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Editorial – Volume 24, Issue 1

Constance Blomgren
Associate Editor

The IRRODL editors welcome our readership to 2023 and to the upcoming year of research publications, literature, and book reviews. As this issue highlights, the world of open and distributed learning continues to change and develop.

We begin this issue with "Using Survival Analysis to Identify Populations of Learners at Risk of Withdrawal: Conceptualization and Impact of Demographics." **Martínez-Carrascal**, **Hlosta,** and **Sancho-Vinuesa** identify and analyze learners who may withdraw from online courses, and then offer intervention strategies to support learner success.

Wang offers MOOC research findings that apply the Technology Acceptance Model in tandem with the theory of planned behavior in the article "The Perception and Behavioral Intention Toward MOOCs: Undergraduates in China."

"An Online Physics Laboratory Delivered Through Live Broadcasting Media: A COVID-19 Teaching Experience" explores the experiences of Indonesian learners with an online nuclear physics laboratory. **Setiaji** and **Santoso's** research extends online learning to a new space and offers insights for successful laboratory learning experiences using Instagram as a broadcasting tool.

"The Design and Psychometric Properties of a Peer Observation Tool for Use in LMS-Based Classrooms in Medical Sciences" is a mixed methods study. The authors, **Mirmoghtadaie**, **Keshavarz**, and **Rasouli** examined medical school instructors and how they used a learning management system and a blended approach as perceived through peer observations.

With the global pandemic, there was a heightened role for parents and caregivers in the online education of their children. **Hanny**, **Graham**, **West**, and **Borup** apply the Academic Communities of Engagement framework in their qualitative study: "'Someone in Their Corner': Parental Support in Online Secondary Education."

This issue provides three *Book Reviews*. The first reviewer, **Parhar,** examines *The Encyclopedia of Female Pioneers in Online Learning* by Athabasca University authors Susan Bainbridge and Norine Wark. Bainbridge and Wark contribute to the history of education with interviews of 30 females with the specialty of online and distance education. The second review considers the open access book *Powering a Learning Society During an Age of Disruption* edited by Sungsup Ra, Shanti Jagannathan, and Rupert Maclean. The comprehensive review by **Misra** encourages IRRODL readers to take some time and learn from this book's contributing authors about the ongoing changes to our national and international understanding of the learning society. In the final review, **Dey** examines the recent book by Martha Cleveland-Innes and Nathaniel Ostashewski, both professors from Athabasca University. *Participant Experience in an Inquiry-Based Massive Open Online Course* provides insights about designing and delivering successful MOOCs for professional development garnered through 10 iterations of the Introduction to Technology-Enabled Learning MOOC (TELMOOC).

This issue also includes a *Literature Review* section with three offerings. The first literature review, "What Are the Indicators of Student Engagement in Learning Management Systems? A Systematized Review of the Literature," is authored by **Ahmadi**, **Mohammadi**, **Asadzandi**, **Shah**, and **Mojtahedzadeh.** Graduate students and supervisors will be interested in "The Online PhD Experience: A Qualitative Systematic Review" by **Melián**, **Reyes**, and **Meneses**. Instructional designers and educational developers will be curious to read **Wilson** and **Berge**'s literature review, "Educational Experience and Instructional Design Effectiveness Within the Community of Inquiry Framework."

These IRRODL articles contribute to the ongoing developments in the world of open and distributed learning. Please read, enjoy, and share with your learning networks.

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Using Survival Analysis to Identify Populations of Learners at Risk of Withdrawal: Conceptualization and Impact of Demographics

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Abstract

High dropout rates constitute a major concern for higher education institutions, due to their economic and academic impact. The problem is particularly relevant for institutions offering online courses, where withdrawal ratios are reported to be higher. Both the impact and these high rates motivate the implementation of interventions oriented to reduce course withdrawal and overall institutional dropout. In this paper, we address the identification of populations of learners at risk of withdrawing from higher education online courses. This identification is oriented to design interventions and is carried out using survival analysis. We demonstrate that the method's longitudinal approach is particularly suited for this purpose and provides a clear view of risk differences among learner populations. Additionally, the method quantifies the impact of underlying factors, either alone or in combination. Our practical implementation used an open dataset provided by The Open University. It includes data from more than 30,000 students enrolled in different courses. We conclude that low-income students and those who report a disability comprise risk groups and are thus feasible intervention targets. The survival curves also reveal differences among courses and show the detrimental effect of early dropout on low-income students, worsened throughout the course for disabled students. Intervention strategies are proposed as a result of these findings. Extending the entire refund period and giving greater academic support to students who report disability are two proposed strategies for reducing course withdrawal.

Keywords: course withdrawal, demographics, distance education and online learning, dropout, intervention design, survival analysis

Using Survival Analysis to Identify Populations of Learners at Risk of Withdrawal: Conceptualization and Impact of Demographics

Academic withdrawal constitutes one of the biggest challenges in education, in particular for online higher education (OHE) institutions, where withdrawal ratios are reported to be higher (Bawa, 2016; Simpson, 2010). Aside from its macroeconomic impact, withdrawal causes frustration in terms of expectations, as well as being a waste of time and money from the student's perspective (Lee & Choi, 2013; Simpson, 2010). These facts justify the interest of and motivate these institutions in designing targeted interventions aimed to reduce it.

A critical first step towards a successful intervention is the accurate and reliable identification of learners at risk (Rienties et al., 2016). This identification is mostly understood in terms of prediction. Most research works focus on determining individual risk and on increasing prediction ratios rather than on understanding the reasons behind the risk. While determining if a particular student is at risk can be valuable, the essential issue when considering an intervention is identifying a common risk factor behind a group of learners who may constitute an intervention target.

Furthermore, timely execution is essential. Time plays a particularly relevant role when designing and implementing interventions oriented to reduce course withdrawal and overall university dropout. The moment when a student decides to abandon a course is critical in terms of the intervention design. At the course level, Simpson (2010) showed that 40% of new students at the Open University withdraw from courses before the first assignment. At the university level, Grau-Valldosera et al. (2019) showed that periods of non-enrolment could result in dropout, despite the intention to continue at the time of the break. In both cases, it would be inefficient to implement interventions after the student has effectively dropped out.

When added to the relevance of time, the concept of population at risk—rather than individual at risk—makes us consider survival analysis as a suitable technique. However, a literature review revealed that research using this technique mainly focused on analysing university dropout (Cobre et al., 2019) or attrition in MOOCs (Rizvi et al., 2022; Xing et al., 2019) and was not linked to interventions. Our article focuses on the use of survival analysis as part of the intervention process, detecting populations of learners at risk of withdrawal at the course level in regular OHE courses. The method described will determine the significance and influence of a set of variables on course withdrawal, providing information to select intervention targets and coherent strategies. Additionally, survival curves will provide additional insight which will help the intervention design.

Besides setting the conceptual framework, we performed a practical implementation based on an open dataset from a world-leading online university: The Open University Learning Analytics Dataset (OULAD; Kuzilek et al., 2017). This dataset contains data from more than 30,000 students enrolled in 22 online course editions from different disciplines, including the withdrawal date for students who abandon different courses. Based on these data, we analysed the impact of students' demographics on withdrawal, determining risk factors and quantifying their impact. Demographics have been identified as some of the causes behind withdrawal (Hachey et al., 2022; Muljana & Luo, 2019) and constitute key features for early dropout prediction in online environments (Radovanovic et al., 2021). Nonetheless, the proposed method is applicable to any other variable of interest such as academic performance, background, or psychological features/traits that may impact it.

Literature Review

The Concept of Withdrawal

The analysis of dropout has long been present in educational literature, with 1900–1950 being considered the age of early development, broadening horizons in the 1990s, and showing rising interest in recent years. Compilations can be found linked to higher education (Aljohani, 2016; Behr et al., 2020; Larsen et al., 2013) and specifically to online scenarios (Hachey et al., 2022; Lee & Choi, 2011; Muljana & Luo, 2019; Xavier & Meneses, 2020).

Works by Tinto (1975) expounded upon one of the most relevant initial models explaining dropout in traditional education. The core of this theory is the student integration model, where persistence is explained by a student's motivation and ability to match the social and academic characteristics of the institution where she is studying. Years later, Bean (1985) introduced the student attrition model, which relies on the concept of behavioural intention, where dropout is conditioned by a mixture of academic, social-psychological, environmental, and socialisation factors.

These two theories and their combination in Cabrera et al. (1992) and later in Rovai (2003) have been at the core of subsequent studies on the topic. According to Rovai (2003), academic performance and dropout are a combination of student characteristics, student skills, external factors, and internal factors. These four make up the composite persistence model (CPM) and reflect the multivariate nature of dropout.

The term *university dropout* is commonly used to describe situations where students leave the university before obtaining a formal degree (Larsen et al., 2013). Behind this definition lies a complex phenomenon, evidenced by the list of related terms such as dropout, departure, withdrawal, failure, non-continuance or non-completion (Xavier & Meneses, 2020). Dropout is the opposite of retention, defined as "continued student participation in a learning event to completion, which in higher education is a course, program, institution, or system" (Berge & Huang, 2004, p. 3).

At the course level, most papers dealing with withdrawal do not provide a formal definition (77.78% according to a recent scoping review; Xavier & Meneses, 2020). In our research, we used the definition provided by the Open University as "cease studying a module without the intention to resume the study of that module" (Open University, 2022, p. 6).

Approaches for the Identification of Populations at Risk: Survival Analysis

The first stage of a correct intervention design is an accurate and reliable identification of learners at risk (Rienties et al., 2016). Surveys and different data mining techniques are typical approaches used in this identification. Prevalent techniques include decision trees and random forest (Behr et al., 2020), but a whole set of methods can be found in the literature (Xing et al., 2019). However, only a low percentage of studies make use of longitudinal data approaches and, in particular, survival analysis. Ameri et al. (2016) indicated that “there is only a limited attempt at using these methods in student retention problems” (p. 904). Xing et al. (2016) also showed that the performance of classical techniques used to predict dropout could be improved by accommodating temporal modelling approaches.

The use of survival analysis at the course level in the literature is focused on MOOC scenarios (recently Moreno-Marcos et al., 2019; Rizvi et al., 2022; Xing et al., 2019). The existing studies covering survival analysis in OHE all focus on analysing the semesters when students drop out from the university rather than withdrawal from within courses (Ameri et al., 2016; Cobre et al., 2019; Villano et al., 2018). Two of the studies (Ameri et al., 2016; Villano et al., 2018) focused more on comparing the prediction capability of survival methods to existing techniques. On the other hand, Cobre et al. (2019) tried to identify in which semesters students are most likely to drop out, applied in two different academic programmes in Brazil.

Although some studies (Ameri et al., 2016; Villano et al., 2018) highlighted its interpretation of results and its suitability for analysing underlying student issues and helping the design of interventions, none of the studies examined survival analysis itself. Moreover, to the best of our knowledge, none of the studies examined within-course withdrawal. Considering the importance of the moment of withdrawal as well as the method’s longitudinal approach and interpretability, we consider it a suitable approach to designing targeted actions oriented to reducing withdrawal.

Influence of Demographics

Rovai’s model indicates the relevance of a student’s personal factors linked to dropout in online studies. Focusing on online education, different compilations (Hachey et al., 2022; Lee & Choi, 2011; Muljana & Luo, 2019) investigated the relevance of these factors and showed a lack of consensus among the studies analysed. As noted by Lee and Choi (2011), “findings of many studies were incompatible with one another regarding the relationship between demographics and online students’ persistence in online courses” (p. 603).

In particular, the correlation between gender and course withdrawal is unclear. Some works have indicated a relation, which can even depend on the field of study (Cochran et al., 2014). This work indicated that males showed higher withdrawal rates in courses linked to disciplines such as education or health, but lower in those related to business and math. A large number of studies, however, did not establish a correlation between gender and withdrawal (James et al., 2016; Strang, 2017).

Regarding age, OHE students are older than those in face-to-face learning environments. Once enrolled, older students would have a lower dropout rate (James et al., 2016). Other research, however, did not identify any age-related effects (Strang, 2017).

Prior academic achievement is linked to persistence in online learning (Lee & Choi, 2011) and can even be used for prediction (Hachey et al., 2014). Regarding socioeconomic status, it is considered a relevant factor

(Hachey et al., 2022). When considering re-enrolment, having a full-time job and cost factors have a negative impact on retention (Grau-Valldosera et al., 2019). Specifically, students requiring financial aid to re-enrol show higher dropout (Cochran et al., 2014).

Few references can be found to the impact of disability. However, in a few studies, disability is cited by some students as a reason for withdrawal (Shah & Cheng, 2019).

Although several research works have used the OULAD dataset, none has been found covering demographics' role in withdrawal. The closest analysis found (Rizvi et al., 2019) considered the impact of these factors on academic outcomes in terms of pass-fail. This study reported that region, neighbourhood poverty level, and prior education constitute strong predictors of failure.

Research Questions

Considering the lack of studies that analyse withdrawal at the course level in regular OHE with a longitudinal approach, the relevance of reliable identification of learners at risk, and the potential of survival analysis, we formulated this research question:

RQ1: How can survival analysis be used to identify populations of learners at risk of withdrawal at the course level, providing insight into the factors behind that withdrawal?

Additionally, considering both the relevance of time and the potential impact of demographics on withdrawal, we posed a second research question, addressing practical implementation:

RQ2: What is the specific impact of demographic factors over time on course withdrawal? Which of these factors impact the withdrawal regardless of the course itself?

Specifically, we decided to analyse the impact of these demographic characteristics based on the OULAD dataset: (a) age, (b) gender, (c) disability, (d) region, (e) previous academic background, and (f) student's economic situation.

As mentioned, the OULAD dataset includes data from 22 editions of 6 different courses. Detailed information on the dataset is provided in the next section.

Method

Survival Analysis

Survival analysis is "a collection of statistical procedures for data analysis where the outcome variable of interest is time until an event occurs" (Clark et al., 2003a, p. 237). The method is particularly used in medical research, where survival time or time to relapse is under consideration (Bradburn et al., 2003a, 2003b; Clark et al., 2003a, 2003b). The portability of the method to other disciplines has been suggested in recent studies (Emmert-Streib & Dehmer, 2019).

Kaplan-Meier (KM) estimates and, specifically, KM curves are common in most survival analyses when the goal is to compare two populations. They are the simplest way to compute survival over time (Clark et al., 2003a). KM estimates help to establish whether life expectancy is different for different populations who have different characteristics, or whether a specific treatment can be more advisable than others. Linked to this estimation, the hazard function indicates the probability of not surviving beyond a certain point in time.

The statistical significance of the resulting curves can be checked with the log-rank test (Clark et al., 2003a). This test compares the estimates of the hazard functions of the two groups at each observed event time under the null hypothesis that both groups share the same hazard functions. The original test assigns equal weight to early and late events. Modified versions use weighted functions. In particular, Peto-Peto's log-rank test (Peto & Peto, 1972) assigns weights depending on the estimated percentile of the failure time distribution, giving higher weight to earlier events, and is commonly used within this group.

However, KM estimates cannot quantify the impact of a given parameter, particularly when dealing with different variables, i.e., the covariates. When this is required, parametric methods must be used. Fully parametric methods need to assume statistical distribution in the data. If this distribution is known, they can provide more precise models. Semi-parametric methods have the advantage of being able to quantify the impact without assuming a specific distribution. The most used semi-parametric method is the Cox proportional hazards model (Bradburn et al., 2003b). This model is based on a proportional hazard assumption and computes a baseline time-dependent hazard associated with a reference group. This hazard is modified based on the multiplicative effect of the values of the different covariates, whose individual influence is considered constant over time. Once the method is computed, the assumptions need to be checked.

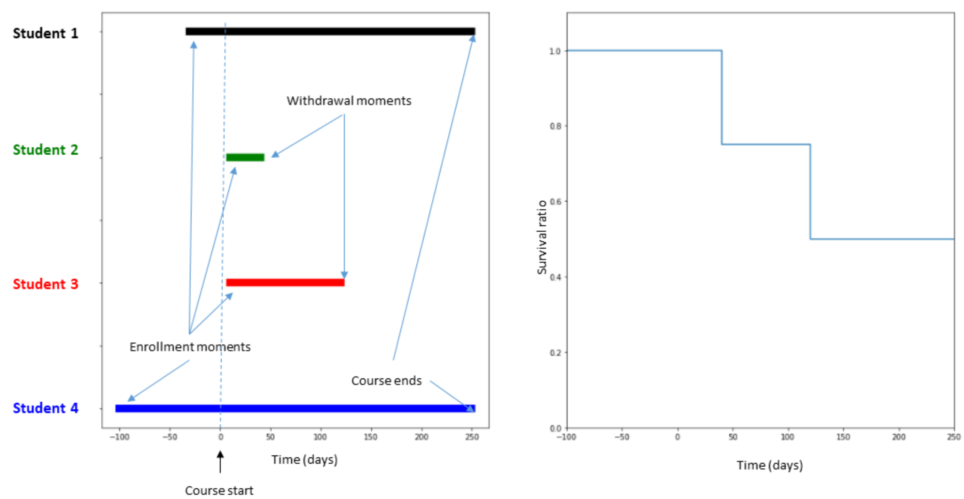
Porting Survival Analysis to Withdrawal Analysis

Approaching a generic problem through survival analysis requires a precise mapping of three concepts: the lifespan, the event under consideration, and the period of observation (Clark et al., 2003a).

In the case of withdrawal, the number of days a student remains enrolled after the specific course starts constitutes the lifespan. The event under consideration is the withdrawal decision. The analysis would also need to monitor on a periodical basis whether the student has withdrawn. To set up a common reference among courses, the course start date would be considered as $t = 0$. Negative values indicate days before the course starts. Survival curves reflect how a population survives after a certain time. Figure 1 depicts these concepts in a hypothetical course lasting 250 days with four students enrolled.

Figure 1

Graphical View of a Hypothetical Course and Associated Survival Curve



Note. Left panel: Enrolment and withdrawal or completion dates for four students. Right panel: Associated survival curve for this group.

On the left, Figure 1 shows four students enrolling on different dates. The first is Student 4, enrolling 100 days before the course starts. Students 2 and 3 enrol ten days after the course has started. In this example, Student 2 withdraws shortly after enrolment (40 days after the course starts), while Student 3 withdraws 120 days after the course starts. Students 1 and 4 complete the course. The associated survival curve for this group is shown on the right, where we can see that the final survival ratio is 0.5 (2 out of 4 students). The curve provides not only the final ratio but a graphical view of its evolution.

KM plots provide a graphical view of the individual impact of specific covariates. To aggregate and quantify the impact of those found relevant, we used the Cox proportional hazards model, due to its simplicity compared to parametric methods.

Dataset

These concepts were translated into practice using the public dataset offered by The Open University (OU; Kuzilek et al., 2017). This dataset provides information about 22 editions (*presentations* in the dataset nomenclature). A total of 32,593 students are enrolled in these courses. The typical presentation length is around nine months.

Courses included in the dataset were offered via a virtual learning environment (VLE), and each had over 500 students. While part of the OU course portfolio, students without a previous academic background could also enrol. Table 1 summarises a high-level view of enrolment and academic results in the courses included. Academic results are summarised in four categories: withdraw, fail, pass, or distinction.

Table 1

Global View of Enrolment and Academic Results

Indicator	Enrolled	Withdraw	Fail	Pass	Distinction
Number of students	32,593	10,156	7,052	12,361	3,024
Percentage of total (%)	100	31.16	21.64	37.93	9.28

As Table 1 shows, withdrawal constituted 31.16% of the global population enrolled. The distribution of academic results was not homogenous among courses as displayed in Table 2.

Table 2

Enrolment and Academic Results (Per-Course View)

Course	Students *n*	Withdraw %	Fail %	Pass %	Distinction %
AAA	747	16.73	12.18	65.19	5.89
BBB	7,903	30.18	22.32	38.93	8.57
CCC	4,434	44.54	17.61	26.61	11.23
DDD	6,266	35.86	22.49	35.54	6.11
EEE	2,934	24.61	19.15	44.10	12.13
FFF	7,758	30.96	22.02	38.39	8.64
GGG	2,534	11.52	28.73	44.12	15.63

Note. Courses are identified with anonymised course names (i.e. AAA) in the OULAD dataset.

These high withdrawal ratios may be explained by the fact that they constitute regular OU courses, with high academic standards, but at the same time, require no prior qualification for enrolment. All courses share a common framework for evaluation, including a set of tutor-marked assignments and optionally some computer-marked assignments. Also, there is usually a final exam at the end of each course.

With respect to those students withdrawing, the dataset includes information regarding the date of withdrawal. This date is either the date on which the student notified the university of her withdrawal or the date on which the student's participation in the module ceased, whichever came first. The Open University actively seeks to reduce withdrawal and may monitor online student activity to detect it. Students considering withdrawal are advised to contact the module instructor and, if their decision is final, formally report their decision (Open University, 2022).

The dataset also includes some personal information. Table 3 summarises those characteristics in the dataset considered relevant to our study.

Table 3

Characteristics in the OU Dataset Linked to the Research Questions

Scope	Variable	Meaning
Presentation	length	Length in days of the module presentation
	date_registration	The day the student registers for the module presentation
Registration	date_unregistration	The day the student unregisters from the module presentation
Demographic characteristic	gender	Gender of the student (male/female)
	region	The geographic region, where the student lived while taking the presentation
	imd_band	The index of multiple deprivation (IMD) band of the place where the student lived during the module presentation
	highest_education	The highest student education level on entry to the module presentation (5 bands)
	age_band	Age band of the student (3 bands)
	disability	Indicates whether the student has declared a disability

Note. Variable names used match those in the OULAD dataset.

This information was required to approach RQ2. Age, gender, and disability are available directly in the dataset. Previous academic background is expressed as the highest educational level the student achieved before the module started. Region indicates the area where the student lives. Student economic situation is expressed by the index of multiple deprivation (IMD) used in the UK (Kuzilek et al., 2017; Rizvi et al., 2019). The dataset presents IMD figures in bands ranging from 0%-10% to 90%-100%; 0%-10% means that a student lives in the most deprived UK areas, while 90%-100% points to the least deprived areas.

Results

The preceding section identifies two main steps for practical implementation:

1. Use KM estimates to determine populations at risk and the impact of individual covariates on withdrawal.

2. Analyse the combined impact, quantifying the simultaneous effect through Cox proportional hazards model.

The Cox model requires a prior setup of reference values for the covariates. For the categorical variables shown in Table 3, we generated dummy variables and considered the values shown in Table 4 as reference values.

Table 4

Reference Groups for the Computation of the Cox Model

Covariate	Reference group
Gender	Female
Region	North region
Highest education	A level or equivalent
IMD band	50%–60%
Age band	Under 35
Disability	No

Note. IMD = index of multiple deprivation.

When the number of possible values was high, we selected reference values that reflected a more central position (e.g., IMD band = 50%–60%). For the specific IMD scales, we grouped low IMD scales (0%–30%) and high IMD scales (above 80%) to reduce the overall number of values.

Significant Differences Based on IMD Band, Prior Education, and Declared Disability

Covariates to perform KM estimates were extracted from Table 3. Using Peto-Peto log-rank tests, we computed *p*-values. Data in Table 2 reflect that different courses show differences in withdrawal ratios. For this reason, we also performed a per-course analysis to determine whether covariates were significant both at the global and individual course levels. The results are shown in Table 5.

Table 5

Statistical Significance of Covariates at the Global and Individual Course Levels

Covariate	Global	Individual course						
		AAA	BBB	CCC	DDD	EEE	FFF	GGG
Gender	ns	*	ns	ns	***	*	*	ns
Region	****	ns	****	ns	ns	**	ns	ns
Highest education	****	ns	****	****	****	***	****	ns
IMD band	****	ns	****	****	****	**	****	ns
Age band	****	ns	**	**	ns	ns	ns	ns
Disability	****	ns	ns	***	****	ns	****	*

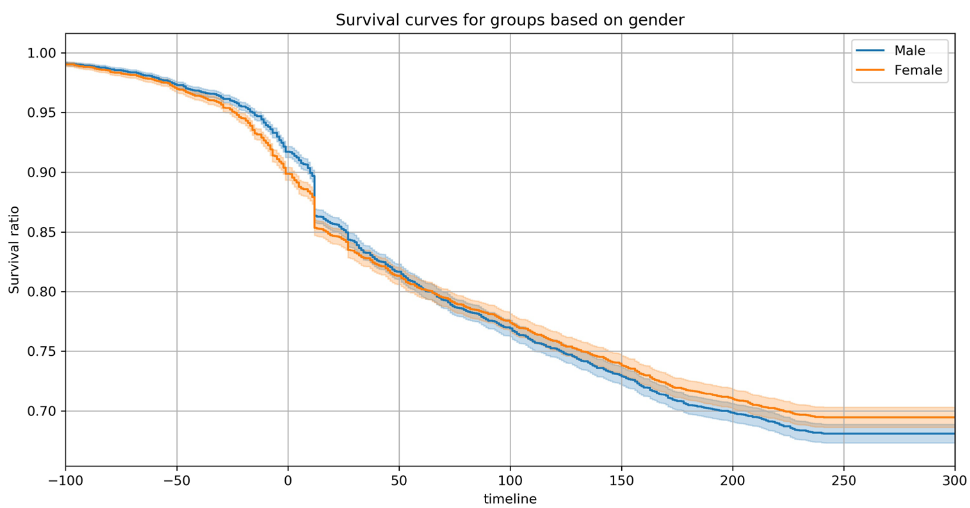
Note: ns = non-significant. IMD = index of multiple deprivation. Courses are identified with anonymised course names (i.e. AAA) in the OULAD dataset. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$. **** $p < 0.0001$.

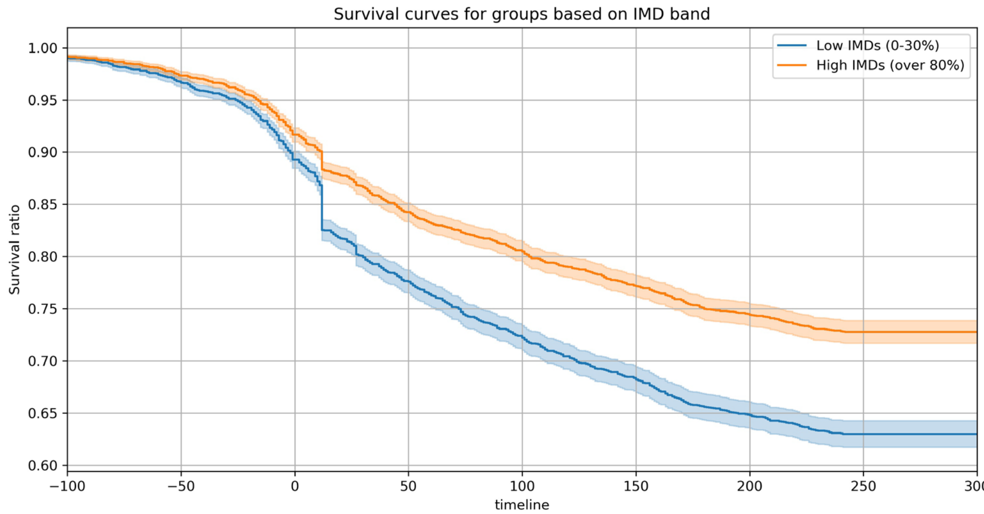
Prior highest education level and IMD band have a clear impact when considering either the global data set or individual courses. At the course level, more data would be needed for course AAA to provide statistically significant results. While age looks relevant globally, its effect disappears in most courses when analysed individually. Thus, no definite conclusion can be extracted at this stage. More data would also be needed, as there is a low ratio of students in one of the scales considered in the dataset.

KM plots help to visualise differences. As an example, we show the global impact of two covariates: gender—not significant according to the test—and the IMD band, which is significant. For clarity, in the case of IMD plots, we compared the high (> 80%) and low (< 30%) groups. The results are shown in Figure 2.

Figure 2

Survival Curves for Different Groups Based on Gender and IMD Band





Note. Top panel: The survival curve for gender. Bottom panel: The survival curve for IMD band. IMD = index of multiple deprivation.

Figure 2 shows minor differences based on gender. Regarding IMD bands, this figure reflects higher withdrawal ratios for the low IMD group, with a higher impact of early withdrawal.

Previous Risk Factors also Present when Considering Simultaneous Effect

We used the Cox model to evaluate and quantify the simultaneous effect of the different covariates. The final Cox models were developed with two strata variables (course and disability) and a set of dummy variables linked to IMD band, region, gender, and previous higher education. Table 6 summarises those variables that appear relevant at either the global or individual course level.

Table 6

Hazard Risk Factor Relative to the Reference Group Based on the Values of Covariates

Covariate	Individual course							Global
	AAA	BBB	CCC	DDD	EEE	FFF	GGG	
Gender: Male	ns	ns	ns	0.83	ns	0.90	ns	0.89
Region: East Midlands	ns	ns	1.23	ns	ns	ns	ns	1.14
Region: London	ns	ns	ns	ns	1.41	1.20	ns	ns
Region: West Midlands	ns	ns	ns	ns	1.39	ns	ns	1.12
Highest education: HE qualification	ns	ns	0.83	ns	ns	ns	ns	0.93
Highest education: Lower than A Level	ns	1.41	1.41	1.30	1.48	1.42	ns	1.38

Highest education: No formal qualifications	ns	1.73	1.48	1.72	2.38	1.38	ns	1.63
Highest education: Post-graduate qualification	ns	ns	0.56	ns	ns	ns	5.51	0.75
IMD band: 0%–30%	ns	1.18	1.33	1.37	1.56	1.44	ns	1.35
IMD band: 30%–40%	ns	ns	ns	1.25	ns	ns	ns	1.14
IMD band: 40%–50%	ns	ns	1.21	1.35	1.75	ns	ns	1.21
IMD band: 80%–100%	ns	ns	ns	ns	ns	ns	1.69	ns

Note: Only covariates significant in at least one course shown. IMD = index of multiple deprivation.

To understand the impact of disability, we compared baseline survival functions for the different strata generated at the course level. Table 7 reflects the withdrawal increase ratio for individual courses when disability was a factor.

Table 7

Impact of Disability on Withdrawal Risk—Individual Course Level

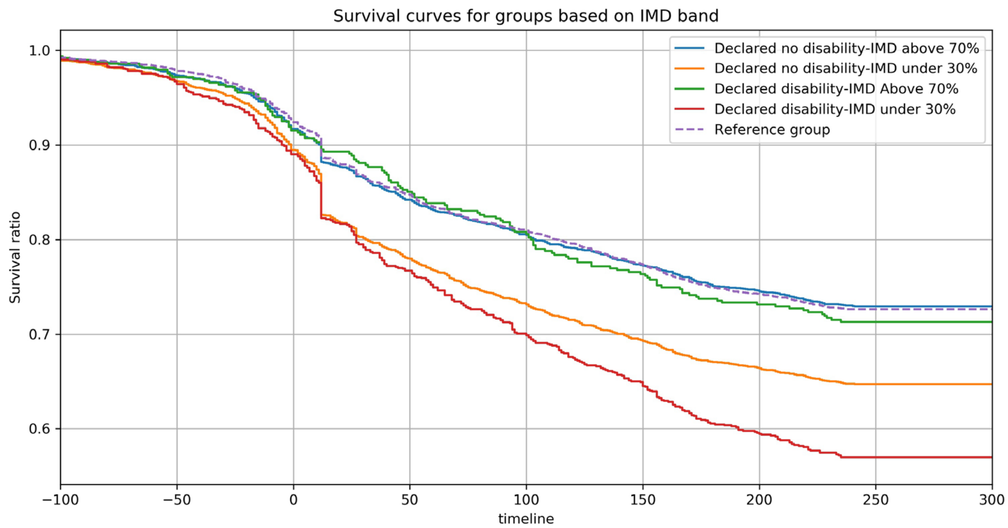
Indicator	Individual course					
	BBB	CCC	DDD	EEE	FFF	GGG
Withdrawal risk increase (declared disability vs declared no disability)	1.14	1.19	1.49	0.99	1.43	1.45

Note. Courses are identified with anonymised course names (i.e. BBB) in the OULAD dataset. Course AAA showed inconclusive results and was omitted from this table.

As a final check, we performed a graphical comparison of withdrawal differences based on the findings above. We generated populations based on the combination of IMD differences—high versus low group—and disability. The results are shown in Figure 3, where a reference group based on data in Table 4 (no disability, IMD band 50%–60%) is also reflected.

Figure 3

Survival Curves for Groups With and Without Declared Disability in High and Low IMD Bands



Note: IMD = index of multiple deprivation.

Figure 3 clearly shows withdrawal risk differences among groups. Besides final survival expectancy—with differences around 35.88% by the end of the course—low-income students drop out earlier. Also, the multiplicative effect of disability and low IMD is clearly displayed. Being in the high IMD group does not significantly reduce withdrawal rates when compared to the reference group. The impact of these findings on potential intervention designs will be addressed in the next section.

Discussion

Two research questions were addressed in this work. The first one, regarding the use of survival analysis, aimed to detect populations at risk of withdrawal and the factors behind it. The second one aimed to translate these concepts into practice, determining the relevance and impact of demographics.

From a methodological perspective, the basics behind the answer to RQ1 are covered in the subsection covering the portability of survival analysis to learning analytics scenarios. Identifying students at risk of withdrawal through survival analysis has required the mapping of three concepts: the event under consideration (the withdrawal decision), the period of observation (a course), and the lifespan (the time the student remains in the course). This mapping allows us to identify both at-risk populations and the associated risk factors. Figure 1 concentrates on the basics behind this mapping.

Survival curves provide a graphical insight into the differences among populations based on a set of factors (Figures 2 and 3 offer clear examples). These curves constitute a relevant difference from other data mining techniques. They do not only provide information on final withdrawal ratios, but also show when withdrawal occurs. Statistical relevance of a given factor can also be determined (see Table 5 for examples), and for those factors considered relevant, the impact can also be quantified (Tables 6 and 7 serve as examples for this point). These facts make survival analysis a particularly suitable technique for analysing withdrawal.

All in all, figures 1 (from a theoretical perspective), 2, and 3 (from a practical approach), combined with the data in tables 6 and 7, demonstrate the potential of survival analysis identifying populations of learners at risk.

The second question (RQ2) translates methodology into practice. The application of the method indicates that certain demographic characteristics have an impact on course withdrawal and that this impact is dependent on the course itself. Specifically, three analysed factors increase withdrawal risk: a previous level of education below the reference group (A level), a low IMD band, and a declared disability (see Table 5). As mentioned, the specific impact is different depending on the course (see Table 7). We can compare these findings with previous literature regarding the impact of demographics on withdrawal.

Withdrawal and Demographics: Comparison with the Literature

From a global perspective, the influence of these personal background factors is consistent with the theoretical models (Bean, 1985; Cabrera et al., 1992; Rovai, 2003; Tinto, 1975) and justifies the interest that literature compilations put on them, in particular in OHE (recently, Hachey et al., 2022; Muljana & Luo, 2019).

Our results have shown a different impact for age and gender across the analysed courses, supporting the inconclusive findings reflected in Hachey et al., 2022 and Muljana and Luo, 2019. We have not found that being male reduces risk in some courses, while increasing it in others (as found in Cochran et al., 2014). However, we agree that the relevance and the specific impact of a factor depend on the course under analysis.

Regarding the economic situation, our results at course level are aligned with those indicating the impact of financial hardship at course and university level (Cochran et al., 2014; Grau-Valldosera et al., 2019). Our work indicates a direct relationship between socioeconomic inequality and educational disadvantage, as shown in the lower panel in Figure 2.

The impact of a poor academic background on withdrawal is consistent with earlier research linking lower previous achievement to higher university dropout (Cochran et al., 2014; Lee & Choi, 2011).

Disability is one of the potential reasons behind some dropouts according to Shah and Cheng (2019). Our results confirm this fact and quantify its impact on course withdrawal. Our findings indicate that students with disabilities taking online courses would be more likely to withdraw from these courses, in particular those students in low IMD bands. Due to our concerns about equity, we believe more studies on this topic should take specific care of anonymisation and ethical issues.

Implications

The intersectionality and the reliable estimation of risk allow us to identify two points for a potential intervention with targeted populations. First, less affluent students could be contacted, even before the start of the course, and offered options regarding financing. Second, disabled students coming from more deprived areas might benefit from continuous support, which might reduce the slowly increasing difference in withdrawal rates when compared with non-disabled students reporting the same economic condition.

While these demographic factors affect all courses analysed, their impact on dropout is different for each course. This difference needs to be considered when evaluating the outcomes of specific interventions.

We can also find factors that show statistical significance in only some courses. To mention just a couple of examples, gender for course DDD or region for course BBB (see Table 5) warrant investigation. For these cases, we encourage a closer look that considers course-specific details which may explain why.

We also remark on the potential of survival analysis to detect situations that would otherwise remain hidden. Figure 2 (lower panel) and Figure 3 reveal a sudden drop around the second week of the course, particularly affecting low-income students. In fact, this week corresponds to the end of the full-refund period for a given course. A potential intervention aimed at reducing withdrawal would consider extending the period of full refund for low-income students. It is important to highlight that this kind of finding would remain hidden if using techniques which focus only on final ratios and not on temporal evolution.

Our detailed analysis also reveals potential fails in intervention design which do not include a proper identification stage. We can consider for instance prior level of education. It is noticeable that course GGG shows a higher risk of withdrawal for students with a previous higher level of education. While this could be shocking at first glance, this course constitutes a propaedeutic course. Those students who already have this knowledge simply abandon the course. Besides this example, and considering potential interventions, the method reveals that analysis at both a global level and at the level of the individual course is critical to properly identify populations at risk.

Finally, survival analysis provides a clear view of the impact of the different factors analysed. For the case of demographics, IMD band, prior educational level, and declared disability have emerged as the most relevant factors in dropout. It is worth noting that these factors emerge as relevant both at the aggregate level and when considering individual courses.

Conclusion

Survival analysis has proven to be a useful tool to reliably identify populations of learners at risk. The method outlined provides risk quantification, and a clear graphical evolutive view. This view highlights insights that otherwise could remain hidden.

Its use has been particularly suited for the analysis of course withdrawal, due to the relevance of time in dropout. We encourage the use of survival analysis as the first stage in the design of interventions aimed at reducing academic dropout. It can also be of interest in learning analytics scenarios where time plays an important role, such as engagement analysis.

Finally, considering the multivariate nature of withdrawal, we advise expanding this research beyond demographics. While focusing on them has shown the method's potential and provided valuable insight, it also constitutes a limiting factor. We encourage the use of the methodology exposed to address the impact of other aspects, such as previous knowledge, activity reflected in VLEs, or course instructional design. Future work should focus on incorporating these dimensions into the analysis to better understand students' behaviour and improve learning experience and academic performance.

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Perception and Behavioral Intention Toward MOOCs: Undergraduates in China

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Abstract

This study incorporated the technology acceptance model (TAM) and theory of planned behavior (TPB) to interpret students' perception of MOOCs. This study was based on a survey questionnaire; all 525 respondents were undergraduates in China. A five-point Likert scale was used to collect data in order to measure relationships among the constructs of perceived usefulness (PU), perceived ease of use (PEOU), attitude (ATT), subjective norms (SN), perceived behavioral control (PBC), and behavioral control (BI). The results showed that the research model that incorporated TAM and TPB provided both desirable fit and validity, and all the proposed hypotheses were positively supported. Compared with ATT and SN, PBC had a much stronger impact than did BI. This study and its findings provided educators and MOOC providers with managerial implications as well as suggestions for designing future MOC offerings.

Keywords: MOOCs, theory of planned behavior, technology acceptance model, TAM-TPB

Perception and Behavioral Intention Toward MOOCs: Undergraduates in China

Massive open online courses (MOOCs) are among the most recent e-learning initiatives to gain widespread acceptance in universities (Goel et al., 2022) with elite universities providing learners worldwide with high-quality education services beyond the constraints of temporal, physical, and geographical boundaries (Hollands & Tirthali, 2014). The functionality and usefulness of MOOCs have advanced university students' perception and awareness of this innovative educational often associated with information technology (Lung-Guang, 2019). Students can enroll themselves in a MOOC as a complement to their residential courses (Zhang, 2016) or to fulfill diverse other objectives (Sun et al., 2019).

The educational effectiveness of MOOCs has been affected by several factors, especially a persistently high dropout rate (Qiu et al., 2019). Meanwhile, numerous studies have been conducted on learning motivation regarding dropout and retention (Hossain et al., 2022; Hossain et al., 2020). Abdullatif and Velázquez-Iturbide (2020) pointed out that motivation is an essential role in explaining learners' behavior in MOOCs. However, it is not clearly known what types of factors could promote learners' motivation and further increase MOOC retention rates (Badali et al., 2022). During the COVID-19 pandemic, most residential courses were transformed into MOOCs. Viner et al. (2020) mentioned that students were forced to receive instruction and knowledge through online platforms. Raja and Kallarakal (2021) demonstrated that higher educational institutions realized the need for online education during the pandemic crisis. As the result of vigorous epidemic prevention policies, universities in China redesigned their offline programs to be offered online, and MOOCs accounted for a large proportion of these (Duan, 2021). Therefore, evaluating students' perception of MOOCs has become crucial to understanding the motivational factors that affect MOOC learners. However, little literature has focused on Chinese students' perception of MOOCs, or what factors will affect their perception and further promote their motivation to use MOOCs. In light of the scant literature available, this study set out to provide theoretical and practical insights regarding the MOOC context that would also be relevant outside China.

The main purpose of this study was to analyze Chinese students' perception and behavioral intention towards MOOCs. Data was collected from universities in China to explore their behavior regarding MOOCs. The technology acceptance model (TAM; Davis, 1989) and the theory of planned behavior (TPB; Ajzen, 1991) were used as a merged theoretical framework to explain students' general perception of MOOCs and this may affect their behavioral intention to enroll in MOOCs. TAM has been widely accepted and employed to study human behavior in terms of technology acceptance and usage (Tao et al., 2019). In the TAM, perceived usefulness (PU) and perceived ease of use (PEOU) are two theoretical constructs connected to the construct of attitude (ATT). TPB has been associated with three conceptual determinants, namely ATT, subjective norms (SN), and perceived behavioral control (PBC; Lung-Guang, 2019). It has been adopted by numerous researchers (Lung-Guang, 2019; Si et al., 2020; Moon, 2021) for predicting and explaining the causal relationship of behavioral intention (BI). In this research, PU, PEOU, ATT, SN, and PBC were defined as independent variables and BI was identified as the dependent variable. Among all the variables, PU and

PEOU measured students' intuitive perception towards the technology of MOOCs. Since TAM and TPB were developed from the same fundamental theory of the theory of reasoned action, TPB was also selected in order to explore students' psychological perception and behavioral intention (Fishbein & Ajzen, 1980).

Literature Review

MOOCs

MOOCs are the product of the open education movement promoting high-quality education and educational resources to global learners (Zheng et al., 2015). According to Milligan et al. (2013) understanding learners' nature and their motivation to engage in a MOOC should be explored, as these are an indispensable part of a successful MOOC (Zheng et al., 2015). Raja and Kallarakal (2021) stated that relevant stakeholders should cultivate more courses free of cost to enhance students' enrollment and participation in MOOCs. Lung-Guang (2019) found that individuals who choose MOOCs usually show evidence of critical foresight that is closely related to their planned behavior. Sun et al. (2019) identified that the three basic psychological needs of autonomy, competence, and relatedness are critical to form intrinsic motivation, which can increase students' psychological engagement in MOOCs. Lu et al. (2019) found that flow and interest were critical variables that enhanced MOOC satisfaction and thus promoted learners' intention to continue using MOOCs. Hossain et al. (2020) found that learners' satisfaction, combined with cognitive need and attitude, were core conditions that enhanced continuance intention. Hossain et al. (2022) found that psychological needs and immersive experiences mediated graduates' skill gap as well as their willingness to enroll in MOOCs. Finally, Padilha et al. (2021) assessed MOOCs as an educational resource to enhance self-management intervention skills, and revealed that students were interested in participating in future MOOCs for their utilitarian value.

Merged Theoretical Framework: TAM and TPB

TAM has been widely applied in different academic contexts as a fundamental theory for predicting individual intentions to adopt a specific technology (Tao et al., 2019). Since PU and PEOU are posited as the determinants of technology usage, these two constructs are related to ATT. PU refers to an individual's perception that a particular technology that can improve ones' job performance, while PEOU refers to a belief that an individual can manage a particular technology free of effort (Davis, 1989). TPB has long been considered a pre-eminent social cognition theory for predicting human behavior, and has been associated with the three determinants of ATT, SN, and PBC (Si et al., 2020). ATT refers to an individual assessing a certain behavior positively or negatively (Moon, 2021) while SN refers to the perceived social pressure that may have an impact on an individual's behavioral intention towards a certain activity (Ru et al., 2019). PBC refers to an individual's perception of their own capacity to perform and engage in a given activity (Lung-Guang, 2019).

A number of empirical studies found TAM and TPB were able to explain an individual's acceptance and intention towards new technology-related services (Choe et al., 2021; Yang & Su, 2017). To improve the predictive power of a research model and overcome the limitation of a single theory in a particular social context, many researchers have added new variables into TAM (Jang et al., 2021; Tao et al., 2019; Unal & Uzun, 2021) and TPB (Lung-Guang, 2019; Moon, 2021; Ru et al., 2019). As well, research has integrated TAM and TPB to examine IT usage and e-service acceptance. The two theories are complementary, and findings have shown that an integrated model is better able to explore phenomena than using TAM and TPB individually (Glavee et al., 2017). Obaid (2021) used a model that incorporated TAM and TPB in an e-commerce context to offer specific recommendations on market strategies towards mobile banking. Choe et al. (2021) used a model that merged TAM and TPB to verify how to foster behavioral intention in the context of drone food delivery service. Gómez-Ramirez et al. (2019) explored the factors that influenced students' adoption of mobile learning through the model that combined TAM and TPB. Addressing MOOCs, Yang and Su (2017) proposed a merged TAM and TPB theoretical model to explain how learners responded to MOOCs with a new teaching method. Wang et al. (2020) merged TAM and TPB as a theoretical model to explore the determinants behind the performance and low completion rate of MOOCs in China.

This study focused on the psychological aspects of students; TPB has been widely adopted to predict individuals' general behavior, while TAM has been used to examine individuals' specific technology acceptance (Choe et al., 2021). It is believed that the MOOC context involves general behavior and specific technology. Therefore, we deliberately integrated TAM and TPB to explore students' perception and behavioral intention to enroll in MOOCs. Framing our work within a merged TAM and TPB theoretical model allowed us to better perceive how students respond to MOOCs while exploring the factors that influence their perception and behavioral intention towards MOOCs.

Hypothesized Relationships

PU and PEOU are the crucial variables of TAM, representing the extrinsic and utilitarian values respectively (Yang & Lee, 2022). Many consumer behavior studies have confirmed the positive impact of PU and PEOU on users' attitude. Choe et al. (2021) identified the positive impact of PU and PEOU on consumers' behavioral intention in the context of the food service industry. Yang and Lee (2022) demonstrated that PU and PEOU were two core variables positively related within sharing economy services. Addressing the MOOC context, Yang and Su (2017) explored the positive impact of PU and PEOU on learners' behavior. Wang et al. (2020) found PU and PEOU positively affected learners' attitude towards MOOCs. Therefore, this study posited the following hypotheses:

H1: Perceived usefulness has a positive impact on a learner's attitude towards using MOOCs.

H2: Perceived ease of use has a positive impact on a learner's attitude towards using MOOCs.

A number of empirical studies have confirmed, within TPB, the positive effect of ATT, SN, and PBC on consumers' behavioral intention. Moon (2021) identified that ATT, SN, and PBC positively impacted consumers' behavioral intention in the green restaurant context. Choe et al. (2021) confirmed that ATT, SN, and PBC were positively related to the formation of behavioral intention towards drone food delivery services. Si et al. (2020) revealed that ATT, SN, and PBC were critical variables for exploring sustainable use intention for bike sharing. Ru et al. (2019) found ATT, SN, and PBC influenced young people's intention to reduce fine particulate matter. Regarding the MOOC context, Luang-Guang (2019) verified the positive impact of SN and PBC on students' behavioral intention to adopt MOOCs. Wang et al. (2020) found that ATT, SN, and PBC had a positive impact on learning performance. Based on the extant literature, this study posited the following hypotheses:

H3: A learner's attitude towards using MOOCs has a positive impact on their behavioral intention.

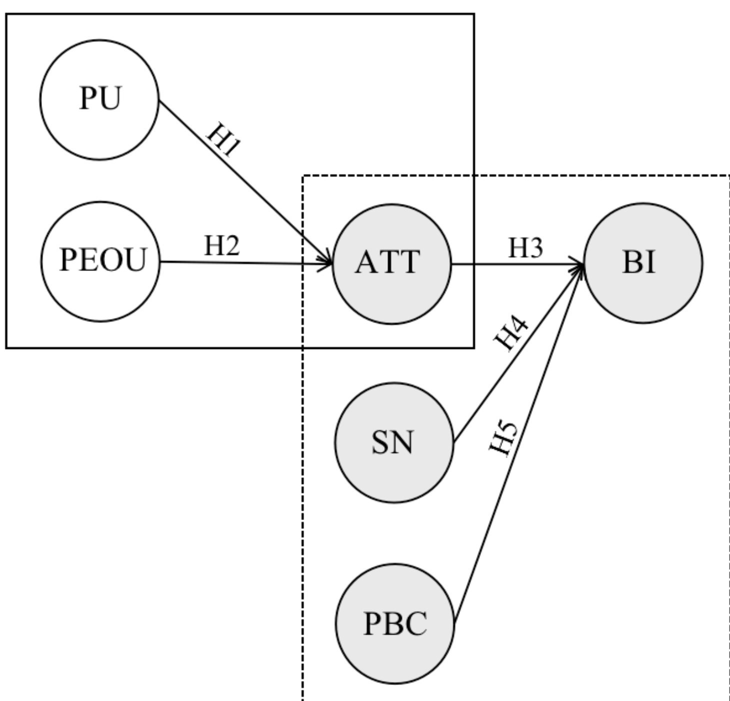
H4: A learner's subjective norm has a positive impact on their behavioral intention.

H5: A learner's perceived behavioral control has a positive impact on their behavioral intention.

Figure 1 depicts the research model for this study, including the relationships among the five hypotheses. The non-shaded constructs within the solid box represent the TAM variables. The shaded constructs within the dotted box represent the TPB variables.

Figure 1

Proposed Research Model



Methodology

Measurement Instrument and Questionnaire Development

This study used a questionnaire to collect data from undergraduates with different academic backgrounds. The questionnaire consisted of two parts—demographic information and a MOOC survey. Demographic questions addressed five aspects, namely (a) gender, (b) age, (c) number of MOOC diplomas, (d) academic background, and (e) academic year. The MOOC survey measured the variables of PU, PEOU, ATT, SN, PBC, and BI. A five-point Likert scale with 1 (*strongly disagree*) to 5 (*strongly agree*) was provided for each MOOC survey item. In total, 28 items were presented as independent and dependent variables.

To better predict students' perception and behavioral intention regarding MOOCs, all the items for measuring the constructs of PU, PEOU, ATT, SN, PBC, and BI were based on Chin et al. (2008), Venkatesh and Goyal (2010), Venkatesh et al. (2011), Zhou (2016), and Lung-Guang (2019). As well, suggestions were sought from content experts regarding how students actually perceive MOOCs. Of the 28 items on the MOOC survey (**See Appendix**), (a) five items addressed PU, (b) four items related to PEOU, (c) eight items applied to ATT, (d) three items dealt with SN, (e) five items applied to PBC, and (f) three items focused on BI.

Data Collection and Demographic Profile

Following the approach of convenience sampling (Taherdoost, 2016), 100 questionnaires were first distributed and recovered at Ningbo University as test samples to check the instrument's reliability and validity. Then, questionnaires were distributed through WJX to students at Fudan University, Zhejiang University, China University of Petroleum, and Capital Normal University. All these universities were well-known, offered courses in a variety of disciplines, and had experience producing online courses.

According to Table 1, a total of 525 students answered the questionnaire; 233 (44.38%) were males and 292 (55.62%) were females. Table 2 shows how the students' ages ranged from 17 to 30; most of the students (92.38%) were aged 18 to 22 years. Table 3 shows the 72.38% of the students did not have a MOOC certificate, 27.62% of the respondents had at least one, and the largest number of certificates by an individual was 28. Table 4 shows the academic fields the represented by the students: (a) arts and humanities (n = 249); (b) health science (n = 60); (c) science (n = 69); (d) social science and law (n = 73); and (e) technology science (n = 74). Table 5 shows that 171 were first-year students, 133 were second-year students, 138 were third-year students, and 83 were fourth-year students.

Table 1

Sample Gender

Gender	Frequency	Percent
Male	233	44.38
Female	292	55.62
Total	38	100

Table 2

Sample Age

Age	Frequency	Percent
17	2	0.38
18	59	11.24
19	112	21.33
20	136	25.90
21	117	22.29
22	61	11.62
23	24	4.57
23	8	1.52
25	3	0.57
28	2	0.38
30	1	0.19
Total	525	100

Table 3

Number of MOOC Certificates

Number of Certificates	Frequency	Percent
0	380	72.38
1	68	12.95
2	38	7.24
3	15	2.86
4	5	0.95
5	5	0.95
6	3	0.57
7	1	0.19
8	2	0.38
9	1	0.19
10	2	0.38
12	1	0.19
14	1	0.19
20	2	0.38
28	1	0.19
Total	525	100

Table 4

Academic Field

Academic Field	Frequency	Percent
Arts and humanities	249	47.43
Health science	60	11.43
Science	69	13.14

Social science and law	73	13.90
Technology science	74	14.10
Total	525	100

Table 5

Year of Study

Year of Study	Frequency	Percent
First year	171	32.57
Second year	133	25.33
Third year	138	26.29
Fourth year	83	15.81
Total	525	100

To determine possible non-response bias and generate an estimated rate of active refusals, we compared the number of questionnaires distributed with the number of responses actually received. We planned for 1,000 participants in the online questionnaire survey; after excluding the incomplete questionnaires, 525 responses were received, which represents a 52.5% rate of non-refusal, well beyond the range of 15% to 20% (Menon et al., 1996). To analyze the possible differences between early and late respondents (i.e., those who responded immediately vs. those who responded after the first or second recall), bivariate analysis was conducted. Table 6 shows there was no significant difference between the earlier and later respondents.

Table 6

Bivariate Analysis

Group	Mean	Standard deviation
Early respondents	3.7515125	0.85698319
Later respondents	3.5025641	0.95988809

Note. Probability > F: 0.0022. Bartlett's test: $chi^2 = 3.1875$. Probability > $chi^2 = 0.074$.

Data Analysis

Confirmatory factor analysis and structural equation modeling, particularly partial least square (PLS), were conducted by using SmartPLS 3.0 to analyze the convergent and discriminant validity of the measurement model. We used the bootstrapping procedure to examine the proposed theoretical research model, evaluate the proposed hypotheses, and assess the relationship among the constructs. Compared with the variance-covariance based structural equation modeling, using partial least square (PLS) for structural equation modeling has effectively evaluated exploratory theories (Henseler et al., 2009). A normal data distribution is not necessary and the approach works well with small sample sizes (Fornell & Bookstein, 1982). The Shapiro-Wilk test has been widely used to verify the normality of data (Villasenor & Estrada, 2009). The results in Table 7 show the data were abnormally distributed, since the *p* value of most variables was less than 0.05. Thus, PLS was considered the most appropriate method for this study.

Table 7

Shapiro-Wilk Test of Normality

Construct	Variable	Prob > Z
ATT	ATT 1	0.00966
	ATT 2	0.00040
	ATT 3	0.00002
	ATT 4	0.00001
	ATT 5	0.00014
	ATT 6	0.08001
	ATT 7	0.01017
	ATT 8	0.00196
SN	SN 1	0.01233
	SN 2	0.00238
	SN 3	0.05271
PU	PU 1	0.09008
	PU 2	0.07676
	PU 3	0.02023
	PU 4	0.04124
	PU 5	0.05380
PEOU	PEOU 1	0.00078
	PEOU 2	0.00069
	PEOU 3	0.00199

	PEOU 4	0.00020
PBC	PBC 1	0.04567
	PBC 2	0.02620
	PBC 3	0.00400
	PBC 4	0.00195
	PBC 5	0.02501
BI	BI 1	0.00611
	BI 2	0.00650
	BI 3	0.00269

Results

The Measurement Model: Assessing Reliability and Validity

Common method bias can occur in studies where both independent and dependent variables are measured within one survey, using the same item context and similar item characteristics (Kock et al., 2021). Following the method proposed by Alegre and Chiva (2013) the results in Table 8 show that in the MOOC context, all the inner variance inflation factor (VIF) values of PU, PEOU, ATT, SN, and PBC are 2.230, 2.230, 2.508, 2.391, and 2.287 respectively, all less than 3.3. The results indicate the research model is free of common method bias (Hair et al., 2017; Kock, 2015).

Table 8

Common Method Bias Test: Inner VIF Values

Construct	ATT	BI
ATT		2.508
BI		
PBC		2.287
PEOU	2.230	
PU	2.230	
SN		2.391

Content validity refers to how well a survey or test measures the construct that it designs to measure. To assure the validity of the measurement instrument in this study, all the scales were selected based on the extant literature (Cronbach, 1971). Boateng et al. (2018) suggested that an effective approach to assessing content validity was through the use of experts. Thus, all the scales in this survey for this study were evaluated by four experts. Two of these were specialists in educational technology and educational psychology, and two were experts in marketing and strategy. The convergent validity was verified through three aspects: (a) factor loading should be significant and higher than 0.5 as the lowest threshold; (b) composite reliability (CR) should be higher than 0.6 (Bagozzi & Yi, 1988; Fornell & Larcker, 1981); and (c) the average variance extracted (AVE) should be higher than 0.5 (Ru et al., 2019; Yang & Su, 2017). Furthermore, Cronbach's alpha is considered an indicator for measuring the reliability of the internal consistency of a scale, and the acceptable threshold should be higher than 0.6 (Cronbach, 1951). According to Table 9, the factor loading of items in this study were higher than 0.8 and the highest value was 0.929, indicating that the model was reliable. The AVE was larger than 0.7 and the highest value was 0.827, indicating that the measurement model had a good convergent effect. All the Cronbach's alpha values were higher than 0.8 and CR of the constructs were higher than 0.9, which indicated that the internal consistency among the constructs was desirable.

Table 9

Factor Loading, Cronbach's Alpha, CR, and AVE of Constructs

Construct	Item	Factor loading	Cronbach's alpha	CR	AVE
ATT	ATT 1	0.852	0.946	0.955	0.726
	ATT 2	0.862			
	ATT 3	0.829			
	ATT 4	0.848			
	ATT 5	0.868			
	ATT 6	0.860			
	ATT 7	0.855			
	ATT 8	0.843			
BI	BI 1	0.894	0.895	0.935	0.827
	BI 2	0.929			
	BI 3	0.905			
PBC	PBC 1	0.853	0.909	0.932	0.733
	PBC 2	0.858			

	PBC 3	0.843			
	PBC 4	0.849			
	PBC 5	0.877			
PEOU	PEOU 1	0.896	0.917	0.941	0.800
	PEOU 2	0.901			
	PEOU 3	0.896			
	PEOU 4	0.885			
PU	PU 1	0.829	0.914	0.936	0.745
	PU 2	0.892			
	PU 3	0.866			
	PU 4	0.887			
	PU 5	0.840			
SN	SN 1	0.882	0.864	0.917	0.786
	SN 2	0.900			
	SN 3	0.878			

Discriminant validity ensures that results are definite (Henseler et al., 2015) and that each construct is different from other constructs (Gómez-Ramirez et al., 2019). Discriminant validity also ensures that items are distinguishable from items associated with different variables. If not, then multiple variables may explain the same issue. By adopting the correlation coefficient between the square root of AVE and all possible constructs for comparison, the value of the square root of AVE must be stronger than the value of all possible constructs, in order to show that there is discriminant validity in the measurement. According to Table 10, the values of square of roots of AVE were stronger than the values of the potential constructs, thus indicating great discriminant validity in the measurement.

Table 10

Simple Correlation Matric and Discriminant Validity

Construct	ATT	BI	PBC	PEOU	PU	SN
ATT	0.852					
BI	0.629	0.909				
PBC	0.704	0.788	0.856			

PEOU	0.727	0.700	0.808	0.895		
PU	0.739	0.728	0.810	0.743	0.863	
SN	0.719	0.621	0.686	0.700	0.790	0.887

Analysis of the Structural Model

The explanatory power of the structural model can be measured through R^2, which was explained in each of the endogenous constructs. The value of each construct should be higher than 0.1 (Falk & Miller, 1992) and the values of 0.75, 0.50, and 0.25 can be viewed as the model's substantial, moderate, and weak explanatory power, respectively (Henseler et al., 2009). The Stone-Geisser test of predictive relevance (Q^2; Geisser, 1975) is a measure for estimating the PLS path model's predictive accuracy. Q^2 values higher than 0, 0.25, and 0.50 depict the PLS-path model's small, medium, and large predictive relevance, respectively (Henseler et al., 2009). The values of R^2 of this study were 0.617 and 0.635, respectively, and the values of Q^2 were 0.441 and 0.521, respectively. Clearly, the model for this study was well suited to explain the data. Figure 2 presents the results of PLS and the relationship of the variables as verified by the bootstrapping method.

Figure 2

PLS Results for the Structural Model

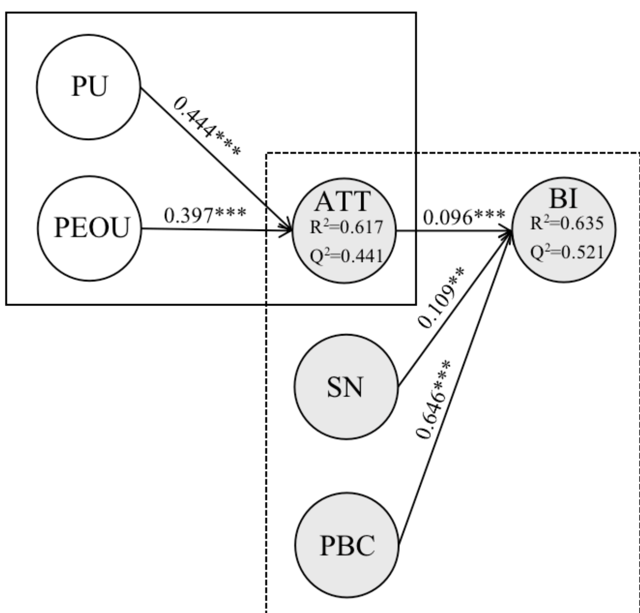


Table 11 shows that the results of the verification among the constructs and the five research hypotheses were positively supported. The path coefficients of the model were 0.444 (PU to ATT), 0.397 (PEOU to ATT), 0.096 (ATT to BI), 0.109 (SN to BI), and 0.646 (PBC to BI). As well, the R2 values of the constructs were 0.617 (ATT) and 0.521 (BI). The results also indicate that 44.4% of ATT was affected by PU, 39.7% of ATT was affected by PEOU. Furthermore; 9.6% of BI was affected by ATT, 10.9% of BI was affected by SN, and 64.6% of BI was affected by PBC.

Table 11

t-Value of Research Hypotheses and Path Coefficients

Research hypothesis	*t*	Path coefficient	*p*	Validated result
H1: PU→ATT	8.860	0.444	0.000***	Supported
H2: PEOU→ATT	7.668	0.397	0.000***	Supported
H3: ATT→BI	2.066	0.096	0.039**	Supported
H4: SN→BI	2.211	0.109	0.027**	Supported
H5: PBC→BI	13.528	0.646	0.001***	Supported

Note. **p<0.05; ***p<0.01.

We followed the approach of Malik et al. (2021) to investigate the mediating role of ATT in the relationships among PU, PEOU, and BI. Table 12 shows the results of mediation analysis. In particular, we identified two indirect effects of PU and PEOU on BI as mediated by ATT at a 90% confidence level.

Table 12

Results of Mediation Analysis

Path	Mediator	Standard deviation	*t*	*p*	Result
PU→BI	ATT	8.860	0.444	0.056*	Supported
PEOU→BI	ATT	7.668	0.397	0.052*	Supported

Note. *p<0.1; **p<0.05; ***p<0.01.

Discussion

This study proposed five hypotheses to interpret the perception and behavioral intention of students towards MOOCs. Two classical theories—TAM and TPB—were integrated in a research model that was positively supported by the empirical data in this study. As PU and PEOU accounted for 44.4% and 39.7% of attitude respectively, and presented a high value of R^2 (0.617), these two essential components of TAM, as well as the antecedents of ATT in this study, were confirmed as statistically effective in explaining intrinsic attitudes towards MOOCs. The findings supported the basic assumption underling the TAM: if students are more likely to experience usefulness and ease of use in MOOCs, they are more likely to accept MOOCs. Our findings were also consistent with previous research explaining technology adoption and behavioral intention towards MOOCs (Wang et al., 2020; Yang & Su, 2017), which indicated that the extrinsic and utilitarian values of the technology could impact students' intrinsic attitude and perception. Furthermore, PU had stronger effect on ATT than did PEOU, in accord with Yang and Lee (2022).

ATT was found to have a direct positive impact on behavioral intention, a finding consistent accord with Gómez -Ramirez et al. (2019) and Wang et al. (2020), confirming that attitude was effective in explaining behavioral intention. However, this finding was in contrast with Lung-Guang (2019) wherein ATT was found to have no significant impact on behavioral intention. In addition, ATT was also confirmed to mediate the relationships among PU, PEOU, and BI. This aligned with Yang and Su (2017), suggesting that ATT played an essential mediation role between technology acceptance and behavioral intention. Additionally, SN and PBC were also positively effective in influencing students' behavioral intention towards MOOCs. This was consistent with Lung-Guang (2019), Wang et al. (2020), and Yang and Su (2017), and indicated students were easily affected by the things and people around them as well as their own positive perceptions towards MOOCs. This finding also showed that PBC took up most of the proportion among the constructs; students were more likely to construct their behavioral intention based on their actual situation regarding accepting MOOCs.

Conclusion, Implications, and Future Directions

This study helped clarify our understanding of MOOC adoption, and explored students' perception and behavioral intention towards MOOCs during the COVID-19 pandemic. This provided useful insight into the determining factors that motivate students to use MOOCs.

In terms of theoretical implications, previous studies have proven the validity of a research model that merges TAM and TPB. This study confirmed the validity of our research model in explaining technology acceptance and behavioral intention in the MOOC context, and contributed robust empirical support to the extant literature. In addition, this study collected data within China, and so informed the cultural dimensions of MOOC research. Furthermore, the mediating effect of ATT was identified, which further expanded the validity of an integrated TAM and TPB model.

Regarding managerial implications, this study offered several findings of importance to educators and MOOC providers. The utilitarian value perceived from MOOCs increased learners' intrinsic perception; the extant literature has also found that learners' intention was determined by their needs (Ossiannilsson et al., 2016). MOOCs as an innovative tool of education provide students worldwide with a new approach to enrich their educational background and develop new skills for future jobs. Blanco et al. (2016) stated that a number of students and employers engaged in MOOCs to bridge employability gaps. Hossain et al. (2022) found that awareness of psychological needs and opportunities for immersive experiences mediated the impact of skill gaps and social interaction on graduates' MOOC acceptance intention. Hence, it is critical to develop MOOC courses that increase learners' employability skills.

In this study, ATT was confirmed as a critical variable in the MOOC context. To attract and engage students in MOOCs, teachers should be aware of various learner characteristics and implement teaching that responds to their audience's attitude and perception of learning (Wang et al., 2020). Compared with ATT and SN, PBC is much more significant. Hence, we recommend that school teachers and MOOC providers explore more utilitarian and convenient approaches for students in order to overcome learning constraints. Universities should also provide students with courses related to self-learning management so students can confidently follow their own learning path.

Regarding future research directions, first, this study involved undergraduate students in China only and did not address regional and cultural differences, which may have affected the research results. Follow-up research could include learners at the master and doctorate levels to broaden the research results. Second, future research could involve regional and cultural factors as control variables or moderators on a comparative study to explore the potential differences among students in different cultural contexts. Third, this study adopted convenience sampling to collect data, which made the findings less generalizable. We suggest that follow-up research designs consider more comprehensive approaches to collect data.

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Appendix

Survey Items

Variable	Item	Main Reference
PU	1. I use MOOCs because I can get diplomas for potential future careers 2. I use MOOCs because I can communicate with other learners during the MOOC learning process 3. I use MOOCs because I can share knowledge among learners during the MOOC learning process 4. I use MOOCs because I can communicate with the instructor or teaching assistant during the MOOC learning process 5. I use MOOCs because I spend less time and gain more than in a traditional class	Chin et al. (2008); Davis (1989); Venkatesh & Goyal (2010)
PEOU	1. I think I can set learning goals according to my own situation 2. I think I have free choice of study path according to my own wishes 3. I think I can manage my learning progress according to my own learning situation 4. I think I can learn specific sections of the course according to my personal needs	Chin et al. (2008); Davis (1989)
ATT	1. MOOCs have multidisciplinary and interesting course content 2. MOOCs have multiple functional modules which allow me to choose what I prefer	Ajzen (1991); Venkatesh & Goyal (2010); Venkatesh et al. (2011)

	3. MOOCs have many types of advanced technical channels (e.g., PC side, mobile side, different browsers)	
	4. MOOCs have many types of teaching methods which make me enjoy the study (e.g., video, ppt, cases, literature)	
	5. I think MOOC study is useful	
	6. I think MOOCs study is enjoyable	
	7. I think MOOCs study is sensible	
	8. I think MOOCs study is interesting	
SN	1. I use MOOCs because many social media has reported the benefits and advantages of using MOOCs	Ajzen (1991); Luang-Guang (2019)
	2. I use MOOCs because many schools are promoting the use of MOOCs	
	3. I use MOOCs because people around me are using MOOCs (e.g., friends, classmates, teachers)	
PBC	1. I think I have enough time and energy to use MOOCs	Ajzen (1991); Luang-Guang (2019); Zhou (2016)
	2. I think I have enough capital to bear the cost of using MOOCs	
	3. I think I have multiple ways to obtain specific knowledge to master course content	
	4. I think I have necessary e-mail as well as network and computer capacity to use MOOCs	
	5. I think I can pass the MOOC-designed courses easily.	
BI	1. In the future, I will use MOOCs as an additional	Ajzen (1991); Luang-

study course	Guang (2019); Zhou (2016)
2. In the future, I will recommend MOOCs to my friends	
3. In the future, I will share my own MOOC learning experience with my friends.	

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An Online Physics Laboratory Delivered Through Live Broadcasting Media: A COVID-19 Teaching Experience

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Abstract

The COVID-19 pandemic has constituted a sudden educational transformation around the world. It has disrupted instructors, including physics educators, forcing them to adjust to remote teaching. The hands-on laboratory, one of the components of physics instruction, has also had to rapidly go online in all branches of this science, including nuclear physics. In this study, live broadcasting media was designed to conduct a remote nuclear physics laboratory. We then evaluated the immediate impact of this new mode of lab instruction on students' learning and attitude toward this type of instruction. Fifty-nine 3rd-year physics students at a public university in Indonesia participated in this study. The effectiveness of instruction was examined by analyzing both weekly reports and open-ended responses about students' learning experiences. In summary, it was evident that live broadcasting media was an effective way to conduct an online nuclear physics laboratory. Accordingly, students' attitudes demonstrated constructive behaviors about their remote laboratorial experiences. Our findings imply that online platforms are one way to offer the physics laboratory during unanticipated transitions such as the COVID-19 pandemic. Students' preference for a hands-on laboratory and the technical issues reported during the broadcasting session should be further examined to help design a remote nuclear physics laboratory that is even more accessible and enjoyable.

Keywords: online laboratory, nuclear physics, live broadcasting media, COVID-19

Introduction

The COVID-19 pandemic has been widely affecting educational practice since lockdown restricts direct interaction between teachers and students. Suddenly, educators worldwide have had to redesign their courses in order to offer remote instruction. Billions of students, teachers, and educational administrators are encountering turbulent situations as they sought to adapt to online learning formats to ensure educational sustainability.

Within the context of physics education, including nuclear physics course, COVID-19 has restricted laboratory activities which are compulsory for many undergraduate physics students. Broadly speaking, laboratory work is a key instructional element in promoting scientific practices that help explain conceptual physics in almost all physics domains. Earlier evidence has documented the potential of lab instruction for physics education (La Braca & Kalman, 2021; Moosvi et al., 2019; Ortiz, 2021; Phillips et al., 2021; Smith & Holmes, 2020; Zwickl et al., 2015). Due to the pandemic, unfortunately, laboratory instruction must be adjusted.

Such disruption can influence the effectiveness of physics labs. Reporting on the effectiveness of physics instruction is broadly acknowledged as the main intention of physics education research (PER; Docktor & Mestre, 2014; Odden et al., 2020; Santoso et al., 2022). In this study, students' performance and their attitude to the disruption were proxies to evaluate the effectiveness of online nuclear physics laboratories during the pandemic. Since the initiation of PER studies, learning transformation has been evaluated most often by probing student performance (Ding et al., 2006; Hake, 1998; Hestenes & Wells, 1992; Hestenes et al., 1992; Maloney et al., 2001). As well as the cognitive aspects, PER scholars are interested in examining the attitudinal variable that could be considered a supportive factor influencing effective instruction (Buxner et al., 2018; Crouch et al., 2018; Douglas et al., 2014; Fox et al., 2021; Kortemeyer, 2007; Mason & Singh, 2010; Werth et al., 2022).

The impact of the pandemic on postsecondary physics courses is particularly worthy of study. Recently, the disruption to education has been investigated, but these studies are focused on different sciences at the high school level (Abdullah et al., 2021; Juanda et al., 2021; Kartimi et al., 2021). Studies at the level of higher education are scant. To fill this gap, we decided that evaluating an online nuclear physics laboratory during the COVID-19 pandemic should be carried out.

A study by Rosen and Kelly (2020), undertaken before the pandemic, categorized online physics laboratories into several varieties. In this study, we selected *live broadcasting media* as the variety we wanted to examine. We evaluated students' learning processes and the impact of this transition on students' performance throughout the semester, and explored their attitudes towards using live broadcasting media to study nuclear physics. We posed two research questions:

1. How did students perform during the online nuclear physics laboratory throughout the semester?

2. What were students' attitudes about the remote nuclear physics laboratory during COVID-19?

COVID-19 has affected many aspects of educational practice. Supporting teachers by communicating PER findings and contributing progressive knowledge should be valuable in the long term. Experiences reported in this paper provide additional insights for physics educators wishing to evaluate learning processes during unanticipated crises such as a pandemic.

Methodology

Course Context

Universitas Negeri Yogyakarta (UNY) is one of the largest centres of Indonesian teachers' educators and educational researchers. Even though it is established in the Javanese region (home to the greatest Indonesian population), UNY's students come from not only the Javanese district but also from around the Indonesian archipelago. The admissions office registers almost 10,000 students every year, and they are distributed among heterogenous majors ranging from educational science, natural science, vocational, social sciences, and the humanities. The Faculty of Mathematics and Natural Science (FMIPA) of UNY organizes undergraduate and graduate programs. Within it, the Department of Physics Education prepares prospective Indonesian physics educators. Nuclear Physics (FIS 6117) is an experimental physics course taught to third-year students of modern physics. This field is populated mostly by experimental physicists. Thus, students must engage in laboratory work to dive into not only the content but also the epistemology of the field. Therefore, laboratory work is a key element of this course.

The nuclear physics laboratory at UNY is administered using an approach called *Learning Assistance*, which was developed at the University of Colorado (Otero et al., 2010). There are laboratory assistants recruited from among experienced students (enrolled in a higher year than the students they are assisting). They qualify for these positions by meeting certain requirements, thus ensuring their ability to handle nuclear physics experiments. Once a week, groups of students and assistants usually meet outside the classroom to discuss the experiments that are part of the course.

The nuclear physics course is taught during the first term of the third year. It starts in September and ends in December. During the 2020 lockdown, the nuclear physics laboratory had to adjust rapidly. The classic physics laboratory at UNY could no longer be administered, and it was instead offered remotely. This required the lab instructor to redesign the physics laboratory. Fortunately, a previous study by Setiaji & Dinata (2020) investigated the readiness of physics students at UNY to follow remote learning formats. Their readiness was measured by three proxies: (a) operating digital technologies, (b) understanding the e-learning system, and (c) interacting with online tools. Therefore, it was already evident that UNY students were prepared to be immersed in online routines.

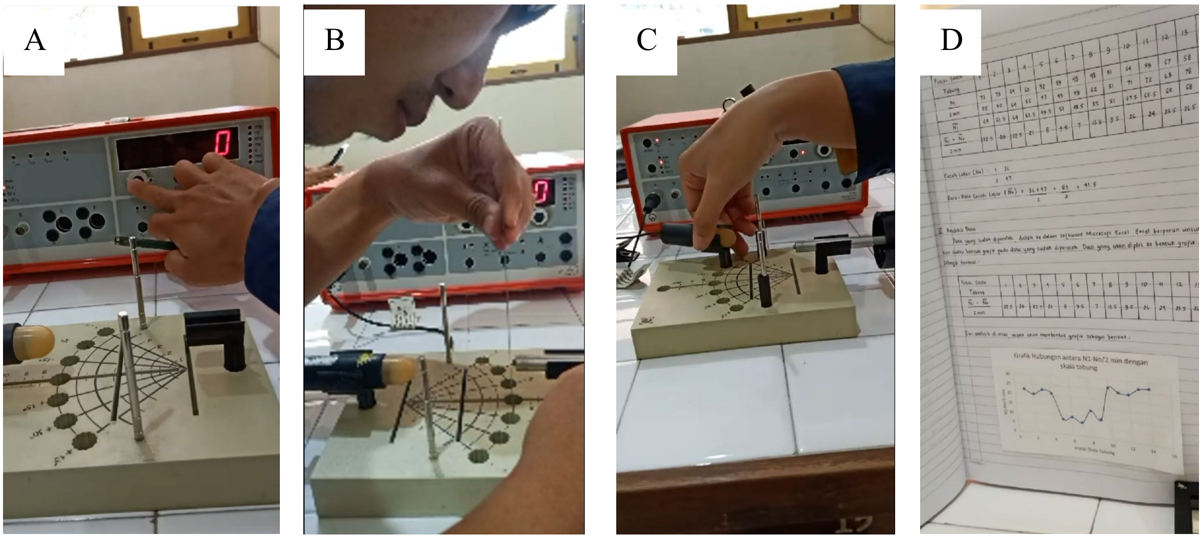
Study Design

This study is exploratory in nature. During COVID-19, the nuclear physics laboratory was designed to be delivered via live broadcasting media on the platform Instagram. Instagram has a live broadcasting channel. As evidenced by its number of users, Instagram is widely accessible and enjoyable for many users, which should include nuclear physics students, laboratory assistants, and lecturers.

This lab was designed to include two sessions, each delivered once a week. Students in each session were divided into three groups (6–7 students each, n = 59 students). Each week, one experiment was presented by the laboratory assistant (see Figure 1). Collaboratively, students carried out the experiment through a worksheet (in PDF format) developed for this online lab.

Figure 1

Live Online Nuclear Physics Laboratory Delivered by Laboratory Assistants



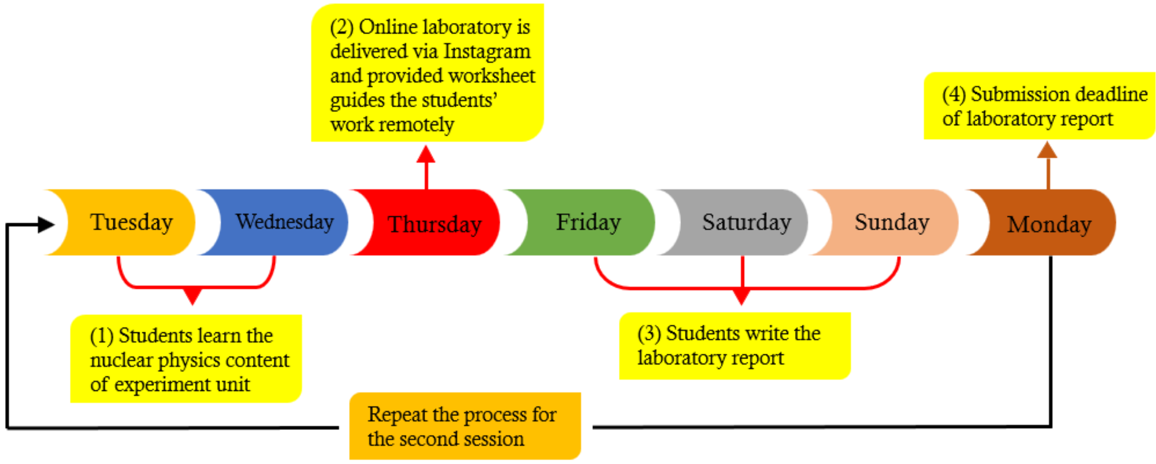
Note. Sample of students' activity through the Instagram Live channel. Panel A: Setting up the counter. Panel B: Preparing the Geiger-Müller detector. Panel C: Varying the mounting of the detector. Panel D: Explaining the format of the weekly laboratory report.

Prior to carrying out the live experiment, students studied material that was developed to provide initial information on a specific topic. This material was designed to help students "warm up" and be able to deal with problems arising from the topic. Providing this initial material ensured they had the ability to understand the lab activity, solve problems, and thus participate more effectively and efficiently.

Before the laboratory work commenced, students were offered, through video conference, introductory sessions during the first two weeks of the lecture. In the first week, the video conference introduced the course syllabus, experimental unit, and the grading rules. In the subsequent week, the lecturer presented the nuclear physics lecture on the topic of the upcoming laboratory work. After that, the weekly activities began (see Figure 2).

Figure 2

Weekly Activity of the Online Nuclear Physics Laboratory



First, students were assigned a worksheet with tasks to be carried out independently. We set up the students to be ready for the upcoming live session. Second, students were invited to the live session to observe the experiment presented by the laboratory assistants. Instead of merely observing the results, students were required to also remotely manipulate as many as five repeated measurements operated by the assistants. Third, a laboratory report of the recent experiment was to be written by students. Students were permitted to meet with their assistants through either the video conference or using the group chat function of the social media application WhatsApp. Difficulties that emerged either during the laboratory work or when writing the report would be addressed by the assistants. The laboratory report was to be submitted by students on the first day of the next week.

Simultaneously, the instructor prepared for the next lecture and graded the submitted reports based on a provided rubric (the rubric is described in the next section). These processes were repeated for the second laboratory session on the same experimental unit, and after two weeks, a new topic was introduced.

This online nuclear physics laboratory was divided into six units per session. Topics of the weekly experiment encompassed the introductory content of the undergraduate nuclear physics course as follows:

- Unit 1: Statistical property of nuclear radiation
- Unit 2: Attenuation coefficient and half-thickness
- Unit 3: Inverse-square law
- Unit 4: Radiation of lantern mantle
- Unit 5: Deflection of beta radiation in the magnetic field
- Unit 6: Radiographic method of filling level monitoring with gamma-ray

The whole remote laboratory activity ended after 16 weeks, which included 2 weeks for the lab introduction, 12 meetings for all live sessions, and 2 weeks for the final examination. The final test was designed to encompass the principle of performance assessment of the laboratory activity. It would be a proxy of the students' performance in this study and will be described in more detail in the next section.

Data Collection and Analysis

Students' performance in this study was measured through a weekly laboratory report and a final test at the end of the semester. Each student submitted one report, graded by the lecturer (the first author), on a weekly basis. In this work, we employed an adapted version of Rutgers' scientific abilities rubric (Etkina et al., 2006; Faletič & Planinšič, 2020) to assess students' laboratory reports. We looked at six aspects, standard to many laboratory reports: (a) clear purpose of experiment, (b) accurate data collection, (c) correct data analysis, (d) robust discussion, (e) solid conclusion, and (f) a complete reference used. After the weekly report had been graded, it was given back to students with attached feedback for their upcoming experiments. Finally, three open-ended items were administered during the final test (~90 minutes). These items were administered to assess students' scientific knowledge and to examine students' performance on data collection, data analysis, discussion, and drawing a solid conclusion. Validity of the final test was evaluated by PER experts with more than ten years' research and teaching experience with nuclear physics courses.

To answer research question 2, an additional set of open-ended items was included as a fourth item during the final examination. Within this item, three sub items were designed to probe student attitudes towards working with an online nuclear physics laboratory. Those aspects surveyed student feedback, experiences, and opinions regarding the effectiveness of their online physics laboratory during the COVID-19 pandemic. Students were encouraged to express themselves honestly and were told they could share their experience without any risk that their comments would be leveraged against their final course grade.

To answer research question 1, students' weekly reports and final exams were scored as a measure of student performance. Each student's data refers to six weekly reports and one final test. Their final course grade was calculated based on a weighted average of these two aspects. As determined by class consensus, weekly reports and final tests contributed 70% and 30% of the final grade respectively. Then, summary statistics were performed based on UNY academic rules. Numerical grades on the 100-point scale were converted to 4-point scaling grades and classified into qualitative predicates summarized in Table 1.

Table 1

Grading Scale of UNY Academic Rules

Interval	Letter grade conversion	
	Point value	Predicate
86 – 100	A	Very satisfying
81 – 85	A-	Satisfying
76 – 80	B+	Very good
71 – 75	B	Good
66 – 70	B-	Not good
61 – 65	C+	Very enough
56 – 60	C	Enough
41 – 55	D	Not enough
0	E	Bad

Then, to test the statistical significance of the effectiveness of our online nuclear physics laboratory, we used nonparametric statistics since, based on the Kolmogorov-Smirnov normality test, our data was not Gaussian distributed ($p > 0.05$; Kraska-Miller, 2013). We then implemented the one-sample Wilcoxon signed rank test (Corder & Foreman, 2014). It is a nonparametric alternative to the one-sample *t*-test when the data cannot be assumed as Gaussian distributed. It was used to determine whether the median of our sample was equal to a minimum passing grade of 56 based on UNY academic rules (Table 1).

To answer research question 2, we analyzed responses to the three open ended items during the final examination. Students' responses were qualitatively analyzed by two authors (B. S. and P. H. S.) and categorized based on nuance in the students' expressions. Conventional thematic analysis was employed to extract the essence of the textual data (Braun & Clarke, 2006; Nowell et al., 2017; Vaismoradi et al., 2016). After following the iterative processes of qualitative data analysis using RQDA packages within the R software environment (http://rqda.r-forge.r-project.org/; Huang, 2016), the same nuanced opinion was coded as the same categorization. Three categories of student attitude were saturated to report the essence of students' experiences in the online physics laboratory. There were three categories of student feedback (positive, negative, and neutral), student experience (Internet data plan, network quality, and no issues), and student opinion (hands-on lab, poor video quality, and still effective). To summarize the results, the number of students representing each of the categories within a sample were counted and visualized as a pie chart (see Figure 5).

Results and Discussion

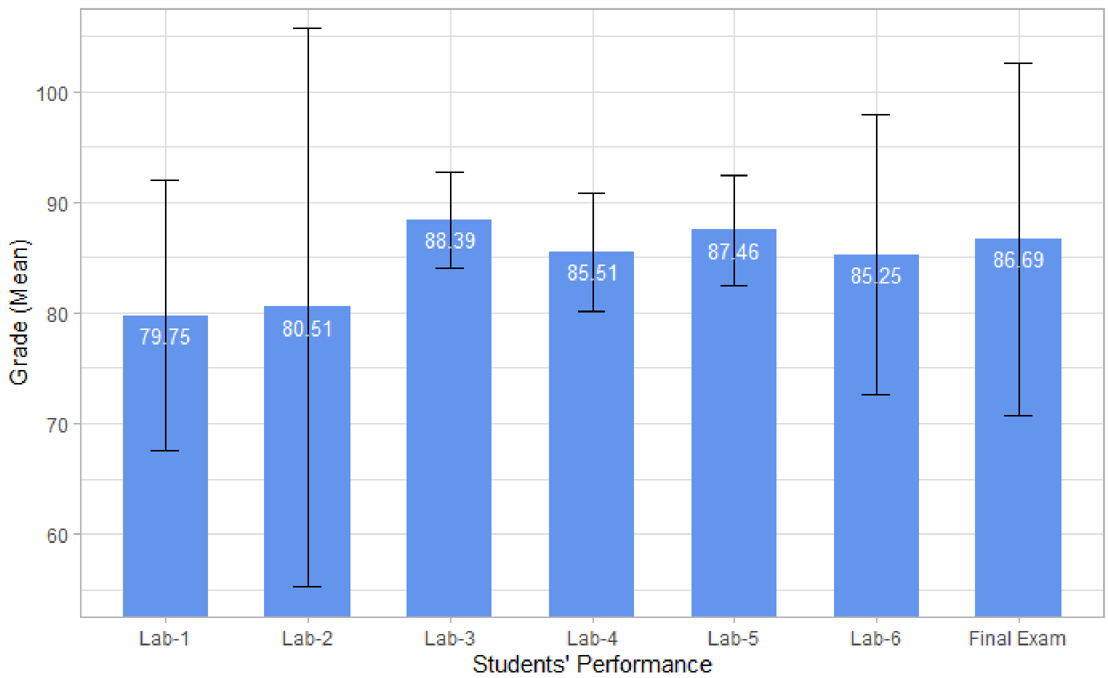
Students' Performances in the Online Nuclear Physics Laboratory (Research Question 1)

Students' performance was initially measured based on the weekly laboratory reports. In each laboratory unit, students had to submit a weekly report of the most recent experiment. This assignment was assumed to be a controlling system of students' attendance. Previous research has demonstrated that this treatment can maintain students' motivation in an online environment (Eckert et al., 2009). We expected that all students would maintain their intentions throughout the learning process.

The class mean of student performance in terms of weekly laboratory reports and final examination throughout the semester is summarized in Figure 3. In general, most students obtained the *very good* predicate as defined in Table 1 on each of the weekly laboratory reports and final exam. Students reached *very satisfying* performance (> 86) in the third and fifth laboratory reports. Unfortunately, the first two experimental units underperform to the subsequent laboratorial activity. This could be explained since the starting experiments required students to plot the decay distribution of the frequency background occurring within 10 seconds for 100 times using a Geiger-Müller detector. Admittedly, students must be able to make sense of the decay distribution on this task. Most students, however, still have limited experience in plotting and interpreting such graphs due to this being their first time in this nuclear laboratory. Even though they should have employed some graphical tasks in their previous learning path—recent reports state that graphical representation is imperative for physics learning (Hidayatulloh et al., 2021; Nixon et al., 2016; Skrabankova et al., 2020)—in fact students still need further training in this area. Accordingly, we tailored a tutorial after the second laboratory unit to help with plotting and interpreting visualizations to improve students' representational ability in nuclear physics.

Figure 3

Mean of Weekly Reports and Final Examination Grade (n = 59).



Note. Horizontal axes represent assessment points during the semester. There were six weekly laboratory reports and one final examination.

The third experiment was designed to study the inverse square law based on radium (Ra) radiation (226.33 becquerels). After conducting the experiment, students needed to examine the interplay between the distance of the radiation source in a thin-walled, cylindrical end-window tube and the decay rate of the radioactive source. After the tutorial, students should be able to achieve better performance based on a significantly improved average grade on this third experiment ($p < 0.05$).

The fourth experiment aimed to allow students to study the radiation decay of a lantern mantle containing 1.3 grams of thorium as a radioactive source. In this experiment, students were still provided with training in graphical representation. However, the average grade decreased non-significantly ($p > 0.05$). During this time, we experienced network problems that distracted students taking part in the live laboratory meeting. To overcome this problem, we uploaded a recorded file of the session, allowing students to access it on other occasions accordingly.

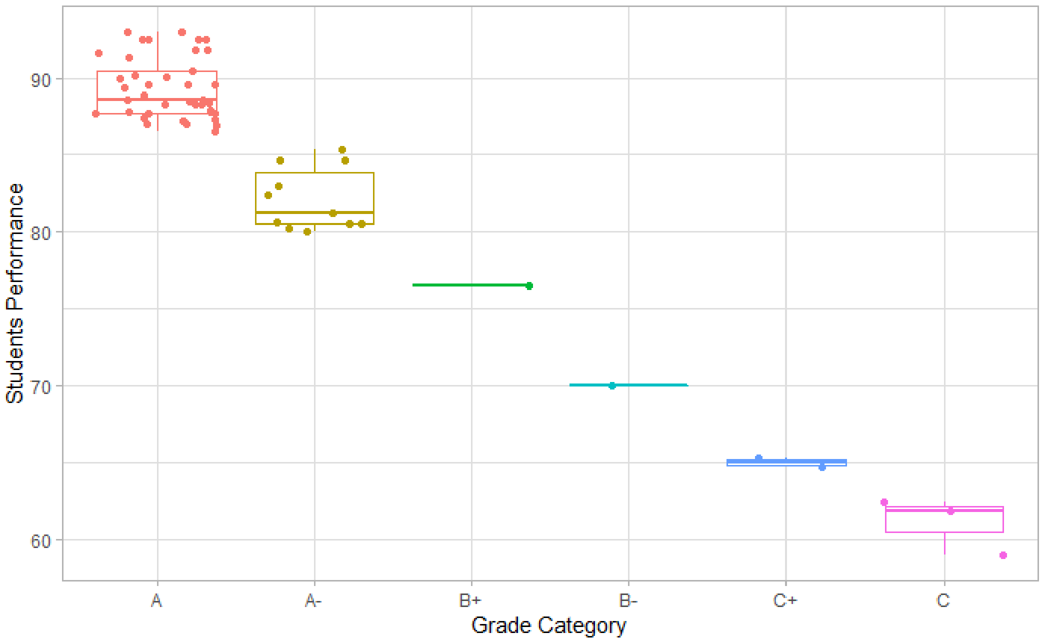
The fifth experiment was designed to observe the deflection of beta radiation within the magnetic field. The beta-ray was produced by Ra-226 radiation in this experiment. As shown in Figure 3, the average student performance increased from the fourth meeting non-significantly ($p > 0.05$). This average was categorized as *very satisfying,* as defined in Table 1. Eventually, students ended their laboratory sessions with a radiographic method of filling level monitoring (FLM) with gamma-rays. This experiment aimed to calculate the filling level using a radiation gate (between the radiation source and a thin-walled, cylindrical end-window tube). This experiment was performed by putting lead powder into a plastic tube. The decrease of students' average grades occurred non-significantly ($p > 0.05$).

In addition to the weekly report assessment, student performance was also probed using a final examination that contributed 30% to the final grade of nuclear physics course (FIS 6117). The final examination aimed to measure students' ability using the Rutgers' scientific abilities rubric (Etkina et al., 2006; Faletič & Planinšič, 2020). Three open-ended items examined students knowledge about their experimental data from the former labs. The mean of the final test was 86 or equal to the *very satisfying* predicate as defined in Table 1.

Eventually, the final grade was calculated using the weekly grades and the final exam. Based on the UNY academic rules (Table 1), the minimum passing grade for our nuclear physics course must be 56 (*C* predicate). Figure 4 summarizes how the students' performances (final course grade) were distributed within our sample.

Figure 4

Distribution of Students' Performance Based on Final Grade



Most students (more than half) were within the *A* predicate, outperforming other groups of predicates. Moreover, only one student obtained each a *B+* and *B–* predicate, thus there is no standard deviation (or box) representing these grade categories in Figure 4. The number of *C+* and *C* students was larger than the *B+* and *B–* predicates.

Inferential statistics were then employed to test the effectiveness of the online nuclear physics laboratory based on the student performance to achieve the minimum passing grade (56). The one-sample Wilcoxon signed rank test was performed to test the difference between the median data and the median test (the minimum passing grade = 56). We discovered a significant difference between median data and the minimum passing grade ($p < 0.05$). This statistical evidence suggests that live broadcasting media can be used with students learning nuclear physics during the unanticipated outbreaks. It can be an alternative way to adapt the physics laboratory to prevailing conditions during times of change such as the COVID-19 pandemic. This supports earlier research that found online media must be effective and efficient to support remote-based learning (Al-Said, 2015).

These findings imply that using live broadcasting media to deliver an online nuclear laboratory could continue beyond the COVID-19 pandemic. This would help students conduct real experiments indirectly and subsequently engage with concepts of nuclear physics during laboratory work. This is in line with an earlier study reported by Moosvi et al. (2019) that argued that online laboratory activity could remain as an alternate form of the physics laboratory in future.

Students' Attitudes About the Remote Nuclear Physics Laboratory During COVID-19 (Research Question 2)

Students' attitudes were measured using three open-ended items. Figure 5(a) shows the results of the first open-ended item which concerned student feedback. Positive feedback dominated the result (58%).

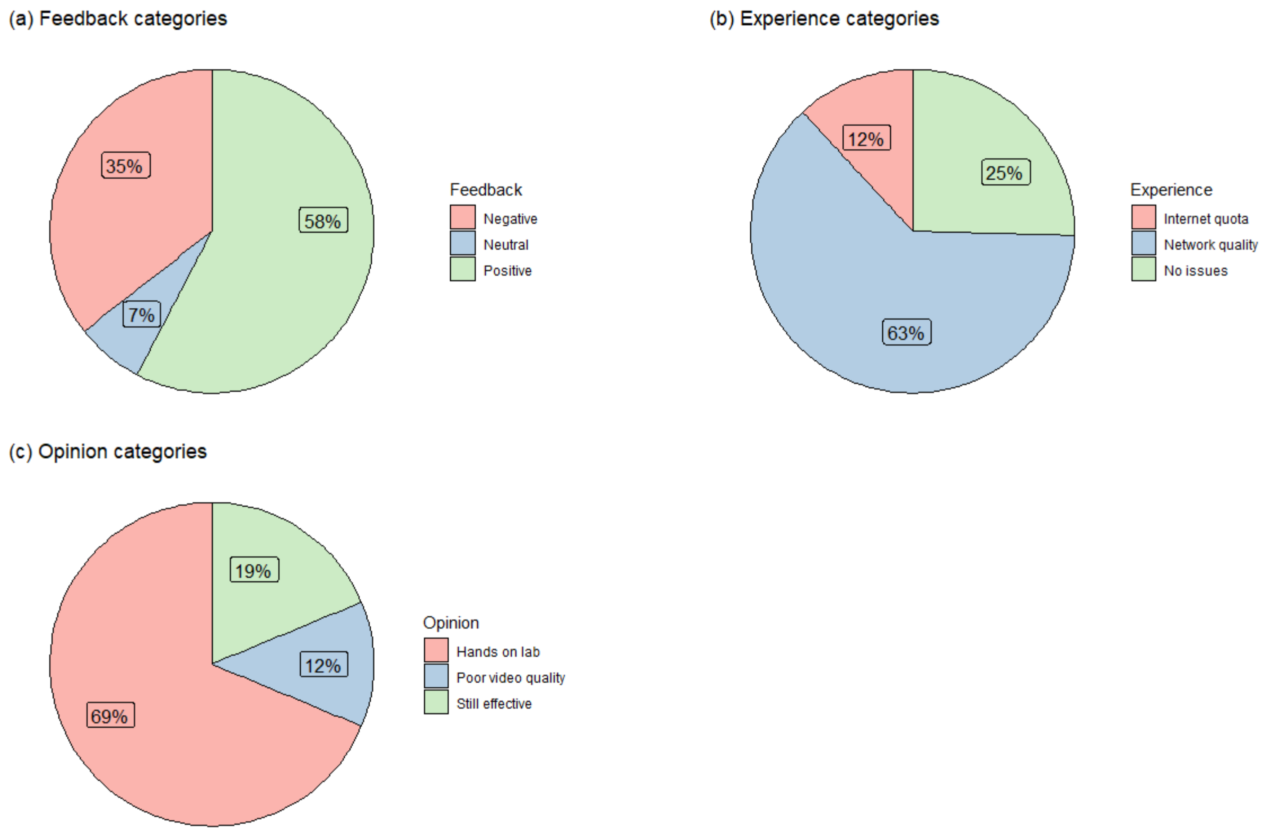
Most students expressed appreciation to the lecturers, laboratory assistants, and administrators for the roles they played facilitating the real experiments during the COVID-19 pandemic. One example of positive student feedback came from Joko:

> Thank you in advance for providing a live session of the laboratory. In general, these online laboratory activities are very helpful for students in solving experimental physics problems during the pandemic. It is valuable to our understanding because we are immersed in the real experiments. The laboratory assistants responsively help us to explain it and even assist us with the analytical calculations.

On the other hand, Figure 5(a) reveals that 35% expressed negative feedback. This should not be ignored. It can be driven since some students encountered technical issues during the live session, i.e., poor network quality. In addition, some students expressed criticism related to the camera angle. These criticisms and suggestions will be discussed in more detail in the section covering students' opinions.

Figure 5

Distribution of Student Feedback, Experience, and Opinion



Note. n = 59.

Students were also surveyed to describe their experiences with the online physics laboratory. Students' experiences are shown in Figure 5(b). Most of the experiences reported were clustered as network quality issues in their homes (63%). There were also a significant number (12%) who expressed frustration with the limited internet data plan. However, about a quarter of our sample reported no significant issues during the live sessions. On the one hand, network quality and data plan availability were still the main concerns of students. As expressed by Kinan, “Signal problems, both from my device and from the live streamer. They sometimes transmit the poor video quality. My internet data plan is limited to follow the live session for hours.”

Undoubtedly, network issues are a fundamental problem for most Indonesian students. Online learning obstacles are due not only to the unaffordable Internet data plan but also to gaps in network infrastructure, particularly in remote areas of Indonesia (Rayuwati, 2020). In fact, UNY had provided assistance of the mobile data plan to our students with their online learning. Moreover, the Indonesian Ministry of Education, Culture, and Higher Education had a policy to support this intention particularly students and lecturers with their Internet data plan (15 GB for a month) during the timeframe of the COVID-19 pandemic.

In the third open-ended question, students were asked for their opinions about the effectiveness of using live broadcasting media to conduct a nuclear physics laboratory. As shown in Figure 5(c), 19% of students believed that an online laboratory delivered through live broadcasting media could be effective. During the COVID-19 pandemic when all students were required to learn from home, using live broadcasting media to conduct experiments enabled students to proceed with their education. However, most students argued that hands-on experiments would be more preferable for experimental physics. They suggested that direct interaction with real apparatus would be better, allowing them to gain more experience with real physics phenomena. Stark (2019) has reported that students’ motivation can be greater in a hands-on physics laboratory.

Additionally, the most dominant opinion concerned video quality. Assistants and lecturers who managed the video capture at that time focused primarily on delivering the nuclear physics laboratory. Focusing on the apparatus rather than the shooting angle was meant to facilitate understanding of how the apparatus should be set up. Thus, it was believed, students would understand the technical part of the physics laboratory more clearly. In future, we should pay greater attention to the angle of the camera in the video.

The biggest problem for students as shown in Figure 5(b) was the network. Tumirah recommended:

> To overcome my slower network problem, I move to a place around my house that performs better signals. If it is still a bad connection, I will find help from my family member whose SIM card signal is good to provide network tethering for my device.

We took these issues into consideration when we later provided a recorded file of the live sessions to students. This facilitated students who were limited by network issues during the live laboratory session to proceed with their coursework.

Moreover, we created a discussion room on Instagram where students could give comments or post questions or feedback. We also created a WhatsApp group for assistants and students outside the live broadcasting session. This communication channel was designed for students who encountered difficulties during the synchronous activity. Live broadcasting media still requires further improvements to make students’ experiences more accessible and enjoyable. Some of the criticisms and suggestions can guide further enhancement of the online form of physics experiments.

One of the advantages of using live broadcasting media for physics laboratories is the sustained interaction during laboratory work. Students can discuss the experiments with lecturers and lab assistants who provide comments or feedback. Interaction is a key element of the successful implementation of remote based learning (Al-Said, 2015; Lu et al., 2018; Rodriguez-Gil et al., 2018). In addition, students who experience network limitations can access the recorded version of the live session. Another benefit is the opportunity for student engagement. They are immersed in laboratory work delivered by laboratory assistants in real time. Hence, students may gain more experience with the actual apparatus than if they were involved in virtual simulation (Finkelstein et al., 2005). As an impact, students will have a better conceptual understanding about nuclear physics.

Our findings on student performance and attitude about learning experiences are supported in several recent studies (Fox et al., 2021; Marzoli et al., 2021). These articulated that online tools such as live broadcasting media, video conference, or the virtual laboratory were options for all physics instructors who wished to maintain the laboratory class during COVID-19. Various learning platforms have been used as communication tools in physics teaching recently, such as Zoom (O'Brien, 2021), PhET (Wieman et al., 2008), Labsland (Orduña et al., 2016), and Olabs (Ortiz, 2021). Students' have demonstrated positive attitudes regarding an online nuclear physics laboratory delivered using live broadcasting media. Though the pandemic was an emergency, students did not give up in studying physics.

On the other hand, physics students still experienced learning obstacles in the context of graphical representation. In fact, this ability is imperative for physics conceptual understanding and problem solving (Docktor & Mestre, 2014; Hidayatulloh et al., 2021; Odden et al., 2020; Santoso et al., 2022). To address this issue, instructors should empower students to acquire this skill, using teaching tools such as scaffolding (Rangkuti & Karam, 2022), contextual tasks (Scheid et al., 2019), and obviously, as we discovered in our third meeting, tutorials (Kohnle & Passante, 2017).

Moreover, Lischer et al. (2021) and Patricia Aguilera-Hermida (2020) discovered another case of using online education during the COVID-19 pandemic. They reported the potential psychological effects encountered by students toward online teaching. In this study, students' opinion (Figure 5(c)) discovered that most of them prefer to acquire the hands-on lab rather than live broadcasting media. In addition, the number of students who experienced network problems during the live session (Figure 5(b)) cannot be avoided from our attention to evaluate our teaching throughout the circumstance. Those effects can correlate with the few students in expressing their negative attitudes in Figure 5(a) toward the online physics laboratory. Even the issue of psychological effects is not intended in our study, future scholars can examine this hypothesis that can contribute to the deeper investigation of the student attitude toward the learning process during the COVID-19 pandemic.

The current study has several limitations that could be addressed within future research. For one, the research design may be questioned. Moreover, the nonparametric statistics employed in this study uses merely the passing grade value as the statistical measure. For greater generalizability, future attempts should acknowledge a more solid experimental design and statistical method to compare different modes of online physics laboratory. In addition, further research is needed to evaluate whether our work could be a best practice in other STEM disciplines. As a final remark, an online physics laboratory offered through live broadcasting media cannot replace a hands-on physics laboratory as indicated in students' responses. The online laboratory reported in this paper was a shared experience of learning adaptation during the challenge of the COVID-19 pandemic. Obviously, further research is warranted to investigate specific impacts of these strategies and their relationships with the remote learning experience in physics.

Conclusion and Recommendation

In this study, live broadcasting media was designed for an online nuclear physics laboratory. This form of course delivery was effective since all students reached the minimum passing grade. Live broadcasting media should be considered as an alternative channel to administer a physics laboratory online during pandemic restrictions. Still, learning graphical representation skills within an online nuclear physics laboratory poses problems for some students. However, students improved in this area after receiving intervention in the form of tutorials created by the authors.

Most students expressed positive attitudes regarding the online laboratory and stated that the live broadcasting media was engaging and effective. On the other hand, poor network quality, limited Internet data plan, and insufficient quality of video transmission were drawbacks reported in our study. Therefore, enhancements to address these problems should be thoughtfully developed. For any further investigation into this area, the live broadcasting media could be compared either with other online media, with offline nuclear laboratory activities, or with other STEM courses. Moreover, configuring the video to improve quality will make the laboratory activity more accessible and enjoyable. Using live broadcasting media for online nuclear laboratory activities can serve as a baseline to develop other online learning resources.

This research offers additional insight for educators. Even without face-to-face interaction, physics education can be effectively delivered, even in the case of the experimental physics laboratory. There remains a question of whether remote activity will remain a part of instruction in future once pandemic restrictions have been lifted. The answer presents a further challenge for future investigations.

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The Design and Psychometric Properties of a Peer Observation Tool for Use in LMS-Based Classrooms in Medical Sciences

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Abstract

In peer observation of teaching, an experienced colleague in the educational environment of a faculty member observes the educational performance of that faculty member and provides appropriate feedback. The use of peer review as an alternative source of evidence of teaching effectiveness is increasing. However, no research has been done in the field of tool design and development to peer review in classrooms that use a learning management system (LMS). This study used mixed methods. In the qualitative stage, after studying sources and interviewing professors active in virtual education, a question bank was prepared and a 26-item initial questionnaire created. In the quantitative stage, the psychometric properties of the developed instruments, such as the face, content, and structural validity, were examined, and reliability tests were performed. IBM SPSS Statistics (Version 20) was used for analysis. Five categories, including content preparation, content presentation, effective interactions, motivation management, and support services, and 26 subcategories were determined to be effective indicators in peer observation in LMS-based classes in medical sciences. During content analysis, 9 items were removed due to lack of necessary criteria. Then, using principal component analysis and varimax rotation in the present mode (Watkins, 2018), 5 components with eigenvalues higher than 1 were extracted, which explained a total of 70.55% of the total variance. The inter-cluster correlation coefficient (ICC) was 0.88. Thus, the peer observation measurement tool, designed with 17 expressions using the answer method “yes/no”, showed good validity and reliability. The research results demonstrate that the evaluation of virtual classes of professors by their peers is effective and that the results can be used in e-learning promotion plans.

Keywords: blended learning, virtual education, psychometrics, validity, reliability

Introduction

Online learning refers to teaching and learning processes that are provided through the Internet. It includes a wide range of applications to access educational materials, as well as to facilitate teacher-student interaction (Keshavarz, Mirmoghtadaie, & Nayyeri, 2022). In recent years, e-learning systems have been increasingly influencing both classroom and campus-based teaching, but more primarily, such systems are leading to new models or designs for teaching and learning (Bates, 2022). In March 2020, with the emergence of the coronavirus, most schools, colleges, and universities across the world were forced to close to protect students and staff from infection (OECD, 2021). Gradually, instructors adopted blended/hybrid learning methods and asynchronous learning in online teaching. During the pandemic, lectures were often recorded and made available to download and replay at any time on online platforms (Bates, 2022). As blended learning systems developed, components and interactions became more complicated, and as a result, the expectations of students and other stakeholders from this educational environment have increased (Andone & Sireteanu, 2009). It should be noted however that certain limitations of e-learning, such as the lack of face-to-face communication and human and emotional interaction, have been largely eliminated (Kintu, Zhu, & Kagambe, 2017; Pinto-Llorente, Sánchez-Gómez, García-Peñalvo, & Casillas-Martín, 2017).

The purpose of blended education is to provide opportunities for students to use both real and virtual spaces to better benefit from learning (Henrie, Bodily, Manwaring, & Graham, 2015). This method optimizes learning outcomes and cost-effectiveness (Donnelly, 2017). Training in the medical field, part of higher education, should provide a wide range of knowledge, attitudes, and skills to students to gain job qualifications (Wood, 2003). Improving the health of the community depends on the presence of efficient and high quality manpower, trained using these new educational methods (Twomey, 2004).

Today, in the digital age, one of the basic requirements of learners is that they have the skills to learn in new digital environments. For this reason, instructors must possess digital-age teaching skills and be familiar with ways to manage and lead online classes using new learning platforms (Keshavarz & Ghoneim, 2021). Since blended learning can provide the benefits of both traditional and virtual methods, it is a good way to achieve teaching-learning goals in medical education. A review of research institutes and universities all around the world looking at the mechanisms of blended learning in medicine shows that, in recent years, blended learning is being used more often than traditional methods such as face-to-face and class lectures. Blended learning is not only capable of a more efficient transfer of concepts and skills, but is also a more effective method of educating and training self-employed and creative graduates (Benner, 2012; Missildine, Fountain, Summers, & Gosselin, 2013).

One of the tasks of medical universities is to empower faculty members to play their role as teachers, and one of the successful and effective ways of achieving this is to use the capacities and experiences of faculty members themselves. Experienced and successful instructors in teaching can contribute to the professional growth and development of their colleagues (Speer, 2010). Nowadays, peer observation of teaching is one of the new components of empowerment programs or evaluation of faculty members in different universities around the world (Johnston, Baik, & Chester, 2020).

Various terms such as *peer review* and *peer evaluation* are used synonymously in the literature, but the most common term in this field is *peer review* or *peer observation of teaching* (POT; Speer, 2010). POT is the presence of an experienced colleague in the educational environment of a faculty member observing that faculty member's educational performance and providing appropriate feedback (Cunningham, Johnson, & Lynch, 2017). The goals of POT include generating awareness of strengths and weaknesses of teaching from the perspective of colleagues, motivating faculty members in order to improve the overall teaching process, improving the teaching ability of individual faculty members, and creating an opportunity to use the experiences of other faculty members in teaching and assessment methods (Fletcher, 2018).

POT provides formative and constructive summative feedback to faculty members for the growth and development of their teaching abilities (Fernandez &Yu, 2007). This facilitates the formation of reflection and thought in teaching processes, and greatly influences the attitude and approach of faculty members towards teaching (Bernstein, Burnett, Goodburn, & Savory, 2006).

According to various studies, the use of peer review as one of the alternative sources of evidence of teaching effectiveness is increasing (Fernandez & Yu, 2007). Peer review in teaching includes two main activities: observing peers' performance in the classroom; and, reviewing written documents used in a course (Gehringer, Chinn, Pérez-Quiñones, & Ardis, 2005). Research has reported many different POT methods, but all are based on peer review/observation. One model is based on four phases: preparation, peer visit, peer reporting, and promotion (Speer, 2010).

In the case of formative evaluation, it is necessary to hold symposiums and provide feedback. Fernandez and Yu (2007) identified four steps in peer review:

1. Review of the educational materials-syllabus-course guide, and a sample presentation (e.g., PowerPoint slides)

2. Observer interaction, teaching observation, counselling, and post-teaching feedback

3. Written evaluation and presentation to the relevant teacher

4. Monitoring the peer review process.

If evaluation is not done according to a predetermined framework, evaluator subjectivity and biases will occur due to factors such as camaraderie, cooperation, and negative feelings. Quality teaching is also important in e-learning (Dill, 2007; Ruiz, Candler, & Teasdale, 2007).

A learning management system (LMS) is software used to implement and evaluate a learning process. A LMS provides an instructor with a way to create and deliver content and monitor student performance. A LMS may also provide students with the ability to use interactive features such as video conferencing and discussion forums. Canvas, Blackboard, and Moodle are examples of LMSs in which teachers and students are able to log in and work within an online learning environment (Bates, 2022).

Using this software, instructors and students can enter the online learning environment at designated time intervals. Course materials are often presented as PowerPoint slides or as audio podcasts or videos. Instructors take charge of teaching and introducing course materials to students. Classes with a large number of students can be divided into small groups. Students have the opportunity to discuss the course online with both the teacher and other students, and at the end of the class, the professor evaluates the learning activities. The LMS is primarily asynchronous in that students can access the learning process at any time and any place with an Internet connection (Bates, 2022).

Despite the extensive research that has been done, we found that there has been no research in the field of tool design and development related to peer review in LMS-based classrooms. Therefore, this study aimed to identify and prioritize the effective issues in peer observation in the LMS-based class in medical sciences.

Methodology

The present study was carried out using a mixed-method approach. It was conducted at the Tehran University of Medical Sciences in 2020. The mean age of the professors participating was 44.36 years, with a standard deviation of 6.47 years. Just over half (54.4%) of participants were male, and the rest were female. They came from three universities: 37.9% were faculty members of the Tehran University of Medical Sciences, 31.9% were from the Iran University of Medical Sciences, and the rest were from Shahid Beheshti University of Medical Sciences.

Qualitative Stage

Semi-structured interviews were used to collect data at this stage. Following a systematic review of related texts and articles, the questions were developed. Preliminary questions were as follows: “What do you think about peer observation in LMS-based education?” “What do you think are the challenges of peer observation?” and “What is the viable solution for improving e-learning using peer review?”

The semi-structured interviews were conducted with expert professors who were selected by purposive sampling. Inclusion criteria were having experience in virtual teaching and willingness to participate in the study. Each interview was conducted at a time and place convenient to the interviewee. The interviews were conducted individually, and the duration of each was 30–45 minutes. All interviews were recorded and then transcribed. Content analysis was performed after each interview.

Quantitative Stage

In the quantitative section, the psychometric properties of the developed instruments such as face validity, content validity, construct validity, and reliability were examined. The questionnaire was developed based on information obtained during the qualitative stage. The sample consisted of faculty members of the Tehran, Iran, and Shahid Beheshti universities of medical sciences who were selected by available sampling method. Inclusion criteria in this stage were having at least two years’ experience in virtual teaching and being interested in participating.

Face Validity

To evaluate face validity, two approaches were used, one qualitative and the other quantitative. In the study of qualitative face validity, items were corrected with a qualitative approach. The impact score index was used to determine the quantitative face validity (Mohammadbeigi, Mohammadsalehi, & Aligol, 2015; Neuendorf, 2017). To do this, a checklist tool with a 5-point Likert scale (1 = *not important at all* to 5 = *absolutely important*) was provided to 15 professors. After calculating the score of each question, questions with a score above 1.5 were deemed acceptable and saved for next steps. A score of 1.5 was considered the minimum acceptable score for an item (Lacasse, Godbout, & Series, 2002; Neuendorf, 2017).

Content Validity

To evaluate content validity, two approaches were used, one qualitative and the other quantitative. In the qualitative approach, a checklist was provided to 10 professors active in the field of virtual education to help them review and comment on issues such as observing Persian grammar, using the right words, placing the items in the right order, and the appropriateness of the items. Then, using their comments, we examined content validity using the content validity index (CVI) and content validity ratio (CVR) to quantify our findings. CVI was reviewed by 10 expert professors based on the formula proposed by Waltz and Bausell (1981). The total number of agreeable scores, i.e., "which is relevant but needs to be reviewed" and "fully relevant," was divided by the total number of specialist professors, and the index scores with a content validity of less than 0.7 were removed. Scores between 0.7 and 0.79 were revised (modified based on the recommendations of the panel members and the research team), and scores above 0.79 remained unchanged on the checklist (Polit, Beck, & Owen, 2007). To determine the CVR, experts were asked to review each item based on a three-part range of "essential," "useful but not essential," and "not essential." Then, answers were calculated according to the following formula, where *Ne* represents the number of panelists indicating "essential," and *N* is the total number of panelists.

$$CVR = \frac{Ne - \frac{N}{2}}{\frac{N}{2}}$$

Based on the number of experts who evaluated the questions, the minimum acceptable CVR value in this study was determined to be 0.49, which is, in turn, based on the Lawshe table for 15 participating specialists. Questions for which the CVR value was less than the minimum were excluded from the test (Lawshe, 1975).

Construct Validity

Construct validity using exploratory factor analysis (EFA) after examining Kaiser-Meyer-Olkin (KMO) sampling adequacy indices and Bartlett's test of sphericity, and after ensuring the ability to perform exploratory analysis with the participation of 182 faculty members of Tehran, Iran, and Shahid Beheshti universities of medical sciences was evaluated using principal component analysis and varimax rotation. In other studies, different ratios for the sample size required for EFA have been expressed. In this regard, a minimum ratio of subjects to variables has been reported as 1 to 3, 1 to 10, 1 to 15, as well as 1 to 20 (Stevens, 2012; Westen & Rosenthal, 2003).

Reliability

Considering that the final tool was a checklist with two options, yes and no, we gave the checklist to five faculty members to evaluate. The degree of their agreement was calculated based on the intraclass correlation coefficient (two-way mixed and consistency).

Data Analysis

Analysis of interview data at the qualitative stage of the study was performed through content analysis. We used Colaizzi's 7-step method which includes: (a) reading important findings to get a grasp on participants' understanding of the topic, (b) extracting important sentences related to the subject under study, (c) giving specific concepts to the extracted sentences, (d) classifying the concepts and clusters obtained, (e) referring to the main and comparative contents of the data, (f) describing the studied phenomenon, and finally, (g) returning the description of the phenomena to the participants to check reliability. After these steps were taken, the main categories and subcategories were coded and extracted (Drisko & Maschi, 2016). Data analysis was performed using MAXQDA software (Version 12). Further quantitative analyses were performed using IBM SPSS Statistics (Version 20).

Trustworthiness of Qualitative Data

Numerous frameworks have been developed to evaluate the rigor or assess the trustworthiness of qualitative data (Patton, 1983), and various strategies for determining credibility, transferability, dependability, and confirmability have been established. In this study, the credibility of the qualitative findings was ensured by using member check and immersion techniques, as well as our ongoing engagement with the data and participation in similar congresses. Then, to complete the data and examine the transferability of our findings, we asked peers who had experience conducting qualitative research to review the initial interviews, coding, and categories. We focused on the research topic and also controlled and checked the findings to increase the reliability of the data.

Ethical Considerations

All ethical considerations were observed in conducting this research. Professors participating gave their informed consent after being told of the objectives of the research, its voluntary nature, our commitment to confidentiality of information, and of their right to withdraw at any time. The university's code of ethics number assigned to this research is IR.SBMUS.REC.1400.1214.

Results

Results of the Qualitative Section

Based on the analysis of interview data and open coding results in the qualitative part of the research, five main categories and 26 subcategories of indicators related to peer observation of teaching in a LMS environment were identified. These are shown in Table 1.

Table 1

Main and Sub Categories Affecting Peer Observation in LMS-Based Classes in Medical Sciences

Category	Subcategory
Content preparation	Provide up-to-date scientific content
	Proportion content to meet the needs of learners
	The fit of content with the course goals
	Observe professional principles for educational design
	Proportion of content volume based on the course unit
	Use of new technologies
	Provide content appropriate to learning styles
	Quality course content (technically)
Content delivery	Provide content at the right time
	Time management
	Course management
	Management of contradictions and conflicts in electronic debates
Effective interactions	Provide appropriate feedback
	Provide timely feedback
	Control and supervision of learners
	Encourage interaction between learners
	Create attractive discussions
	Observe the appropriate period for completing homework
Motivation management	Follow up on the reason for students' non-participation
	Encourage and encouragement to provide creative assignments
	Comparison of students' assignments and introduction to the top student
	Create an environment for the free expression of opinions
	Guidance and encouragement for group work
Supportive services	In-person appointment guide

Follow-up development of students

Debugging classes

The conceptual model of the qualitative part of this study is shown in Figure 1. Five general categories affect the main focus of the research, namely, effective indicators in observing peers: content preparation, content delivery, effective interaction, motivation management, and supportive services.

Figure 1

Conceptual Model of the Qualitative Part of the Research

Results of the Quantitative Section

Face and Content Validity

The results of qualitative face validity measurement showed that five items needed to be corrected and applied to the checklist. Quantitative face validity measurement on the 26 subcategories showed that all items had a score above 1.5 and were suitable for content validity testing.

In the qualitative part of content validity, the checklist was revised and modified based on the opinions of 10 professors participating in this part of the study. Based on quantitative content validity results, according to 15 participating experts, nine items were deleted due to not receiving an appropriate content validity index, and finally, 17 items remained (Table 2).

Table 2

Initial CVR and CVI Values of Peer Review Checklist Questions

Row	Item	Content validity	
		CVR	CVI
1	The scientific content is up to date.	1	1
2	The content presented is relevant to the objectives of the training.	1	1
3	Professional principles of educational design are observed.	0.73	1
4	The volume of content fits the course unit.	0.86	1
5	New technologies are used to deliver content.	0.73	1
6	Feedback is given appropriately.	0.73	1
7	Learners are monitored during the training process.	0.73	1
8	By creating forums, the interaction between learners is created.	0.6	1
9	Appropriate discussions have been organized.	0.6	1
10	Content is provided at the right time	0.6	1
11	The appropriate period for completing homework is observed.	0.6	1
12	The assignments presented are tailored to the needs of learners.	1	1
13	Meeting time and consultation are provided.	0.73	0.86
14	Class time is well managed.	0.6	1
15	The course is well managed.	0.6	1
16	Contradictions and conflicts in online discussions are well managed.	0.6	1
17	Feedback is given at the appropriate time.	0.86	1
Total		0.74	0.99

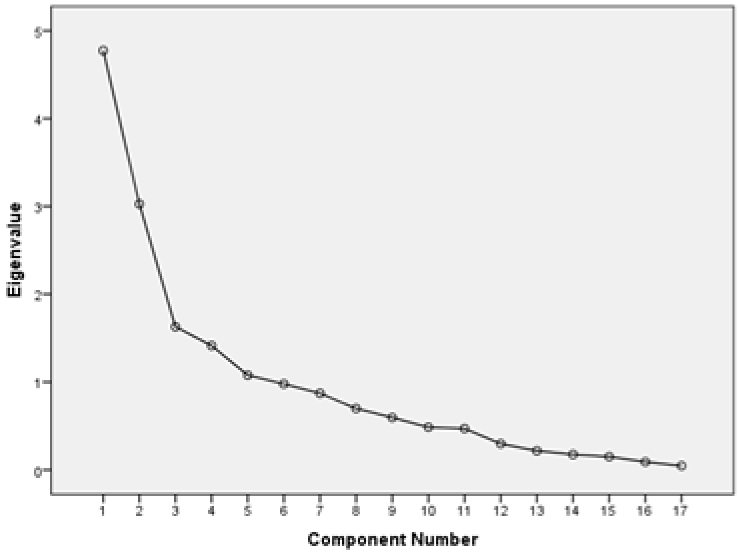
Construct Validity

The possibility of factor analysis on the research sample was investigated using the Bartlett test and the KMO sampling adequacy index where KMO = 0.61 and the approximate chi-square = 187/32, p = 0.000, and df = 136.

In the study of item commonality, it was found that all items had more than 0.5 subscriptions. Factors in the test were extracted by principal component analysis and varimax rotation. In the present model, five components with eigenvalues higher than 1 and scree plot diagrams were obtained (Figure 2).

Figure 2

Pebble Test (Scree Test) on Peer Evaluation Checklist Factors



The five extracted factors with eigenvalues higher than 1 in total explained 70.55% of the total variance of the test variables. The eigenvalues values of the 5 factors extracted after rotation were 3.92, 3.04, 1.64, 1.56, and 1.11, respectively, each of which was 24.51%, 19.04%, 10.27%, 9.76%, and 6.95% of the variance explained respectively (Table 3).

Table 3

Primary and Extractive Exploration of Exploratory Agent Analysis of the Peer Review Checklist

	Factors extracted by rotation			Extracted agents without rotation			Special value		
	Compression variance %	Explanation variance %	Total	Compression variance %	Explanation variance %	Total	Compression variance %	Explanation variance %	Total
1	24.51	24.51	3.92	26.32	26.32	4.21	26.32	26.32	4.21
2	43.56	19.04	3.04	45.13	18.81	3.01	45.13	18.81	3.01
3	53.83	10.27	1.64	55.07	9.93	1.58	55.07	9.93	1.58
4	63.6	9.76	1.56	63.82	8.74	1.40	63.82	8.74	1.40
5	70.55	6.95	1.11	70.55	6.73	1.07	70.55	6.73	1.07

Based on factor analysis with varimax rotation, all questions with a factor load of at least 0.5 were examined (Yong & Pearce, 2013), and finally, a 17-item checklist was extracted in the form of five factors. The factors were: (a) content management (five items), (b) classroom management (five items), (c) conflict management (two items), (d) assignment management (2 items), and (e) feedback management (3 items). These are shown in Table 4 along with the results of factor analysis.

Table 4

Rotated Factor Matrix by Principal Component Analysis and Varimax Rotation After Exploratory Factor Analysis

Item	Factor bar				
	1	2	3	4	5
Factor 1: Content management					
The scientific content is up to date.	0.910				
The content presented is relevant to the objectives of the training.	0.860				
Professional principles of educational design are observed.	0.909				
The volume of content fits the course unit.	0.769				
New technologies are used to deliver content.	0.834				
Factor 2: Classroom management					
Feedback is given appropriately.		0.558			
Learners are monitored during the training process.		0.870			
By creating forums, the interaction between learners is created.		0.911			
Appropriate discussions have been organized.		0.639			
Content is provided at the right time.		0.532			
Factor 3: Conflict management					
The appropriate period for completing homework is observed.			0.835		
The assignments presented are tailored to the needs of the learners.			0.783		
Factor 4: Assignment management					
Meeting time and consultation are provided.				0.827	
Class time is well managed.				0.845	
Factor 5: Feedback management					
The course is well managed.					0.837
Contradictions and conflicts in online discussions are well managed.					0.861
Feedback is given at the appropriate time.					0.791

Reliability

The result of the intracluster correlation coefficient (ICC) for the checklist was 0.88 which shows acceptable reliability.

Discussion and Conclusion

In this study, a Peer Observation Tool (POT) to be used in LMS-based classrooms was designed, comprised of a list of items related to the homogeneous observation of five main categories: content preparation, content presentation, effective interactions, motivation management, and support services. Furthermore, the results of face validity, content validity, and design tool reliability show that the tool has appropriate validity and reliability for peer observation.

Continuous evaluation of teaching plays an important role in improving the quality of teachers. How the evaluation is performed and the criteria measured are very important. According to Keig (2000), teaching should be seen as a process and follow a path similar to what a research manuscript goes through before being published in a reputable scientific journal, which includes a review and strict judgments by peers.

Peer review, according to Min (2006), is still unknown in e-learning. With the new technological developments in the field of education over the last two decades, these components should be reviewed. Assessing quality in an e-learning system requires attention to the criteria of teaching in general and the field of e-learning in particular. On the other hand, many criteria of the face-to-face classroom must be transferable to the virtual learning space to be examined. The results of this study show that, from the perspective of peers, the items “electronic content enrichment,” “interaction promotion,” “appropriate timing of course delivery,” “content assurance,” “face-to-face interaction,” and “process maturity teaching” are of great importance.

The work done in the development and distribution of multimedia content has raised the hope that students will have access to a wider range of content (Garrison, 2016). New technologies have provided many possibilities for professors to produce attractive and rich content (Collis & Moonen, 2012). As content moves from static and inactive to multimedia, the volume of cognitive processing of memory is reduced and learning is facilitated (Garrison, 2016).

Another important point that was obtained in the research is “promoting teacher-student interaction.” Roslin et al. also showed that for interaction to occur at a high level, effective teaching must be participatory and emphasize teamwork (Amira & Jelas, 2010). Many educators are not aware of the importance and effective methods of live or virtual interactions with learners, and teachers need to be trained to design and implement appropriate interactions (Ibrahimzadeh, Zandi, Alipour, Zare, & Yazdani, 2010).

Another important feature important in evaluating an e-learning system is whether lessons and assignments are uploaded by the instructor following an appropriate schedule. One of the main concerns in this area is the production and management of educational content (Snyder, 2009). A study titled *Academic Quality Assessment* showed two important criteria of a good professor: ability in scientific reasoning and knowledge of how to teach to convey understanding of concepts (Clipa, 2011). Other research has shown that the specialty of a professor is another factor in student satisfaction. Educational equipment and facilities, as well as intimate teacher-student interaction and cooperation, are equally important factors in evaluation (Butt & Ur Rehman, 2010). The results of another research study have shown that emotional factors and having a correct and appropriate social relationship play an important role in education (Opre, Calbaza-Ormenisan, & Opre, 2011).

Lee has stated that although the goal of the e-learning method is self-learning, feedback plays a major role (2009). On the other hand, for producing quality electronic content, one of the important points to pay attention to is learning styles, and the cognitive and emotional preferences of learners (Kay & Knaack, 2008). E-learning, with all its benefits, is defective due to a lack of direct social interaction and face-to-face contact and the absence of non-verbal cues (Al-Qahtani & Higgins, 2013).

Research has shown that e-learning can be very useful when combined with face-to-face training. In blended learning, the learner benefits from the combination of e-learning and face-to-face learning (Akkoyunlu & Soylu, 2006). In the present study, the emphasis on creating a face-to-face block during the term was confirmation of these past findings.

The criteria described in this research, in addition to being useful in the evaluation of professors in the field of e-learning, may also empower professors in this field. The empowerment of faculty members, especially in virtual education, will help achieve the mission and goals of higher education institutions and improve performance in this field.

Limitations

In this study, researchers have tried to simultaneously design a valid tool for peer observation in virtual classes as well as evaluate the validity and reliability of that tool, so that the reader will be aware of and able to themselves evaluate the quality of the designed tool. The design of this tool was based on a psychometric process, using the opinions of the target group and specialists and experts. This, being the first time such a research path was taken, is one of the positive points of this tool. However, since the validity and reliability of this tool have only been performed by medical professors, such tests would need to be undertaken in different populations.

In this study, researchers provided complete and accurate information on how to determine the validity and reliability of the designed tool, which has contributed to the clarity of the issues in this field. On the other hand, it should be noted that in medical science education, e-learning is blended learning and not just virtual and LMS-based education. This may affect results in other disciplines. Evaluation of virtual classes by professors' peers can clarify the status quo, and the results can be used in e-learning promotion plans. To confirm or reject the components obtained in this study, it is suggested that these indicators be tested in future research both before and after the empowerment of professors in virtual learning.

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Conflict of Interest

There was no conflict of interest.

Ethical Affirmation

The present study is part of an educational process, and the meetings were conducted with the coordination and approval of relevant authorities. The participation of faculty members in this research was voluntary.

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"Someone in Their Corner": Parental Support in Online Secondary Education

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Abstract

Despite increased interest in K–12 online education, student engagement deficits and the resulting student attrition remain widespread issues. The Academic Communities of Engagement (ACE) framework theorizes that two groups support online student engagement: the personal community of support and the course community of support. However, more evidence is needed to understand how members of these communities, especially parents, support students in various contexts. Using insights gleaned from 14 semi-structured interviews of parents with students enrolled in online secondary school, this study adds support to the roles identified in the ACE framework by presenting real examples of parents supporting their online students' affective, behavioral, and cognitive engagement. Findings also confirm patterns found in previous research that are not explained using the ACE framework, such as parental advocacy, communication with teachers, and self-teaching. We discuss how a systems approach to conceptualizing the ACE communities allows the framework to more accurately capture parents' perceived experiences within the personal community of support. We also discuss implications for both practitioners and members of students' support structures.

Keywords: learner engagement, distance education, electronic learning, virtual schools, secondary education, parent role

Introduction

Enrollment in K–12 online learning continues to increase, despite attrition rates that are higher than those for in-person classes (Freidhoff, 2021). One explanation could be a lack of student engagement (Borup, 2016), defined as a student’s ability and drive to apply themselves cognitively, affectively, and behaviorally to their coursework—something that may be more difficult to develop in online settings due to fewer opportunities for interaction and increased learner isolation (Martin & Bolliger, 2018).

In the Academic Communities of Engagement (ACE) framework, Borup et al. (2020) proposed that student engagement in online courses increases when two communities support students: the course community, which includes teachers, classmates, and other supports within the course, and the personal community, which exists independently of students’ course enrollment. K–12 students’ parents or guardians are primary actors within their personal community of support, as research has shown parental influence is important to student achievement in traditional, in-person classes as well as online courses (Black, 2009; Jeynes, 2007).

The ACE framework also highlights types of support students could receive from their personal communities to increase their affective, behavioral, and cognitive engagement, such as academic mentoring, behavior monitoring, and encouragement (Borup et al., 2020). However, limited research exists on specific parental roles within the personal community of support, how those roles appear in various contexts, and how they support student engagement. Without such evidence, researchers lack a foundation to explore the implications of the framework. Additionally, practitioners, parents, and other supportive actors in students’ education may struggle to apply implications built on theoretical underpinnings instead of relatable case studies.

Statement of the Problem

This research sought to more deeply understand the roles parents play in secondary students’ online education through the lens of the ACE framework. Parental roles in the personal community of support are particularly important in online school settings, as parents or guardians are often the adults who are physically present when students are engaging in remote education. Understanding the parental role is therefore an important step in knowing how to assist both students and their support structures in these settings. In exploring this problem, we analyzed parents’ support from the parents’ perspectives to understand how they perceive both their supportive roles and their experiences therein.

Literature Review

The purpose of this review is to (a) briefly introduce the research base studying student engagement, (b) explain what the ACE framework adds to our understanding of student engagement, and (c) review current research regarding parental support roles.

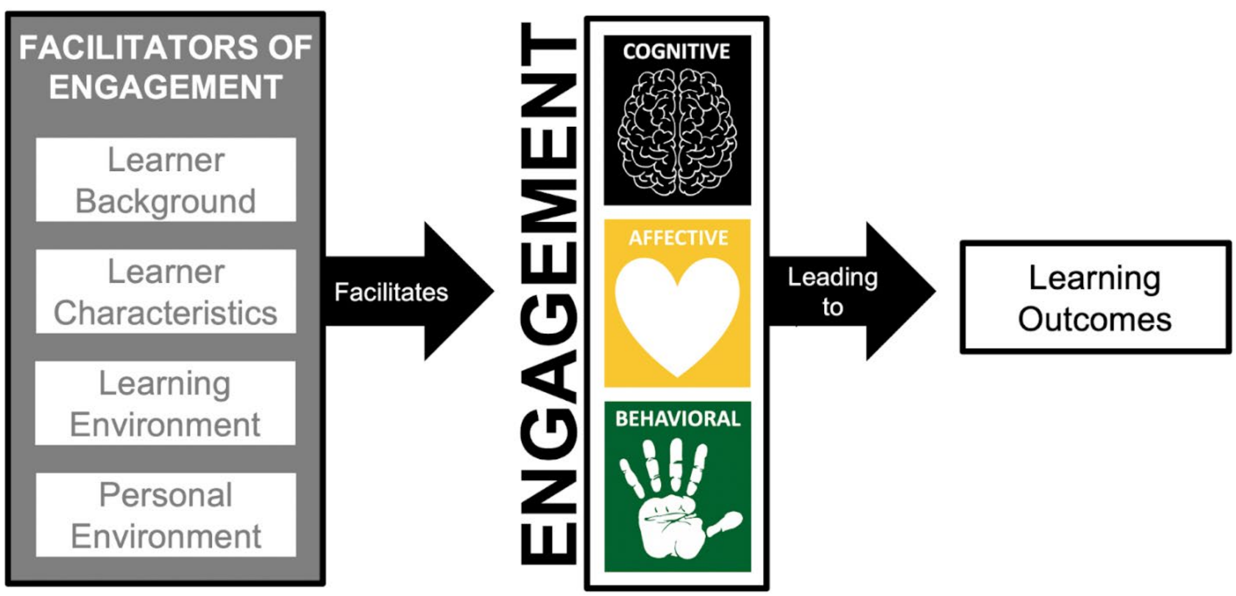
The Construct of Student Engagement

Student engagement has been described as the "holy grail of learning" (Sinatra et al., 2015, p. 1)—an appropriate phrase emphasizing both the importance and elusiveness of the construct. Its importance has been reaffirmed by research linking engagement to student achievement, academic persistence, better mental health, and fewer delinquent behaviors (Wang & Degol, 2014). However, research has also confirmed the construct's elusiveness, as many can agree on its multidimensional nature but not on the specific dimensions that compose it (Reschly & Christenson, 2012). These disagreements relate to what types of engagement are considered in defining student engagement and what grain, or scope, should be considered as affecting student engagement (Sinatra et al., 2015).

For the purposes of this study, we adopted Borup et al.'s (2020) definition of engagement. Specifically, following a review of the literature, Borup et al. (2020, p. 813) identify and define three dimensions of learner engagement: affective ("emotional energy associated with involvement"), behavioral ("physical behaviors [energy] required to complete course learning activities"), and cognitive ("mental energy exerted towards productive involvement"). For scope, we consider the individual student, as opposed to a school or class, but we attempt to account for the learner's characteristics and their personal and learner environments, since each of these influences the student's ability to engage in learning activities (Borup et al., 2020; Figure 1). With engagement, as Reschly, Christenson, and Wylie (2012) summarize, "both the individual and context matter" (p. vi).

Figure 1

Facilitators, Dimensions, and Results of Engagement



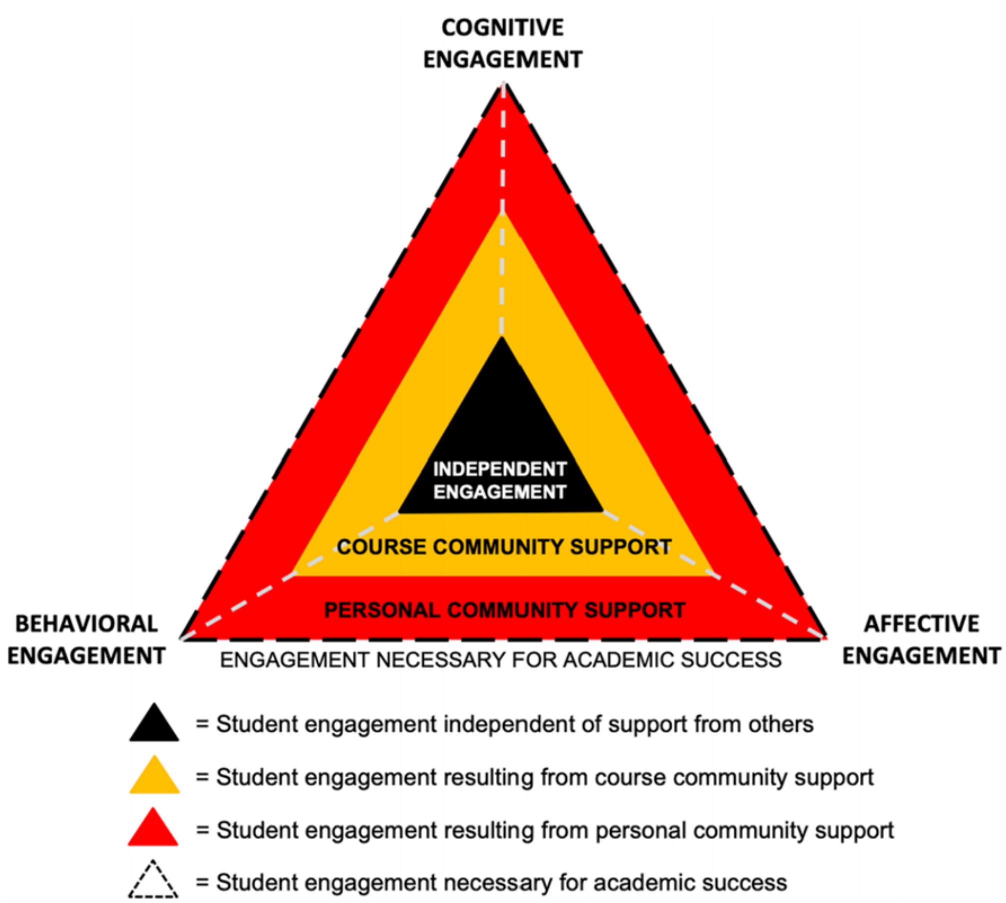
Note. Adapted from "Academic Communities of Engagement: An Expansive Lens for Examining Support Structures in Blended and Online Learning," by J. Borup, C. R. Graham, R. E. West, L. Archambault, & K. J. Spring, 2020, *Educational Technology Research and Development*, *68*(2), p. 811 (https://doi.org/10.1007/s11423-020-09744-x).

The Academic Communities of Engagement Framework

The ACE framework is founded on the theory that others' support can increase students' academic engagement. This theory considers the entire system supporting the learner and has ideological roots in Bronfenbrenner's (1977) ecological theory of child well-being and development and Vygotsky's (1978) zone of proximal development, which postulates that the level of achievement students can accomplish is greater with the help of others. The ACE framework groups the support actors within Bronfenbrenner's mesosystem of support into two communities: the personal community of support (i.e., the actors who support a student before, during, and after a specific course) and the course community of support (i.e., the actors associated with the student because of and for the duration of a particular course) (see Figure 2). Given online students' lack of physical contact with the course community, the personal community—especially the parent(s)/guardian(s)—is of particular importance in online school settings.

Figure 2

Academic Communities of Engagement (ACE) Framework



Note. The support communities help bridge the gap between what the student can do alone (inner black triangle) and what they need for academic success (outer triangle depicted with black, dashed lines). From “Academic Communities of Engagement: An Expansive Lens for Examining Support Structures in Blended and Online Learning,” by J. Borup, C. R. Graham, R. E. West, L. Archambault, & K. J. Spring, 2020, *Educational Technology Research and Development*, *68*(2), p. 810 (https://doi.org/10.1007/s11423-020-09744-x). Copyright 2020 by Springer Nature.

The Roles of Parents

This section summarizes typical parental support roles in online settings. While some roles serve multiple dimensions, most can be categorized as supporting either affective, behavioral, or cognitive engagement. Hanny (2022) conducted a thorough examination of parental roles and how they fit into the three dimensions of engagement; highlights are given here.

Previous studies have shown several ways parents help their online students emotionally invest in learning. For example, parents help students have a positive academic experience by encouraging and nurturing them (Borup et al., 2019; Borup et al., 2015; Hasler Waters, 2012). They also provide support by motivating students and helping them set goals (Borup, 2016; Curtis & Werth, 2015; Hasler Waters, 2012; Hasler Waters & Leong, 2014; Keaton & Gilbert, 2020).

Parents can inspire behavioral engagement by supporting and enabling student participation in course-based activities. These can be one-time acts, such as providing space to complete schoolwork (Downes, 2013; Novianti & Garzia, 2020), or occasional acts, such as monitoring student work (Borup et al., 2015; Oviatt et al., 2018) and helping with weekly schedules (Hasler Waters, 2012; Oviatt et al., 2018). Similarly, parents can support student participation in extracurricular activities, and for some families, this schedule flexibility is the primary motivation behind enrolling their children in online courses (Harvey et al., 2014). However, behavioral support can also be constant, such as when parents manage student work (e.g., checking every submission for completeness; Borup et al., 2019; Rice et al., 2019) or provide daily organizational support (Hasler Waters & Leong, 2014; Curtis & Werth, 2015).

Parents also help online students cognitively engage in their work. This primarily occurs as tutoring or teaching students required content (Borup & Kennedy, 2017; Keaton & Gilbert, 2020). However, a few studies have reported parents providing cognitive support by assessing student knowledge (Cwetna, 2016; Downes, 2013) and otherwise reinforcing learned content (Hasler Waters, 2012).

Additional roles exist in the literature that do not fit cleanly in the ACE framework. These roles include leveraging external resources (Cwetna, 2016; Rice et al., 2019), communicating with the teacher or school (Borup et al., 2019), analyzing student needs (Downes, 2013; Hasler Waters, 2012), self-teaching content (Curtis & Werth, 2015; Cwetna, 2016), aiding student development (e.g., helping students develop study skills or integrity; Borup & Kennedy, 2017; Hasler Waters, 2012), and advocating on behalf of the student (Franklin et al., 2015; Rice et al., 2019). These roles are important aspects of what parents do within the personal community of support, but the ACE framework does not currently account for them.

While the abovementioned studies provide a view of parental roles in various capacities and environments, additional case studies in varied contexts are needed to develop the transferability of the ACE framework. Just as important as the situations in which the ACE framework explains parental roles are those it cannot explain, as these negative cases may reveal additional insights. Finally, a variety of sources is necessary to understand these roles, including self-reported data from parents of online students.

Methods

In this study, we sought to further understand the role of parents in the personal support community as well as the interconnections between parental support, students' abilities to independently engage, and the support of course communities. In this section, we will describe the school setting and our method for recruiting participants. Then we will describe our methods for data collection and analysis, as well as possible limitations and ethical considerations in our research design.

Participants

Participants in this study were parents of students enrolled full-time in a public online secondary school in the Intermountain West region of the United States. We administered a recruitment survey via the school's regular parent e-mail and selected participants from those who responded based primarily on students' grade levels and parents' self-reported involvement levels. Within these strata, we considered other demographic information to recruit diverse experiences and voices.

Sampling limitations include limited transferability of parents' experiences since we recruited from a single school. Self-selection bias was possible, as parents willing to complete a recruitment survey and commit to an interview are likely more engaged in their child's education. We did not collect demographic information such as sex and socioeconomic characteristics, so it is unclear if interviewed parents represented a distribution across these and other demographics.

Setting

The fully online school served students in grades 7 to 12. Each grade level housed 200 to 300 students, all from within the state. The school website contained an information page encouraging parents to participate in their child's education but reassuring them that involvement was optional due to low teacher–student ratios. The website also advertised an optional parent–teacher social media connection and regular parent-focused meetings. While the school's characteristics and approach to parent–school partnerships may limit transferability for this study's results, it provided an environment in which parents were neither required nor pressured to participate.

Data Collection

We sampled and interviewed 14 parents. The purpose of the 30–45-minute, semi-structured interviews was to reveal parents' roles and involvement in their students' online education. Initial questions inquired about parents' typical roles, parents' levels of involvement, and how parental roles interacted with other elements of students' education. However, the semi-structured format allowed for the exploration of themes within parents' responses.

Data Analysis

We analyzed the interview data in two phases. The first phase followed open coding based on Creswell and Poth’s (2018) approach to grounded theory. Open coding was the most appropriate coding approach for this study due to its exploratory and case study nature (Creswell & Poth, 2018). Three researchers formed the data analysis team. We each read one to two interviews, looking for roles that parents described having in their student’s online education. We then discussed the codes we found before analyzing two to four more interviews each. At the next meeting, we combined codes into common categories (axial codes) for use in analyzing the remaining interviews.

Next, the three researchers met again to discuss the axial codes. While this first set of axial codes was influenced by prior research completed regarding the ACE framework, another underlying coding structure that ran across these axial codes was noticed. While they were not true “selective” codes as defined by Creswell and Poth (2018), these categories acted as another axis by which the codes could be arranged in a matrix (Figure 3). The initial axial codes related to how parents were supporting their students (affectively, behaviorally, or cognitively), but the secondary axial codes reflected patterns in how parents delivered this support, whether directly to the students or by influencing one of the other communities of support.

Figure 3

Matrix Depicting Intersections Between Initial and Secondary Codes

		Initial Axial Codes		
		Affective Roles	Behavioral Roles	Cognitive Roles
Secondary Axial Codes	Supporting Students Directly			
	Increasing the Parent’s Ability			
	Cultivating Student Capability			
	Pursuing Course Community Support			

Intrigued by this second set of codes, we read through the interviews, looking specifically for examples that fit within each box of the matrix. Codes were indexed based on interview number, a subjective rating on the example’s strength, and a rough description or quote indicative of the example. The primary author then organized the strongest and most prevalent examples into a summary of results that was confirmed with the research team and the original interview participants.

Trustworthiness

In qualitative research, the researchers are considered the “primary instruments” (Merriam, 1992, p. 20); as such, proving the trustworthiness of the data analysis is important. In this study, the researchers were a mix of parents, nonparents, and grandparents, and were biased to some extent in that they believed the role of the parent was important in children’s education. While only one of the researchers has had children enrolled in full-time online education, each has studied student support, student engagement, and online education. As blended and online modalities of education become more prevalent, we believe the role of parents will become more important and that the gap between students with home support and those without will become increasingly apparent.

We sought to strengthen the trustworthiness of our findings through member checks on themes and findings, a diverse selection of authors for this research, and thick description in the form of extensive quotations within the results section. Five parents (36%) responded to member checks; each agreed with our findings. Some provided additional comments, but on all accounts, these addressed topics outside the scope of this paper. The trustworthiness of our results was further strengthened by stratifying research participants and considering each individual’s responses as a form of source triangulation to ensure the findings were not isolated occurrences.

Limitations

Limitations for this study include the usual transferability concerns of convenience sampling. However, the participants within the school were purposively chosen to collect diverse experiences. Further limitations include nonresponse bias created by lack of survey responses and availability for interviews. Observational and additional case study research may be required to include experiences of parents who are less likely to participate in a study such as this one.

Findings and Discussion

As foreshadowed by Figure 3, this study provided additional evidence for the ACE framework’s personal community of support, including case studies for parental affective, behavioral, and cognitive support mechanisms. However, the data also revealed a phenomenon new to the ACE framework: outside of the ACE roles, parents support students indirectly by influencing the support the student, parents, and course community can each provide. The results first present the direct support offered by parents, then the indirect support they provided. Each section is subdivided by how parents’ actions benefited student engagement.

Directly Supporting the Student

Parents in this study performed many roles similar to those found in previous research and corresponding to roles of the personal community of support as defined in the ACE framework (Borup et al., 2020; see Figure 2).

Affective Support

In this study, the most represented affective roles parents played were in increasing student interest and motivation and creating an emotionally secure environment. Motivating students when their internal motivation failed is an echo of findings from previous research (Hasler Waters, 2012; Oviatt et al., 2018), but parents also emphasized encouraging students to pursue topics the students found engaging. Parents talked about being a "cheerleader" and "being present" so their children could feel like home was a healthy environment where "school is just a positive thing." Previous research has mentioned parents needing to love and nurture school-aged children (Borup et al., 2019; Borup & Kennedy, 2017; Borup et al., 2015), but more research could be done on how parents create emotionally healthy home environments when children participate in online school. Research in higher education suggests emotional support may have a greater impact on student outcomes than financial support (Roksa & Kinsley, 2019), underscoring the need for researchers and practitioners to understand the impact and practice of providing emotional support in secondary education.

Behavioral Support

Results of this study emphasize three ways parents behaviorally support their students: organizing, monitoring, and managing—role tasks found in previous research. However, this study revealed important new nuances.

For example, while many researchers have noted that parents help their online students with organization (Borup, 2016; Downes, 2013), parents in this study emphasized two subcategories: organizing time—such as scheduling and setting routines—and organizing space, by providing materials necessary for participation.

While previous research has described both monitoring (Borup et al., 2015; Curtis & Werth, 2015; Cwetna, 2016; Oviatt et al., 2018) and managing roles (Borup et al., 2017; Hasler Waters, 2012), this study illuminated an important differentiation. Monitoring was an almost universal role task; even the least involved parents expressed thoughts such as this: "My involvement was zero except for checking his grades." Monitoring included checking on students, occasionally interfering to remove distractions, and tracking student progression. However, parents noted that this "depend[ed] on how [their children were] doing in school. If [they were] not doing well, it is harder, because we do have to be a little bit more strict with how we're approaching [them]." This inclination sometimes compelled parents more comfortable in a monitoring role to assimilate a managing role, even metaphorically "holding [the student's] hand" as they worked. Other managing roles included waking students, keeping them on a schedule, and "making sure that they get food throughout the day, meals, and making sure they also get outside." While former research has noted that monitoring activities "varie[s] greatly across parents" (Borup et al., 2017, p. 7) and flexes based on students' self-regulation (Borup et al., 2015), this study adds that this spectrum involves more than the time parents dedicate to their student's academics; it also includes ownership as management of students' schooling shifts from student to parental control.

Cognitive Support

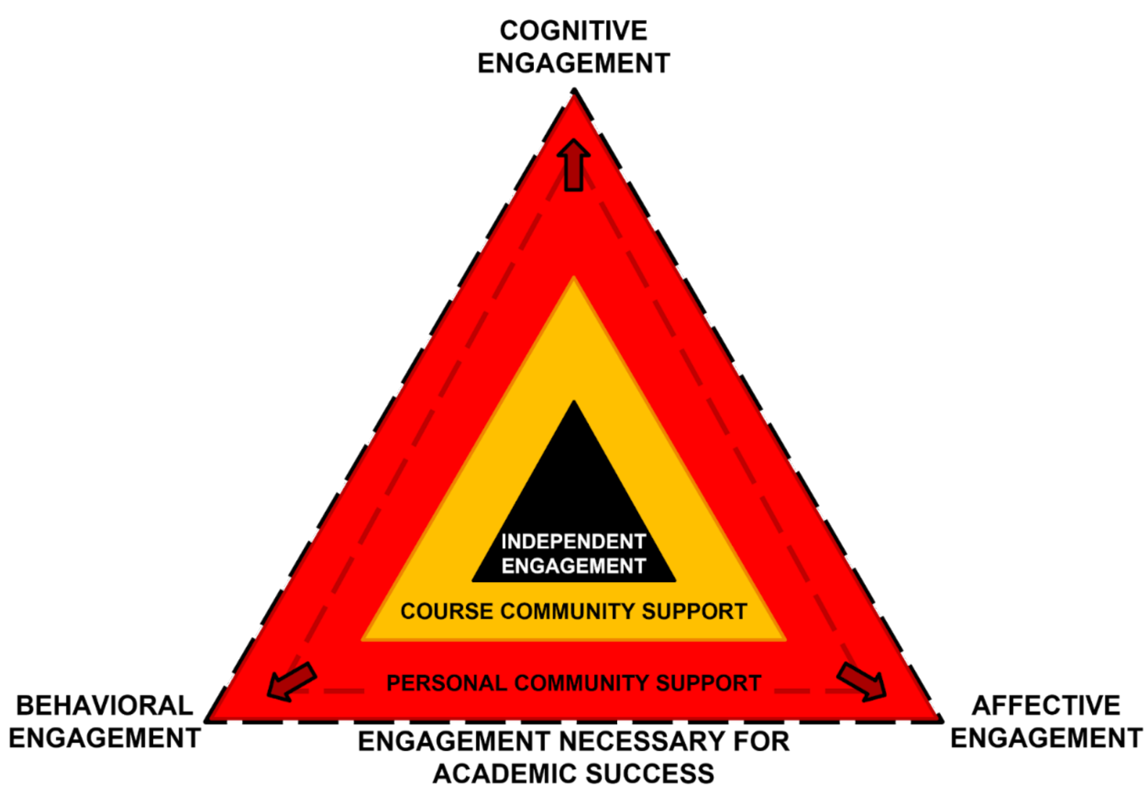
Similar to that reported in previous research, most cognitive support roles parents reported involved tutoring (Borup, 2016; Borup & Kennedy, 2017; Keaton & Gilbert, 2020). Parents described this role on a wide spectrum, from editing papers to answering questions to “basically, be[coming] a teacher for seven or whatever hours of the day, because [my child] needed me to be.” Some parents had the academic and experiential background for these roles (e.g., “My degree is in accounting and finance [and] I have a strong science background, too”), but others needed help from external sources (e.g., “For the most part we’ve been able to Google stuff and find videos to help [our students] ... If you [want to] figure something out, you can find it on the Internet”). The varied sources parents report using for their tutoring information give merit to Stevens and Borup’s (2015) concern that parents should be careful in offering cognitive support, as their lack of subject matter expertise may disadvantage students (see also Borup, 2016).

Increasing Parents’ Ability

Parents realized they could not always support their children in their schooling as much as they desired, or enough to guide students to academic success. The second major finding of this study was that parental support included more than directly helping students with their academic needs, as presented in the ACE framework. One indirect category of support is when parents increase their capacity to further support students. Instead of acting as the personal community, parents seek to increase the support the personal community can provide in the future (see Figure 4). Like the direct support roles parents play, indirect roles in this category can be grouped into affective, behavioral, and cognitive roles.

Figure 4

Parents Increasing Their Own Abilities: Effect on the Personal Community of Support



Note. To help students reach the engagement necessary for academic success, parents increased the support the personal community could provide. Adapted from “Academic Communities of Engagement: An Expansive Lens for Examining Support Structures in Blended and Online Learning,” by J. Borup, C. R. Graham, R. E. West, L. Archambault, & K. J. Spring, 2020, *Educational Technology Research and Development*, *68*(2), p. 810 (https://doi.org/10.1007/s11423-020-09744-x). Copyright 2020 by Springer Nature.

Indirect Affective Roles

Parents reported many indirect affective role tasks, but the most prevalent were increasing parental ability to motivate and changing parental perspectives of success. For example, one parent said she had not yet mastered motivating her son, but she was learning by “just do[ing] things by trial and error.” Another mom echoed these sentiments, saying, “I’m learning how to motivate my kids, what works best.” She then explained she had learned to let her son work independently, but her daughter needed someone present to motivate her. Parents often initially struggled to motivate their children because “some things that worked in the past, maybe, on [another] day doesn’t really work because [the student is] just not in the mood.” It took time to learn effective techniques for offering affective support.

Additionally, parents initially found offering emotional support difficult because their expectations clashed with their children’s desires or capabilities. Previous research has mentioned the parental role of setting expectations (Borup et al., 2019; Borup et al., 2015; Hasler Waters & Leong, 2014), but parents also have the prerequisite task of learning what expectations are appropriate. A parent in a study by Curtis and Werth (2015) also describes this role, calling it a “painful process” (p. 182). In our study, a mother explained,

> I’ve had to learn that not everyone was like me … Her [the student’s] talents and interests are so different from mine … and so just learning to appreciate that her school experience is going to be different from mine and that’s okay and her grades are going to be different from mine and that’s okay.

Working to understand and change her perspective helped this mother situate herself to better motivate and encourage her daughter.

Indirect Behavioral Roles

The most prevalent way parents built their capacity to offer behavioral support was rearranging their schedules to be present while their child worked. Research has shown parents view physical presence as a supportive role (Curtis & Werth, 2015; Hasler Waters & Leong, 2014). Some parents found it sufficient, and had the flexibility, to change the hours they worked professionally. For example, one parent said, “[I] ended up starting my day super early so that I could get a big chunk of work done before he was up and going, and then I would be available” (for another example, see Hasler Waters, 2012). Other parents quit professional work to increase their availability. One mom was working and attending evening classes at a local college when she moved her children to online school. She recounted, “When we made the decision to go online, that made the decision for me to stay at home.” She left her job to be present with her students during the day and continue her own schooling at night.

Indirect Cognitive Roles

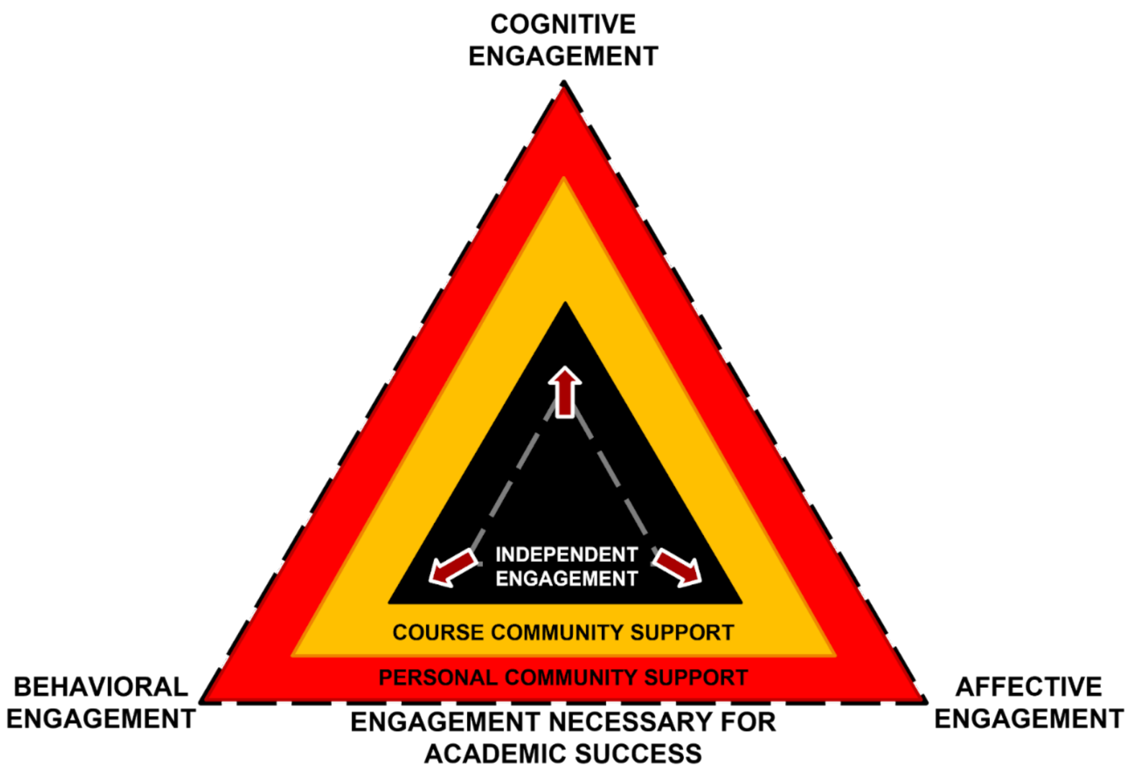
Parents' indirect cognitive engagement support roles frequently centered around a need for direct cognitive roles. Two frequent scenarios were (a) students requiring tutoring, for which parents needed to refresh their memory on a topic or teach themselves with the course resources, and (b) students soliciting help with an assignment, for which parents needed to learn to navigate software, such as a learning management system. One parent commented that online school facilitates parents' ability to learn content for tutoring their children, because "if I need to help them … I can watch and do the materials. As opposed to a brick-and-mortar school where … they bring homework and I was like, 'sorry can't help you, you don't have a textbook.'" Other studies have also noted that parents watch students' class sessions before tutoring their students (Curtis & Werth, 2015; Cwetna, 2016).

Cultivating Student Capability

In addition to parents increasing their ability to support their students, they also indirectly supported students by increasing students' capability to help themselves (see Figure 5). By teaching students to be more independent in the future, parents often found their role in students' personal community of support could decrease.

Figure 5

Parents Cultivating Student Capability: Effect on Independent Engagement



Note. To help students reach the engagement necessary for academic success, parents increased students' ability to independently engage. Adapted from "Academic Communities of Engagement: An Expansive Lens for Examining

Support Structures in Blended and Online Learning," by J. Borup, C. R. Graham, R. E. West, L. Archambault, & K. J. Spring, 2020, *Educational Technology Research and Development*, *68*(2), p. 810 (https://doi.org/10.1007/s11423-020-09744-x). Copyright 2020 by Springer Nature.

Organizational Independence: Behavioral

As a counterpart to monitoring and managing, some parents taught students to create schedules and manage assignment expectations independently. This usually involved more work upfront—parents walked students through processes, gave them organizational tools, and consistently set expectations that they needed to monitor themselves. While this support did not directly impact students' immediate success in specific classes, it gradually allowed parents to reduce direct behavioral roles without compromising academic success. Interestingly, parents did not always attribute this act to supporting academic success; instead, they were helping students "be prepared to be out on their own." Previous research supports this finding as parents report feeling a duty to teach students "how to learn" (Hasler Waters, 2012; see also Borup et al., 2015; Hasler Waters et al., 2018).

Emotional Resilience and Perspective: Affective

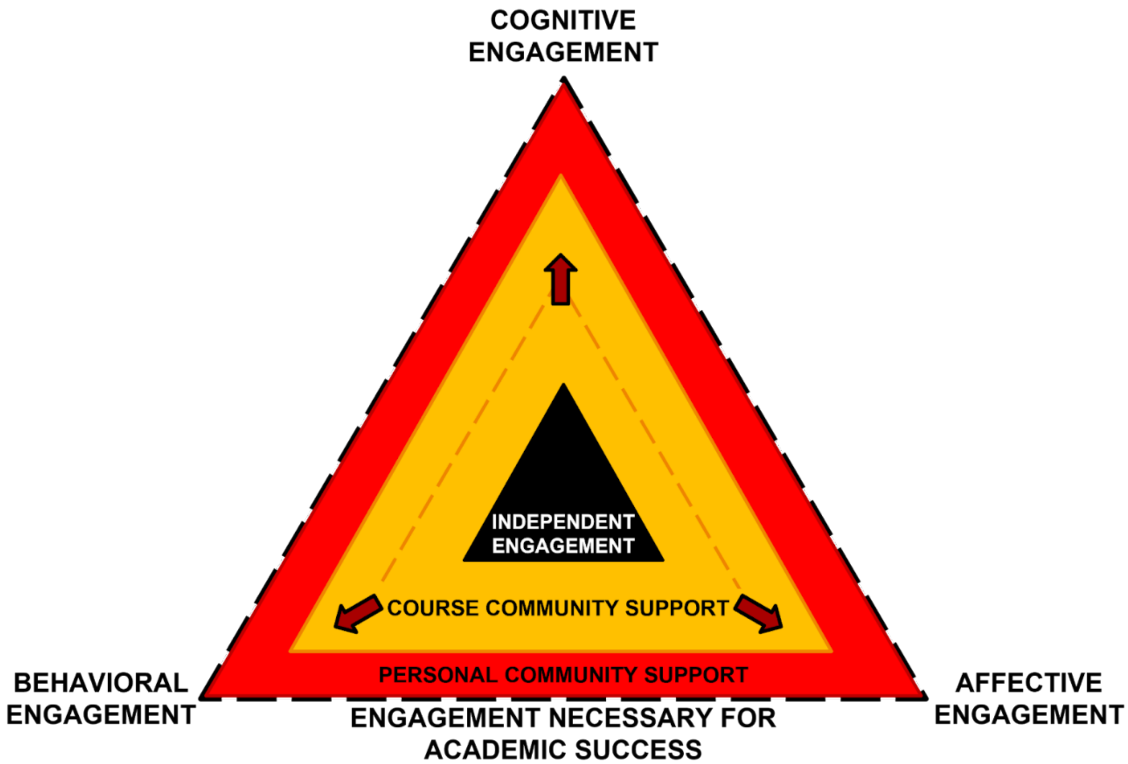
Parents increased the long-term affective independent engagement of their children by helping them become emotionally resilient. One parent repeatedly taught the mantra "I just haven't learned this yet" to help her son overcome his frequent frustration in education and sports. Another parent described helping her daughter develop the perspective that effort in school affects opportunities to attend desired college programs. One mother allowed her high-achieving child to gain this perspective by experience; she stated, "You have to let kids fail [struggle] so they can learn." This mother deliberately watched her daughter's progress from afar, allowing her to work through obstacles and intervening only occasionally. Unlike establishing high expectations (Borup et al., 2019; Borup et al., 2015; Hasler Waters & Leong, 2014), giving perspective increases intrinsic motivation and students' future ability to independently engage.

Pursuing Course Community Support

A final indirect role clarified by this research was the support parents offered students by engaging with and helping to expand the influence of the course community (see Figure 6).

Figure 6

Parents Pursuing Course Community Support: Effect on Course Community of Support



Note. To help students reach the engagement necessary for academic success, parents increased the support the course community was providing. Adapted from "Academic Communities of Engagement: An Expansive Lens for Examining Support Structures in Blended and Online Learning," by J. Borup, C. R. Graham, R. E. West, L. Archambault, & K. J. Spring, 2020, *Educational Technology Research and Development*, *68*(2), p. 810 (https://doi.org/10.1007/s11423-020-09744-x). Copyright 2020 by Springer Nature.

Selecting the Course Community

This study is not unique in noting that participants actively chose to switch their children from traditional to online school environments (Borup & Stevens, 2016; Curtis & Werth, 2015). Usual reasons for this choice confirmed those noted in previous research (Borup & Stevens, 2016): a perceived deficit in the local traditional school, a family need, or, in the case of previously homeschooling parents, a perceived deficit in their own support. However, previous research has not acknowledged that entirely changing the course community of support is a primary task parents take on in helping their children receive the support necessary for academic success. Many parents spent extensive time researching school environments, experimenting with school systems, and asking for references from friends and family in trying to fulfill this role.

Connecting Students to School Resources

Parents also played a role in connecting students to resources and support offered by the school. Especially because students were physically distant from their teachers, parents often redirected questions or concerns from the student, asking if they had contacted the teacher for support or reminding them to e-mail the teacher during office hours. Parents reported the importance of reading school communications so that both they and their children could be informed of school programs and other available resources. Cwetna (2016) notes that parents “make sure their child gets help, whether it be from the parent, teacher, or another resource” (p. 94). When schools make resources easy for parents and students to find, parents can support student engagement by helping students access these resources.

Advocating

In addition to ensuring students’ awareness of school resources, parents also occasionally advocated with the school to increase awareness of students’ needs. This was especially true for parents of students with disabilities and parents whose children struggled with specific subjects. Researchers studying these populations often identify advocate as an important role (Franklin et al., 2015; Rice et al., 2019). However, this study adds that advocacy is also important when students are enrolled in online and traditional schools simultaneously, as some physical schools were unaccustomed to the policies involved in dual enrollment, necessitating parental involvement to ensure students were not penalized for their online school enrollment.

Conclusion

This study has provided additional evidence supporting the ACE framework and identified patterns in past literature’s roles that did not neatly fit into the ACE framework, such as advocating and aiding student personal development. With this expanded view of the functions of the personal community of support comes important implications for research and practice.

Implications for Research

The ideological background for the ACE framework is founded in part on Bronfenbrenner’s (1977) ecological systems theory—that is, the idea that social interactions cannot be studied as individual pieces but must instead be studied within the systems in which they occur. Applying this ideology to the present study, student engagement cannot only be studied from the sole perspective of students, teachers, or parents but rather in terms of the interactions among the three.

The ACE framework currently depicts interactions, but only those between the individual community actors and the student or, more precisely, their interactions with the student’s engagement (referred to as an egocentric approach in social network analysis; see Hanneman & Riddle, 2005). This study suggests that the ACE framework could be used more broadly to analyze the interactions between the various actors and how these interactions enhance or deter online student engagement. It further suggests that parental roles move beyond direct interactions with a student’s engagement in a specific course. Additional research could study whether the student, the course community, or other actors within the personal community also have indirect roles in supporting student engagement. Research could also triangulate these self-reported results with evidence from teachers and students and analyze the respective effects of indirect and direct roles on student engagement.

Another aspect of studying student engagement as a system is understanding that students are not the only actors that have context to consider. Parents, as the target of this research, also have individual backgrounds impacting the amount and type of support they provide. Parents make decisions and hold different roles based on these contexts. Additional research could study the motivations and contexts of parents to better understand parents' desires and obstacles in providing both direct and indirect support. In this study, parents interacted not just with teachers but with the school itself. This indicates the course community also brings the context of existing within a larger school community. Interactions between this community and the individual course communities, as well as the personal community, may also shed light on the support students can receive from various support actors.

Implications for ACE Community Members

While implications for the various community actors are vast and nuanced by context, practitioners, parents, and students can all benefit from research surrounding student engagement and academic success.

The importance of parents in the personal community of support is expanded when they become the supervising adult in their student's education, as made evident during the COVID-19 pandemic (Novianti & Garzia, 2020). This research revealed that while parents almost universally accepted and filled many roles, some stumbled upon roles they did not anticipate. For example, multiple parents were surprised when they realized they could move their students out of brick-and-mortar school. Parents also discovered that if they invested time into understanding students' needs, preparing themselves to support students and delegating responsibility to students, they had fewer direct supportive roles. Borup et al. (2013) found the amount of time parents were involved in supporting student schoolwork was not directly correlated with student academic success, which they attributed to parents becoming more involved after students fall short. Based on our findings, we agree that, in these situations, monitoring often changes to managing. However, this change involves not only an increase in parents' time but also in parental control of students' academic progress. This increase in control potentially decreases student ownership over their own work and may negatively affect students' long-term academic engagement.

While the parents in this study strove to improve their own abilities, it is important to remember that most parents of secondary students have never attended online school due to its recently becoming a mainstream option. Like families of first-generation college students that struggle in knowing how to offer support (Irlbeck et al., 2014), parents who never attended online school may need help understanding how to best support their children in online school. Additionally, while the increased availability of subject-specific content for parents enables them to perform direct cognitive support in ways more similar to those attributed to teachers (Borup et al., 2020), such increased confidence without formal instructional training may prove problematic if it leads to parents trying to replace the teacher as the content matter expert (Stevens & Borup, 2015).

Practitioners might benefit from knowing that, in this study, even in a school that emphasized student independence, almost all parents held an active role. While the course community supports students directly, practitioners can develop indirect support systems to help parents in their efforts to support students. Many parents noted the importance of open, regular communication with the school and teachers in helping them provide behavioral support; it may also be helpful to provide resources for parents giving affective and cognitive support as well. This can be as simple as making course materials available for parents in order to avoid parental reliance on YouTube and other external sources for tutoring support. Organizing parent help groups, in which parents can trade advice on effective strategies for helping online students, could also be helpful. Practitioners could lighten their supportive load in the same way parents do: by increasing student ability. For example, online schools could provide student training and templates for organization, making them available to parents who may also be helping students with self-development.

The importance of practitioner support may depend on the household. For example, parents in this study often increased the personal community’s indirect support by rearranging or reducing professional work schedules. However, some parents may lack the flexibility and financial means to use these strategies. Parents sometimes struggled to navigate school software, an even more difficult task for parents doing so in a second language. Parents with multiple children attuned to their students’ needs to prioritize their involvement with the most dependent child, but this strategy may leave other children unsupported. Practitioners should seek awareness of students’ and parents’ greater contexts so they can provide increased support, whether directly for the student or indirectly by mentoring parents about the demands of online school, the needs of their students, and the resources available for support.

In conclusion, the ACE framework is a valuable depiction of student engagement support structures, with many of the roles currently held by parents nicely fitting within its umbrella. However, by using the framework as a tool to analyze the networks and interactions between the communities of support, we have gained a more complete view of how student support plays out in real contexts. What we lose in parsimony, we gain in ability to use the framework to capture the experiences of those supporting student engagement and, therefore, to understand and influence student academic success.

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International **R**eview of **R**esearch in **O**pen and **D**istributed **L**earning
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Book Review: The Encyclopedia of Female Pioneers in Online Learning

Authors: Susan Bainbridge and Norine Wark (Routledge, 2022, 472 pages). ISBN: 978-1-032-23035-1 (hardcover), ISBN: 978-1-003-27532-9 (e-book). https://doi.org/10.4324/9781003275329

Reviewed by: Prof. Madhu Parhar, Indira Gandhi National Open University, India

Encyclopedias are good reference tools that provide concise information that may or may not be available in other information sources. One feature of encyclopedias is that they are comprehensive. An encyclopedia consists of a particular category of knowledge or covers all branches of knowledge. One example is the *Encyclopedia of Distance Learning* (Rogers et al., 2009), which covers concepts, trends, issues, and technologies in the field of distance learning with over 100 research articles. Another example is *The SAGE Encyclopedia of Online Education* (Danver, 2016), which has around 350 entries and provides theoretical dimensions of technological aspects of implementing online courses.

The Encyclopedia of Female Pioneers in Online Learning by Susan Bainbridge and Norine Wark is a specialized encyclopedia that provides detailed works, accomplishments, and challenges faced by 30 female pioneers who have contributed to online courses, populated the use of learning management systems in their respective organizations, and overcome barriers to achieve success. These women pioneers have redefined the ways online education is applied and learned from. Results show that these pathfinders are focused on and involved in technology innovations, as well as having different approaches than men in various fields.

The Encyclopedia of Female Pioneers in Online Learning is presented in two parts. Part One includes the chapter titled "Initial Thoughts," which provides the introduction and background to the book, explaining its aim, scope, and structure. According to the authors, "The primary aim of this book is to introduce female pioneers in online learning to researchers, historians, writers, students, and other stakeholders of DE [distance education] and online learning" (p. 4). It covers 30 interviews of women pioneers who tell their own stories and experiences in the field. This approach provides a personal perspective of the women leaders and honors their achievements.

The interviews cover the following 13 questions:

- What was your educational and experiential background before you became involved in online distance learning?
- In what year did you begin to look specifically into online distance learning (ODL)?

- What were the circumstances in your world that initiated this interest in ODL?
- Which female researchers or female colleagues piqued your interest in ODL?
- Who would you identify as the early female leaders/founders in the field of ODL?
- What are some of the goals that you strove to achieve in the field of ODL?
- What are some of your accomplishments in the field of ODL that you would like to share?
- What are some of the challenges that you faced in the field of ODL over the years?
- What was the state of DE when you first entered the field as opposed to ODL in 2019?
- What interesting memories would you like to share about the beginning of ODL?
- What were your specific ODL research interests, and have they changed/evolved over the years?
- Could you please describe the learning environment that you currently work in or have recently worked in?
- Can you suggest names of other female pioneers in distance education or ODL that you think we should include in the book? (p.451)

Each interview provides the academic profile of the female pioneer, a picture of the leader, awards received, a list of publications, and a transcript analysis summary. A link to the recorded interview along with a QR code is also included.

Part Two of the encyclopedia presents the analysis of the 30 interviews (Worlds Who's Who) and a chapter entitled "Final Thoughts." The first section of Part Two is presented in the form of a research report, which includes the research methodology, results, discussion, and conclusion from the 30 interviews. Based on the interviews with the female pioneers, a few salient findings are synthesized as follows:

1. Implementation of the new initiatives was the most popular response from pioneers.
2. Important accomplishments reported were:
    - Introduction of new programmes and/or courses
    - Networking
    - New policies
    - New funding structures
    - Setting up new centres and institutions

- Literary contributions
- Distance education advocacy initiatives

3. Another accomplishment reported was the research conducted in open and distance learning. The research interest was in the following areas:
    - Instructional design
    - Distance education learning environments
    - Open distance learning theory
    - Quality assurance
    - Institutional development
4. On benefits of distance education, the pioneers reported the following benefits:
    - Social justice
    - Information and communication technologies
    - Continuing education
    - Community development and flexibility
    - Job opportunities
    - Asynchronous learning

While analyzing the interview transcripts, the authors also reflect on themes emerging from the data and their interpretation. While the qualitative nature of the study and its execution are comprehensive and systematic, the authors also highlight the limitations of the study, which come from heavy dependence on English-speaking pioneers and resources available to the researchers. The authors mention that they used "a snowball strategy … in this study to gather information as other search strategies yield sparse results" (p. 448). The authors suggest that other researchers could employ this strategy to collect meaningful information.

The last chapter of the book covers pertinent and other interesting findings derived from the data. The authors point out the key implications of the study for policymakers, administrators, and others in the business of ODL and online learning. The profound finding is that women have not been adequately represented in the literature. Data provided a partial explanation of the reasons for underrepresentation. However, conclusions elaborate on team accomplishments by women. One of the possible reasons for underrepresentation alluded to in the discussion, though not critically examined, is less self-citation in research published by women scholars. Another finding is that changing people's mindsets can be daunting, especially in the context of technology adoption in the future. Based on the interviews, the authors also allude to the possibility of the "Matilda effect" (i.e., more work by women leads to more profit and recognition of men) in distance and online learning. While more work may be needed in these areas, the book highlights some areas of future research. Women pioneers used different terms and definitions of DE, and the authors accepted the definitions.

Six questions arose from this study for future research:

1. Can the hypothesis of the Matilda effect be validated?
2. Is a patriarchal approach by female pioneers recognized more in the academic community?
3. Are female pioneers who emulated self-confidence and pro-social attributes more likely to achieve high status?
4. Are male pioneers more likely than female pioneers in the field to cite themselves in publications?
5. Why can only a few female pioneers who held leadership positions in the field be identified?
6. Would the same study conducted with male pioneers yield the similar results? (p. 488)

The objective of this encyclopedia is to capture the voices and contributions of female pioneers in online learning. It is a specialized encyclopedia that provides detailed and technical information on experiences of pioneers of online learning. The authors interviewed the female pioneers of DE about their innovations in online education, culminating in a wealth of information, experience, and practical strategies for all practitioners and leaders.

The encyclopedia is unique in many respects. Challenging the Matilda effect in the usually known men's world of ODL, the book documents significant contributions by 30 pioneering women scholars who made the ODL and online learning world richer and better. The choice of methodology is another novel feature. While the interviews took the form of case studies, the methodology deviated from the known critical, natural, and appreciative inquiry models. By coding information, the authors have tried to restrict the influence of their personal perceptions and worldviews in assessing the contributions of the selected women pioneers.

In short, this volume will not only interest researchers, students, and teachers, but it will also provide policymakers and EdTech companies leading in online education a comprehensive view of online learning as perceived by 30 female scholars from six continents, and it will catch everyone's attention. The world will wait for another volume containing information about more pioneers that will answer the research questions raised by the authors in this volume.

The Encyclopedia of Female Pioneers in Online Learning should find a place in all reputed libraries for the novelty of the subject and methodology and its rich content. Readers will find the individual stories as inspiration to change the world of distance and online learning for the better.

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International **R**eview of **R**esearch in **O**pen and **D**istributed **L**earning
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Book Review: Powering a Learning Society During an Age of Disruption

Editors: Sungsup Ra, Shanti Jagannathan, and Rupert Maclean (Springer, 2021, xvii + 321 pages). ISBN: 978-981-16-0985-5 (paperback), ISBN: 978-981-16-0983-1 (e-book). https://doi.org/10.1007/978-981-16-0983-1

Reviewed by: Pradeep Kumar Misra, Professor & Director, Centre for Policy Research in Higher Education, National Institute of Educational Planning and Administration, New Delhi, India

Learning, one of the most discussed terms across different sections of society in the 21st century, is an integral part of our lives. Humans' association with learning keeps evolving and changing. The starting point of this association was to make provisions for the learning of young individuals, which shifted later to the learning of all, including adults. We have now reached a stage where learning is discussed in terms of learning societies. Governments, international organizations, and policy documents across the globe have started viewing and analysing every aspect of society through the learning lens. Realizing this turnaround, this volume, *Powering a Learning Society During an Age of Disruption*, edited by Sungsup Ra, Shanti Jagannathan, and Rupert Maclean, discusses the concept, modalities, and realities of learning societies from a 360-degree perspective. This open access book, containing 21 chapters and covering 321 pages, presents readers with various shades and patterns of learning societies. Importantly, the book also assesses the impact of COVID-19, one of the most devastating pandemics of our times, on learning societies and offers solutions for the future.

The editors of this book define a *learning society* as "a continuum that takes place well beyond the early stages of school, secondary, and postsecondary education, and in formal and informal settings outside institutions" (p. 3). Accordingly, the editors have presented the stories, experiences, and challenges of and about learning societies under six sections: Introduction (two chapters), Learnability and the Learning Crisis (four chapters), Future-Proofing Postbasic Education (four chapters), Communities as Learning Platforms (four chapters), Learning Societies and Industry 4.0 (four chapters), and Technology Solutions to Build a Learning Society (three chapters). The authors of different chapters include policymakers, academics, industry experts, and practitioners from nongovernmental organizations, professional organizations, and international development organizations. These authors differ in their qualifications, experiences, and professions but unite on one front; that is, they all critically discuss the roles and benefits of encouraging and actively promoting learning societies during a time of all-pervasive change.

As a whole, the 21 chapters of this book present thought-provoking and engaging stories of learning societies. The book (a) discusses the roles of schooling, higher education, teaching, training, and assessments on learning; (b) talks about formal, non-formal, and informal sectors offering learning opportunities; (c) details different initiatives of governments, nongovernmental organizations, enterprises, and business sectors to promote learning; and (d) tells stories of learning from India, South Korea, the European Union (EU), and Singapore. There are discussions on the benefits of learning, improving learning, quality assurances in learning, learning assessments, and learning crises. Further, the book tackles issues such as learning in professional and technical sectors, workplace learning, technologies for learning, the learning crisis, the role of teachers and communities in promoting learning, lifelong learning, and the need to and benefits of nurturing learning societies. The message from this book is clear: any nation, community, or sector cannot remain isolated from discussions on learning societies, as learning has far-reaching influence and impacts on philosophical, social, political, and economic aspects of individual and collective lives.

The arguments and descriptions presented in most chapters include relevant and recent references, data, figures, and prevalent practices. While reading the chapters, one comes across certain remarks and observations that are helpful in reflecting, fresh thinking, and remaining both cautious and positive while supporting or propagating new avenues for learning. The chapters included in this book show directions and suggest ways to build learning societies out of cities, communities, and regions. For example, in Chapter 8, the authors argue that “a learning society is not only about having isolated educated and skilled citizens. It takes multiple and complex interactions to grow an ecosystem that connects, supports, and makes the best out of individuals’ learning” (p. 116). Another author adds that “a learning society can only be possible when everyone can learn throughout their lifetime to change and adapt as the context requires, and empower others to learn as well” (p. 186). In addition, perspective is also given. For example, “most world leaders and officials in ministries of education are extremely well educated. … However, the education that they have received, to a high degree, is an academic curriculum, and therefore they have less experience in relation to vocational subjects” (p. 141).

Powering a Learning Society During an Age of Disruption is also full of visions and practices from which any individual, institution, or nation can learn. As an example, Chapter 14 states that the half-life of skills is only about 5 years means those embarking on a 30-year career will have to update and refresh their skills at least six times throughout their working life (p. 198). Chapter 7 offers a lesson for universities across the globe. The discussion about the National University of Singapore’s policy, where enrolment is valid for 20 years from the point of undergraduate admission, making alumni automatically eligible for continuing education courses at any time in 20-year period, emerges as a must-adapt policy for every university. Similarly, based on the discussions in chapter 8, nations outside of Europe can think about reframing their education policies in light of the European Commission’s “twin transitions” vision, which advocates for a green EU and making the best use of digital and technological advancement.

A few chapters focus more on advertising what they are doing rather than detailing how their practices can be emulated and adapted in a broader context. Then some chapters forget that this book is about learning societies, and they have to justify or align their discussions accordingly. Barring these few deviations, the chapters as a whole assure us that even the worst of crises (e.g., COVID-19) comes with opportunities and “opens the door for us to challenge and reframe education systems to become more inclusive and equitable” (p. 84). The book also makes clear that the fate of future learning societies will depend on governments and private sectors but also, most importantly, on us (individuals), by rightly stating, “nothing about us, without us” (p. 81)

With hearty congratulations to the worthy editors, I recommend *Powering a Learning Society During an Age of Disruption* as a must-read for all those who believe that “learning is for life” or go further to claim that “learning *is* life.”

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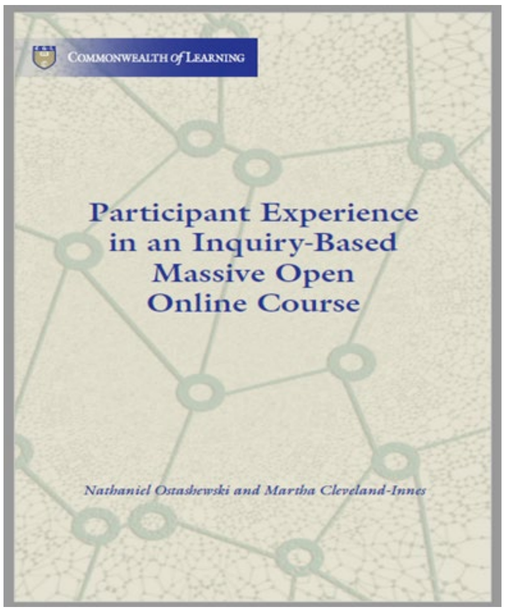
Book Review: Participant Experience in an Inquiry-Based Massive Open Online Course



Authors: Nathaniel Ostashewski and Martha Cleveland-Innes (Commonwealth of Learning, 2022, viii + 111 pages). ISBN: 978-1-7772648-9-5. https://doi.org/10.56059/11599/4132

Reviewed by: Niradhar Dey, Indira Gandhi National Open University, New Delhi, India

Participant Experience in an Inquiry-Based Massive Open Online Course, published by the Commonwealth of Learning, is a unique and original work that provides valuable insights into the design, development, and delivery of massive open online courses (MOOCs). The book provides a comprehensive overview of 10 iterations of the Introduction to Technology-Enabled Learning MOOC (TELMOOC) offered between 2017 and 2021 by the Commonwealth of Learning and Athabasca University. Based on data collected from participants during the MOOC offering, this book provides substantial insights about designing and delivering successful MOOCs for professional development. The book is designed in eight chapters along with a reference section.

Brief Summary of the Chapters

Chapter 1 introduced TELMOOC and explains the specific model of MOOC used, which the authors call interactive MOOC or iMOOC, and its instructional design, a review of the literature, the methodology used for conducting the study, and analyses of participants' responses. This chapter explains the results of one of the important research questions: How did participants respond to the design and delivery of TELMOOC? Overall, it is noted, 87% of respondents were satisfied.

Chapter 2 presents a brief historical development of the concept of the MOOC. Interestingly, this chapter also provides readers with space to imagine the future of MOOCs in regard to content, language, learners' diversity, and teaching–learning design that would result in quality delivery. This chapter also further explains outcomes of MOOCs for ensuring lifelong learning by establishing a healthy educational ecosystem. The contribution of MOOCs in the Global South and how TELMOOC fits into strengthening teachers' capacities to integrate technology-enabled learning are also discussed.

Chapter 3 compares general MOOC participation with the TELMOOC participants' data. This chapter clearly explains the difference in experiences of general MOOC delivery and TELMOOC delivery in view of demographics, learning patterns, provision of supports to globally diversify participants, group work, and collaboration.

Chapter 4 emphasizes the ways learners engage in the TELMOOC. In any course, learners' engagement and learning discourses are key to the course's success. In view of this, the present chapter critically analyses distance education modes of interaction such as learner–content, learner–learner, and learner–teacher used in the TELMOOC. Learner–content interaction is highlighted by ensuring learners' engagement in course-based continuous activities and feedback; learner–teacher interaction is shown through the inspirational and facilitating role of the teachers; and learner–learner interaction is shown to be supported by peer and group discussions on many issues relating to course content. The interactive and participatory design of TELMOOC tells the success story of learners' engagement in active learning processes.

Chapter 5 emphasizes data relating to MOOC completion and their critical analyses based on research findings on completion rates of MOOCs over the years. The chapter discussion leads to one of the important research questions of TELMOOC participants' survey: Are there other metrics that can better articulate the completion of MOOC objectives? Research literature on MOOCs shows that MOOC completion rates are lower than those of conventional classroom learning courses. While it is understood that learners in open learning join courses and programmes with different intentions, the low completion rates are a concern among teachers and policymakers. The authors analyse the completion data for the 10 TELMOOCs offered and find that, on average, it is 20.32%. However, they go further to present an alternative model of analysis, completion and recommend that completion rate may be analysed on the basis of "fully active learners" (those who complete the first week of the course). Accordingly, the average completion rate in TELMOOC is 70.3%. This in an incredible piece of data supporting the effectiveness of the MOOC.

Chapter 6 of the book discusses a framework of a MOOC's success. Discussion centres on the research question: What instructional approaches and strategies result in increased levels of TELMOOC learner certification? The authors present the PAGE MOOC success framework (Pedagogy, Attributes of the learners, Goals, and Engagement) as four pillars of successful MOOC design. The first pillar, Pedagogy, emphasizes integration of a variety of activities and systematic content delivery participatory–interactive mechanism adopted in different types of MOOCs [Extended Massive Open Online Courses (xMOOC), Institutional Massive Open Online Courses (iMOOC), and Connective Massive Open Online Courses (cMOOC)]. The second pillar, Attributes of the learners, includes motivation and grit, as well as reasons for taking a course. The third pillar, Goals, emphasizes the goals of the MOOC and the fourth pillar, Engagement, encompasses learners' engagement while taking a MOOC in terms of content, activities, assessment, and so on.

Chapter 7 addresses the professional development aspect of the TELMOOC design. Discussions exemplify the course components that directly empowered the teachers' professional development at different levels of their engagement in schools, colleges, and universities. Teachers' professional development components such as opportunities for the teachers to rethink their own practices and construct new classroom roles, as well as expectations about student outcomes and teaching in innovative ways, are covered in the TELMOOC. The TELMOOC professional development design also follows a networked teacher professional development approach that includes relevant teacher professional practice, easy access and support, pedagogically sound activities, learner support at varied experience levels, opportunities for networked learning skill development, sharing and discourse among learners, and learning connections within the broader networked community. Design and development of TELMOOC primarily addressed the professional development needs of teachers that also support creating a professional community in which students can learn innovatively by using technology with new methods and techniques.

Chapter 8 provides a brief summary and recommendations based on research done in TELMOOC. While analysing completion rates, the recommendations of TELMOOC highlight three categories of learners to consider: registrants, active learners, and fully active learners. For MOOCs with an online or a blended course design, TELMOOC recommends the iMOOC model, which focuses on peer interactions, pacing instruction weekly to sustain the learner community, providing flexible assessment strategies, and practising the PAGE success framework for MOOCs.

Significance of the Book

The research conducted on the participants of 10 successful iterations of TELMOOC emphasizes its effectiveness and popularity among global learners. TELMOOC provides different experiences to learners; they can acquire a quality knowledge base by actively engaging with content, instructors, peers and groups, learning environments, course-based activities, and assessments. Provision of rigorous learner support and addressing of teachers' professional development have been integral parts of TELMOOC.

This book fills the gap on research about MOOCs using a longitudinal approach and data from different iterations of one MOOC. It provides guidelines and research-based support to faculty members who want to develop and successfully deliver a quality MOOC. This book is equally helpful for researchers, as it provides an authentic review of conducting research on different aspects of online and blended programme development, as well as designing and conducting an online programme evaluation study.

Overall Assessment

Participant Experience in an Inquiry-Based Massive Open Online Course is a significant contribution to research on MOOCs and online learning. Currently, teachers and educators in all levels of education across the globe are engaged with conceptualizing, designing, and delivering online and blended courses in the form of MOOCs. This book will be a ready reference example for understanding issues around designing and delivering any professional development MOOC. This short book is a must read for researchers, academics, and administrators, as well as policymakers in the field of education, in both developed and developing countries.

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What Are the Indicators of Student Engagement in Learning Management Systems? A Systematized Review of the Literature

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Abstract

Student engagement has an important role in academic achievement in all learning contexts, including e-learning environments. The extent of monitoring and promoting student engagement in e-learning affects the quality of education and is a determining factor for ensuring student's success. Log data of students' activities recorded in a learning management system (LMS) can be used to measure their level of engagement in the online teaching–learning process. No previous studies have been found stating a consistent and systematically raised list of LMS-based student engagement indicators, so this systematized review aimed to fulfill this gap. The authors performed an advanced search in the PubMed, Ovid, Google Scholar, Scopus, Web of Science, ProQuest, Emerald, and ERIC databases to retrieve relevant original peer-reviewed articles published until the end of June 2021. Reviewing the 32 included articles resulted in 27 indicators that were categorized into three themes and six categories as follows: (a) log-in and usage (referring to LMS, access to course material), (b) student performance (assignments, assessments), and (c) communication (messaging, forum participation). Among the categories, access to course material and messaging were the most and the least mentioned, respectively.

Keywords: e-learning, student engagement, learning management system, LMS, log data

What Are the Indicators of Student Engagement in Learning Management Systems? A Systematized Review of the Literature

Student engagement, being a multidimensional concept, is defined as the student's amount of time and physical and psychological ambition devoted to fulfilling academic activities (Shah & Cheng, 2019). This includes students' levels of attention, curiosity, interest, optimism, and passion while partaking in the teaching–learning process (Soffer & Cohen, 2019). Student engagement influences academic success regardless of the type of learning context and strategy; however; engagement is critical in an e-learning environment because of the physical distance between instructors and learners (Henrie et al., 2017). Moore (1993) explains his theory of transactional distance and points out that three elements—dialogue, course structure, and learner autonomy—are factors that affect students' feelings of transactional distance. He argues that instructors, learners, and educational organizations can use these elements to plan for effective and deliberate learning (Moore, 1993). This theory of transactional distance has been used as the theoretical framework for research in online and technology enhanced learning, in which the medium of learner–instructor communication provides the chance for higher levels of interaction and engagement (Moore, 2018). This is important because the extent of monitoring and promoting student engagement in e-learning affects the quality of education (Henrie et al., 2017) and is a determining factor in whether an e-learning strategy is productive for educational institutions through ensuring students' success (Meyer, 2014). Several studies have mentioned low levels of student engagement as the most important reason for student drop out in e-learning (Lee & Choi, 2011; Kim et al, 2017). Moreover, the level of student engagement shows the university's level of commitment to academic activities and active learning (Lee et al., 2019). Implementing strategies to replace an e-student's sense of isolation with relatedness and closeness facilitates their being more active in online courses, which results in the student's higher satisfaction as well (Young & Bruce, 2011). Moreover, monitoring student engagement in e-learning environments helps in improving instructional events through recognizing the learners that need more support for following their studies on the path toward success (Henrie et al., 2015).

Studies on student engagement focus on two main aspects: learning behaviors and feelings of emotional belonging. In contrast to emotional belonging, learning behaviors are often measured quantitatively based on generic indicators of student engagement, which assess, report, and value the university's performance. Such a qualitative analysis provides authorities and stakeholders with a feeling of certainty in understanding whether an educational process goes well or not (Zepke, 2015). Several studies have addressed the characteristics or constructs that make up student engagement assessment in a quantitative method, though a few have focused on the e-learning context (Lee et al., 2019). Most of these are cross-sectional studies, in which engagement self-reporting methods were used rather than continuous monitoring (Henrie et al., 2017). Meanwhile, an e-learning context with the possibility to instantly record indicators of student's behaviors and learning activities within a learning management systems (LMS) provides a valid and approximate measure for student engagement in courses (Henrie et al., 2017; Motz et al., 2019).

LMSs are Web-based software used mainly for asynchronous interaction between instructors and students by delivering a course's information, materials, and activities (Raza et al., 2021). Generated log data in LMS-based courses can be used as predictors of student achievement (Macfadyen & Dawson, 2010). Records of user's activities within a software are labeled as *log data*, which include items such as number of clicks or page views, time spent on an action, and results of performed tasks or activities. Reviewing log data demonstrates a user's real-time interaction with the software and can be analyzed to understand any changes in a user's behavior (Henrie et al., 2017). The advantage of log data is that the data are automatically collected without any interference from instructors and staff. In addition, log data present objective information about aspects of a user's behavior that are not easily measured in other ways (Macfadyen & Dawson, 2010; Zanjani, 2015). In fact, intelligent and effective analysis of LMS log data—that is, learning analytics—not only assists in promoting student's success and retention rate and supporting at-risk learners (Atherton et al., 2017) but also provides the possibility to implement personalized learning, which is a revival of the learner autonomy concept in Moore's (2018) transactional distance theory.The result of such analysis displays a student's level of engagement and learning pattern, even at the initial stages of a course, and provides evidence for timely interventions to improve a student's performance (You, 2016).

Hence, regarding the benefits of analyzing LMS log data to approximately measure student engagement, this systematized review of relevant literature was conducted to identify LMS indicators that can be used for this purpose.

Methods

The Cochrane Collaboration's Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Moher et al., 2009) was followed to conduct this systematized review. A systematized review follows the methodology of a systematic review and includes some of its elements; however, it cannot meet all the criteria for a full systematic review (Grant & Booth, 2009).

An advanced search was conducted in the PubMed, Ovid, Google Scholar, Scopus, Web of Science, ProQuest, Emerald, and ERIC databases on February 5, 2021, to retrieve relevant articles up to the end of June 2021. The search operators included Boolean operators (AND, OR, and NOT), parentheses, and truncation; the following keywords were searched as single terms or in combination with others: *online learning*, *online education*, *distance learning*, *distance education*, *virtual learning*, *virtual education*, *e-learning*, *electronic learning*, *mobile learning*, *M-learning*, *distance study*, *distributed education*, *distributed learning*, *open learning*, *engagement*, *achievement*, *performance*, *progress*, *students*, *adult learners*, *learners*, and *users*. Due to the limited number of articles dealing with the indicators of student engagement in LMSs, the search was not limited by keywords related to LMSs. The following is an example of a Web of Science search query:

> TS = ((“online learning” OR “online education” OR “distance learning” OR “distance education” OR “virtual learning” OR “virtual education” OR “e-learning” OR “electronic learning” OR “mobile learning” OR “M-learning”) AND (“student engagement” OR “student achievement” OR “learners engagement” OR “learner's achievement” OR “users engagement” OR “user's achievement” OR “student involvement” OR “learner's involvement”))

After extracting articles, duplicate ones were excluded using Endnote X8.2 (Clarivate Plc, London, UK).

The inclusion criteria for this review were as follows: (a) English language, (b) original articles, (c) student engagement in e-learning software being the subject of the study, and (d) availability of articles' full texts. Studies that had used only special software or hardware facilities for monitoring student engagement, such as equipment for eye tracking, face recognition, or monitoring of mouse scrolling or movements, were not included. The reason was the focus of study was on data that were logged within routinely accessible e-learning software, independent of other external equipment or software. However, the articles including both types of monitoring were considered, and the results relevant to the aims of the review were retrieved. Studies on indicators of student engagement in online synchronous classes were omitted.

After article retrieval, two independent researchers reviewed the articles' titles and abstracts using a standard checklist form to exclude irrelevant articles. Then they separately performed an in-depth assessment on articles' full texts to determine their eligibility. At this stage, any inconsistencies between reviewers were resolved.

In the next step, the bibliographic data from each eligible article were extracted, and key findings and results were summarized and recorded. The PRISMA diagram (Figure 1) was considered for assessing the articles' retrieval, extraction, and removal. Moreover, the Critical Appraisal Skills Programme checklist was used to investigate each article's quality (Critical Appraisal Skills Programme, 2018).

Finally, two independent researchers thoroughly read the included articles in order to extract mentioned indicators of student engagement in an LMS log. As mentioned, any inconsistencies between these two researchers' results were resolved by a third researcher's review.

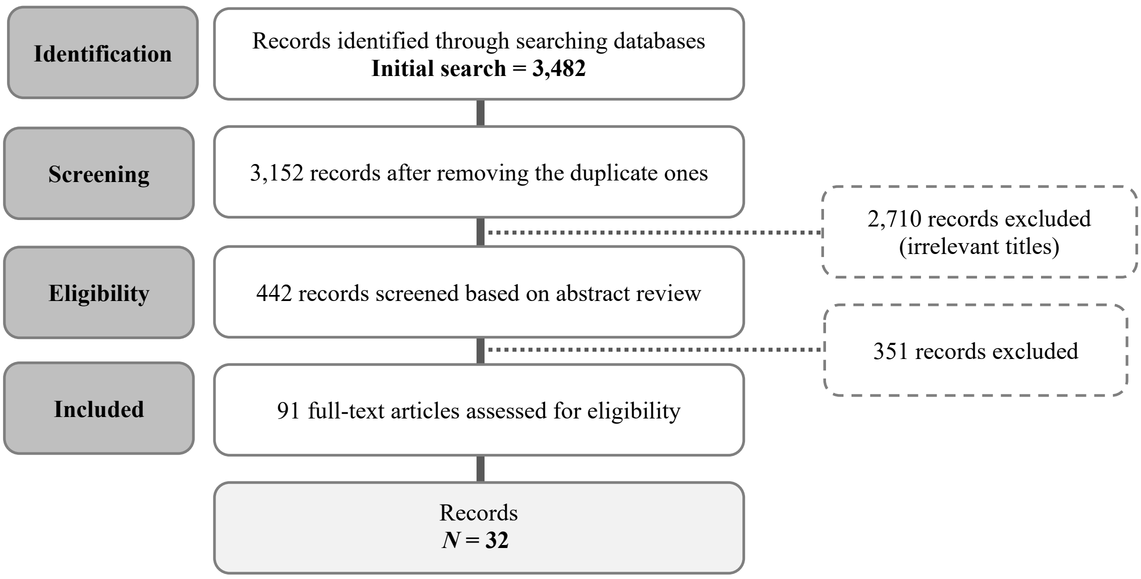
Results

Articles' Retrieval and Bibliographic Information

After performing article retrieval steps, 32 articles were eligible to enter the study. Figure 1 shows the PRISMA diagram for this review, and Table 1 shows the search results based on databases.

Figure 1

PRISMA Flow Diagram for Retrieving Articles



Note. Adapted from Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement by Moher, D., Liberati A., Tetzlaff J., & Altman D. G., 2009, BMJ, p. 339 (https://doi.org/10.1136/bmj.b2535)

Table 1

Search Results

Database	No. of records
ERIC	90
PubMed	1,015
Scopus	470
Web of Science	1,219
Ovid	13
ProQuest	497
Emerald	15
Google Scholar	163
Total	3,482
Duplicates	330
Total with duplicates removed	3,152

Table 2 includes information on included articles' bibliographic characteristics. The 32 articles were published in 28 journals, among which *Computers & Education* had the highest number of publications (4 articles).

Table 2

Bibliographic Information of Included Articles in Chronological Order

Article no.	First author (year)	Study objectives	Study design	Assessed platform
1	Leah P. Macfadyen (2010)	Identifying the data variables that would inform the development of a data visualization tool for instructors	Exploratory research (analysis of LMS tracking data)	Blackboard Vista
2	Marcia D. Dixson (2015)	Validating the OSE's ability to measure student engagement	Correlational analysis	Blackboard
3	Curtis R. Henrie (2015)	Measuring student engagement in a blended educational technology course	Exploratory research (analysis of self-reported and observational data)	Canvas
4	Dongho Kim (2016)	Constructing and validating proxy variables that represent the specific	Data mining process (construct proxy	Moodle

Article no.	First author (year)	Study objectives	Study design	Assessed platform
		behavioral and psychological characteristics of high achievers in asynchronous online discussion to provide suggestions for practice	variables and prediction model)	
5	James Ballard (2016)	Proposing a conceptual model of engagement	Activity theory-based methodology (demonstrated through a desk analysis of VLE data)	Moodle
6	Rosalina Rebucas Estacio (2017)	Finding effective ways to sift through the vast quantity of data generated by Web-based learning environments	Data mining process (using log data in a university using a Moodle platform)	Moodle
7	Rodney A. Green (2017)	Providing insight into student behavior and study practices by reporting on use of online resources	Relationship finding (retrospective cohort study)	Moodle
8	Curtis R. Henrie (2017)	Exploring the potential of LMS log data as a proxy Measuring student engagement	Cross-sectional correlation analysis	Canvas
9	Wang Peng (2017)	Introducing the student engagement model	Analyzing the students' behavior engagement mode, cognitive engagement behavior, and emotional engagement behavior	Local software
10	Kenneth David Strang (2017)	Visualizing the relationship between student activity and performance	Relationship finding (learning analytics)	Moodle
11	Mirella Atherton (2017)	Providing a current insight into the factors that can be measured online that are important for academic success	Relationship finding (learning analytics)	Local software
12	Feng Hsu Wang (2017)	Exploration of how online behavior engagement affects achievement in flipped classroom	Model development (from data sets derived from the log data)	Moodle
13	Naomi Holmes (2018)	Monitoring of engagement through VLE use	Correlational	Local software
14	Raj Kapur Shah (2018)	Developing literature on students' interaction with online learning	Relationship finding (learning analytics)	Blackboard

Article no.	First author (year)	Study objectives	Study design	Assessed platform
15	Chris A. Boulton (2018)	Measuring VLE activity for students	Relationship finding (learning analytics)	Moodle
16	Chaka Chaka (2019)	Establishing a proxy measure of student engagement	Relationship finding (learning analytics)	Local software
17	Maria Toro-Troconis (2019)	Exploring student engagement with online content	Relationship finding (learning analytics)	Canvas
18	Yousra Banoor Rajabalee (2019)	Understanding the relationship between students' engagement in an online module with their overall performances	Relationship finding (learning analytics)	Moodle
19	Kristof Coussement (2020)	Improving student dropout predictions	Relationship finding (learning analytics)	Local software
20	Ahmed Al-Azawei (2020)	Predicting students' performance in a VLE	Relationship finding (learning analytics)	Local software
21	Abdallah Moubayed (2020)	Identifying metrics to provide better insight into students' engagement	Data mining (clustering model)	Local software
22	Ani Grubišić (2020)	Assessing the level of student engagement in four e-learning platforms	Developing model for tracking student learning and knowledge	Local software and Moodle
23	Dongho Kim (2020)	Exploring student- and teacher-level factors associated with the duration of student use in an online learning platform	Association finding (learning analytics)	Local software
24	Valentina Franzoni (2020)	Proposing a visual interface for learner monitoring	Developing tool for learning analytics in LMSs	Moodle
25	Jeantyl Norze (2020)	Examining relationship between online student engagement and academic achievement	Relationship finding (learning analytics)	Moodle
26	Larian M. Nkomo (2021)	Discovering students' engagement patterns in a blended learning environment	Educational data mining technique (discovering patterns)	Moodle
27	Robert J. Summers (2021)	Predicting future behavior and future outcomes by early measuring of engagement	Relationship finding (learning analytics)	Local software
28	Eseta Tualaulelei (2021)	Exploring online student engagement and course design	Course mapping using course learning analytics	Local software
29	Sarra Ayouni (2021)	Specifying and developing a model comprising	Developing model for comprising student	Local software

Article no.	First author (year)	Study objectives	Study design	Assessed platform
		student engagement in an online context	engagement in an online context	
30	Joanna Krasodomska (2021)	Examining the relationship between university students' engagement in a blended learning course and their performance	Relationship finding (learning analytics)	Moodle
31	Si Na Kew (2021)	Investigating students' cognitive engagement in e-learning through content analysis of forum posts	Quantitative content analysis	Local software
32	Taha Mansouri (2021)	Presenting a brand new approach for student performance prediction	Learning fuzzy cognitive map approach	Moodle

Note. LMS = learning management system; OSE = online student engagement scale; VLE = virtual learning environment.

Identifying LMS Indicators for Student Engagement

After reviewing the articles, 27 indicators of student engagement in LMS log data were identified and classified into three themes and six categories based on their similarities. Table 3 includes these indicators and the article numbers (based on Table 2) that they are stated in.

Table 3

Student Engagement Indicators in LMS and Articles Stating Them

Theme	Category	Indicator	Article no.
Referring to LMS	Log-in and usage	Number of days present in LMS	14, 26, 29, 30, 32
		Time-stamped log of student interaction with LMS (including date and time)	3, 4, 8, 10, 13, 14, 15, 21, 22, 23, 27, 29, 32
		LMS visit intervals regularity	4, 24, 32
	Access to course material	Number of course content views	5, 6, 7, 8, 10, 11, 12, 14, 16, 21, 24, 26, 27, 28, 29, 32
		Time spent viewing course content	7, 12, 15, 16, 20, 23, 24, 29
		Proof of reading course content	19, 22, 29
		Number of views of additional pages (e.g., glossary, search, hyperlinks, help, announcements)	3, 5, 6, 8, 12, 16, 18, 23, 24, 27, 28, 29, 32
		Time spent viewing additional pages	3, 12, 20, 24
		Studying course content before doing tasks and activities	23, 26

Theme	Category	Indicator	Article no.
		Evaluating course content (likes, comments, questions)	5, 19, 23, 24, 28, 29
Student performance	Assignments	Number of views of assignments	2, 24
		Time spent viewing assignments	6, 8, 12, 21, 24, 29
		Number of submitted assignments	2, 6, 10, 12, 14, 19, 24, 26, 29
		Number of late submitted assignments	21, 29
		Number of correct answers (success rate)	18, 19, 29
	Assessments	Number of exam participations	1, 2, 5, 6, 18, 22, 24, 27, 28, 29
		Number of exam views	6, 8, 24, 28
		Time spent participating in exams	21, 24, 29
		Number of passed exams (success rate)	22, 26, 32
Communication	Messaging	Number of sent messages	1, 2, 5, 16, 19, 28, 29
		Number of read messages	1, 2, 8, 16, 28, 29
	Forum participation	Forum visit interval regularity	4, 24, 31
		Number of sent posts	1, 2, 4, 5, 6, 7, 9, 10, 12, 16, 18, 21, 24, 25, 26, 28, 29, 31, 32
		Number of posts edited	25, 31
		Number of follow-up (responding) posts	1, 2, 9, 19, 25, 26, 28, 29, 31
		Time spent in forums	1, 2, 6, 8, 12, 20, 21, 24, 26, 31, 32
		Length of sent posts (short or long posts)	4, 29, 31

Note. LMS = learning management system.

Descriptions of each category are as follows:

Log-in and usage: This category and its indicators show not only the amount of time spent in an LMS but also the regularity and intervals of referring to it.

Access to course material: This category consists of indicators that demonstrate how much a student has interacted with course content and additional pages. Furthermore, the student's preference to study the content before doing activities and their evaluation of the content are considered indicators of student engagement.

Assignments: Assignments are one of the main learning activities in an LMS-based course, so all potential LMS log data related to assignments are considered a category of student engagement indicators.

Assessments: LMS-based assessments provide objective data for estimating a student's level of engagement with the course. Hence, in this category, all LMS log data related to assessments are listed.

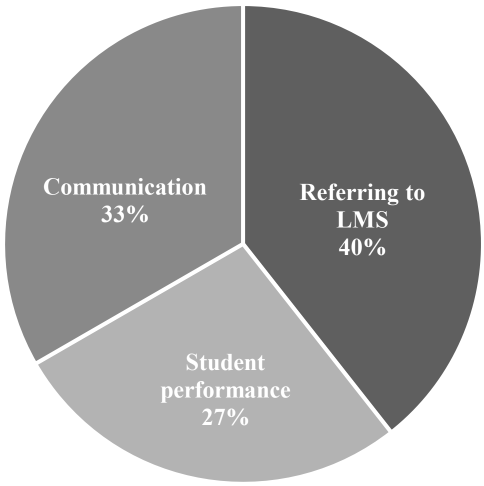
Messaging: By default, students have access to the LMS messaging module to communicate with other LMS users. Sent and read messages show how much a student has interacted with instructors and peers in a course.

Forum participation: Indicators listed in this category estimate a student's level of activity in forums or discussion groups in an LMS.

Figure 2 demonstrates the percentage of obtained indicators for each theme out of the total number of indicators, and Figure 3 depicts the frequency of articles stating each category. Moreover, among 32 articles, 13 (40.6%), 3 (9.4%), 3 (9.4%), and 13 (40.6%) used Moodle, Blackboard, Canvas, and other local LMSs, respectively. We calculated the number of citations of the indicators pertaining to each category in the related articles of each LMS type and conducted a Chi-square analysis to determine if there was any statistically significant difference among these LMS types in this regard. The results showed no significant difference except for in the messaging category (p = 0.033) (Table 4).

Figure 2

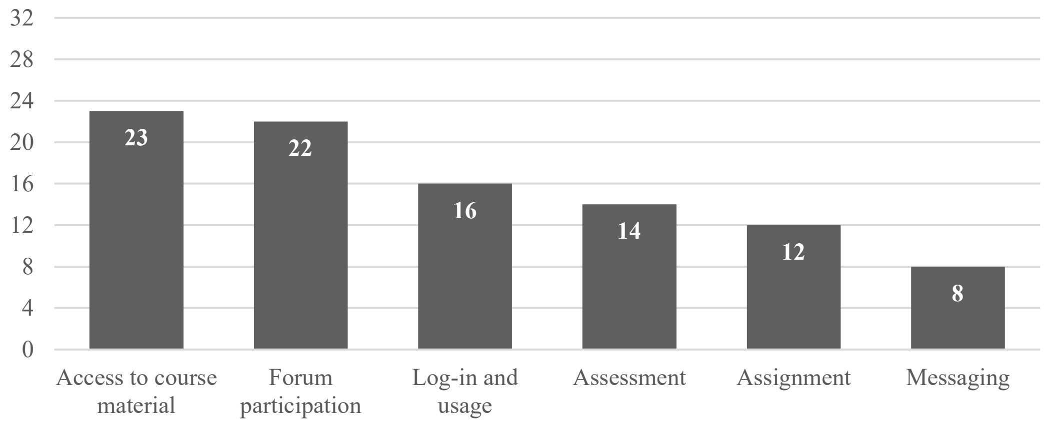
Student Engagement Themes



Note: LMS = learning management system.

Figure 3

Frequency of Articles Stating Each Category of Student Engagement Indicators in LMSs



Note: LMS = learning management system.

Table 4

Comparison of Indicators' Number of Citations in the Articles Related to Each LMS Type in Total and for Each Category

Category	LMS	No. of citations[a]	Total	*p**
Log-in and usage	Blackboard	2	21	0.752
	Canvas	2		
	Moodle	10		
	Other	7		
Access to course material	Blackboard	1	52	0.949
	Canvas	4		
	Moodle	23		
	Other	24		
Assignments	Blackboard	3	22	0.729
	Canvas	1		
	Moodle	10		
	Other	8		
Assessments	Blackboard	2	20	0.697
	Canvas	1		
	Moodle	9		
	Other	8		
Messaging	Blackboard	4	13	0.033
	Canvas	1		
	Moodle	1		
	Other	7		
Forum participation	Blackboard	6	49	0.481
	Canvas	2		
	Moodle	25		
	Other	16		
All categories	Blackboard	18	177	0.363
	Canvas	11		
	Moodle	78		

Other	70

Note. [a] Number of citations of the indicators pertaining to each category in related articles of each LMS type. $^{*}p < 0.05$.

Discussion and Recommendations

In this systematized review on 32 articles, student engagement indicators based on LMS log data were identified and categorized into three themes of referring to LMS, student performance, and communication, which included six categories. Among these categories, access to course material was the most mentioned (23 articles), followed by forum participation (22 articles), log-in and usage (16 articles), assessments (14 articles), assignments (12 articles), and messaging (8 articles).

Despite the positive relationship between students' activity levels within LMSs and their success in their courses (Grubišić et al., 2020), no study was found that cumulatively addressed LMS-based student engagement indicators. Hence, the results of this review provide insight into the indicators used for assessing student engagement in LMSs and their relative priority.

According to the findings of this study, access to course material in the LMS was the most mentioned indicator of student engagement in the literature. LMSs provide the option of uploading course materials to create a virtual learning environment in both fully online and blended courses (Chaka & Nkhobo, 2019). The opportunity to monitor and control students' access to course material is one of the must-have features of LMSs and proves to be an indicator of student engagement level within the course (Krasodomska & Godawska, 2021). Students prefer having access to course material 24 hours a day, 7 days a week; and use this feature more than other LMS features. This results in increased engagement with the course and provides the possibility for students' cognitive involvement, self-regulation, and self-paced learning (Chen, 2020). These results show the importance of monitoring such data as an indicator of student engagement in LMSs.

Forum participation was found to be the next considerable indicator for monitoring student engagement in LMSs in this study. In fact, LMSs have the feature of providing an environment for faculty and students communication, which helps in building a community of practice for collaborative learning rather than personalized individualized instruction (Moore, 2018). Moreover, students communicate with peers. A frequently used LMS communication tool is the discussion board or forum, which facilitates asynchronous collaboration among faculty members and students (Kew & Tasir, 2021). Analysis of data recorded in communication tools of LMS is supportive for assessing students' behavioral, emotional, and cognitive engagement within e-learning environments (Henrie et al., 2017; Yassine et al., 2016). Forums allow for provision of feedbacks and comments on students' work in order to promote academic goals (Kim, 2017). In addition, students' active and passive participation in forum dialogues is positively associated with learning outcomes, and instructors and course designers concentrate on ensuring high levels of participation from students. Analysis of data gathered from forum participation helps in understanding its impacts on academic indicators, including the level of student engagement. Even though participation in forums can be obligatory, the level of students' participation in forums may vary and shows their interest and engagement in course activities (Henrie et al., 2017; Yassine et al., 2016). In this regard, while students' behavioral engagement is determined by the general use of the communication tools and platform (Mogus et al., 2012), their emotional engagement is analyzed through their self-expression in forums or discussion environments (Wang, 2017).

Log-in and usage, as a category within the referring to LMS theme, is the third ranked indicator for student engagement. Based on the existing research, LMS usage log data can be effectively used to measure student engagement (Wang, 2017; You, 2016). Student's log-in and log-out data, as indicators of their behavioral engagement, have a strong positive correlation with their final grades (Mogus et al., 2012). In fact, spending more time within the LMS is associated with more engagement with the course's activities and resources (Wang, 2017).

Other indicators extracted in this review are the categories under the themes of student performance, namely, assessments and assignments. Behaviors such as viewing and uploading assignments and participating in and completing quizzes play an important role in students' academic performance and engagement (Franzoni et al., 2020). In fact, data such as the number of submitted assignments and completed online quizzes are used to quantify students' regularity of participation in course activities and can show the level of students' persistence in fulfilling learning expectations and engagement (Rajabalee et al., 2019). In other words, the more students are engaged in a course through revisiting and performing such activities, the more effectively they learn (Krasodomska & Godawska, 2021).

Messaging in the communication theme is the last ranked indicator of student engagement based on this review, with only 8 out of 32 articles stating it. The low number of mentions in these studies may be due to internal messaging not being a must-have feature of LMSs, and sometimes off-system messengers and social networks are preferred for this purpose (Ross, 2019; Zaaruka & Mosha, 2019). Meanwhile, communication activities in LMSs, such as number of messages, indicate students' engagement in virtual environments (Ramesh et al., 2014). For example, in one study, students' participation within an e-learning environment was analyzed by using the total number of students' sent messages and total access; a moderate relationship was found between such participation and final grades (KunhiMohamed, 2012).

Finally, understanding such indicators is important because LMS usage is increasing in the academic sector, and students are spending more time and effort in these e-learning environments than ever before. Therefore, it is important to choose the appropriate LMS for a course, because it controls the way that learners engage with the course activities and interact with the material, their instructors, and their peers (Roach & Attardi, 2021). In this study, the number of citations of the indicators pertaining to each category in related articles showed that only messaging had a significant difference among LMS types, with institutions' local LMSs having the highest number of citations of the indicator. This result may be due to the low number of the articles for each LMS type. However, even if LMS features are basic ones, it is possible to use them without compromising the quality of teaching through appropriate course design (Roach & Attardi, 2021). An effective course design needs gathering information about students' participation and engagement through features offered by most LMSs that is helpful in substituting the insight that teachers gain about students' learning in traditional classes.

Limitations

Despite the researchers' efforts, this study has some limitations that must be considered. Although the literature search was conducted in multiple databases, as recommended for review articles (Cronin et al., 2008), possible bias in selecting databases or formulating search strategies may have resulted in missing relevant publications. Moreover, this review included only English-language articles. Articles in other languages and non-article publications, such as dissertations, may contain other indicators.

Future Research

Since research on student engagement in e-learning environment is still emerging, there are opportunities for future studies. Analyzing student engagement based on identified indicators of this study and comparing the results with the findings of the students' self-reports of their engagement may expand knowledge in this regard. Furthermore, working on predictive models of student performance based on these indicators would provide the chance for early interventions to support students, prevent dropouts, and improve student retention. In spite of the usefulness of such quantitative analysis, in which course activities have the same weights, it is recommended to work on solutions to determine student engagement levels according to the importance and alignment of activities with learning objectives.

Conclusion

The results of this systematized review enrich the current literature. No previous studies have addressed a cumulative list of certain LMS-based indicators for measuring student engagement in e-learning environments. Hence, identifying such indicators has expanded the literature in this regard. Institutions and academics can use this list of indicators to (a) constantly monitor students' engagement in asynchronous e-learning platforms, (b) determine strength and weaknesses of delivered e-courses, (c) identify and support students with low engagement levels, (d) plan for implementing personalized learning, (e) plan for faculty development programs to familiarize faculty with the activities that bring about higher levels of student engagement, and (f) compare institutions' current LMS features and logs with the list of indicators to determine the ones that can be added to the software, if there are any, to promote the chance of engagement.

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The Online PhD Experience: A Qualitative Systematic Review

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Abstract

The online doctoral population is growing steadily worldwide, yet its narratives have not been thoroughly reviewed so far. We conducted a systematic review summarizing online PhD students' experiences. ERIC, WoS, Scopus, and PsycInfo databases were searched following PRISMA 2020 guidelines and limiting the results to peer-reviewed articles of the last 20 years, yielding 16 studies eligible. A thematic synthesis of the studies showed that online PhD students are generally satisfied with their programs, but isolation, juggling work and family roles, and financial pressures are the main obstacles. The supervisory relationship determines the quality of the experience, whereas a strong sense of community helps students get ahead. Personal factors such as motivation, personality, and skills modulate fit with the PhD. We conclude that pursuing a doctorate online is more isolating than face to face, and students might encounter additional challenges regarding the supervision process and study/life balance. Accordingly, this review might help faculty, program managers, and prospective students better understand online doctorates' pressing concerns such as poor well-being and high dropout rates.

Keywords: qualitative review, online higher education, online PhD program, online doctoral student, lived experience, student's perspective

Introduction

There has been a dramatic increase in recent years in the number of students enrolled in online doctoral programs (Burrus et al., 2019; Sverdlik et al., 2018). The COVID-19 pandemic has only accelerated what was already a strong trend towards virtuality in this educational stage. The most common profile of this population is distinct from the traditional PhD student. Whereas the traditional doctoral candidate was young and studied on site and full-time, the non-traditional candidate is a working adult with family responsibilities pursuing their degree online and part-time (Offerman, 2011).

Historically, the doctoral population has experienced very high attrition and delayed completion rates (Baltes & Brown, 2018; Lovitts, 2001). This situation is even more concerning in the case of online doctorates where dropouts are in the range of 40–70% (Marston et al., 2019; Rigler et al., 2017). But these are not the only potential troubles PhD students might deal with. Recent literature has highlighted what can be considered a mental health epidemic among this population ("Being a PhD Student Shouldn't Be Bad for Your Health," 2019; Evans et al., 2018). Poor well-being, high stress, and burnout from overworking are more widespread than previously thought, putting PhD students at an increased risk of developing a psychiatric disorder relative to the general population. These circumstances have dire implications. High attrition rates are costly in personal, institutional, and societal terms (Kelley & Salisbury-Glennon, 2016; Litalien & Guay, 2015). On the one hand, individuals face emotional hardship and might lose personal and professional opportunities. On the other, institutions fail to retain talent and waste their limited resources, while society at large loses the potential for knowledge growth and innovation.

Over the last few decades, a substantial body of research has been conducted on the factors promoting persistence or, alternatively, causing dropout in higher education (Tinto, 1975; Vossensteyn et al., 2015) and doctoral studies (Castelló et al., 2017; Lovitts, 2001; Sverdlik et al., 2018). Scarce research has been devoted, however, to examine this phenomenon in the context of online doctoral programs. Thus, there is a need to address this gap in the understanding of adult learners' experiences and challenges within the online doctoral environment. Deeper awareness about this student body may help program chairs strengthen their online PhD programs, faculty better comprehend the demands of their students, and future students adjust their expectations about what pursuing an online PhD degree actually entails.

Several reviews have been conducted aiming to understand PhD candidates' experiences and perspectives (Akojie et al., 2019; Gray & Crosta, 2019; Rigler et al., 2017; Spurlock & Cunningham, 2016; Sverdlik et al., 2018). However, most of them have not focused exclusively on the context of online PhD programs, often pooling together in-person, blended, and online programs. Such approach does not allow us to discern the specific characteristics and challenges a fully online context might exert on students. Akojie et al.'s review (2019) is, thematically, the closest to our own. Nonetheless, these authors exclude part-time students, which we include and consider a crucial profile closely related to adult, non-traditional students. Akojie et al. also limited the timespan to five years, which we expand to the last two decades to grasp a fuller picture of the phenomenon.

Accordingly, the purpose of this study was to comprehensively examine and critically analyze the available evidence on the experiences and perceptions of PhD students pursuing their degrees in an online modality. We specifically sought to synthesize the aspects facilitating or hampering the doctoral journey and the reasons why these students persist and eventually complete their studies or, alternatively, delay completion or drop out from their programs.

Method

Systematic reviews are the method of choice when aiming to describe a phenomenon, summarize the available evidence, and document the remaining gaps in the literature (Gough & Thomas, 2016). This approach is particularly useful to decision makers. Hence, we adopted this approach while additionally following the preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement (Page et al., 2021) to report the search and article selection process.

Research Questions

The general research question guiding this review was: What are the experiences, perceptions, and attitudes of online PhD students along their doctoral journey? Derived from this broad question, we posed two additional sub-questions: What are the main perceived factors affecting online students' persistence in their programs? How satisfied are they with the PhD program, the supervisory relationship, and the sense of community?

Search Strategy

We searched four scientific databases, accounting for both educational-focused (ERIC) and comprehensive scientific repositories (Web of Science, Scopus, and PsycInfo). Results were limited to peer-reviewed articles written in English from 2002 to 2021. Including research performed over this time span gave us a broad longitudinal picture of the phenomenon. Focusing on primary empirical studies, we excluded literature reviews, grey literature, and anecdotal papers. The search was performed in June 2021 and included three semantic blocks of terms: *(PhD OR doctoral OR doctorate) AND (online OR distance OR off-campus) AND (experiences OR perceptions OR attitudes).*

The first and second blocks aimed to specify the target population of the search, while the third block aimed at incorporating the type of qualitative results we were seeking. The search string terminology and truncations were deliberately kept simple in order to retrieve the maximum number of articles and to avoid unintended mistakes derived from each database's particular functioning.

Inclusion and Exclusion Criteria

Studies had to meet the following criteria to be included in the review: (a) written in English; (b) from the last 20 years; (c) peer-reviewed; (d) empirical; (e) include online PhD students among its participants; and (f) gather accounts of the participants' experiences throughout their online PhD programs.

We excluded studies that covered professional doctorates since their characteristics are quite different from research-intensive doctorates. Additionally, we discarded studies that did not collect first-person narratives (either coming from interviews or open-ended questionnaire items) and studies focused on specific courses or interventions that do not address the whole PhD degree.

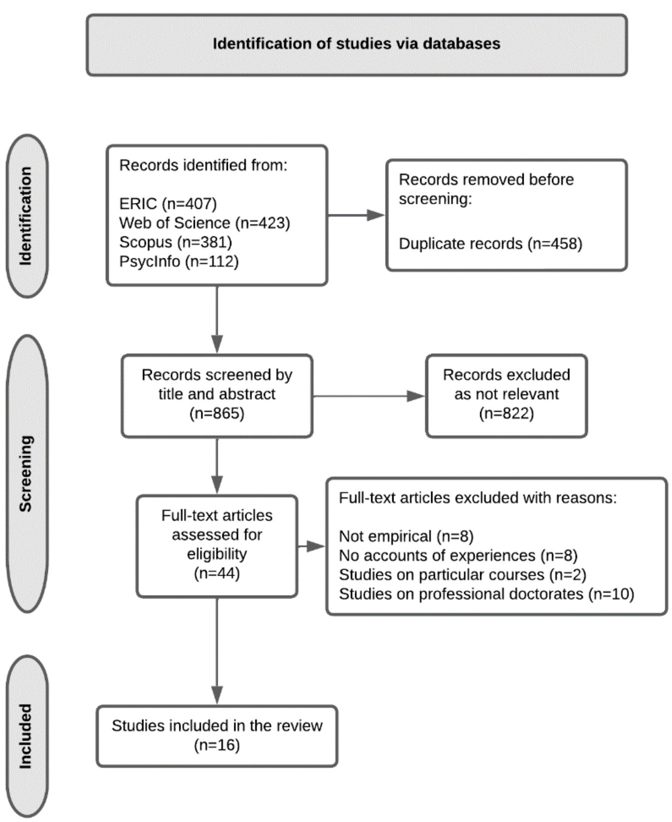
Study Selection

Once we conducted the database search and retrieved the references, we first imported them to Zotero to manage the whole collection and remove duplicates. Then, we uploaded the collection to Rayyan (Ouzzani et al., 2016), a software tool specifically developed to facilitate collaboration among researchers in the initial screening stages of systematic reviews. The first and second authors carried out a title and abstract screening, discarding thematically non-relevant studies and discussing disagreements about the application of the inclusion and exclusion criteria. Subsequently, we conducted a full-text reading of the remaining articles which allowed a final selection of articles to be included in this review.

Figure 1 shows the articles' search and selection procedure following the PRISMA statement (Page et al., 2021). PRISMA guidelines were developed to ensure detailed and transparent reporting of the review process, allowing for its trustworthiness and reproducibility. We initially recovered 1,323 articles using our search string in all four databases. After removing 458 duplicates, two independent coders screened 865 articles by title and abstract, deeming 43 articles for full-text assessment. After reading the whole text, 27 articles were further discarded due to several reasons such as not being empirical, not including students' first-person accounts, or referring to interventions or courses and not to the general PhD program. Ultimately, 16 articles were included in the review.

Figure 1

PRISMA 2021 Flowchart



Data Extraction and Analysis

To make sense of the corpus of data, the first and second authors agreed on extracting the following information: bibliographic data (title, authors, year); context (country, field); methodology; participants; aim of the study; domains and themes; main findings; and limitations. We used thematic synthesis (Thomas & Harden, 2008) to analyze the results sections of the papers. This approach was specifically developed to guide data analysis in qualitative systematic reviews, providing a rigorous framework through a qualitative lens. Following the scheme outlined by Thomas and Harden (2008), we first conducted line-to-line coding of the studies' findings, while inductively developing a set of codes and descriptive themes that were progressively refined. In a second stage, we interpreted these descriptive themes to generate analytical themes that aimed to cover the whole spectrum of the phenomenon under review. These descriptive and analytical themes will serve as the basis for structuring our analysis in the following section.

Results

Sixteen articles were eligible for inclusion in this review. Table 1 displays the articles' findings and other key information. Except for one study conducted in Zimbabwe, all studies came from the USA, UK, and Australia. The fields of study gravitated heavily towards education (n = 7), while there were also some papers from medicine (n = 3) and psychology (n = 2). In four studies, the field was not explicitly mentioned. Most studies used a qualitative approach (13 studies with a total of 367 participants), whereas three used mixed methods (801 participants). The most frequent domains were the supervisory relationship (n = 6) and the overall PhD experience (n = 5), while other domains alluded to the sense of community (n = 2), emotions (n = 1), motivation (n = 1), and received support (n = 1).

Table 1

Descriptive Summary of Included Studies

Citation	Country	Participants	Design: Instrument	Aim of the study	Main findings
Andrew (2012)	AU	3 students	Qualitative: Interviews	Explore the challenges around distance PhD supervision	Supervision at a distance has the advantage of flexibility and convenience to reconcile with personal life. It does not hamper creativity, but there is potential for loneliness. Peer and institutional support are preconditions for engagement.
Berg (2016)	US	228 current and recently graduated students	Mixed methods: Survey	Understand the experience of African American and Latinx online PhD students	Students carefully assess the risks and rewards derived from the decision of pursuing a doctoral degree. Challenges in the online doctorate: financial pressures, feelings of self-doubt, isolation, family, and work responsibilities (70% took an unscheduled break). Advantages: demographically blind and culturally diverse.
Brown (2017)	US	75 students	Qualitative (phenomenology): Interviews	Explore perceived supports that contribute to persistence	Main reasons for choosing an online program are flexibility, best fit with work and family schedule, and no need to travel. Advisors, family members, and co-workers are valuable sources of support. Excessive workload, and professors' lack of empathy regarding personal responsibilities are reasons for quitting.
Byrd (2016)	US	12 students	Qualitative (phenomenology): Interviews	Understand factors that contribute to students' sense of community	Sense of community affects online doctoral experience positively. Being in a cohort provides security and lessens anxiety. Initial f2f seminars contribute greatly to togetherness.

Citation	Country	Participants	Design: Instrument	Aim of the study	Main findings
					Facing challenging situations strengthens the bond between participants.
Erichsen et al. (2014)	US	295 students	Mixed methods: Survey	Investigate distance doctoral students' satisfaction with supervision	Students are moderately satisfied with their supervisors, but many feel isolated and abandoned. Men are more satisfied than women. Students in blended programs are more satisfied than students in online programs. An online program is harder than a f2f one; but students value flexibility, freedom, and the sense of empowerment it provides.
Fiore et al. (2019)	US	18 current and recently graduated students	Qualitative: Interviews	Understand online doctoral students' perceptions about supervision and persistence	Supervision is the most cited factor related to persistence. Many students feel independent research is daunting and feel frustrated with the lack of or inconsistent advice received. Students do not expect the loneliness and isolation the doctoral journey entails.
Halter et al. (2006)	US	5 students	Qualitative (phenomenology): Interviews	Understand the experience of online doctoral students	The benefits of an online PhD program (convenience, flexibility) outweigh the costs (isolation). Introverted, shy, and independent people fit best. Students learn new skills such as catching up with technology, communicating online, and building community.
Ivankova & Stick (2007)	US	278 current and former students	Mixed methods: Interviews	Identify factors contributing to students' persistence	Persistence is affected by program quality, relevance for professional life, quality advisor's feedback, and student's writing skills. Lack of synchronous and f2f interaction is a dropout factor.

Citation	Country	Participants	Design: Instrument	Aim of the study	Main findings
					Beneficial instructors are responsive, provide quality advice, and are willing to accommodate students' needs.
Jameson & Torres (2019)	US	40 students	Qualitative: Survey and interviews	Explore mentor-student relationship and its influence on student's motivation to persist	Internal locus of control is a predictor of persistence. Students at the early stages are excited and motivated but have unrealistic expectations and overestimate their skills to conduct independent research. The relationship with the supervisor is the most rated factor (~75%) in supporting students' motivation.
Kennedy & Gray (2016)	UK	24 students	Qualitative: Survey and interviews	Explore doctoral students' affective practice within the online environment	Main positive emotions felt are pleasure, satisfaction, excitement, and belonging; main negative emotions are upset, frustration, anger, fear. Emotions circulate around three sites of intensity: sense of personal progression, interaction with the community, and advisor and peers' feedback.
Kumar et al. (2013)	US	9 recently graduated students	Qualitative: Interviews	Identify strategies used to mentor online doctoral students through their dissertation	Students value mentors using different means of communication and providing structure, with clear deadlines and expectations. Encouragement, positive reinforcement, and gentle criticism are motivating. Challenges: taking mentor's feedback constructively and acting on it; developing a "tough skin"; finding time to write; receiving enough peer support; implementing research at a distance.
Lee (2020)	UK	13 current and recently graduated students	Qualitative (Phenomenology): Interviews	Explore the experiences of online PhD students	Students have unrealistic expectations by assuming an online PhD is easier than a traditional one. Initial residential activities foster sense of community and help students overcome their initial feelings of uncertainty.

Citation	Country	Participants	Design: Instrument	Aim of the study	Main findings
					Students feel increasingly competent as they advance through the dissertation phase. When graduating, many feel "scholarly" but not "scholars."
Madhlangobe et al. (2014)	ZW	5 PhD and 6 master's students	Qualitative: Interviews	Describe motivational factors that increase successful doctoral and master's graduation	Students take cultural (being labelled a failure by family and friends), social (self-initiated exile from friends), and financial (borrowing money from loan sharks) risks. "Team power," including family and friends, is a strong predictor of success.
Natal et al. (2020)	US	17 students	Qualitative (phenomenology): Interviews	Examine the experiences of Asian and Latinx online doctoral students	Both Asian and Latinx are collectivists, experience a sense of duty, and rely on their families to earn their degree. Asian students feel pressure to attain an "honorable profession." Latinx are more likely to be first-generation college students and want to reduce the stigma associated with their culture. The online modality erases being perceived as culturally different.
Naylor et al. (2018)	AU	115 students	Qualitative: Survey	Examine the expectations and experiences of off-campus PhD students	Students expect the PhD to be time-consuming, challenging, and personally rewarding; but also, solitary and difficult to balance with personal life. 80% find the experience positive. 70% say they are overworked, but that perception is unrelated to PhD satisfaction. Inadequate supervision is heavily linked to a negative PhD experience.
Studebaker & Curtis (2021)	US	21 current and recently graduated students	Qualitative: Email interview	Explore how institutions can build sense of community in an	Being part of a cohort and courses' structure help build sense of community.

Citation	Country	Participants	Design: Instrument	Aim of the study	Main findings
				online doctoral program	Connections, although mainly asynchronous (e.g., instant messaging, group chats, video conferencing), contribute to success.

Note. AU = Australia. ZW = Zimbabwe. *N* = 16.

We identified three analytical themes that run through the sixteen reviewed articles: (a) the overall online PhD experience, encompassing students' expectations, perceived challenges, and satisfaction with the program; (b) relational factors such as the supervisory relationship and the community of peers; and (c) personal factors such as motivation, emotions, skills, and personality.

Analytical Theme 1: The Overall Online PhD Experience

The online modality allows students to access educational opportunities that would not be available otherwise (Erichsen et al., 2014; Halter et al., 2006). They choose to pursue a doctorate online for a variety of reasons, mainly for the flexibility it provides to work at their own pace and from any location and also for the convenience of not having to travel or commute to campus (Halter et al., 2006). This is essential if we consider the non-traditional profile of most of these students. They are usually working professionals who must reconcile their studies with job and family responsibilities, thus having to juggle multiple roles and usually managing chronic time scarcity. Furthermore, many participants value joining a global community and the networking opportunities it entails (Kennedy & Gray, 2016), while ethnic minority students appreciate the "demographically blind" context (Berg, 2016) that erases perceptions of cultural differences and allows them to be just regular students (Natal et al., 2020).

Prior expectations about the doctorate are rather inaccurate, however. Students frequently underestimate some issues such as the difficulty of online programs compared to traditional ones —with many assuming the former to be somewhat easier—(Lee, 2020), the workload requirements (Brown, 2017), or the level of isolation that working on their thesis will entail (Fiore et al., 2019). These unrealistic expectations gradually adjust as participants progress in their programs, which is relevant since realistic expectations are correlated with satisfaction and persistence (Naylor et al., 2018).

The online doctorate is a non-linear, arduous journey. Studying online requires more self-discipline, commitment, and focus than studying in a traditional format (Erichsen et al., 2014). More than half the participants in Brown (2017) and Jameson and Torres (2019) contemplated dropping out at some point. Without going that far, taking a break is very frequent. In Berg (2016), almost 70% of the participants took a break due to financial constraints, family responsibilities, or academic issues. Students find the most challenging aspects of their PhD journeys are feelings of loneliness or abandonment and having to fend for themselves; the difficulty in attending to the demands of the program while meeting job and family obligations; and the debt burden and general financial struggles.

Despite the hardships, most students are satisfied with their online PhD programs. In Naylor et al. (2018), 80% of learners described a positive experience, regardless of their demographic characteristics. Meanwhile, satisfaction was strongly linked to effective supervision in Erichsen et al. (2014), and it grew as the student persisted and advanced with the program in Ivankova and Stick (2007). One of Halter et al.'s (2006) participants put words to this generalized perception:

> I did feel that isolation sitting behind my computer. It was a small price to pay for having an opportunity to sit in a course on a winter night and be in my pajamas and coffee with me. The good outweighs the bad. (p. 102)

Analytical Theme 2: Relational Factors

The supervisory relationship is the most important factor (Fiore et al., 2019; Naylor et al., 2018) affecting students' satisfaction, persistence, and successful completion of the doctorate. It is pivotal in facilitating the transition from the coursework stage of the PhD journey to the often perceived as daunting dissertation stage, where more independent research and writing are required. This central role of the advisor in facilitating students' advancement works also in the opposite direction: a poor relationship with the advisor is a direct path toward lack of motivation (Jameson & Torres, 2019) and disaffection (Naylor et al., 2018), and consequently lies behind many decisions to drop out (Fiore et al., 2019; Jameson & Torres, 2019).

Online delivery introduces some additional challenges to PhD supervision. For instance, the initial matching of the student with the supervisor is crucial but often challenging (Lee, 2020). Communication can also be hampered by distance and should be facilitated proactively by advisors (Kumar et al., 2013). On the students' side, difficulties lie in acting on an advisor's feedback and developing a "tough skin" to be able to cope with the constant criticism constructively (Kumar et al., 2013). Overall, Kumar et al.'s participants valued mentors that provide structure, clear expectations, and deadlines; timely and specific feedback on the strengths and weaknesses of the work done; and gentle criticism and positive reinforcement, all of which acted as motivators.

On the other hand, students highly appreciate having a community of peers (Andrew, 2012) and think it contributes decisively to their adjustment and success in the program (Lee, 2020; Studebaker & Curtis, 2021). Having a strong community is closely related to engagement and thus persistence (Byrd, 2016), and it is a protective factor when intentions to drop out arise. Reliance on peers helps students alleviate isolation and develop coping mechanisms to face challenges during their doctoral studies (Halter et al., 2006). In this sense, having a cohort with which students experience the same milestones at the same time gives them a sense of security and consistency, in what they describe as a "family-like" sentiment (Byrd, 2016; Studebaker & Curtis, 2021). In-person contact at some point during the PhD program, in the form of initial residencies or sporadic face-to-face meetings, markedly helps build this togetherness, igniting community-building (Berg, 2016; Byrd, 2016; Halter et al., 2006).

Finally, alongside advisors and peers, online PhD students rely on other sources of support such as significant others, family, friends, or co-workers to help them push ahead (Byrd, 2016). They receive assistance from these persons in areas such as childcare, running errands, or addressing financial issues. However, despite this support, their persistent feeling is one of not being able to meet their whole range of responsibilities (Brown, 2017).

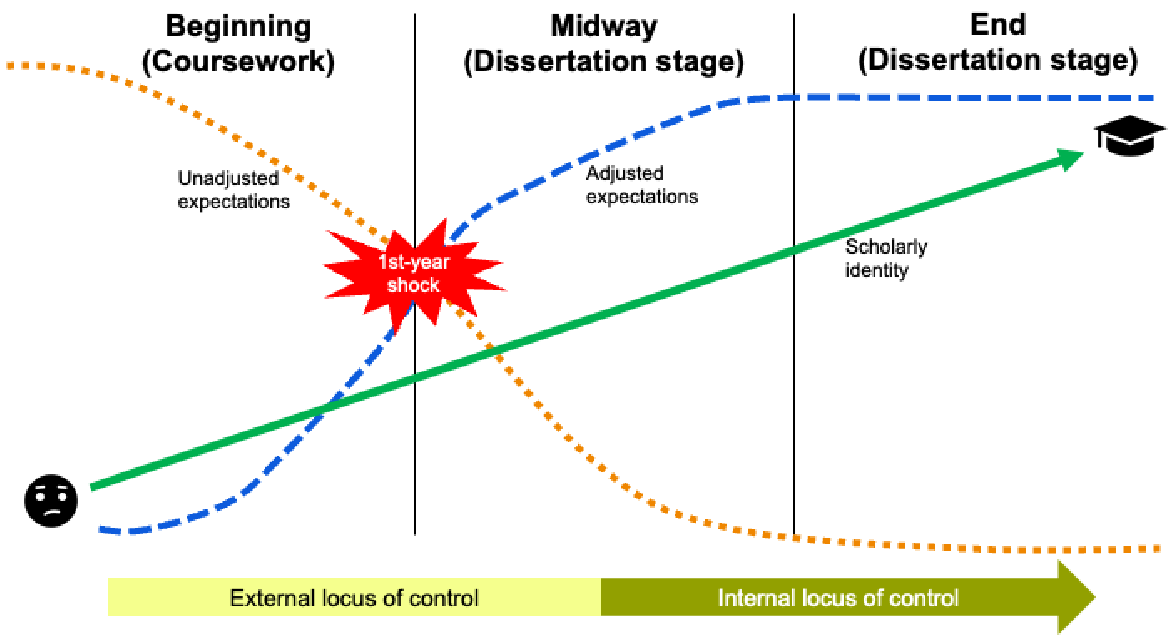
Analytical Theme 3: Personal Factors

Personal factors such as motivation, emotions, skills, and personality impact students' achievement in a program, dynamically interacting with the abovementioned relational factors. Intrinsic motivation in the form of self-direction, passion, and drive has a remarkable effect on students' persistence across studies, even outweighing external factors such as the characteristics of the program, the quality of the advisor's performance, or the students' work/life balance (Fiore et al., 2019; Ivankova & Stick, 2007). Emotion wise, Kennedy and Gray (2016) found that students felt the most positive about personal sense of progression and belonging to the community, while the absence of embodied communication, inflexible deadlines, and study “invading” nights and weekends elicited the most negative affects. In addition, some personalities, such as independent, introverted, or goal-oriented people, seem to better adapt to online PhD work (Halter et al., 2006).

The stage students are in the program is relevant. Studies differentiate between the *course stage* and the *dissertation stage* of the PhD program. In the former, the student takes compulsory courses, while the latter progressively entails actual independent research and writing. Figure 2 summarizes some trends, derived from our analysis, on the modulating effect of the PhD stages on personal variables.

Figure 2

Observed Trends in the Online Doctoral Journey



Initially, students are highly motivated (Ivankova & Stick, 2007) but have an inaccurate perception of what a distance PhD program implies (Jameson & Torres, 2019; Lee, 2020). During the 1st year, unadjusted expectations confront reality, while motivation is based on an external locus of control. Around the end of the 1st year or at the beginning of the 2nd year, expectations tend to adjust as students get to know the reality of an online doctorate. They are entering the dissertation stage. This transition is often lived as a time of shock and crisis (Fiore et al., 2019; Jameson & Torres, 2019; Lee, 2020) since the harshness of the program becomes evident and self-competence is not yet fully settled. In this period, students are particularly vulnerable to frustration if some external factors, particularly the supervisory relationship, fail to motivate them (Fiore et al., 2019). Progressively, while advancing in the program, students start to gain more confidence in their ability to carry out independent research (Jameson & Torres, 2019), and thus, intrinsic motivation grows (Ivankova & Stick, 2007). This higher level of perceived competence is accompanied by the development of a scholarly identity and the confidence in being able to successfully complete the PhD program (Natal et al., 2020).

Discussion

The purpose of this systematic review was to summarize current knowledge about the experiences and perceptions of online PhD students along their academic journey. To follow, we outline the main arguments derived from this work.

First, online doctoral students are generally satisfied with their programs, yet feelings of isolation, the study/life balance, and financial constraints are challenging. We found that students' satisfaction with their programs was high across disciplines. Previous studies provided conflicting evidence in this regard, with some finding, as in our case, no difference in students' satisfaction among disciplines (Barnes & Randall, 2012) and others (Nettles & Millett, 2006) lower satisfaction in the social sciences than in natural sciences. Unsurprisingly, the most predictive factor related to satisfaction was the number of semesters students have been enrolled in the program. This can be related to evidence indicating that as students advance in a program, so do their perceived skills in conducting independent research, adjusted expectations on what a PhD program entails, and intrinsic motivation to pursue their goals. Satisfaction is also closely related to online doctorates' profiles. As non-traditional students, pursuing an online degree allows them to balance their studies with personal responsibilities and better manage chronic time scarcity.

Nonetheless, taking a break for one or more semesters and considering leaving the program was a very frequent occurrence. There are several reasons for this circumstance. Loneliness, difficulties with managing study with work and family responsibilities, and financial issues all take a toll on online doctoral candidates. The studies reviewed indicated students were often not prepared for the isolation they would go through during a PhD program. Even though loneliness is commonly referred to in the literature as a hampering factor in the general doctoral population (Rigler et al., 2017), the distance modality seems to aggravate this predicament. In this regard, students experienced ambivalent feelings: they chose the online modality for its flexibility and "anytime, anywhere" features, but eventually found themselves craving physical proximity. Ultimately, they felt it was extremely helpful for programs to have some kind of face-to-face interaction, which helped ignite a sense of community later in the program. Indeed, Conrad (2005) noted an "enormous surge in connectedness and satisfaction with the program design" (p. 9) in online doctoral students who were able to meet face-to-face at least once.

Previous research showed that while flexibility provides educational opportunities, it also demands more self-regulatory skills on the students' side (Xavier & Meneses, 2021). Our results point to an equivalent concern regarding study/life balance. The same flexibility that allows adult learners to pursue an online PhD program is to blame for blurred borders between their academic and personal lives, and the sensation that the latter progressively shrinks. Relatedly, Akojie et al. (2019) highlighted how this feeling of being chronically time-deprived is particularly pervasive among online doctoral students. This is relevant since Evans et al. (2018) found that perceived poor study/life balance is a risk factor for depression and anxiety during a PhD program. Financial hurdles are another factor jeopardizing students' progress. Many online doctorates do not give an accurate picture of the actual costs of a PhD program, even more so because they usually prolong their studies, which adds to mounting costs and uncertainty. Rigler et al. (2017) linked ongoing enrolment with current costs, opportunity costs, and the expected benefits of attaining a PhD degree. Similarly, the studies reviewed pointed at students carefully assessing the worth of earning a doctorate considering its trade-offs. Minority students and those living in low-income countries were particularly affected by financial concerns. All the above-mentioned challenges might be causally connected to the mental health vulnerabilities detected in PhD candidates, which greatly exceed those of the general population ("Being a PhD Student Shouldn't Be Bad for Your Health," 2019; Evans et al., 2018).

The second argument derived from this study concerns two common factors affecting success and satisfaction: the supervisory relationship determines the quality of students' academic experience, while a strong sense of community helps them to get ahead.

Supervision was the most frequent domain covered in the studies reviewed and a central factor in students' testimonies when it comes to not only successfully completing their online PhD degree but also facilitating future career prospects. This protagonist role of the supervisor in the PhD student's academic life has been extensively examined in the literature, from the classic work of Tinto (1975) to recent reviews on doctoral students (Madan, 2021; Sverdlik et al., 2018). Golde (2000) described how behind many attrition stories lies a bad relationship with the supervisor. This is also true in our results, where online students think an initial match with the supervisor, in their first year, is crucial but often challenging. Golde also stated that poor supervision has often more to do with indifference than downright neglect or abuse. In this respect, among the dissatisfied doctorates in the studies reviewed, many felt stuck with unsupportive supervisors who did not seem to care, and ended up having to resort to internal motivators like passion or drive to cope and persist in their studies. Gray and Crosta (2019) remarked that the qualities of a good supervisor are independent of the delivery modality, but also that counseling students online introduced additional challenges to interaction. Doctoral students in the studies also felt building satisfactory relationships and rapport was harder in the absence of face-to-face interaction. For this reason, they preferred a supervisor who takes a proactive stance on accompaniment but who is also flexible enough to take into account that most students are working adults with multiple responsibilities.

While the supervisor is a central figure in facilitating students' progress, having a community of supporting peers is what helps online doctorates cope when the former or other aspects of the PhD program do not go as expected. Sakurai et al. (2012) observed that while there is often ambivalence regarding the supervisor's impact on their engagement and performance when students happen to have a community of peers, it has almost always a positive net effect. Our findings support this reflection. Separately, previous research highlighted the importance of the cohort-based program structure (Akojie et al., 2019), and how not being in a cohort program is detrimental to students' socialization, resulting in increased perceived isolation (Spurlock & Cunningham, 2016). In our findings, the cohort-based community was progressively seen by online doctoral students as an academic "family." It helped them overcome academic difficulties, fight loneliness, and, above all, keep motivated. Peers shared knowledge in an informal way and helped each other emotionally. In this regard, we should bear in mind that community-oriented students perform better than those working individually (Spurlock & Cunningham, 2016).

The third main argument concerns how personal factors such as expectations, motivation, emotions, and skills modulate students' fit throughout a PhD program. Past research (Sakurai et al., 2017) noted that engagement and persistence in the PhD journey are influenced by personal aspects such as motivation, self-regulatory strategies, and skills. Yet these factors are, in turn, dynamic and evolve as the individual progresses from the initial stage of a PhD program to a more advanced one in which conducting research independently and writing the thesis take centre stage. In this sense, we identified several trends in this review. Online doctoral students begin the PhD journey highly motivated but with unrealistic expectations of what lies ahead and feeling insecure about their writing skills. As they begin facing the reality of the doctorate, expectations adjust, but this period around the end of the first year can be one of crisis. Our findings reflect both Sakurai et al.'s (2012) remarking that motivation needs to be continuously nurtured, and Sverdlik et al.'s (2018) stressing that lack thereof is, for many, the main reason for dropping out, and thus the need for institutional support in times of crisis. For those who advance in their programs, however, the perception of increased ability to do research is accompanied by a developing "scholarly" identity —even though many, as working professionals, do not aim towards an academic path— with drive and inner motivation following.

Limitations and Future Research

We reviewed the available literature regarding online doctoral experience, and most of it came from Western, English-speaking countries and the fields of education and psychology. A more diverse set of studies encompassing populations from other geographical areas, ethnicities, genders, and scientific fields would certainly add nuance and complexity to our findings. In this regard, it would be especially instructive to use an intersectional approach that examines how the interaction of race, class, and gender influences the lived experiences of online PhD students. In this review, we have stressed the online feature of the PhD experience. Still, reviewing part-timers' specific struggles (Gardner & Gopaul, 2012; Gatrell, 2020) might widen understanding of this doctoral population. Although there is partial overlap with full-timers in terms of challenges encountered, part-timers are a particularly understudied, precarious, and peripheral doctoral population. Likewise, we have indicated some crucial differences between the online and face-to-face doctoral experience. However, not being the focus of our work, further research on this topic in terms of its impact on persistence and students' well-being would be valuable. Finally, it would be enlightening to research the voices of those doctoral candidates who left academia. The studies reviewed remark that enrolled students and those ahead in their programs are the most satisfied, yet we lacked hearing from those who dropped out.

Conclusions

Pursuing an online doctorate is more isolating than face to face and introduces additional challenges to the supervision process and students' study/work/life balance. This review showed that relational factors, either as part of a supervisory relationship or in a community of peers, were crucial in assisting online doctoral students to persist in their studies and avoid intentions to drop out. Accordingly, institutions can improve the online PhD experience by strengthening cohort-based structures, providing some type of in-person opportunity throughout the programs to boost socialization, and facilitating awareness and training among supervisors with regards to adult, working professional students' particular needs in terms of flexibility and accompaniment.

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Declaration of Interest Statement

The authors declare no potential conflict of interest.

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Educational Experience and Instructional Design Effectiveness Within the Community of Inquiry Framework

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Abstract

Within its 20 years of development, the Community of Inquiry (CoI) framework has become the most widely used theoretical framework in e-learning. It is considered in much of the distance education literature to be a robust collaborative-constructivist process model that uses three essential elements to interpret educational experience: cognitive presence, teaching presence, and social presence. Widespread use of the CoI framework has resulted in several criticisms, such as having no guidelines for implementation, no incorporation of assessment and evaluation metrics, and no widespread consensus on the current model's ability to represent all the contributing factors that promote a positive educational experience. However, there is an opportunity to overcome these shortcomings, some of which may exist, and to use the CoI's extraordinary strength in creating a positive education experience, by adding instructional design effectiveness. The purpose of this combination of a literature review and opinion is to present the CoI framework and its major controversies to shine a light on its importance as one approach to designing critical parts of e-learning. Additionally, given the CoI's purpose of creating a positive educational experience, this paper argues to make explicit to instructional designers and instructors the need to address using the CoI framework within an effective overall design.

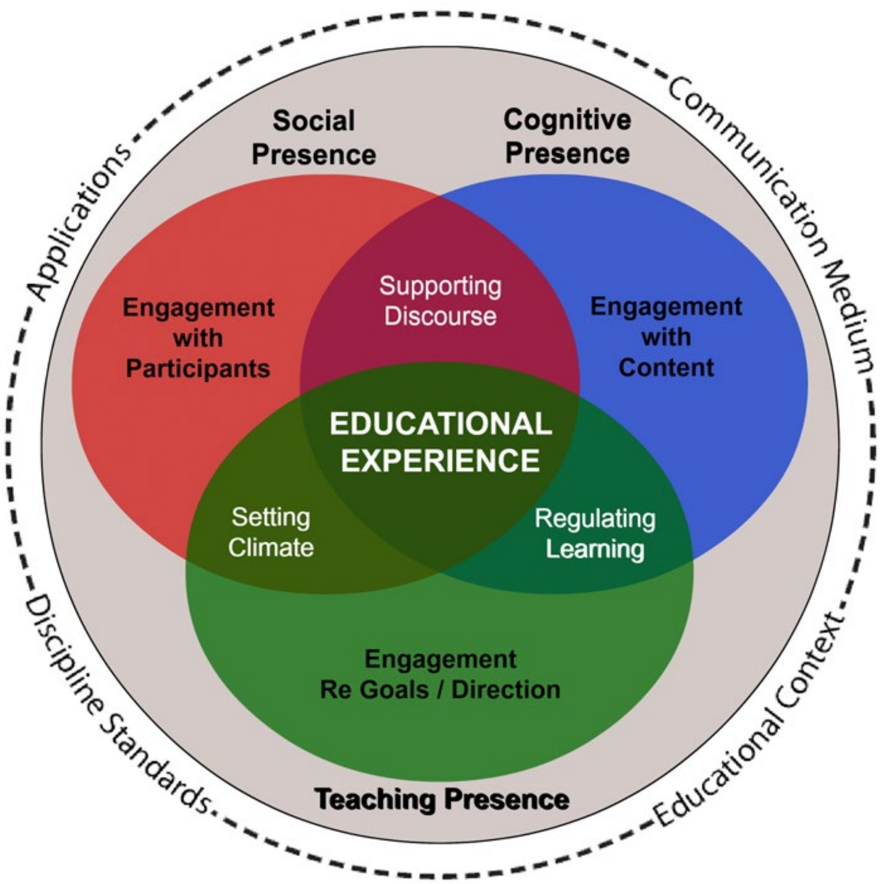
Keywords: community of inquiry (CoI) framework, instructional design outcomes, elearning, assessment and evaluation

Introduction

For more than 20 years, the Community of Inquiry (CoI) framework (Garrison et al., 1999) has been considered by many distance education scholars to be a robust collaborative-constructivist process model that includes three essential elements to promote a successful online learning experience (Castellanos-Reyes, 2020; Kozan & Caskurlu, 2018). The three essential elements are cognitive presence, social presence, and teaching presence as depicted in Figure 1.

Figure 1

Community of Inquiry Framework



Note. From "About the Framework: Social, Cognitive, and Teaching Presence," by The Community of Inquiry, n.d. (https://www.thecommunityofinquiry.org/framework). CC BY-SA 4.0.

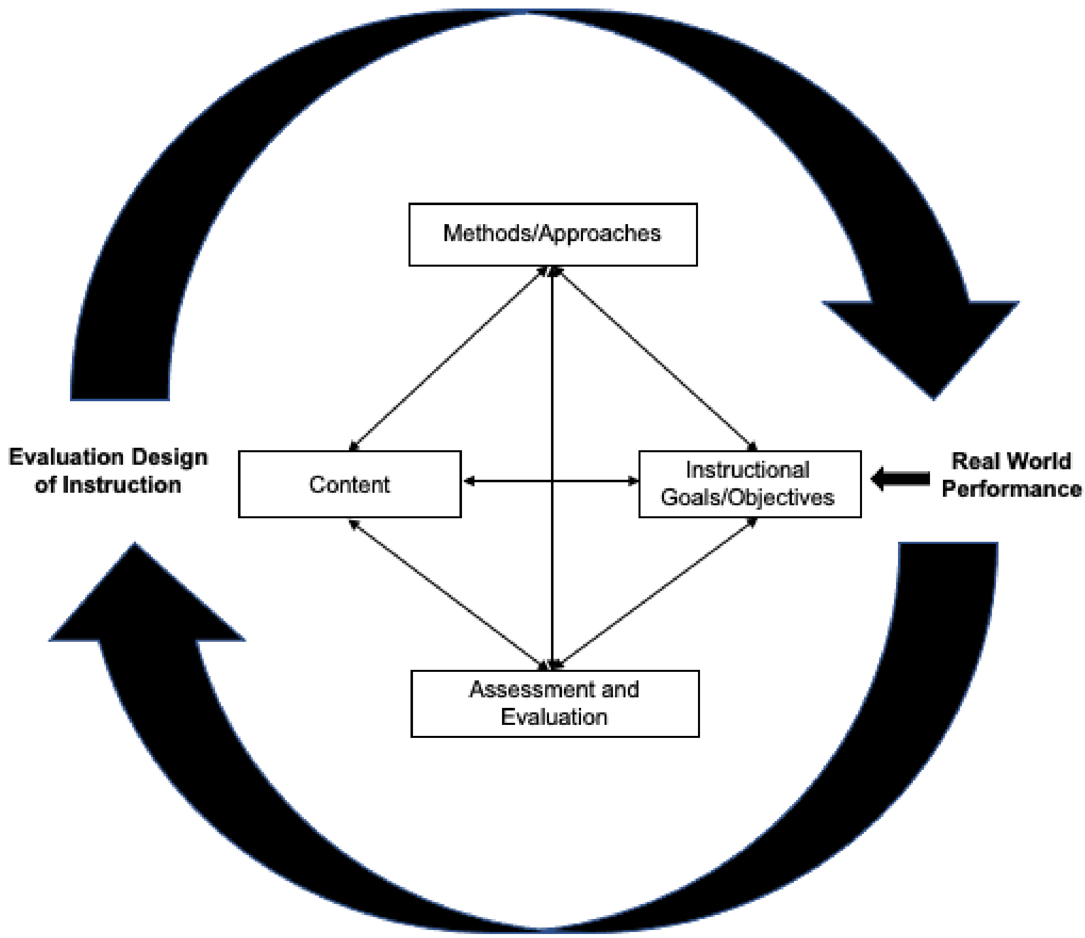
Cognitive presence relates to the ability and extent to which learners may construct knowledge, confirm meaning through discourse or discussion, solve problems, and use critical thinking and/or reflection (Fiock, 2020; Garrison & Arbaugh, 2007; Kozan & Caskurlu, 2018). It focuses on the process of learning, which makes it an important indicator of quality in an online learning experience (Martin et al., 2022; Sadaf et al., 2021). Meanwhile, social presence relates to open, purposeful communication that serves as the foundation for building a trusting environment such as working towards a common goal (Martin et al., 2020; Garrison & Arbaugh, 2007; Kozan & Caskurlu, 2018). It is the most heavily researched element because a sense of community encourages a collaborative learning environment (Castellanos-Reyes, 2020; Cleveland-Innes, 2019). Teaching presence relates to the distribution of authority and the shared role of participating in directing, designing, and facilitating among the participants in the CoI-related learning experience (Cooper & Scriven, 2017; Dempsey & Zhang, 2019; Fiock et al, 2021; Garrison & Arbaugh, 2007).

Conversely, there is equally widespread criticism about the CoI framework that includes at least the following three problems. First, there are no practical guidelines or implementation processes for instructional designers and practitioners (Fiock, 2020; Garrison & Arbaugh, 2007). This is a problem because it requires individuals to rely on their interpretations of the literature and/or past teaching experiences, and practitioners often have little or no instructional design training. As a research-based framework, the lack of systematic guidelines and expectations fails to provide a method to assess the effectiveness of an online course (Kebritchi et al., 2017). For example, Fiock (2020) pointed out that discussion boards can be an invaluable way to promote an online community of learners but warned they can be ineffective when designed poorly.

The second problem is that the CoI framework does not include assessment and evaluation procedures. This is a problem because one of the four basic elements of instructional systems is assessment and evaluation as depicted in Figure 2. Furthermore, the use of assessment and evaluation procedures is essential for online courses because they provide a way for both instructors and instructional designers to measure learning outcomes and the overall effectiveness of a course (Kebritchi et al., 2017; Martin et al., 2021).

Figure 2

Secret of Instructional Design



Note. From "Secret of Instructional Design Revisited," by Z. L. Berge, 2021, *Frontiers in Education Technology*, *4*(4), p. 27 (https://doi.org/10.22158/fet.v4n4p26). CC BY 4.0.

The third problem is that there is no widespread consensus about the composition of the framework (Castellanos-Reyes, 2020). There are ongoing debates about revising the model to include more presences (e.g., Cleveland-Innes, 2019; Kozan & Caskurlu, 2018; Wertz, 2022) and verifying the validity of the current framework (e.g., Dempsey & Zhang; 2019; Heilporn & Lakhal, 2020; Stenbom, 2018). However, there seems to be a workable solution to address all three problems through assessment and evaluation procedures (see e.g., Stinnette & Luxbacher, 2021).

The unprecedented demand for high-quality, online learning experiences has caused an equal demand for research-based pedagogy to support the effective use of technology in education (Kebritchi et al., 2017; Olpak, 2022; Park & Shea, 2020). Kebritchi et al. (2017) considered any dynamic online learning environment as consisting of three major components that continuously affect one another: content, instructors, and learners. Both novice and seasoned instructors need effective models and strategies to encourage exploration with a focus on improving the quality of online education (Kebritchi et al., 2017; Martin et al., 2019). Research conducted by Martin et al. (2019) found using a conceptual framework was a helpful tool for explaining effective online teaching and learning practices to both faculty and support staff.

A systematic literature review conducted by Valverde-Berrocoso et al. (2020) between 2009–2018 revealed that there were only two educational theories about e-learning used in international high-impact scientific journals: the CoI framework and the technology acceptance model (TAM). However, the authors pointed out that the CoI framework was found to be the most relevant in their selected investigation (Valverde-Berrocoso et al., 2020). In a second review conducted by Park and Shea (2020) between 2008–2017, the authors determined that the CoI framework was being continuously researched over the past decade, with two books and four peer-reviewed articles that related to the CoI framework being included in the top 20 most frequently cited publications. In a third systematic review between 2000–2020, conducted by Olpak (2022), the author discovered that the study conducted by Garrison et al. in 1999 was the most referenced study. Furthermore, the same review revealed the CoI framework and its basic elements as being the subject of the top 10 most frequently referenced studies (Olpak, 2022).

Based on the educational research trends noted in the literature for over 10 years, we believe this to be a strong indication that the CoI framework is a robust, research-based e-learning theory that can be easily incorporated by both novice and seasoned educators interested in creating both meaningful and high-quality educational experiences online. Therefore, the purpose of this combination literature review and opinion is to discuss the complexities, controversies, and a possible more meaningful future for the CoI framework when combined with explicit attention to effective instructional design.

About the CoI Framework

In 1999, the CoI framework was developed and presented by Garrison et al. as an original framework to support the thoughtful design of online education while providing opportunities for students to learn with active and shared learning strategies (Fiock, 2020; The Community of Inquiry, n.d.). Nine years later, a 34-item survey instrument was developed to validate the framework by measuring the perception of a learner's educational experience with multiple items to detect each presence (Castellanos-Reyes, 2020; Sadaf et al., 2021; The Community of Inquiry, n.d.). Recently, Stenbom (2018) conducted a systematic review of the CoI survey on 103 studies from 2008–2017. The author discovered the following:

> The CoI survey provide[s] a reliable and valid measure of cognitive, social, and teaching presence as outlined in the CoI framework. The structural relationship between the elements indicates that teaching presence predicts student perceptions of cognitive presence with social presence as a partial mediator. (p. 27)

Each element in the CoI framework has an independent identity that requires interdependence to function, like vital organs in the human body. No human can function without their brain (cognitive presence), their heart (social presence), and their lungs (teaching presence). Thus, it is essential for all three presences in the CoI framework to be present and work together to create authentic and effective learning environments (Cooper & Scriven, 2017; Dempsey & Zhang, 2019; Garrison & Arbaugh, 2007).

Criticism of the CoI Framework

The CoI framework has become one of the most widely used theoretical frameworks. It describes e-learning as an open, collaborative, and flexible learning process (Cleveland-Innes, 2019; Fiock, 2020; Valverde-Berrocoso et al., 2020). Conversely, it has received a fair amount of criticism such as confusion about implementation (no guidelines), not being meaningful enough (no assessment and/or evaluation[i]), and various suggestions to revise the framework (the framework is incomplete; Castellanos-Reyes, 2020). Also, there are limitations to the two methodologies used in researching the CoI framework: content analyses of online discussion posts and student self-reported data from structured questionnaires (Castellanos-Reyes, 2020; Cooper & Scriven, 2017). Both rely on the perception of learning which is subjective. Castellanos-Reyes (2020, p. 559) advocated for researchers "to move from making sense of what an efficient online experience is to designing such an experience." In other words, it is time to use the CoI framework as a method of designing effective, researched-based online learning environments.

Lack of Assessment and Evaluation Procedures

According to Berge (2021), all instructional systems should consist of the following four elements: objectives, methods, content, and evaluation. Specifically, assessment and evaluation were identified as essential elements in online courses for their ability to measure students' achievement of learning outcomes and determine the overall effectiveness of a course (Martin et al., 2021). Mekonen and Fitiavna (2021) defined assessment as a two-fold process of collecting information to compare to the intended objectives for grading purposes while providing opportunities for students to improve their learning with feedback. On the other hand, an evaluation measures all aspects of academic endeavors to determine the validity and usefulness of outcomes (Bin Mubayrik, 2020). The lack of evaluation in the CoI framework has resulted in it being criticized for not being meaningful enough for learners to achieve the intended learning outcomes (Castellanos-Reyes, 2020). Therefore, it is important to review the literature for insights into how successful online course design relates to effectiveness by incorporating assessment and evaluation.

Lack of Guidelines and Implementation Procedures

A second long-standing criticism of the CoI framework relates to its implementation. About 15 years ago, Garrison and Arbaugh (2007) discussed the need for practical strategies and guidelines such as how to create social presence, especially when learners are more academically focused, with a preference for more instructor engagement. Recently, Fiock (2020) highlighted the persistent lack of guidelines for instructors and instructional designers on how to foster the three essential elements of the framework. The lack of clear guidelines and expectations for faculty members often results in no way to evaluate the effectiveness of online courses (Kebritchi et al., 2017).

If we consider teaching presence in the CoI framework (see Figure 1), it should have the strongest influence on communicating high expectations for learning because it is present in the overlapping areas of "setting climate" and "regulating learning." Thus, the instructor plays a significant role "in cultivating cognitive presence and high-level learning … to structur[e] course content, implemen[t] instructional strategies and facilitat[e] collaborative learning" (Sadaf et al., 2021, p. 10). Furthermore, this relates to Kozan and Caskurlu's (2018) perspective that teaching presence functions as a bridge between course design (cognitive presence) and course facilitation (social presence). Each presence influences the others since the CoI framework is comprehensive (Garrison & Arbaugh, 2007). Lastly, it is important to note that the CoI framework may not be appropriate for all online learning environments. For example, Cooper and Scriven (2017) acknowledged that not all learners want to participate socially. In other words, it is important to consider the content, instructors, and learners when selecting instructional strategies as well as the framework. Additionally, there is a need to make more explicit the context and target population for Fiock's recommendations (Kebritchi et al., 2017; Stenbom, 2018). Taken together, the literature reviewed indicates that there still is a need for guidelines and implementation procedures.

Uncertainty About Completion and Validity

A third criticism relates to the CoI framework being incomplete, which has sparked debates about revising the framework (Castellanos-Reyes, 2020; Cooper & Scriven, 2017). Kozan and Caskurlu (2018) reviewed suggestions from other researchers and identified four new presences as well as opportunities to expand the existing presences. The four new proposed presences were autonomy, emotional, instructor, and learning. Autonomy presence is defined as being different from cognitive presence because it relates to intrinsic motivation (Kozan & Caskurlu, 2018). Emotional presence has been identified in previous studies (e.g., Cleveland-Innes, 2019) as being different from social presence. It relates to the outward expression of emotion, affect, and feelings when learners interact with course content, learning technologies, other learners, and the instructor. Kozan and Caskurlu (2018) did not provide an explicit definition for instructor presence but insisted that it was related to an instructor's social behavior such as communication strategies and level of personability. Lastly, Kozan and Caskurlu (2018) defined learning presence as relating to the online learner's self-efficacy and self-regulation. In addition, Wertz (2022) had a similar presence named "learner presence" that relates to self-regulation and the psychological perspective of the learner. It should be noted that these criticisms are not definitive. Garrison has written extensively in response to them, contending that many of these suggestions violate the core premise of the shared role in each of the three CoI presences (e.g., Garrison, 2017; 2022).

The CoI Framework: Exploring Beyond the Diagram

Although these researchers may believe strongly that there are more presences, there is a growing amount of research that suggests the CoI framework is more complicated than illustrated by the widely accepted diagram (see Figure 1). The CoI framework has been displayed as a simple three-set Venn diagram with each circle representing a presence. The convergence of the three presences represents the educational experience in the center (Cleveland-Innes, 2019; Fiock, 2020; Stenbom, 2018). Then there are three overlapping areas in between each presence. The overlap of cognitive and teaching presences relates to regulating learning; the overlap of social and teaching presences relates to setting the climate for learning; and the overlap of cognitive and social presences relates to supporting discourse (Fiock, 2020: The Community of Inquiry, n.d.).

Dempsey and Zhang (2019) used survey results from graduate students to reevaluate the CoI framework and instrument and obtained an important insight that the CoI model is more complex than typically displayed. Each of the essential elements is multidimensional and hierarchical. In addition, Heliporn and Lakhal (2020) used the French-translated version of the CoI instrument to confirm the existence of 10 categories within the three essential elements as depicted in Table 1.

Table 1

Summary of Categories Within the CoI Framework

Presence	Category	Definition
Cognitive	Triggering event	"Some issue or problem has been identified for further inquiry" (Garrison & Arbaugh, 2007, p. 161).
	Exploration	"Students explore an issue, both individually and corporately through critical reflection and discourse" (Garrison & Arbaugh, 2007, p. 161).
	Integration	"Learners construct meaning from the ideas developed during exploration" (Garrison & Arbaugh, 2007, p. 161).
	Resolution	"Learners apply the newly gained knowledge to educational contexts or workplace settings" (Garrison & Arbaugh, 2007, p. 161).
Social	Affective communication	Learners develop social connections by sharing personal experiences (Garrison & Arbaugh, 2007).
	Open communication	Learners feel secure enough to interact and accomplish a common goal or purpose (Garrison & Arbaugh, 2007).
	Group cohesion	Learners have achieved a sense of camaraderie while being intellectually focused (Garrison & Arbaugh, 2007).

Teaching	Instructional design and organization	This role relates to making decisions about course planning and design; adjustments while the course is in progress; and interaction and evaluations procedures (Garrison & Arbaugh, 2007).
	Facilitating discourse	"This role is associated with sharing meaning, identifying areas of agreement and disagreement, and seeking to reach consensus and understanding" (Garrison & Arbaugh, 2007, p. 164).
	Direct instruction	"Responsibilities of the instructor … are to facilitate reflection and discourse by presenting content, using various means of assessment and feedback" (Garrison & Arbaugh, 2007, p. 164).

Cognitive presence contains four categories that occur in a cyclic, hierarchical order: a triggering event, exploration, integration, and resolution (Cleveland-Innes, 2019; Cooper & Scriven, 2017; Dempsey & Zhang, 2019; Garrison & Arbaugh, 2007; Kozan & Caskurlu, 2018; Martin et al., 2022; Sadaf et al., 2021). Social presence contains three categories: affective communication, open communication, and group cohesion (Cooper & Scriven, 2017; Dempsey & Zhang, 2019; Garrison & Arbaugh, 2007). Lastly, teaching presence contains three categories: instructional design and organization, facilitating discourse, and direct instruction (Dempsey & Zhang, 2019; Fiock et al., 2021; Garrison & Arbaugh, 2007).

If we compare the definitions of the four suggested emerging presences, we notice a familiar equivalent within the CoI framework. First, Kozan and Caskurlu's (2018) learning presence and Wertz's (2022) learner presence both relate to instructional design and organization. Learners can only self-regulate based on the design and organization of the course along with the actions of the instructor. For example, individual learning activities such as self-assessments have been identified as being intertwined with self-regulated learning and enhancing engagement (Yan, 2020; Yang et al., 2022).

Second, emotional presence depends on the learner, course, and content. Thus, we would place emotional presence within all three presences. Socially, learners can express emotions and develop relationships with other students as well as their instructors (Kozan & Caskurlu, 2018). Also, emotions can be incited from engagement with content and course design. Thus, it is important to keep in mind that learning often incites an emotional response as a learner participates in the learning process. Furthermore, this supports insights from Dempsey and Zhang (2019) who stated that future studies on the CoI framework need to consider how factors such as age, ethnicity, and online experience can impact survey results. Lastly, instructor presence most likely relates to the facilitation of discourse. Martin et al. (2020) classified social facilitation as a strategy used to encourage meaningful human relationships while modeling behaviors to help build community.

Opportunities Within the CoI Framework

Over the last two years, the COVID-19 pandemic has compelled more institutions of higher education to provide adult learners with greater access to online education. This shift has compelled Child et al. (2021) to believe that online education will eventually become the dominant delivery format in higher education. Kebritchi et al. (2017) considered online education to be critical to the future of higher education but noted there were major challenges and issues related to teaching online courses. Thus, three literature reviews were used to gain insights into how to incorporate assessment and evaluation strategies within the CoI framework so researchers could combine capturing educational experiences with measuring the effectiveness of reaching learning outcomes.

Between 1990 and 2015, a literature review was conducted on 104 peer-reviewed journals to identify issues and challenges with teaching online courses in higher education (Kebritchi et al., 2017). The results were grouped into three major categories: content, learners, and instructors. According to Kebritchi et al. (2017), content-related issues tend to correspond to content development such as adjusting course materials to an online environment, integration of multimedia in content, and the role of instructional strategies. Learner-related issues tend to relate to expectations, identity, mindset, and participation (Kebritchi et al., 2017). Lastly, instructor-related issues tend to focus on changing roles, time management, and teaching styles.

If we compare the results of this study with the CoI framework, the three major categorized challenges align with it. Challenges with content resemble cognitive presence, challenges with learners relate to components within social presence, and challenges to the shared role of instructing are connected to teaching presence. It is important to note that Kebritchi et al. (2017) discussed how institutional support of instructors, learners, and content developers had a critical role to play in enhancing the quality of online education.

Three years later, Caskurlu et al. (2021) conducted a thematic synthesis using literature published between January 2007 and August 2019 to explore the online learning experience of students by integrating primary findings to go beyond each individual study. The results revealed three overarching categories with 10 descriptive themes that relate to the CoI framework (Caskurlu et al., 2021). The overarching categories were course design that resembles aspects of cognitive presence, instructor actions that relate to categories in teaching presence, and student actions that correspond with social presence.

Lastly, Child et al. (2021) surveyed more than 30 academic research institutions and reported their practices and conducted ethnographic market research on 29 students in the United States and Brazil. The results revealed three overarching principles and eight key dimensions of an online learning experience. The three overarching principles were: (a) create a seamless journey (build an education road map and enable seamless connections); (b) adopt an engaging approach to teaching (offer a range of learning formats, ensure captivating experiences, use adaptive learning tools, and include real-world applications); and (c) create a caring network (provide academic and non-academic support and foster a strong community; Child et al., 2021). If we compare these three overarching principles to the CoI framework, the first principle relates to cognitive presence, the second to teaching presence, then the third to social presence.

Based on an analysis of the three literature reviews, each study was able to simplify its results into three categories that correspond with the essential elements in the CoI framework. Also, they align with previous research findings that show all three presences in the CoI framework need to be present and work together to create authentic and effective learning environments (Cooper & Scriven, 2017; Dempsey & Zhang, 2019). Therefore, using assessment and evaluation strategies that incorporate each of the major elements should provide insights into the effectiveness of a course.

Incorporating Assessment and Evaluation in the CoI Framework

Martin et al. (2019) conducted interviews involving eight award-winning faculty to construct a conceptual framework for online course design, assessment and evaluation, and facilitation. The results of this study indicated the use of a variety of online course assessments for students, with the faculty using student feedback surveys for evaluation. Also, Bin Mubayrik (2020) conducted a literature review of 22 peer-reviewed studies to discover new trends in adult education. The results indicated a new trend toward increased assessments while encouraging instructors of adults to use a wide variety of pre- and post-assessment tools to meet the needs of learners. Peer assessments were found to be most beneficial when feedback was presented as a learning opportunity (Day et al., 2017). Also, Stinnette and Luxbacher (2021) found implementing quizzes after each module to be effective for competency and knowledge retention.

Martin et al. (2022) reported cognitive presence as the least researched element in the CoI framework, but it is considered an important indicator of the quality of the online learning experience. Surprisingly, the literature revealed that the approach to online assessments differs from face-to-face course assessments. For example, there is a growing amount of research to support that online students are more willing to complete coursework if they are given a grade for it (Agnew et al., 2021). Day et al. (2017) reported that learners tend to exert more effort if they have something to gain such as bonus points or grades. Also, Bin Mubayrik (2020) encouraged faculty to break formative assessments into three cycles that allow students opportunities to receive immediate feedback and critical evaluations. Sadaf et al. (2021) advocated for the use of various instructional strategies to support high-level online learning such as article critique, collaborative learning, debate, reflection, and project-based learning. Other recommendations included online tutorials, small group discussions, and supportive learning communities (Kebritchi et al., 2017).

Conclusions

Although the CoI framework is a widely accepted theoretical framework in higher education, it is much more complex than the simplistic, traditional diagram would indicate on first examination. There is ongoing criticism about the validity of the three presences. However, several research studies have also shown three contributing factors that align with the CoI framework. Thus, we do not see the need to focus on the validity of the framework, because it has been examined quite extensively over the past two decades.

Additionally, many researchers might be unaware of or neglect to mention the categories within each of the three major elements. Ignoring the existence of the 10 categories (see Table 1) may lead to inaccurate results (Dempsey & Zhang, 2019). Within cognitive presences, there are four categories: a triggering event, exploration, integration, and resolution. Kozan and Caskurlu (2018) considered these categories as one of the best models of knowledge construction, being connected to both perceived and actual learning outcomes. Social presence consists of three categories: affective communication, open communication, and group cohesion. Within teaching presence, there are also three categories: facilitation of discourse, direct instruction, and instructional design and organization.

In conclusion, we do not believe anything should be added to the CoI framework. However, we believe future research should focus on using instructional strategies as well as assessment and evaluation methods that support each of the 10 categories. Stinnette and Luxbacher (2021) demonstrated that it is possible to measure course effectiveness by incorporating assessment and evaluation procedures. Therefore, a better understanding of how the categories function from an assessment and evaluation perspective may encourage researchers to focus on the effectiveness of courses while maintaining high-quality educational experiences.

At the center of the CoI framework is developing a positive, educational experience. *Education* means there is an institution or sponsor of the endeavor that has a significant stake in successful learning and teaching. The institution plays a critical role in enhancing quality (Kebritchi et al., 2017). This brings with it certain needs such as accreditation, financial obligations, and reputation. What we are saying is that using the CoI framework is not a goal itself but is one approach that is often used to engage participants in a larger educational system. Educational enterprises need to have learning outcomes that are effective, efficient, and appealing to the learner. Therefore, regardless of the teaching methods or approach taken, it is important to be mindful that they are part of a system where learning goals must integrate or align with real-world performance, and the teaching method(s) must be consistent with the goals, content, and evaluation of learning.

Limitations

The Community of Inquiry framework was chosen because of its longevity and robustness over the past two decades. There have been many dozens, or more, of published papers concerning the CoI. These include reports on research, literature reviews, and practitioner-oriented articles. We could not read all of them, let alone include them all in this paper. Our selection of literature to include was no doubt biased by our opinions and the point we tried to make herein. A separate set of papers may have led to a different opinion or conclusion.

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[i] Assessment is feedback from the student to the instructor about the student's learning. Evaluation uses methods and measures to judge student learning and understanding of the material for the purpose of grading and reporting. Evaluation is feedback from the instructor to the student about the student's learning. The basic difference between assessment and evaluation lies in the orientation. While assessment is process oriented, evaluation is product oriented (Alsaedi, 2021, p. 1104). Therefore, assessment and evaluation should not be used interchangeably because assessment is process-oriented, and evaluation is product-oriented.