The Impact of Computer Self Efficacy on Student Engagement and Group Satisfaction in Online Business Courses

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Abstract: As countless regional, national, and international accrediting bodies continue to employ student engagement measures as mechanisms for quality assurance, universities become more intent on achieving this important gauge of student success. Specifically, the growth in enrollment in distance learning programs adds a unique level of complexity leading researchers to search for ways to increase engagement in the online course environment. Organizations continue to value teamwork and many instructors have incorporated group work into their online courses to teach students this important skill. The present study examines the impact of student engagement on group satisfaction. Furthermore, this research places student engagement at the center of a structural equation model to determine both predictors and outcomes of this important element of student learning. Specifically, this analysis examines whether students' perceptions of computer self-efficacy impact student engagement and group satisfaction in online business courses. Our findings indicate that computer self-efficacy leads to student engagement and, further, that student engagement influences group satisfaction. Importantly, the relationship between student engagement and group satisfaction is mediated by group expectations. Discussions of findings can be utilized to understand the factors that lead to student engagement and its outcomes in online courses.

Keywords: Student engagement, online information systems courses, course design, groups, expectations, computer self-efficacy

1. Introduction

As many regional, national, and international accrediting bodies continue to employ student engagement measures as mechanisms for quality assurance, universities become more intent on achieving this important gauge of student success. There exists some lack of consensus in the literature regarding the conceptualization of this multi-faceted term; however, for the purposes of this research, a definition of engagement is adopted and is reflective of the variable's complex nature. Engagement is defined as "a positive, fulfilling, work-related state of mind characterized by vigor, dedication, and absorption" (Schaufeli, et al., 2002, p.74). Student engagement is correlated with multiple measures of student success. Specifically, increased levels of student engagement have been linked to student retention (Tinto, 1975), graduation rates (Lee, 2014), classroom motivation (Flynn, 2014), and course achievement (Kuh, et al., 2006). Moreover, the growth in enrollment in distance learning programs adds a unique level of complexity to the pursuit of increased student engagement and these important learning metrics.

Online enrollments are consistently growing at a faster pace than overall enrollments in higher education, particularly in public institutions (Babson College, 2016). Specifically, the number of AACSB accredited schools offering fully online MBA programs increased 48% from 2011 to 2016 (Nelson, 2017), and currently, more than half (283) of all AACSB-accredited business schools offer online MBA programs. Unfortunately, despite the continued growth in demand for distance education, attrition rates are frequently 10%–20% higher for online courses than for traditional classroom settings (Holder, 2007; Nash, 2005). Researchers have cited issues of communication (Rausch and Crawford, 2012), isolation (Bocchi, Eastman and Swift, 2004), reduced motivation (Phipps and Merisotis, 1999; Street, 2010) as well as lack of student engagement (see, for example, Christophel, 1990; Klein, Noe and Wang, 2006) as possible reasons for these higher attrition rates. Furthermore, research indicates that sustained student engagement is a primary factor in ensuring student success in an online learning environment (Carraher Wolverton 2018; Fredrickson, 2015; Phipps and Merisotis, 1999; Street, 2010). Thus, given the accrediting bodies' mandates and the growth in online education, this study seeks to provide a better understanding of what drives student engagement and its influence on student groups in an online learning

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environment. To this end, computer self-efficacy and perceptions related to group expectations and satisfaction were examined.

2. Literature review

While several studies have addressed the causes of higher attrition rates in online learning contexts (see for example, Angelino, et al., 2007; Chyung, 2001; Jones, Moeeni and Ruby, 2005; Liu, et al., 2010; Schwarz and Zhu, 2015), the distance learning research stream has yet to conclude whether this can be attributed to students' perceptions of self or their work group. In other words, does a student's perceptions of their technological abilities influence their level of engagement in an online course? Furthermore, in what way does student engagement impact their perceptions related to group expectations and satisfaction in this environment?

2.1 Computer Self-Efficacy

This research draws upon Bandura's (1986) social cognitive theory and his conceptualization of self-efficacy, and the work of Compeau and Higgins (1995) in establishing the foundation for the use of computer self-efficacy (CSE) to represent a student's individual performance perceptions. With consideration of Bandura's theoretical model, Compeau and Higgins (1995) define CSE as "a judgment of one's capability to use a computer" (p.192), which has since been expanded into various contexts (i.e., Carraher Wolverton, et al., 2019; Dang, et al., 2016; Paradice, et al., 2018).

Researchers began studying this construct in the context of online learning environments approximately a decade ago. Lim (2001) found CSE was significantly correlated with student satisfaction in online learning. Moreover, CSE has been shown to exert a positive and significant impact on online learning readiness of students (Achukwu, et al., 2015), and a positive influence on performance expectations in blended e-learning system environments (Wu, Tennyson and Hsia, 2010). However, there are conflicting findings regarding the relationship between CSE and student engagement. In their 2012 study of online students, Sun and Rueda found that although situational interest and self-regulation were found to be significantly correlated with three factors of engagement (behavioral, emotional, and cognitive), CSE did not appear to be associated with any of the engagement constructs.

Contrarily, Pellas (2014) reported that CSE, metacognitive self-regulation, and self-esteem in online courses were positively correlated with several aspects of student engagement including cognitive and emotional factors. Also, learning engagement has been shown to be positively related to computer self-efficacy Chen (2017). More specifically, Laird and Kuh (2005) discovered that a higher level of computer self-efficacy is related to a higher level of information and communications technology (ICT) engagement. Finally, several studies suggest that a student's belief about their abilities related to the use of technologies is a critical factor in determining the level at which they will engage in learning environments that are technologically integrated (see, for example, Tzeng, 2009).

These contradictory findings present inconsistencies in the literature, and this study seeks to further clarify this relationship.

2.2 Student Engagement

As student engagement has been linked to various measures of student success (e.g., student learning and student satisfaction), evidence and examples of this construct are often required as part of the accreditation reporting process. Thus, institutions of higher learning frequently examine aspects of engagement with a focus on improving learning outcomes (Kuh, et al., 2006). In response, researchers have suggested several methods for increasing student engagement in an online setting. For instance, Nelson Laird and Kuh (2005) and Thurmond and Wambach (2004) demonstrated that collaborative work and information technology play an important role in promoting student engagement. In addition, research indicates that the use of visual programming tools (Dekhane, Xu and Tsoi, 2013), case studies (Taneja, 2014), and simulations (Riordan, Hine and Smith, 2017) improve levels of student interaction and engagement in online courses.

Additionally, generational research on the personality characteristics of our current student bodies suggests that these individuals equate their student experience with higher levels of digital engagement (Preville, 2018). Some researchers suggest that to leverage student engagement and enthusiasm, online instructors need to possess an appreciation of the differences in how students learn and the variables that contribute to these differing characteristics (Coy, Marino and Serianni, 2014). Therefore, online learning environments can create barriers or opportunities for student engagement based on individual student traits. Regardless of the method suggested, tool employed, or theory proposed, all researchers agree that student engagement is an important, and often elusive, objective in online learning environments.

2.3 Group Performance Interactions

Likewise, group activities have been found to exhibit positive outcomes in distance learning courses, such as improved performance, critical thinking, and interaction (Bliss and Lawrence, 2009). Collaborative work results in positive outcomes in online contexts, with some research reporting increased student engagement as a result of shared learning efforts (see, for example, Nelson Laird and Kuh, 2005; Robinson and Hullinger, 2008). In addition, researchers indicate that instructors often find distance learning students eager to work in teams, and instructors even experience complaints when a course does not offer adequate opportunities for group work (Williams, Duray and Reddy, 2006). Further, limiting the interaction amongst students in an online setting frequently results in feelings of isolation that may lead to attrition (Yuan and Kim, 2014). Muilenburg and Berge (2005) studied social interaction in online learning environments and found that a strong correlation exists between learning satisfaction and social interaction. Thus, employing team-based approaches to distance learning has the potential to improve levels of satisfaction, especially as student interaction increases (Williams, Duray and Reddy, 2006). Yet, it is also important for this outcome to ensure students have realistic expectations for group interactions. In fact, Zhu and Schwarz (2015) found that group expectations impact both group satisfaction and student engagement. Therefore, since extant research finds that group work is highly beneficial to the online learning experience (see, for example, Palloff and Pratt, 2005), it is essential to better understand the relationships among/between variables which impact these group interactions.

Thus, given the proven importance and often conflicting findings of these constructs, this study also seeks to determine whether a student's level of engagement directly impacts group expectations and satisfaction. This is critical, as student engagement constitutes one of the principal elements of effective instruction and effective learning in online course settings (Fredrickson, 2015). Additionally, many accrediting bodies are utilizing various measures of engagement (e.g., student, university, and community) as indicators of university effectiveness (Dostaler, Robinson and Tomberlin, 2017). Given these internal and external emphases, it is essential to further our understanding of student engagement in all classroom settings.

3. Data collection

We collected data from students in online business courses at a public university in the southeastern United States. The students completed the online survey for additional bonus points in their related courses.

Eighty-three students completed the survey, for a response rate of 62%. According to the "10 times" rule, the sample size should be at least 10 times the number of incoming paths to the construct with the greatest number of incoming paths (Barclay, Higgins and Thompson, 1995; Chin and Newsted, 1998; Hair, Ringle and Sarstedt, 2011). Therefore, the sample size is sufficient.

Most of these respondents were female (59.6%), with 40.4% male respondents. A slight majority of the respondents (52.6%) were under 25 years of age. The other respondents were 30 years of age (26.3%) or between 25 and 30 years of age (21.1%).

4. Measures

The purpose of this study is to determine whether computer self-efficacy (CSE) impacts student engagement and determine its impact on group satisfaction and group expectations. Computer self-efficacy represents an individual trait regarding an individual's beliefs about their abilities to competently use computers (Compeau and Higgins, 1995). The original CSE measure from Compeau and Higgins (1995) has been adapted in multiple contexts such as post-adoptive usage (Tams, Thatcher and Craig, 2018), IS security deterrence (Paradice, et al., 2018), and online education (Carraher Wolverton, et al., 2019; Dang, et al., 2016).

We utilized group expectations and group satisfaction as dimensions of successful group interactions. The group expectations measure and the group satisfaction measure were adapted from Premkumar and Bhattacherjee (2008). Utilizing these interactional constructs, this research sought to better understand the relationships between the student's level of satisfaction with their group, their expectations about their group, and their level of engagement in the course. Further, the multidimensional student engagement measure from Schaufeli, et al. (2002) was used. This measure has been adapted for use in online education in extant studies (Schwarz and Zhu, 2015).

5. Data analysis

The first step in analyzing the measurement model involves an examination of the adequacy of the measures. Examining the individual item reliabilities, represented by their loadings to their respective construct, ensures that the items are measuring the constructs as they were designed. As Chin, Marcolin and Newsted (2003) state, "standardized loadings should be greater than 0.707" (p.325).

As some items exhibited a coefficient alpha below the .70 threshold (Nunnally, 1978), they were removed from further analysis. Thus, the analysis was able to ensure that the sampling domain had been adequately captured (Churchill, Jr., 1979) without including items that make progressively less of an impact on the reliability (Carmines and Zeller, 1979).

6. Analysis and results

6.1 Data Analysis

Data were analyzed using structural equation modeling. Given the small sample size (n=83) and the corresponding lack of statistical power in utilizing a covariance-based approach (Westland, 2010), the partial least squares (PLS) approach was selected, specifically Smart PLS 3.0 (Ringle, Wende and Becker, 2015) software. We chose to utilize PLS because it provides advantages for datasets with small sample sizes (e.g., Barclay, Higgins and Thompson, 1995; Chin, Marcolin and Newsted, 2003; Chin, 1998; Gefen, Straub and Boudreau, 2000).

To test the hierarchical component model (Lohmöller, 2013), researchers employed the two-stage HCM analysis as recommended by Hair, et al. (2017) and Wetzels, Odekerken-Schröder and Van Oppen (2009).

Table 1: Loadings and Cross-Loadings of Hierarchical Component Model

	Computer Self-Efficacy	Engagement	Engagement-Absorption	Engagement-Dedication	Engagement-Vigor	Group Expectations	Group Satisfaction
CSE_1	0.813	0.344	0.132	0.366	0.374	0.178	0.127
CSE_10	0.783	0.297	0.201	0.297	0.273	0.225	0.073
CSE_2	0.795	0.245	0.138	0.189	0.313	0.197	0.030
CSE_3	0.826	0.393	0.152	0.363	0.490	0.156	0.027
CSE_4	0.760	0.232	0.194	0.097	0.346	0.147	-0.053
CSE_7	0.797	0.373	0.233	0.383	0.348	0.420	0.246
CSE_8	0.772	0.301	0.055	0.345	0.343	0.305	0.039
ENGA_1	0.260	0.753	0.750	0.645	0.634	0.487	0.338
ENGA_1	0.260	0.753	0.750	0.645	0.634	0.487	0.338
ENGA_2	0.123	0.500	0.787	0.328	0.304	0.408	0.196
ENGA_2	0.123	0.500	0.787	0.328	0.304	0.408	0.196
ENGA_3	0.078	0.667	0.805	0.575	0.450	0.338	0.217
ENGA_3	0.078	0.667	0.805	0.575	0.450	0.338	0.217
ENGA_4	0.159	0.661	0.879	0.496	0.466	0.271	0.084
ENGA_4	0.159	0.661	0.879	0.496	0.466	0.271	0.084
ENGD_1	0.351	0.872	0.657	0.920	0.697	0.683	0.398
ENGD_1	0.351	0.872	0.657	0.920	0.697	0.683	0.398
ENGD_2	0.393	0.826	0.517	0.895	0.718	0.621	0.405
ENGD_2	0.393	0.826	0.517	0.895	0.718	0.621	0.405
ENGD_3	0.401	0.901	0.621	0.953	0.766	0.636	0.323
ENGD_3	0.401	0.901	0.621	0.953	0.766	0.636	0.323
ENGD_4	0.251	0.782	0.581	0.861	0.587	0.656	0.328
ENGD_4	0.251	0.782	0.581	0.861	0.587	0.656	0.328
ENGV_1	0.466	0.773	0.516	0.665	0.854	0.463	0.115
ENGV_1	0.466	0.773	0.516	0.665	0.854	0.463	0.115

ENGV_2	0.529	0.677	0.429	0.524	0.835	0.399	0.073
ENGV_2	0.529	0.677	0.429	0.524	0.835	0.399	0.073
ENGV_3	0.204	0.717	0.440	0.608	0.839	0.374	0.104
ENGV_3	0.204	0.717	0.440	0.608	0.839	0.374	0.104
ENGV_4	0.351	0.842	0.607	0.761	0.852	0.552	0.257
ENGV_4	0.351	0.842	0.607	0.761	0.852	0.552	0.257
GEXP_1	0.236	0.646	0.445	0.692	0.533	0.951	0.555
GEXP_2	0.245	0.603	0.434	0.624	0.509	0.947	0.566
GEXP_3	0.315	0.630	0.392	0.663	0.571	0.920	0.567
GEXP_4	0.320	0.636	0.450	0.674	0.524	0.966	0.697
GEXP_5	0.264	0.556	0.448	0.645	0.345	0.841	0.734
GSAT_1	0.073	0.287	0.259	0.353	0.132	0.643	0.974
GSAT_2	0.102	0.308	0.203	0.402	0.174	0.679	0.949
GSAT_3	0.072	0.310	0.265	0.374	0.165	0.612	0.958
GSAT_4	0.134	0.339	0.297	0.406	0.177	0.672	0.965

6.2 Measurement Model

The first step in a PLS analysis is the analysis of the measurement (or outer) model. Following the procedures outlined by Wright, et al. (2012), the first step was the creation of a first-order measurement model. The analysis began by investigating the loadings and cross-loadings of all items to ensure that they each loaded on their respective constructs (see Table 2). All loadings were greater on the intended construct than on any other constructs. Consequently, upon determining that none of the items loaded higher on any construct other than the intended construct, all items were included. Next, researchers evaluated the reliability, discriminant, and convergent validity of the first-order measurement model. Utilizing the item loadings, internal composite reliability (ICR) was calculated to evaluate the measure's reliability, finding that all the dimensions exceeded the .70 threshold and were all above 0.88 (bottom of Table 2). Moreover, to estimate convergent validity, each dimension's average variance extracted (AVE)was evaluated. Utilizing the threshold value of 0.50 for AVE, the findings support convergent validity (Barclay, Higgins and Thompson, 1995).

Table 2: Loadings and Cross Loadings

	Computer Self-Efficacy	Engagement - Absorption	Engagement- Dedication	Engagement- Vigor	Group Expectations	Group Satisfaction
CSE_1	0.849	0.16	0.33	0.376	0.008	0.17
CSE_10	0.815	0.213	0.234	0.286	0.09	0.194
CSE_2	0.835	0.179	0.216	0.439	-0.021	0.068

CSE_3	0.777	0.14	0.269	0.523	-0.031	-0.05
CSE_4	0.82	0.121	0.129	0.367	0.018	0.016
CSE_5	0.712	0.073	0.145	0.245	0.256	0.278
CSE_7	0.719	0.115	0.245	0.248	0.301	0.319
CSE_8	0.754	-0.018	0.11	0.357	0.124	0.055
ENGA_1	0.048	0.748	0.628	0.409	0.21	0.175
ENGA_2	0.111	0.796	0.44	0.333	0.312	0.248
ENGA_3	0.166	0.828	0.635	0.505	0.208	0.176
ENGA_4	0.218	0.824	0.511	0.45	0.164	0.023
ENGD_1	0.197	0.611	0.86	0.464	0.387	0.35
ENGD_2	0.258	0.599	0.905	0.601	0.371	0.259
ENGD_3	0.328	0.621	0.892	0.654	0.443	0.216
ENGD_4	0.157	0.53	0.704	0.417	0.205	0.132
ENGV_1	0.424	0.396	0.496	0.814	0.139	0.056
ENGV_2	0.419	0.424	0.49	0.817	0.137	-0.05
ENGV_3	0.299	0.483	0.573	0.83	0.229	0.132
ENGV_4	0.413	0.473	0.562	0.855	0.205	0.109
GEXP_1	0.057	0.256	0.375	0.175	0.95	0.534
GEXP_2	0.037	0.212	0.319	0.185	0.954	0.536
GEXP_3	0.086	0.211	0.379	0.242	0.938	0.552
GEXP_4	0.155	0.253	0.416	0.248	0.952	0.618
GEXP_5	0.077	0.323	0.454	0.151	0.84	0.656
GSAT_1	0.143	0.257	0.292	0.09	0.579	0.943
GSAT_2	0.168	0.143	0.279	0.079	0.577	0.955
GSAT_3	0.109	0.14	0.239	0.052	0.604	0.961
GSAT_4	0.163	0.194	0.287	0.077	0.652	0.968
First Order Reliability and AVE						
AVE	0.619	0.639	0.712	0.688	0.86	0.915
ICR	0.928	0.876	0.907	0.898	0.968	0.977
Cronbach's Alpha	0.913	0.812	0.862	0.849	0.959	0.969

Table 3:Intercorrelations of the Latent Variables for First-Order Constructs1

	Computer Self-Efficacy	Engagement - Absorption	Engagement - Dedication	Engagement - Vigor	Group Expectations	Group Satisfaction
Computer Self-Efficacy	0.787					
Engagement-Absorption	0.284	0.844				
Engagement-Dedication	0.467	0.641	0.829			

Engagement-Vigor	0.172	0.7	0.537	0.799		
Group Expectations	0.091	0.425	0.216	0.275	0.928	
Group Satisfaction	0.152	0.287	0.078	0.192	0.632	0.957

[1] Square root of the AVE on the diagonal.

Researchers then evaluated the construct's convergent and discriminant validity (Table 3). The Fornell-Larcker criterion was utilized, as suggested by Hair, et al. (2017), to assess discriminant validity. As the square root of the AVE exceeded the highest correlation with any other construct, it was concluded that there was adequate discriminant validity among the measures.

6.3 Results

The study's results (see Figure 1) indicate that computer self-efficacy (CSE) leads to student engagement (β = 0.350, t=3.785, p <0.001). Student engagement then leads to group expectations (β = 0.361, t=3.223, p <0.001), and group expectations predict group satisfaction (β = 0.632, t=7.280, p <0.001). However, student engagement does not impact group satisfaction (β = -0.001, t=0.013, *ns*) directly; instead, that relationship is fully mediated by group expectations (Hair, et al., 2017; Zhao, Lynch and Chen, 2010).

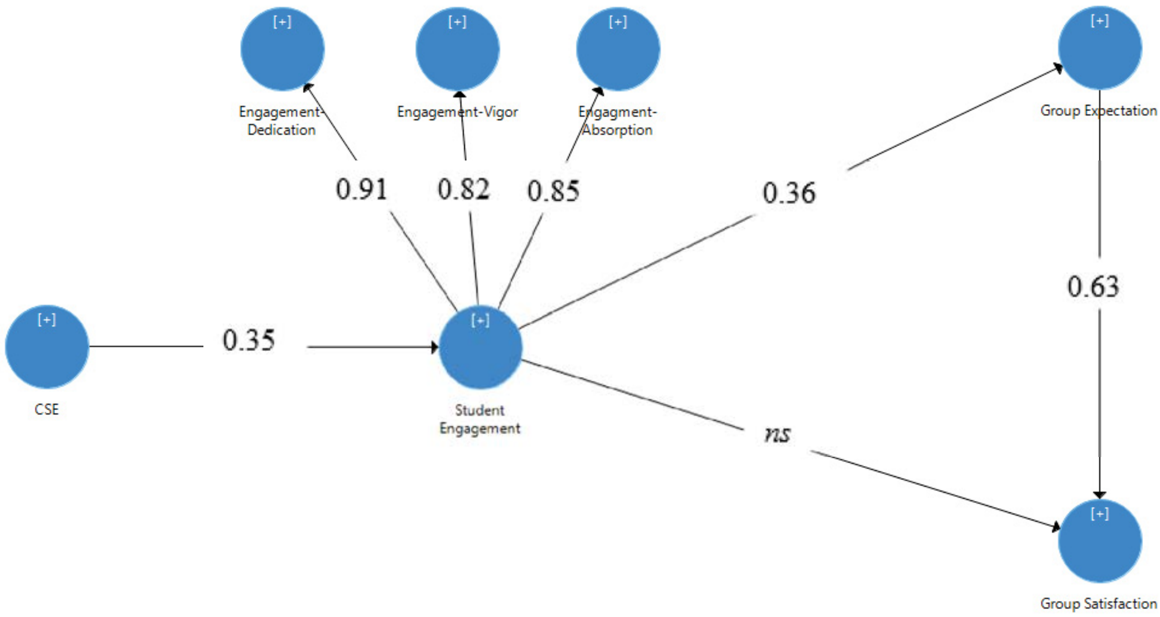

Figure 1: Results of the Structural Model

7. Discussion

The findings of this study indicate that student engagement is driven by a student's perception of their computer self-efficacy. This outcome evinces that a student who perceives themselves as being able to competently use computers is more likely to be engaged in an online course. Moreover, the findings also demonstrate that student engagement leads to higher levels of group satisfaction in online settings. However, this relationship is fully mediated by group expectations. Although the analysis found no direct relationship between student engagement and group satisfaction, student engagement did trigger more positive feelings about the group's ability to successfully perform.

As a result of this finding, it is recommended that instructors devote meaningful time during distance learning students' orientation to the understanding of utilized technology in order to facilitate higher levels of computer self-efficacy. However, it is not essential that students possess a mastery of technology utilized in the online learning environment. A working knowledge that establishes a comfort level would be sufficient. This would allow students to have more time to focus on course content as well as increase students' self-esteem as online learners. It follows that greater feelings of self-esteem and technological comfort could secure more active participation in group activities. Furthermore, by recognizing that group expectations mediate the relationship between engagement and satisfaction, an instructor should focus on increasing future expectations, or perceptions of positive future group experiences, rather than concentrating on increasing present group satisfaction. Successful learning online (or in the classroom) is supported by the creation of a community of learners (Borup, et al., 2020). Although the findings and subsequent implications of this study are insightful in offering potential ways in which instructors can increase student engagement in their online courses, the results must be viewed in light of a few limitations. Since data from a survey administered to students enrolled in an online business course was used for the purposes of this research, all information was self-reported. The results of this analysis are, therefore, subject to common method variance (Schwarz, et al., 2017). Further, a replication of this study in other settings and across disciplines is encouraged to address the issue of generalizability. Additionally, future research conducted at other universities would also aid in confirming the results of this empirical research. Because increasing our understanding of the factors that influence engagement in online settings has potentially significant implications, future research in this area is encouraged. Further, the increase in online course offerings requires further research to better understand the role of computer self-efficacy in online learning settings.

8. Conclusion

Student engagement remains a desired outcome in education, especially in online learning environments (Schwarz and Zhu, 2015). This study's findings indicate that engagement in online course settings is driven by a student's individual perception of their computer-related abilities. Further, our analysis found a more complex relationship exists between engagement and the group interaction factors, group expectations, and group satisfaction. Results indicate that prior or early course perceptions/expectations significantly impact the eventual course experience. Both perceptions of computer self-efficacy and group expectations are most likely determined prior to real course activity. Yet, these pre-conceived attitudes are extremely relevant for the role they play in the latter sentiments of engagement and satisfaction.

Studies have shown that computer self-efficacy improves as there are increases in the number of experiences and familiarity with technology (Lee 2015; Ozerbas and Erdogan, 2016). It naturally follows that individuals with greater exposure to different learning technologies will possess key computer competencies necessary for success in an online learning environment. Additionally, researchers suggest that accessibility to digital learning technologies has an influence on computer self-efficacy and the academic success of online students, noting a move towards improvement in higher-level skills such as problem-solving and critical thinking (see, for example, Chang, et al., 2014). Yet, students' attitudes towards online learning can also impact their levels of computer self-efficacy. For example, Prior, et al. (2016) found that students with more positive attitudes towards online learning environments also possessed more positive levels of self-efficacy. Thus, the current study's findings are consistent with those of extant literature, suggesting that greater emphasis be placed on improving students' individual technological confidence levels since computer self-efficacy is a critical component for learning content in online settings (Parkes, et al., 2015). Yet, our results also suggest that additional importance be placed on managing students' expectations specifically towards group activities. Positive pre-existing student perceptions and attitudes can significantly improve the online student's experience. Only with a clear understanding of these important constructs can instructors hope to meaningfully create engaged and satisfied students in online courses.

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Appendix – Survey Items

Group Expectations I believe that…	Adapted from Premkumar and Bhattacherjee (2008)
1. Being in a group in this class will help me better understand new course material (Strongly disagree…Strongly agree).	
2. Being in a group in this class will help me learn new material (Strongly disagree…Strongly agree).	
3. Being in a group in this class will increase my interest in the course material (Strongly disagree…Strongly agree).	
4. Being in a group in this class will provide me with insight into the course material (Strongly disagree…Strongly agree).	
5. Being in a group in this class will facilitate interesting discussions (Strongly disagree…Strongly agree).	
Student Engagement (Utrecht Work Engagement Scale for Students) From more/less after the face-to-face case study discussion	Adapted from Schaufeli, et al. (2002)
Vigor 1. When I'm studying for this class, I feel mentally strong. 2. I can continue for a very long time when I am studying for this class. 3. When I study for this class, I feel like I am bursting with energy. 4. When studying for this class, I feel strong and vigorous. 5. When I get up in the morning, I feel like going to this class. Dedication 1. I find this course to be full of meaning and purpose. 2. This course inspires me. 3. I am enthusiastic about this course. 4. I am proud of my studies in this course. 5. I find the course challenging. Absorption 1. Time flies when I'm studying for this class. 2. When I am studying for this class, I forget everything else around me. 3. I feel happy when I am studying intensively for this class. 4. I can get carried away by my studies for this class.	
Computer self-efficacy	Adapted from Compeau and Higgins (1995)
I could complete my coursework using technology if… …there was no one around to tell me what to do …I had never used a package like it before …I had only the software manuals for reference …I had seen someone else using it before trying it myself …I could call someone for help if I got stuck …someone else helped me get started …I had a lot of time to complete the assignments for which the software was provided …I had just the built-in help facility for assistance …someone showed me how to do it first …I had used similar packages like this one before to complete my coursework.	from not confident to very confident

Group Satisfaction	(Premkumar and Bhattacherjee, 2008)
I am _ with my group. 1. Extremely displeased . . . Extremely pleased. 2. Extremely frustrated . . . Extremely contented. 3. Extremely disappointed . . . Extremely delighted. 4. Extremely dissatisfied . . . Extremely satisfied.	