American Journal of Distance Education

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/hajd20

Predicting Student Success in Online Physical Education

Tyler Goad, Emily Jones, Sean Bulger, David Daum, Nikki Hollett & Eloise Elliott

To cite this article: Tyler Goad, Emily Jones, Sean Bulger, David Daum, Nikki Hollett & Eloise Elliott (2021) Predicting Student Success in Online Physical Education, American Journal of Distance Education, 35:1, 17-32, DOI: 10.1080/08923647.2020.1829254

To link to this article: https://doi.org/10.1080/08923647.2020.1829254

Published online: 20 Oct 2020.

Submit your article to this journal

Article views: 792

View related articles

View Crossmark data

Citing articles: 10 View citing articles

Full Terms & Conditions of access and use can be found at
https://www.tandfonline.com/action/journalInformation?journalCode=hajd20

AMERICAN JOURNAL OF DISTANCE EDUCATION
2021, VOL. 35, NO. 1, 16–31
https://doi.org/10.1080/08923647.2020.1829254

Routledge
Taylor & Francis Group

Check for updates

Predicting Student Success in Online Physical Education

Tyler Goad[a], Emily Jones[b], Sean Bulger[c], David Daum[d], Nikki Hollett[e], and Eloise Elliott[c]

[a]Emporia State University; [b]Illinois State University; [c]West Virginia University; [d]San Jose State University; [e]University of Wisconsin-Whitewater

ABSTRACT

Currently, limited data are available on student retention rates and attrition factors in online physical education (OLPE) courses. Several early OLPE studies as well as the 2007 NASPE Initial Guidelines for Online Physical Education have suggested that certain prescreening efforts be in place prior to student enrollment in OLPE; however, at present no such empirically sound and theoretically based screening instruments exist. The purpose of the study is to identify online student cognitive characteristics and environmental factors associated with success and/or failure within college online health-related fitness (HRF) courses. Students (N = 821) enrolled in a 16-week online HRF course at a university during the Fall 2017 participated in the study. Data were collected at the beginning of the course with two previously validated research instruments, the Educational Success Prediction Instrument Version-2 (ESPRI-V2) and the Distance Learning Survey (DLS). Results reveled a relationship between course completion and six variables: GPA, class standing, hours worked outside of school, achievement, organization and study environment). The full model containing all predictors was statistically significant (χ 2 (6, N = 821) = 94.296, p <.001), indicating that the model was able to distinguish between students who completed and did not complete the online course. This analysis provides an initial understanding of the unique student characteristics affecting OLPE course completion.

Introduction

Distance education programs provide students the flexibility and access to education that may not be readily available otherwise. Distance education programs have become increasingly popular as institutions look to not only cut cost, but to also expand beyond their traditional regions without investing in brick and mortar operations (Saba, 2005). Recent estimates indicate 5.8 million high school students will enroll in online courses (Allen & Seaman, 2016). This upward trend is likely to continue as states such as Virginia, Alabama, Florida, Michigan, Idaho, New Mexico and Georgia enact legislation that mandates students complete an online course as a high school graduation requirement (Kennedy & Archambault, 2012; Rice & Yang, 2013). While online learning has been practiced for over two decades, the amount of research has not kept pace with its rapid expansion (Barbour, 2010; Rice, 2006). It has been suggested a next step for research in this K-12 field is greater examination between subject areas and educational contexts (Smith, Clark, & Blomeyer, 2005). However, not all disciplines have fully embraced online education.

CONTACT Tyler Goad tgoad@emporia.edu Health, Physical Education and Recreation, Emporia State University
© 2020 Taylor & Francis Group, LLC

Hesitancy to support online delivery within the physical education profession has been evident (Daum & Buschner, 2014). Physical education content primarily focuses on promoting healthy lifestyles through physical activity and the teaching of fundamental motor skills and movement patterns (Buchanan & Brock, 2016; Rink, 2013). Concerns within online physical education (OLPE) surround instruction, assessment, and accountability of physical activity completed by students (Daum & Buschner, 2012; Mohnsen, 2012; Society of Health and Physical Educators [SHAPE], 2007). Despite these concerns, OLPE is becoming more prevalent. According the 2016 SHAPE of the Nation Report, 31 states allow students to satisfy required physical education credits online, with the number of states that permit OLPE having increased by 11 since 2010.

In response to the emerging trend of OLPE in K-12 settings, national governing bodies such as SHAPE America established guidelines for OLPE. The 2007 SHAPE America *Initial Guidelines for Online Physical Education* offer suggestions OLPE course content, site management, instructional design, technology, and assessment. These guidelines are used to inform the OLPE program development and provide a framework for evaluating courses currently being delivered in K-12 and post-secondary settings alike. However, at the time of their formation, only a single peer-reviewed OLPE research study (Goc Karp & Woods, 2003) was available to inform the guidelines.

Although OLPE practices have expanded across the country since the 2007 SHAPE America Initial Guidelines for OLPE, research in the area remains limited. Initial studies provide a foundation for understanding the characteristics of OLPE stakeholders and highlight areas that warrant further investigation. Research in this area raises questions about course delivery, design, and instructional methods in relation to student learning and fitness gains (Daum, 2012; Daum & Buschner, 2012; Daum & Woods, 2015; Futrell, 2009; Goad & Jones, 2017; Goc Karp & Woods, 2003; Kane, 2004; Mosier, 2010; Mosier & Lynn, 2012; Williams, 2014). However, limited work within OLPE has focused program characteristics that accommodate learner needs and promote successful completion of OLPE courses in both K-12 and university settings.

Conceptual frameworks guiding online course design

Many Internet and web-based health behavior interventions are grounded in behavior change theories such as Self Determination Theory, Theory of Reasoned Action, Social Cognitive Theory, and account for the challenges associated with individual persistence and goal attainment, yet none account for the influence of administering the intervention online (Ritterband, Thorndike, Cox, Kovatchev, & Gondev-Frederick, 2009). The conceptual framework used to inform the current study is the Online Behavior Change Model, which was designed to help guide the development and explain health behavior change produced by Internet interventions. The Online Behavior Change Model provides a framework to develop and enhance online health-related fitness (HRF) courses by helping to conceptualize, identify, and measure factors affecting instructors (e.g., course design and delivery, mid-course adaptations) and students (e.g., persistence and successful course completion).

In 2012, Hilgart, Ritterband, Thorndike, and Kinzie proposed a reorganization of the Online Behavior Change Model into three process-oriented segments: 1) analysis, 2) evaluation, and 3) strategy to better guide and support the use of the Internet in the delivery of discipline-specific content (Hilgart, Ritterband, Thorndike, & Kinzie, 2012). Process models provide the needed balance between emerging technologies, curriculum, learner support, and student characteristics. Online course components such as appearance, content delivery, student use, and support represent variables that can be responsive and influenced by student and environmental characteristics (Ritterband et al., 2009). The reorganization provides a theoretical-based approach for identifying and targeting factors contributing to student persistence, attrition, and drop out, specifically related to user and environmental factors.

Ritterband et al. (2009) describe user characteristics (i.e. gender, age, ethnicity, etc.) as fixed; however, we posit they can still be influenced by environmental factors such as family, friends, employer, school, or societal-level influences such as social media, policy, and other cultural factors. These environmental factors can then affect website use and student persistence through an online course. Instructional frameworks that account for the impact of the Internet on variables such as user characteristics and environmental factors can help guide OLPE programs better accommodate and respond to the needs of the modern student. The current study focuses on the *analysis* segment of the framework and examines user and environmental characteristics that may help predict student success and persistence within OLPE courses.

Examining barriers to student success in online learning assist in the development of early warning systems for OLPE programs. Currently, data are limited in the area of student retention and attrition rates in OLPE. Mosier's 2010 investigation of the K-12 Florida virtual schools (FLVS) OLPE program offered insight to student demographic data such as age, gender, ethnicity, GPA, reasons for enrolling, and completion rates. The study found that 52% of students were designated as completers (n = 10,333), 40% non-completers /never activated/no grade (n = 8,054), and 8% non-completers, who withdrew or failed the course (n = 1,557). Moiser's findings did not provide explanations of factors that contributed to student completion. In fact, very few studies have explored the potential factors associated with retention and attrition in OLPE. While Ransdell et al (2008) suggested program quality was a primary factor linked to student dropout, others have attributed dropout rates in online physical activity courses to lack of support, poorly designed courses, and inexperienced and/or incompetent instructors (Brewer, 2001).

Despite the growing body of knowledge in online student success and retention, attrition rates still pose a significant problem to distance education programs (Alem, Plaisent, Bernard, & Chitu, 2014; Hart, 2012; Simpson, 2013). Intervention strategies relating to online course delivery, faculty interventions and advisement have been shown to be increasingly effective. However, factors associated with the learner and learning environment must also be identified and better understood to effectively support at-risk students these through intervention strategies (Hilgart et al., 2012; Ritterband et al., 2009).

Identifying factors that influence student completion or non-completion in OLPE courses would provide valuable information for students, academic advisors, online instructors, instructional designers, and K-12 and post-secondary administrators. Equipped with the knowledge of factors that associate with and may predict student completion or non-completion can assist OLPE stakeholders make more informed decisions related to necessary supports, strategies, tools, course design, pacing, and communication tactics (Roblyer, Davis, Mills, Marshall, & Pape, 2008). Scholars have called for empirical and theoretical research to identify predictive factors of success in online learning (Alem et al., 2014). Similar work is needed in OLPE. This would allow for a deeper understanding of the support, design, and delivery strategies needed in OLPE to facilitate student success.

The purpose of the study was to identify student characteristics and environmental factors associated with success and/or failure within OLPE courses. Four research questions guided the study: (1) To what extent do student cognitive characteristics influence success in a university-level OLPE course? (2) To what extent do student demographics influence course completion in a university-level OLPE course? (3) To what extent do student environmental characteristics influence course completion in a university-level OLPE course? (4) What combination of student cognitive characteristics, environmental characteristics, and demographics produce a model that best predicts course completion in university-level OLPE courses?

Methods

Participants and setting

Students (n = 862) enrolled in a 16-week OLPE course at a university in the southeast region of the United States during the Fall 2017 semester were invited to participate in the study. The university was selected as the site of the study due to their implementation and development of model OLPE courses grounded in the Appropriate Instructional Practice Guidelines for Higher Education Physical Activity Programs (Melton, Russell, Moore, & Sweeney, 2009; Russell, Wadsworth, Hastie, & Rudisill, 2014). The asynchronous online course is designed to expose students to the basic concepts associated with the development and maintenance of physical activity. Instructors of the OLPE course are graduate assistants trained by the program coordinator on the proper procedures of delivering the course. Specifically, the pre-course orientation focuses on effective instructional technology use and online pedagogy (Russell et al., 2014). Instructors of the OLPE course are primarily responsible for maintaining gradebooks and communicating with the students (Brock, Wadsworth, Hollett, & Rudisill, 2016). The course delivery, presentation of content, assessment and grading are standardized across all sections of the OLPE courses. Quizzes and fitness tracking goals were automatically assessed by the institutional learning management system.

Survey instruments

To address the research questions, two validated research instruments founded in models of attrition and retention to identify factors influencing the success and failure in online learning environments were used, the ESPRI Version-2 (Roblyer et al., 2008) and the Distance Learning Survey (DLS; Osborn, 2001). Instruments such as the ESPRI-V2 and DLS have been used to identify the potentially successful and at-risk students who enroll in online courses (Osborn, 2001; Roblyer et al., 2008). The survey instruments define student success as ʻone who completes a course with a passing grade and failure as either non-completion or completion with a failing grade. For the purposes of the current study the pass/fail criteria were defined as: students completing the course with a grade of A, B, or C were designated as completers (i.e. passing); students who withdrawal (W), drop (I), or complete the course with a grade of D or F were identified as non-completers.

The ESPRI-V2 is a 23-item survey that consisting of four cognitive factors: (1) technology use/self-efficacy, (2) achievement beliefs/locus of control, (3) instructional risk-taking, and (4) organization strategies. Within each construct, respondents indicate their level of agreement (strongly disagree 1 – strongly agree 7). The ESPRI-V2 was found to have a high level of internal consistency (Cronbach alpha = 0.92) among its four factors (Roblyer et al., 2008). While the ESPRI-V2 addresses student cognitive characteristics, the survey items associated with those factors pertain to the high school aged population and did not account for concerns relevant to those enrolled in post-secondary education; therefore, Osborn's (2001) DLS was used to address student environmental and demographic characteristics as items within each construct focus on college and university-age population. High internal consistency of the DLS (Cronbach alpha = 0.90) has been reported among the factors measured (Osborn, 2001).

The two surveys were pilot tested with four sections of the OLPE course during the Summer 2017 term. Minor edits were made to survey questions and protocol instructions as a result of the pilot study. For the current study, the single-item predictor variables as well as the financial support and study environment factors relating to a collegiate population from each of the two instruments – Roblyer's et al. (2002, 2008) ESPRI-V2 and Osborn's (2001) DLS – are outlined in Table 1.

The survey items were built into the learning management system (LMS) course shell for all OLPE course section to be completed as a pre-course task. Students had two weeks at the beginning of the term to respond to the Pre-semester survey that took approximately 15 minutes to complete. Data from the surveys were automatically collected in the institution LMS grade recording tool. Student responses were exported from the LMS as a Microsoft Excel file, de-identified, and assigned a research code by a person uninvolved in the research to ensure participant anonymity. Incomplete and duplicate survey responses were removed from the final data set before data were inputted into SPSS version 21.

Data analysis

To examine the relationship between each of the independent variables (cognitive, environmental, and demographic factors) to the dependent variables (online course completion and non-completion) different bivariate statistical methods were employed (Table 2). For scaled data, a one-way analysis of variance (ANOVA) comparing the mean scores for each of the ESPRI-V2 and DSL cognitive factors to the dependent variable were used. For the categorical data (i.e., student demographic and environmental factors), a Pearson's Chi-Square test was performed.

Table 1. Description of factors and examples of the survey instruments.

Factor	Number of Items	Factor Description
[a]Technology Skills/Self-efficacy	6	Computer skill and access technology.
[a]Achievement beliefs	6	Belief in oneself and in one's ability to achieve.
[a]Instructional risk-taking	6	Taking responsibility for one's actions and taking individual initiative.
[a]Organization	5	Ability to approach tasks in an organized and goal-oriented way.
[b]Study Environment	7	Perception of the environment, including physical space and time.
[b]Demograhpics	5	Age, Gender, Ethnicity, Class standing, and self-reported GPA

[a]Factors and items from ESPRI-V2 (Roblyer et al. (2008)
[b]Factors and items from DLS (Osborn, 2001)

Table 2. Overview of analysis.

Research Question	Independent Variable(s) (Instrument)	Dependent Variable	Analysis
RQ 1	Cognitive Factors: (ESPRI-V2)	*Course completion status	ANOVA
RQ 2	Demographics: Age, Gender, Ethnicity, Class standing, and self-reported GPA (DLS)	*Course completion status	Descriptive statistics, frequency distribution, and Pearson's Chi Square test
RQ 3	Environment: Course load, Previous online course experience, Type of student, Hours of work outside of school, and Financial stability (DLS)	*Course completion status	Descriptive statistics, frequency distribution, and Pearson's Chi Square test
RQ 4	Cognitive Characteristics (ESPRI-V2) Demographics (DLS) Environment (DLS)	*Course completion status	Binary logistic regression

*Course completion status: Students completing the course with a grade of A, B, or C will be designated as successful (i.e. passing); students who withdrawal (W), drop (I), or complete the course with a grade of D or F will be identified as unsuccessful (i.e. failing).

Replicating the Roblyer et al. (2008) data analysis methodology, the use of a logistic regression was employed to determine if cognitive, environmental, and demographic variables could be combined to create a model to better predict student success in online PE courses. Significant factors derived from the above analysis were used as predictors in a binary logistic regression with course completion status as the dependent variable (completers = 1, non-completers = 0). From the bivariate analyses computed for the demographic and environmental categorical variables, the following were used in the logistic regression; GPA (0 = 2.6–4.0, 1 = 0–2.5), class standing (0 = sophomore/junior/senior, 1 = freshmen), hours worked outside of school (0 = 1–20, 1 = 21–40+) and with 3 cognitive factors (achievement beliefs, organization, and study environment) as independent variables. For the interpretability of the model based on an overall test of parameters, categorical data from the inventory were grouped for the purposes of visibility between the dichotomous outcome of completers and non-completers (Tabachnick & Fidell, 2014). Although the sample sizes are not equally distributed, they do reflect the true difference in the various types of students at the university. For example, it is unlikely that the results from the student population here – 85.7% White, 96% between ages of 18–23, with a relatively high completion rate – are transferable to a distance education program with a more diverse population of students and/or higher non-completion rate. However, consistent with the purpose of the current study: to identify at-risk students in OLPE courses and, thus, allow faculty and administrators to give appropriate assistance to these students the categorical data were grouped for visibility with respects the demographic make-up of the university. Various combinations of student demographic, environmental, and cognitive factors were inputted into a logistic regression to determine the optimal model to predict student course completion or non-completion.

Results

Of the 862 students enrolled in the OLPE course, 821 completed the ESPRI-V2 and DLS for a response rate of 95%. Of the total sample of students (N = 821) responding to the surveys, 634 were identified as completers (male = 238, female = 396) and 187 as non-completers (male = 77, female = 110). The majority of students were White/Caucasian (85.7%) between

Table 3. Comparison of student demographics between completers and non-completers.

	Completer		Non-Completer		Total	
Factor	n	%	n	%	n	%
Age						
18–23	610	77.4	178	22.6	788	96
23–40+	24	72.7	9	27.3	33	4
Gender						
Male	396	78.3	110	21.7	506	61.6
Female	238	75.6	77	24.4	315	38.4
Ethnicity						
Non-Minority	547	77.7	157	22.3	704	85.7
Minority	87	74.4	30	25.6	117	14.3
*Class Standing						
Upper-Classmen	509	78.9	136	21.1	645	78.6
Freshmen	125	71	51	29	176	21.4
*GPA						
2.6–4.0	572	81.6	129	18.4	701	85.4
0–2.59	62	51.7	58	48.3	121	14.6

*Pearson Chi-Square Results p <.05

the ages of 18–23 (96%). A Pearson's Chi-Square analysis revealed no significant differences between completers and non-completers in relation to the demographic factors of age, gender, and ethnicity (Table 3). However, significant effects for class standing (χ^2 (1, N = 821) = 4.90, p = .027) were found, indicating that completers were more likely to be upperclassmen. It was also found that completers (χ^2 (1, N = 821) = 52.19, p = .000) were generally above a 2.6 GPA.

Again, a Pearson Chi-Square analysis was employed for a comparison of student environmental factors between completers and non-completers. The analysis found no significant differences between the two groups in relation to course load, financial situation, or whether the student lived on or off-campus (Table 4). A significant difference between the two groups number of hours worked outside of school (HWOS) was found (χ^2 (1, N = 821) = 15.99, p = .000). Students were more likely to complete the online HRF course if they worked no more than 20 hours outside of school. It was also found that there were differences between the completers and non-completers previous online course experience (χ^2 (3, N = 821) = 10.08, p = .018). The most pronounced difference was found between completers and non-completers with no prior online course experience.

An ANOVA was employed to compare completers and non-completers mean scores for each ESPRI-V2 and DLS cognitive factors (i.e. study environment). No statistically significant difference was found between completers and non-completers mean scores for instructional risk-taking and technology skills/self-efficacy. Both completers and non-completers rated themselves highly in technology skills/self-efficacy and low in instructional risk-taking. However, a significant difference was observed between the two groups mean scores for achievement beliefs (F(1, 819) = 17.35, p = .000), organization (F(1, 819) = 27.53, p = .000), and study environment (F(1, 819) = 20.60, p = .000). Those who completed the online HRF course rated themselves higher in study environment, organization, and achievement beliefs than those who did not complete the course.

A direct binary logistic regression was performed to assess the impact of significant factors from the previous analysis on the likelihood that student would complete or not complete an online HRF course. The model contained six independent variables (GPA, class standing, hours worked outside of school, achievement, organization, and study environment). The full model containing all predictors was statistically significant (χ^2 (6,

Table 4. Comparison of student environmental factors between completers and non-completers.

	Completer		Non-Completer		Total	
Factor	n	%	n	%	n	%
Course Load						
1–4 Courses	119	73.5	43	26.5	162	19.7
5+ Courses	515	78.1	144	21.9	659	80.3
*Online Experience						
0 Courses	8	50	8	50	16	1.9
1–2 Courses	478	78.7	129	21.3	607	73.9
3–4 Courses	117	77	35	23	152	18.5
5+ Courses	32	67.4	15	32.6	46	5.6
Type of Student						
Distance Learner	292	75.6	94	24.4	386	47
On Campus	342	78.6	93	21.4	435	53
*HWOS						
1–20 Hours	549	79.8	139	20.2	688	83.8
21–40+ Hours	85	63.9	48	36.1	133	16.2
Financial Dependents						
Yes	27	69.2	12	30.8	39	4.8
No	607	77.2	175	21.3	782	95.2
Financial Aid						
Parents	333	76.6	102	23.4	435	53
Scholarship/Grant	173	82	38	18	211	25.7
Self-pay/Loan	89	71.8	35	28.2	124	15.1
Other	39	76.5	12	23.5	51	6.2
Financial Stability						
Confident	548	77.8	156	22.2	704	85.7
Uncertain	86	73.5	31	26.5	117	14.3

*Pearson Chi-Square Results p <.05

N = 821) = 94.296, $p < .001$), indicating that the model was able to distinguish between students who completed and did not complete the online HRF course. For the present logistic regression model, the C-statistic 0.727 represents the goodness of fit as measured by the area under the Receiver Operating Characteristic (ROC) curve. The ROC curve ranges from .5 to 1 demonstrating the predictive accuracy of a logistic regression model (Peng, Lee, & Ingersoll, 2002). A value of .5 and below indicates a very poor model, meaning that the model is no better than predicting an outcome than random chance (Peng et al., 2002). A value of 1 means that the model assigns higher probabilities to all the observed data in the model correctly. For the current studies model, this means for 72.7% of all possible pairs of students – one completer and one non-completer – the model assigned a higher probability to those who completed the online HRF course. As shown in Table 5, only four of the independent variables made a unique statistically significant contribution to the model: (1) GPA, (2) Class Standing, (3) Hours Worked Outside of School and (4) Organization. The strongest predictor of online HRF course completion was 2.6–4.0 GPA, recording an odds ratio of 3.96. This indicated that students who entered the course with a GPA above a 2.6 were almost 4 times more likely to complete an online HRF course than those who entered with a lower GPA, controlling for all other factors in the model.

Discussion

The purpose of this study was to identify online student characteristics and environmental factors associated with success and/or failure within online HRF courses. By analyzing profiles of completer and non-completers of a university-level OLPE course, factors

Table 5. Direct binary logistic regression predicting student success.

Predictor	B	SE	Wald	P	Odds Ratio	95% CI for Odds Ratio	
						Lower	Upper
GPA	1.385	.224	38.186	.000*	3.994	2.574	6.196
Class Standing	.789	.219	13.313	.000*	2.221	1.447	3.409
HWOS	.588	.230	6.533	.011*	1.800	1.147	2.825
Online Experience			7.707	.052			
0 Courses	−.286	.652	.192	.611	.752	.209	2.699
1–2 Courses	.753	.753	4.415	.036	2.123	1.052	4.285
3–4 Courses	.534	.394	1.844	.174	1.706	.789	3.691
Achievement	.023	.021	1.133	.287	1.023	.981	1.067
Organization	.066	.025	6.965	.008*	1.068	1.017	1.122
Study Environment	.071	.040	3.194	.074	1.074	.993	1.162
(Constant)	−5.256	.874	36.158	.000	.005		
Model Summary							
Final Step	−2 Log likelihood			C-Statistic		Asymptotic 95% CI	
	779.346			.727		.685	.770

*Direct Logistic Regression Results *p* <.05

associated with the learner and the learning environment can assist in future predictions of persistence and attrition. The aim of screening tools like the ESPRI-V2 and DLS is not to exclude students from enrolling in OLPE courses, rather to gain insights to help inform the design and implementation of evidence-based interventions. The discussion of study findings has been organized around the three analysis phase variables of the Instructional Design Process for the Online Behavior Change Model: *learners, learning context*, and the implications to support students at-risk of not completing *learning task/goal*.

Learners

Similar to previous findings, the current study did not find learner characteristics of age, gender, and ethnicity to be significantly different between completers and non-completers (Lee & Choi, 2011; Park, Boman, Care, Edwards, & Perry, 2008; Willging & Johnson, 2009). While these learner traits have been found to be moderators in some cases (Fryer & Bovee, 2016; Osborn, 2001; Xu & Jaggars; 2014), Roblyer et al (2008) assert that it is unlikely these non-malleable factors (e.g. age, gender and ethnicity) alone would predict completion or non-completion of an online course. To date, no consensus has been met among researchers on the importance of a student's age, gender, and ethnicity upon entry to the online course in predicting student success (Alem et al., 2014).

Consistent with previous research, the results of this study found a significant difference between completers' GPA and class standing (Hart, 2012; Osborn, 2001; Rankin, 2013; Roblyer et al., 2008). In the current study, students with a cumulative GPA above 2.6 were four times more likely to complete the online HRF course. Hart (2012) postulated that students with a higher GPA have adopted successful behaviors that allow them to better maneuver online course work. Differences between completers and non-completers to cognitive characteristics survey factors support Hart's (2012) contention. In the current study, a significant difference was found between completers and non-completers on achievement beliefs and organization, with completers rating themselves higher in each of these categories. The highly autonomous and asynchronous format of the OLPE course could have benefited students who perceive themselves to possess high achievement beliefs and organization skills, while creating an obstacle for those students who do not. This could be especially true if those students adhered to the common misconceptions that online courses are not as rigorous as face-to-face courses and take less time to complete (Williams, 2015).

Class standing was also found to be significantly different between completers and non-completers. OLPE students were over two times more likely to complete the course if they entered the course as a sophomore, junior or senior. Mosier's (2010) study examining high school students enrolled in online HRF courses within the Florida Virtual Schools found similar, statistically significant results regarding class standing and course completion. Specifically, Moiser found that 59% of seniors (n = 5,512) completed the online HRF course in comparison to 44% of freshman (n = 704) students (2010). Moiser speculated that a student's proximity to graduation might contribute to the differences observed in course completion rates; that is, upper-level students could have been more motivated to enroll in the online course to fulfill graduation requirements while underclassmen could have chosen the course based on personal preferences (Mosier, 2010).

Additionally, in the current study the influence of class standing in course completion could have been attributed to a student's lack of prior exposure and use of the institutions' LMS, Wellness Dashboard, and fitness tracker used within the OLPE course. Because the data were gathered in the Fall 2017 means that enrolled freshmen could have been interacting with the specific software and hardware required for the OLPE course for the first time. It stands to reason that tapping into student's previous experience with course-specific software and hardware is worth exploring due to freshman completion rates being significantly different from upperclassmen. It is possible that freshman in this study did not have previous experience navigating the specific software and hardware employed by the OLPE course which could have attributed to the discrepancies between class standing and course completion, as opposed to their general experience with online courses alone.

Findings related to cognitive characteristics appear to support this notion as well. Contrary to previous research (Hayatt, 2015; Osborn, 2001; Rankin, 2013; Roblyer, Blomeyer & Rankin-Reed, 2006; Roblyer et al., 2008), this study found no significant difference between completers' and non-completers' instructional risk-taking and technology skills/self-efficacy. Specifically, in the field of OLPE students' difficulty navigating technology has often been cited as a negative contributing factor (Brewer, 2001; Futrell, 2009; Goc Karp & Woods, 2003; Kane, 2004). Daum and Buschner (2014) point out, "It is easy to wonder how many of the issues the teacher and students faced in [Goc] Karp and Woods (2003) and Kane's (2004) studies were due to the technology of the time … " (p. 209). Yet, studies that are more recent have pointed to similar instances where students did not persist to completion in OLPE (Daum & Buschner, 2012; Williams, 2014).

In the current study, both completers and non-completers rated themselves highly in technology skill/ability. Instructors of online HRF courses are now teaching a generation of students, often referred to as "digital natives" who have never known a life without computers, mobile devices, and the Internet (SHAPE, 2007). Most recently, Trent's (2016) descriptive overview of an OLPE course in Georgia found that over 90% of students surveyed indicated they knew how to use the Internet, audio, video, presentation, and word processing software. However, personal technology use does not equate to a student's ability to use technology for learning. Similar thoughts have been expressed by PETE instructors in regard to their students, who they perceive as having a limited functional skillset and generally a superficial understanding of technology's role in instruction (Daum, 2012; Goad & Jones, 2017). Again, it may be more appropriate in future studies to adjust technology self-efficacy/skills screening questions to reflect the specific hardware and software used throughout the course rather than focusing on a student's self-beliefs of their general proficiencies.

Learning environment

The design of learning environments within online courses has been found to influence student success (Rice, 2006). Hilgart et al. (2012) define the learning environment as the context in which the instruction will take place, specifically focusing on three domains – physical, social, and institutional. The physical domain refers to the environment where the learner will complete tasks; the social reflects interactions with others, such as peers and influential networks (e.g. family, friends, employer, etc.); and institutional considerations relate to the goals and views held by the organization offering the course. Researchers posit that by examining these three environmental domains, one can construct a snapshot of how a student's willingness and ability to persist through an online course is influenced (Hilgart et al., 2012). The physical components of an online course such as appearance, content delivery, student use, and support have the potential to be responsive to student and environmental characteristics (Ritterband et al., 2009). Ritterband et al. (2009) describe user characteristics (i.e. gender, age, ethnicity, etc.) as fixed, however, influenced by environmental and societal-level factors including but not limited to friends and family, finances, employer, school, social media, policy, cultural norms, etc. These environmental factors have been seen to affect student website use and persistence through online courses (Hart, 2012; Ivankova & Stick, 2005; Osborn, 2001; Xu & Jaggers, 2014). To better understand the impact of these variables on enrolled students, needs assessments can inform online course designers and instructors in selecting relevant motivation, learning, and instructional theories to leverage environmental factors to meet course objectives.

Contrary to previous online student success research, the current study found no significant difference between completers and non-completers regarding course load, type of student, and financial dependents/aid/stability (Hart, 2012; Ivankova & Stick, 2005; Osborn, 2001; Xu & Jaggars, 2014). However, a significant difference between completers and non-completers was reported for hours worked outside of school. Students who worked 20 hours or less outside of school were nearly two times more likely to complete to course. Hart (2012) referred to factors such as hours worked outside of school (HWOS) as "non-academic issues" that present unique barriers to student success. For example, Shin and Kim (1999) examined the relationship among learner background characteristics and course success through a path analysis that revealed an interrelationship among GPA and job load (i.e. HWOS). Demonstrating how "non-academic issues" can affect a student's academic performance. Additionally, research has found statistically significant differences in the amount of time spent engaged in course activities (e.g. time spent viewing content, reading/responding to posts, etc.) between completers and non-completers of online courses (Foon Hew, 2016; Hart, 2012; Shelton, Hung, & Lowenthal, 2017). In the current study, it is possible that the amount of HWOS affected some student's ability to access and actively engaged in course content.

Implications for learning goals and tasks

When applying the IDT Behavior Change Framework, Hilgart et al. (2012) describe the Analysis Phase as finding the gaps between "what is" and "what should be." The use of the ESPRI-V2 (Roblyer et al., 2008) and DLS (Osborn, 2001) in the current study, served to analyze the possible gaps between students who persisted to complete the online PE course and those who did not. By identifying the gaps between ideal performance and reality, the causes of those gaps can begin to be quantified. The results of the study revealed that upon course entry, students who did not complete the course generally reported a combination of the following factors: GPA below 2.6, worked more than 20 hours outside of school, freshmen in class standing, and perceived themselves to possess weak organizational beliefs.

Given the results of previous research possible remediation strategies for students who fit the above profile could benefit from early identification and pre-course orientation modules. Roblyer, Blomeyer and Rankin-Reed (2006) suggest pre-course orientation sessions for students that focus on goal-orientation and self-management strategies. Ideally, pre-course orientations that utilize stories or scenarios that illustrate subject matter content and are designed with scaffolded learning opportunities encouraging goal setting, planning, and reflection (Roblyer et al., 2006). The objectives of these pre-course intervention strategies align with findings from research examining self-regulated learning strategies on online student success (Broadbent, 2017; Hart, 2012; Hyatt, 2015). Broadbent (2017) found that time management and effort regulation strategies emphasizing scheduling, planning, self-management, and effort during study time were found to positively influence online student grades. This aligns with Hyatt's (2015) findings that suggest successful students reported the use of self-awareness, self-efficacy, and goal setting strategies to stay motivated throughout online courses. For example, teaching students to use an agenda for weekly planning, prioritizing tasks, and creating short, medium, and long-term plans could foster self-management skills in at-risk students.

Non-academic issues should also be considered in designing support strategies for online students. Research has shown a significant difference between completers and non-completers of online course in the amount of time spent engaged in course activities (Foon Hew, 2016; Hart, 2012; Shelton et al., 2017). To encourage students to engage more frequently with online course materials and peers, it has been suggested that, when possible, course content be made personally relevant and easily accessible to students (Foon Hew, 2016; Shelton et al., 2017). For students who work more than 20 hours outside of school, mobile learning strategies could make the course more accessible, meet the demands of their schedule, and provide individualized content.

While previous success and retention studies have focused on the influences of non-malleable traits such as demographics and cognitive style, Roblyer et al. (2008) and Osborn's (2001) studies hypothesized that online success was a function of various factors, at least some of which could be modified with pre-course orientation and course design/delivery methods. Findings from previous studies indicate that a combination of student factors and learning conditions can predict online student success, though predicting success will probably be much easier than predicting failure. Results from the current study provide insight into potential differences between ideal student performance and attrition in an

OLPE setting. This information can be used to better inform the design, delivery, and development of programs to support student success in online HRF courses.

Limitations

Limitations of this study included student self-reporting procedures and the generalizability of results. Discipline-specific factors related to online student motivation to exercise were incomplete due to the distribution of surveys at the midterm. Many non-completers who filled out the pre-course ESPRI-V2 and DSL surveys did not complete the midterm survey, diluting the sample size. Group size relations between completers and non-completers affected the variability between some environmental and demographic categorical data, which may have contributed to not finding a significant relationship between variables when statistical methods were applied. This affected the study's ability to find meaningful significant relationships between completers and non-completers. For example, of the 821 students who completed the survey only 16 reported no prior online course experience. Additionally, the pass rate was 77.47% with 185 students not completing the online HRF course. It is possible that this level of group variability increased the probability of a Type II error for factors that indicated no level of significance due to a low number of non-completers results.

Lastly, results from the study are not generalizable to other OLPE courses due to the unique context of the university programs. It seems likely that a set of factors specific to an institution's population must be generated to calculate meaningful probability of passing scores for online students. However, the use of the screening instruments used in the current study can be replicated at another site to identify relevant student demographic and environmental factors.

Future directions

There is considerable diversity in online student success literature about the factors influencing student completion and non-completion (Alem et al., 2014; Hart, 2012). Studies have shown that factors included in the ESPRI-V2 and DSL play a role in identifying successful and unsuccessful students. However, no one set of characteristics or factors have emerged as dominant due to a lack of replication studies, measurement of different student populations, and disciplines. The focus of future research should examine the application and impact intervention strategies have in relation to supporting student success.

While it is beyond the scope of the current study to determine at what point the non-completing students withdrew from the course, future research should consider when student dropout occurs. Research has shown that students who withdraw tend to disengage from online courses within the first few weeks, usually before the first exam is scheduled or major assignment due (Murphy & Stewart, 2017; Simpson, 2013). Additionally, research has found significant differences in the amount of time spent engaged in online course activities (e.g. time spent viewing content, reading/responding to posts, etc.) between completers and non-completers (Foon Hew, 2016; Hart, 2012; Shelton et al., 2017). It would appear from these recent studies that online course dropout occurs in the first few weeks and is associated with the frequency that student engage in the course. This would suggest that online instructors should closely monitor the rate at which students are engaged in the course at the beginning of the term and contact those who are not.

Furthermore, students who disengage early from course work have also been found to be those who are repeating the course (Murphy & Stewart, 2017). This also appears to be the case in OLPE, Moiser (2010) found that only 34% of students who were non-completers in previous semesters completed the OLPE course. Students who are repeating online HRF courses should be identified by advisement and retention specialist at enrollment. At a minimum this information should be communicated to the instructor so that student repeating the online HRF course can be closely monitored at the beginning of the term. Support strategies and early monitoring of online student engagement may help facilitate course completion. Future research would benefit from examining this predominately at-risk population of students to better understand the characteristics and factors affecting student who does not complete an online course.

ORCID

Emily Jones http://orcid.org/0000-0002-3319-1267

References

Alem, F., Plaisent, M., Bernard, P., & Chitu, O. (2014). Student online readiness assessment tools: A systematic review approach. *The Electronic Journal of e-Learning*, *12*(4), 375–382.

Allen, E., & Seaman, J. (2016). Online report card tracking online education in the United States. MA. *Sloan Center for Online Education*.

Barbour, M. (2010). Researching K-12 online learning: What do we know and what should we examine? *Distance Learning*, *7*(2), 7–12.

Brewer, J. D. (2001). *The impact of a web-based versus face-to-face instructional format of a lifetime fitness course on students' wellness knowledge, attitudes and behaviors and levels of health-related physical fitness* [3019351 Ph.D.]. Kansas State University.

Broadbent, J. (2017). Comparing online and blended learner's self-regulated learning strategies and academic performance. *The Internet and Higher Education*, *33*, 24–32. doi:10.1016/j.iheduc.2017.01.004

Brock, S., Wadsworth, D., Hollett, N., & Rudisill, M. (2016). Using moving technology to support online learning: An effective approach to maximizing resources in kinesiology. *Kinesiology Review*, *5*(4), 289–294. doi:10.1123/kr.2016-0028

Buchanan, A. M., & Brock, S. (2016). What if they see me miss? Nuances of teaching in a movement-based environment. *Strategies*, *29*(3), 16–20. doi:10.1080/08924562.2016.1159154

Daum, D. N. (2012). *Physical education teacher educator's attitudes toward and understanding of online physical education* [3570649 Ph.D.]. University of Illinois at Urbana-Champaign.

Daum, D. N., & Buschner, C. (2012). The status of high school online physical education in the United States. *Journal of Teaching in Physical Education*, *31*(1), 86–100. doi:10.1123/jtpe.31.1.86

Daum, D. N., & Buschner, C. (2014). Research on teaching blended and online physical education. In R. Ferdig & K. Kennedy (Eds.), *Handbook of research on K-12 online and blended learning* (pp. 201–221). Pittsburgh, PA: ETC Press.

Daum, D. N., & Woods, A. M. (2015). Physical education teacher educator's perceptions toward and understanding of K-12 online physical education. *Journal of Teaching in Physical Education*, *34*(4), 716–724. doi:10.1123/jtpe.2014-0146

Foon Hew, K. (2016). Promoting engagement in online courses: What strategies can we learn from three highly rated MOOCS. *British Journal of Educational Technology*, *47*(2), 320–341. doi:10.1111/bjet.12235

Fryer, L. K., & Bovee, H. N. (2016). Supporting students' motivation for e-learning: Teachers matter on and offline. *The Internet and Higher Education*, *30*, 21–29. doi:10.1016/j.iheduc.2016.03.003

Futrell, J. (2009). *A comparative study of virtual high school instruction versus traditional instruction of high school student outcomes and attitudes in physical education* [3360073 Ph.D.]. Capella University.

Goad, T., & Jones, E. (2017). Training online physical educators: A phenomenological case study. *Education Research International*, *2017*, 12. doi:10.1155/2017/3757489

Goc Karp, G., & Woods, M. L. (2003). Wellness NutriFit online learning in physical education for high school students. *The Journal of Interactive Online Learning*, *2*, 2.

Hart, C. (2012). Factors associated with student persistence in an online program of study: A review of the literature. *Journal of Interactive Online Learning*, *11*(1), 19–42.

Hayatt, S. (2015). Motivating and retaining online students: Research based strategies that work. *Journal of College Student Retention Research Theory and Practice*, *19*, 1.

Hilgart, M. M., Ritterband, L. M., Thorndike, F. P., & Kinzie, M. B. (2012). Using instructional design process to improve design and development of Internet interventions. *Journal of Medical Internet Research*, *14*(3), 3. doi:10.2196/jmir.1890

Ivankova, N., & Stick, S. (2005). Collegiality and community - Building as a means for sustaining student persistence in the computer - Mediated asynchronous learning environment. *Online Journal of Distance Learning Administration*, *8*, 3.

Kane, J. (2004). The dog ate my disk: Teacher and student perspectives of an online personal fitness course. *Florida Alliance for Health, Physical Education, Recreation, Dance & Sport*, *42*(2), 8–12.

Kennedy, K., & Archambault, L. (2012). Offering preservice teachers field experiences in K-12 online learning- A national survey of teacher education programs. *Journal of Teacher Education*, *63*, 3.

Lee, Y., & Choi, J. (2011). A review of online course dropout research: Implications for practice and future research. *Educational Technology Research & Development*, *59*(5), 593–618. doi:10.1007/s11423-010-9177-y

Melton, B., Russell, J., Moore, C., & Sweeney, M. (2009). *Appropriate instructional practice guidelines for higher education physical activity programs (2nd ed.* Reston, VA: National Association for Sport and Physical Education.

Mohnsen, B. (2012). Implementing online physical education. *Journal of Physical Education, Recreation & Dance*, *83*(2), 42–47. doi:10.1080/07303084.2012.10598727

Mosier, B., & Lynn, S. (2012). An initial exploration of a virtual personal fitness course. Online. *Journal of Distance Learning Administration*, 15(3), n.p.

Mosier, B. A. (2010). A descriptive study of Florida virtual school's physical education students: An initial exploration. (3462335 Ph.D.), The Florida State University, Tallahassee.

Murphy, C. A., & Stewart, J. C. (2017). On-campus students taking online courses: Factors associated with unsuccessful course completion. *The Internet and Higher Education*, *34*, 1–9. doi:10.1016/j.iheduc.2017.03.001

Osborn, V. (2001). Identifying at-risk students in videoconferencing and web-based distance education. *American Journal of Distance Education*, *15*(1), 41–54. doi:10.1080/08923640109527073

Park, C. L., Boman, J., Care, W. D., Edwards, M., & Perry, B. (2008). Persistence and attrition: What is being measured? *Journal of College Student Retention: Research, Theory & Practice*, *10*(2), 223–233. doi:10.2190/CS.10.2.g

Peng, C.-Y. J., Lee, K. L., & Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting. *The Journal of Educational Research*, *96*(1), 3–14. doi:10.1080/00220670209598786

Rankin, D. (2013). Predictors of success for high school students enrolled in online courses in a single district program. (Doctor of Philosophy), Virginia Commonwealth University, Richmond.

Ransdell, L. B., Rice, K., Snelson, C., & Decola, J. (2008). Online health-related fitness courses. *The Journal of Physical Education, Recreation & Dance*, *79*(1), 45–52. doi:10.1080/07303084.2008.10598119

Rice, K., & Yang, D. (2013). Idaho's K-12 online teaching endorsement: Lessons learned in online teacher preparation. *Paper presented at the International Association for K-12 Online Learning, Blended and Online Learning Symposium*, Orlando, FL.

Rice, K. L. (2006). A comprehensive look at distance education in the K-12 context. *Journal of Research on Technology in Education*, *38*(4), 425–448.

Rink, J. (2013). *Teaching physical education for learning*. Boston, MA: McGraw-Hill.

Ritterband, L. M., Thorndike, F. P., Cox, D. J., Kovatchev, B. P., & Gonder-Frederick, L. A. (2009). A behavior change model for internet interventions. *Annals of Behavioral Medicine: A Publication of the Society of Behavioral Medicine*, *38*(1), 18–27.

Roblyer, M. D., Blomeyer, R., & Rankins-Reed, R. (2006). Systematically Designed Online Support for virtual school students: A theory into practice product. *Paper presented at the Society for Information Technology & Teacher Education International Conference 2006*, Orlando, Florida, USA.

Roblyer, M. D., Davis, L., Mills, S. C., Marshall, J., & Pape, L. (2008). Toward practical procedures for predicting and promoting success in virtual school students. *American Journal of Distance Education*, *22*(2), 90–109. doi:10.1080/08923640802039040

Roblyer, M. D., & Marshall, J. C. (2002). Predicting success of virtual high school students: Preliminary results from an educational success prediction instrument. *Journal of Research on Technology in Education*, *35*(2), 241. doi:10.1080/15391523.2002.10782384

Russell, J., Wadsworth, D., Hastie, P., & Rudisill, M. (2014). Incorporating E-learning to enhance instruction and student experiences in collegiate physical activity courses. *Kinesiology Review*, *3*(4), 247–252. doi:10.1123/kr.2014-0066

Saba, F. (2005). Critical issues in distance education: A report from the United States. *Distance Education*, *26*(2), 255–272. doi:10.1080/01587910500168892

SHAPE. (2007). *Initial guidelines for online physical education position statement*. Reston, VA: Author.

SHAPE-America. (2016). *Shape of the nation: Status of physical education in the USA*. Reston, VA.

Shelton, B., Hung, J.-L., & Lowenthal, P. (2017). Predicting student success by modeling student interaction in asynchronous online courses. *Distance Education*, *38*(1), 59–69. doi:10.1080/01587919.2017.1299562

Shin, N., & Kim, J. (1999). An exploration of learner progress and drop-out in Korea National Open University. *Distance Education*, *20*(1), 81–95. doi:10.1080/0158791990200107

Simpson, O. (2013). Student retention in distance education: Are we failing our students? *Open Learning*, *28*(2), 105–119. doi:10.1080/02680513.2013.847363

Smith, R., Clark, T., & Blomeyer, R. L. (2005). A synthesis of new research on K-12 online learning.

Tabachnick, B. G., & Fidell, L. S. (2014). *Using multivariate statistics* (6th ed.). Boston, MA: Pearson/Allyn and Bacon.

Trent, M. (2016). *Investigating virtual personal fitness course alignment with the national guideline for online physical education* [Doctor of Philosophy Dissertation]. Georgia State University, Atlanta.

Willging, P., & Johnson, S. (2009). Factors that influence students' decision to dropout of online courses. *Journal of Asynchronous Learning Networks*, *13*(3), 115–127.

Williams, L. (2014). A case study of virtual physical education teachers' experiences in and perspectives of online teaching. (Ph.D.), University of South Florida, Tampa.

Williams, T. (2015, March 9). 7 myths about online education. *U.S. News and World Report*. Retrieved from http://www.usnews.com/education/online-education/articles/2015/03/09/7-myths-about-online-education

Xu, D., & Jaggars, S. S. (2014). Performance gaps between online and face-to-face courses: Differences across types of students and academic subject areas. *The Journal of Higher Education*, *85*(5), 633–659. doi:10.1353/jhe.2014.0028