured the extent to which students employed the planning, monitoring, and regulating strategies during learning. The course organisation and planning scale was taken from Liu (2012) and queried students' perceptions of the instructor's organisation and planning of the course. A six-point Likert scale was used in the aforementioned measures where 1 denoted "not at all true of me" or "strongly disagree" and 6 denoted "very true of me" or "strongly agree." The e-resources scale asked students to indicate on a six-point Likert scale the extent to which they perceived the e-resources provided by the instructor to be adequate. The COVID-19 impact variable assessed whether students' family financial situations were affected by the COVID-19. The questionnaire also collected students' background variables, including gender (male, female), prior online learning experience (having previous online learning experience or not), and private learning space (having private learning space for participating in online courses or not).

The Cronbach's alphas (α) for the outcome and predictor scales derived from this study ranged from 0.844 to 0.953, indicating good internal consistencies across the scales (see Table 2). A confirmatory factor analysis of the outcome and predictor scales demonstrated acceptable data–model fit, showing acceptable factorial validity of the measurement model for the sample of this study (see Table 3).

Table 2

Scales and Reliability Estimates

Scale	No. of items	α	KMO
Perceived learning outcomes	5	0.953	
Learner–instructor interaction	6	0.856	
Learner–learner interaction	8	0.940	
Learner–content interaction	4	0.895	0.944
Course organisation and planning	5	0.943	
Intrinsic goal orientation	4	0.849	
Meta-cognitive self-regulation	11	0.844	

Note. KMO = Kaiser-Meyer-Olkin.

Table 3

Results of Confirmatory Factor Analysis

Index	χ^2	*df*	χ^2/df	TLI	CFI	SRMR	RMSEA
Recommended thresholds			< 3.000	> 0.900	> 0.900	< 0.080	< 0.080
Models	1632.160	829	1.969	0.907	0.915	0.050	0.062

Note. TLI = Tucker–Lewis index; CFI = Comparative fit index; SRMR = Standardized RMR; RMSEA = Root Mean Square Error of Approximation. Recommended thresholds from "Reporting Structural Equation Modeling and Confirmatory Factor Analysis Results: A Review," by J. Schreiber et al., 2013, The Journal of Educational Research, p. 323-338, (https://doi.org/10.3200/JOER.99.6.323-338). Copyright 2013 by Taylor & Francis.

Data Collection and Analysis

All students taking the Intermediate Accounting course were invited to complete an online questionnaire about their online learning experience immediately after the semester ended. They were informed and assured that anonymity and confidentiality were guaranteed, that their participation was completely voluntary, and that declining to participate would not affect them in any way. One week after sending the invitation, we sent a reminder to those who had not completed the questionnaire.

A five-level hierarchical multiple regression model was employed to address the first research question. The outcome variable was the mean score from the four-item learning outcomes scale. The background variables (i.e., gender, prior online learning experience, private learning space) were entered in the first step of the hierarchical regression analyses. The three types of interactions were entered in the second step. The student variables (i.e., intrinsic goal orientation, meta-cognitive self-regulation) and the instructor/course variables (i.e., course organisation and planning, provision of e-resources) were entered in the third and fourth steps, respectively. Family financial hardship caused by the COVID-19 was entered in the last step.

To address the second research question, a multinominal regression was run on students' intentions to continue online learning. The outcome variable was students' intentions regarding three learning modes (i.e., continuing online learning, switching to traditional learning, and switching to blended learning). The predictor variables included gender, prior online learning experience, private learning space, family financial hardship caused by COVID-19, three types of interactions, intrinsic goal orientation, meta-cognitive self-regulation, provision of e-resources, and course organisation and planning.

Results

Regression Analyses on Learning Outcomes

Table 4 presents descriptive statistics for the variables, and Table 5 shows the correlations among all the interval variables. As shown in Table 5, the correlations among the interval variables were significant and moderate (ranging from 0.473 to 0.825). Except for the correlation between learner–content interaction and learning outcomes, all other correlations were less than 0.80, which suggests that multicollinearity was not a serious concern.

Table 4

Descriptive Statistics

Variable name	Mean	*SD*	Range
Learning outcomes	4.43	0.883	1–6
Learner–instructor interaction	4.49	0.783	1–6
Learner–learner interaction	4.34	0.890	1–6
Learner–content interaction	4.42	0.905	1–6
Adequacy of e-resources	4.66	0.890	1–6
Course organisation and planning	4.82	0.824	1–6
Intrinsic goal orientation	4.44	0.774	1–6
Meta-cognitive self-regulation	4.13	0.610	1–6
Gender (male = 0)	0.81	0.395	0–1
Prior online learning experience (no = 0)	0.60	0.490	0–1
Private learning space (no = 0)	0.91	0.281	0–1
Family financial situation (not affected = 0)	0.45	0.499	0–1

Table 5

Correlations Among the Outcome Variable and Continuous Predictors

Variable	1	2	3	4	5	6	7	8
1. Learning outcomes	1							
2. Learner–instructor interaction	0.615*	1						
3. Learner–learner interaction	0.632*	0.678*	1					
4. Learner–content interaction	0.825*	0.610*	0.629*	1				
5. Provision of e-resources	0.497*	0.404*	0.319*	0.487*	1			
6. Course organisation and planning	0.654*	0.613*	0.541*	0.624*	0.401*	1		
7. Intrinsic goal orientation	0.663*	0.527*	0.614*	0.580*	0.318*	0.600*	1	
8. Meta-cognitive self-regulation	0.635*	0.526*	0.563*	0.552*	0.298*	0.473*	0.569*	1

Note. * $p < 0.01$.

Table 6 presents the effects of demographics, interactions, learner and instructor variables, and family financial situation on students' perceived learning outcomes. As shown in Table 6, in model 1, only prior online learning experience ($\beta = 0.138$, $t = 2.196$, $p = 0.029$) was significantly and positively associated with student learning outcomes. This means that students with prior online learning experience reported significantly higher learning outcomes than their counterparts without prior online learning experience. However, the model just approached statistical significance ($F[3, 252] = 2.349$, $p = 0.073$), and the variance explained by the model was only 1.6% (Adj. $R^2 = 0.016$).

Table 6

Regressions on Perceived Learning Outcomes

	(1) M1	(2) M2	(3) M3	(4) M4	(5) M5
Gender (male = 0)	−0.095	−0.033	−0.040	−0.015	−0.015
	(−1.518)	(−0.962)	(−1.215)	(−0.480)	(−0.471)
Prior online learning	0.138**	−0.009	−0.012	−0.042	−0.039
experience (no = 0)	(2.196)	(−0.266)	(−0.356)	(−1.303)	(−1.217)
Private learning space	0.003	−0.026	−0.024	−0.010	−0.011
(no = 0)	(0.043)	(−0.739)	(−0.710)	(−0.327)	(−0.361)
Learner–instructor		0.113**	0.038	0.014	0.026
interaction		(2.283)	(0.748)	(0.304)	(0.541)
Learner–learner		0.134***	0.127**	0.031	0.027
interaction		(2.636)	(2.582)	(0.636)	(0.552)
Learner–content		0.673***	0.571***	0.505***	0.503***
interaction		(14.434)	(11.436)	(10.572)	(10.570)
Provision of			0.102***	0.098***	0.092**
e-resources			(2.632)	(2.710)	(2.533)

Course organisation			0.164***	0.101**	0.095**
and planning			(3.566)	(2.247)	(2.114)
Intrinsic goal				0.165***	0.163***
orientation				(3.668)	(3.647)
Meta-cognitive				0.165***	0.167***
self-regulation				(3.993)	(4.042)
Family financial situation (not affected = 0)					−0.055* (−1.749)
Constant	4.446***	4.576***	4.587***	4.534***	4.577***
	(19.376)	(36.143)	(37.305)	(39.379)	(39.047)
N	255	255	255	255	255
Adj. R^2	0.016	0.703	0.725	0.760	0.762

Note. t statistics appear in parentheses. M = model. * $p < 0.1$. ** $p < 0.05$. *** $p < 0.001$.

The variance explained by model 2 reached 70.3% ($F[6, 248] = 101.063$, $p < 0.001$) after learner–instructor, learner–learner, and learner–content interactions were added in step 2. Learner–instructor ($\beta = 0.113$, $t = 2.283$, $p = 0.023$), learner–learner ($\beta = 0.134$, $t = 2.636$, $p = 0.009$), and learner–content ($\beta = 0.673$, $t = 14.434$, $p < 0.001$) interactions were all significant and positive predictors of student learning outcomes. Prior online learning experience was no longer a significant predictor. The effect size of the learner–content interaction ($\beta = 0.673$) was over five times greater than those of the other two types of interaction ($\beta = 0.113$, $\beta = 0.134$).

After perceived adequacy of e-resources and course organisation and planning were added in model 3, learner–learner ($\beta = 0.127$, $t = 2.582$, $p = 0.010$) and learner–content ($\beta = 0.571$, $t = 11.436$, $p < 0.001$) interactions remained significant predictors of student learning outcomes, but the learner–instructor interaction ($\beta = 0.038$, $t = 0.748$, $p = 0.455$) was no longer a significant predictor. The effect sizes of learner–learner interaction and learner–content interaction decreased from 0.134 and 0.673 to 0.127 and 0.571, respectively. Moreover, both perceived adequacy of e-resources ($\beta = 0.102$, $t = 2.632$, $p = 0.009$) and course organisation and planning ($\beta = 0.164$, $t = 3.566$, $p < 0.001$) were significant and positive predictors of student learning outcomes. These findings indicated that learner–instructor interaction was mediated by perceived adequacy of e-resources and course organisation and planning. The model was significant ($F[8, 246] = 84.626$, $p < 0.001$) and explained 72.5% of the variance in perceived student learning outcomes.

Following the addition of intrinsic goal orientation and meta-cognitive self-regulation in model 4, learner–content interaction ($\beta = 0.505$, $t = 10.572$, $p < 0.001$), perceived adequacy of e-resources ($\beta = 0.098$, $t = 2.710$, $p = 0.007$), and course organisation and planning ($\beta = 0.101$, = 2.247, $p = 0.026$) remained significant predictors of student learning outcomes, but learner–learner interaction was no longer a significant predictor ($\beta = 0.031$, $t = 0.636$, $p = 0.525$). The effect sizes of learner–content interaction, perceived adequacy of e-resources, and course organisation and planning decreased from 0.571, 0.102, and 0.164 to 0.505, 0.098, and 0.101, respectively. Moreover, both intrinsic goal orientation ($\beta = 0.165$, $t = 3.668$, $p < 0.001$) and meta-cognitive self-regulation ($\beta = 0.165$, $t = 3.993$, $p < 0.001$) were significant and positive predictors of student learning outcomes. These findings indicate that learner–learner interaction was mediated by intrinsic goal orientation and meta-cognitive self-regulation. The model was significant ($F[10, 244] = 81.548$, $p < 0.001$) and explained 76% of the variance in perceived student learning outcomes.

Finally, the impact of COVID-19 on family financial situation (β = −0.055, t = −1.749, p = 0.082) was found to be a marginally significant and negative predictor of student learning outcomes in model 5. This means that students whose family financial situations were affected by the COVID-19 pandemic reported significantly lower perceived learning outcomes than did their peers whose family financial situations were not affected by COVID-19. The significant predictors identified in model 4 remained significant, and their effect sizes did not change much. The model was significant (F[11, 243] = 75.039, p < 0.001) and explained 76.2% of the variance in perceived student learning outcomes.

Multinominal Regression Analyses on Intentions to Continue Online Learning

The multinominal logistic regression performed to model the relationships between the predictors and the students' intention to continue online learning was significant (χ^2[22, N = 255] = 40.868, Nagelkerke's R^2 = 0.185, p = 0.009) and correctly classified 64.7% of the cases.

As shown in Table 7, three factors had a significant parameter for comparing the online group with the traditional group. The odds ratio shows that with a one-unit increase in learner–learner interaction, the change in the odds of switching to traditional learning as opposed to continuing online learning is 3.485. This means that students with higher reported learner–learner interaction were more likely to switch to traditional learning. In contrast, with a one-unit increase in learner–content interaction, the change in the odds of switching to traditional learning was 0.294. In other words, students with higher reported learner–content interaction were less likely to switch to traditional learning. In addition, the odds ratio also shows that as private learning spaces changes from no (0) to yes (1), the change in the odds of a student with private learning space switching to traditional learning was 1 in 6.086. This shows that students with a private learning space were much less likely to switch to traditional learning than their counterparts without a private learning space.

Table 7

Multinominal Logistic Regression on Intention to Continue Online Learning

Predictors	Online vs.	*B*	*SE*	Wald	Exp(B)	*p*
Intercept	Traditional	2.475	0.692	12.776		< 0.001
	Blended	3.456	0.674	26.256		<0.001
Learner–instructor interaction	Traditional	−0.831	0.506	2.694	0.436	0.101
	Blended	−1.254	0.498	6.345	0.285	0.012
Learner–learner interaction	Traditional	1.248	0.450	7.687	3.485	0.006
	Blended	1.228	0.423	8.443	3.415	0.004
Learner–content interaction	Traditional	−1.225	0.556	4.856	0.294	0.028
	Blended	−0.554	0.536	1.070	0.575	0.301
Provision of e-resources	Traditional	−0.378	0.415	0.830	0.685	0.362
	Blended	−0.299	0.405	0.544	0.742	0.461
Course organisation and planning	Traditional	0.341	0.446	0.583	1.406	0.445
	Blended	0.504	0.431	1.364	1.655	0.243
Intrinsic goal orientation	Traditional	0.287	0.416	0.477	1.333	0.490
	Blended	0.152	0.396	0.146	1.164	0.702
Meta-cognitive self-regulation	Traditional	0.410	0.404	1.030	1.507	0.310
	Blended	0.349	0.389	0.805	1.418	0.370
Gender (male = 0)	Traditional	−0.556	0.714	0.607	0.573	0.436

	Blended	−1.061	0.692	2.352	0.346	0.125
Prior online learning	Traditional	1.091	0.795	1.885	2.978	0.170
experience (no = 0)	Blended	1.254	0.775	2.621	3.505	0.105
Private learning space	Traditional	17.924	0.539	1,106	6.086	< 0.001
(no = 0)	Blended	18.239	0.000		8.335	
Family financial situation	Traditional	−0.875	0.742	1.388	0.417	0.239
(not affected = 0)	Blended	−1.252	0.723	2.996	0.286	0.083

Note. N = 255. Reference group = online. $\chi^2(22, N = 255) = 40.868$, Nagelkerke's $R^2 = 0.185$, $p = 0.009$. 64.7% of the cases were correctly classified.

Two factors had a significant parameter for comparing the online group with the blended group. The odds ratio shows that with a one-unit increase in learner–learner interaction, the change in the odds of switching to blended learning rather than continuing online learning was 3.415. This indicates that students with higher reported learner–learner interaction were more likely to switch to blended learning as opposed to continuing online learning. In contrast, with a one-unit increase in learner–instructor interaction, the change in the odds of switching to blended learning was 0.285. This suggests that students with higher reported learner–instructor interaction were less likely to switch to blended learning.

Discussion

With regard to RQ1, factors influencing students' learning outcomes, our findings show that all three types of interaction were significantly related to students' perceived learning outcomes after controlling for demographic variables. Specifically, the effect of learner–content interaction was five times greater than those of learner–learner and learner–instructor interactions. This finding is largely consistent with findings from previous research (Kuo et al., 2013; Lin et al., 2017a). In an investigation of factors affecting students' perceived progress in online language courses, for example, Lin et al. (2017a) find only learner–content interaction to be a significant predictor of students' perceived progress. However, the present study found that the effect of learner–instructor interaction on perceived learning outcomes disappeared after the instructors' provision of e-resources and course organisation and planning were added to the regression model. This indicates that the effect of learner–instructor interaction was mediated by instructors' provision of e-resources and course organisation and planning. Similarly, the study also revealed that the effect of learner–learner interaction was mediated by students' intrinsic goal orientation and meta-cognitive self-regulation. This echoes Zhu et al.'s (2020) finding that students with high levels of self-regulation strategies are inclined to attach less importance to learner–learner interaction. After controlling for the instructor and learner factors, only learner–content interaction was significantly associated with students' perceived learning outcomes. These instructor- and learner-level factors, as well as other similar factors, might explain why some studies found learner–content interaction to be the only significant predictor of learning outcomes, whereas others found all three types of interaction to be significant predictors (Kuo, Walker, Schroder, et al., 2014). This finding highlights the need for "a comprehensive perspective" to analyse and understand interaction in online learning (Garrison & Cleveland-Innes, 2005, p. 144). Indeed, from the community of inquiry perspective, "simple interaction, absent of structure and leadership, is not enough" to promote deep learning (Garrison & Cleveland-Innes, 2005, p. 145). Likewise, according to the theory of transactional distance, interaction is closely intertwined with design or structure in distance or online education

(Moore, 1989, 1997).

Furthermore, both intrinsic motivation and meta-cognitive self-regulation significantly predicted students' perceived learning outcomes. The finding about intrinsic motivation is consistent with that of Eom and Ashill (2016, p. 185), who also found that "intrinsic student motivation affects learning outcomes." However, the finding about meta-cognitive self-regulation is inconsistent with that of Eom and Ashill (2016), who found that students' self-regulation was not significantly associated with their learning outcomes. Finally, we also found that family financial hardship due to the COVID-19 pandemic had a marginally significant effect on students' perceived learning outcomes. In a similar vein, Chu (2010) finds that tangible family support significantly predicts adult learners' perceived effects of e-learning. These findings point to the important roles of interactional, affective, and situational factors in emergency online learning (Aguilera-Hermida, 2020). Specifically, they demonstrate the differential effects of different types of interaction on student learning outcomes as well as the mediation of learner–instructor and learner–learner interaction effects by instructor- and learner-level factors.

Regarding RQ2, factors influencing students' intentions to continue online learning, the study found that private learning space, learner–instructor interaction, and learner–content interaction were significant and positive predictors of students' intentions to continue online learning, but learner–learner interaction was a significant and negative predictor. These findings are only partially consistent with the findings from previous research. For example, both Kuo et al. (2013) and Lin et al. (2017a) have found learner–instructor and learner–content interactions to be significant predictors of student satisfaction with online learning but learner–learner interaction to be a nonsignificant predictor. However, Luo et al. (2017) found both learner–learner and learner–instructor interactions to be significant predictors of learners' satisfaction and "stickness with the e-learning platform" (p. 153). Unlike typical online learning, the emergency online learning examined in this study was characterized by intact class instruction and provision of e-resources that might not be available in other contexts. Therefore, both learner–instructor and learner–content interactions were found to be significant predictors of student intentions to continue online learning. In a similar vein, because the students in this study knew each other and the course had been taught in person, they might have missed the face-to-face interaction after the pandemic started. Hence, the higher the learner–learner interaction, the more likely they would wish to switch back to traditional face-to-face learning. Alternatively, these findings may also mean that learner–instructor and learner–content interactions are easier to transfer to an online setting than learner–learner interactions.

However, contrary to some previous studies (e.g., Abdullatif & Velázquez-Iturbide, 2020; Ifinedo, 2017; Park et al., 2012; Zhu et al., 2020) that have identified intrinsic goal orientation and meta-cognitive self-regulation as significant predictors of students' continuation intentions, this study found neither to be a significant predictor. This might be attributed to the emergency nature of this course—delivered synchronously to intact classes in which learners already knew each other—which differs from typical online education where learners are likely to be strangers. As Lou et al. (2006) point out, "synchronous undergraduate DE [distance education] is simply a form of simulated classroom experience that is not overly affected by distance from the host site and the use of a medium of communication such as videoconferencing" (pp. 162–163). Finally, the study also showed that students with access to a private learning space were significantly more likely to continue online learning compared with their peers without access to a private learning space. These findings underscore the importance of interaction and private learning spaces in shaping students' intentions to continue online learning.

Conclusion

This study set out to investigate the influencing factors on students' learning outcomes and continuation intentions in emergency online learning. It has yielded several noteworthy findings. First, it revealed that while learner–content interaction was positively associated with both learning outcomes and continuation intentions, learner–instructor and learner–learner interactions were only significantly related to continuation intentions. Second, it was found that while learner–content and learner–instructor interactions were positively associated with continuation intentions, learner–learner interactions were negatively related to continuation intentions. Third, intrinsic goal orientation and meta-cognitive self-regulation mediated the effect of learner–learner interactions on learning outcomes and were only significantly related to learning outcomes. Fourth, the study showed that while family financial hardship caused by COVID-19 was a marginally significant negative predictor of students' learning outcomes, access to private learning space was a significant positive predictor of students' continuation intentions. These findings contribute to our understanding of the differential effects of various types of interaction, instructor-, learner- and situation-level factors on learning outcomes and continuation intentions in emergency online learning settings. Given the context and scope of this study, caution should be exercised in generalising these findings to other contexts. Nonetheless, they provide several implications for facilitating emergency online learning.

First, the significant effects of learner–content interaction, provision of e-resources, and course organisation and planning on perceived learning outcomes point to the importance of providing adequate learning materials and organising them in ways that facilitates learner–content interaction. Second, the significant association between students' intrinsic goal orientation and meta-cognitive self-regulation and their learning outcomes suggests the need to cultivate students' intrinsic goal orientation and develop their meta-cognitive self-regulation strategies. Third, the significant effect of family financial hardship on students' perceived learning outcomes indicates the need to provide financial support for students facing financial hardships during crises. Fourth, since learner–instructor and learner–content interactions were significant predictors of students' continuation intentions, it is important to strengthen learner–instructor and learner–content interactions if we are to enhance students' intentions to continue online learning. However, this study was not able to tease out the mechanisms that link learner–learner interactions and continuation intentions. More research is needed to unravel these relationships. Finally, the study also points to the need to secure private learning space to bolster students' intentions to continue online learning.

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