Collaboration, Connectedness, and Community: An examination of the factors Influencing Student Persistence in Virtual Communities

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ABSTRACT

Institutions of higher education are being called upon to provide a more robust pathway to a college degree and improve upon the advanced workforce for the needs of the 21st century. While active collaborative learning environments have been encouraged in higher education to improve student engagement, there is a gap in the literature when it comes to connecting the two research areas of collaborative learning and student intention to persist. This research fills this gap by creating and conducting research to examine a model that measures the factors that significantly influence a student's persistence in a virtual collaborative learning environment. The model examines how collaborative learning, campus connectedness, sense of community, organizational commitment, and turnover intention influence student persistence. The model was tested using a sample of students who participated in a virtual learning community (VLC) and the results suggest that all but one of the factors were found to significantly influence student persistence, with the final factor dependent on the number of hours of system usage. We discuss the implications of the research and the model for team-based theory and organizational practice in education and teamwork.

Keywords: virtual learning community; persistence; engagement

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1. Introduction

Higher education institutions are being called upon to provide more robust pathways to a college degree and thereby improve the workforce for the needs of the 21st century. Nevertheless, there are challenges that these institutions face in achieving these objectives. For example, the demographic makeup of the student population is increasingly varied in age, enrollment status (full-time versus part-time), and institution type (2 year or 4 year) (U.S. Department of Education, National Center for Education Statistics, 2013). To compound the situation, there is a lower degree attainment rate for non-traditional students (Ross, Kena, Rathbun, Kewal Ramani, Zhang, Kristapovich, & Manning, 2012), and despite prior efforts to improve retention rates (Bean & Metzner, 1985), the trend is not in the desired direction (Snyder & Dillow, 2012). Thus, a commitment to a more highly educated workforce will require a more supportive environment for student success. This becomes ever more important as educational programs move more courses to online settings, where students have few or no physical connections with the university campus and other students. Our objective in this research is to help researchers and educators better understand the factors that influence student success in online settings by proposing and testing a model of student retention.

The modern workplace incorporates technology, predominately information technology, to support organizations in their efforts to become more agile and to acquire knowledge about their operations and competitive environment. In doing so, they have to evolve to become *learning organizations*, which implies that knowledge is captured, managed and used to foster organizational success (Senge & Suzuki, 1994). Structuring the workplace to achieve these outcomes requires that organizations leverage not only individual employee skills and knowledge, but also employees' willingness and ability to work with others though effective collaboration. As a result, employers are increasingly demanding that employees possess a larger and more diverse set of skills and knowledge. The challenge for many firms is in finding employees who possess the requisite skills and this is particularly problematic as the path to a degree in higher education has become more challenging. Because of factors like increasing costs of higher education and fewer sources of funding, students often need to pursue their education in non-traditional settings, such as from a distance or while working full time. Thus, time and distance are now important factors as students seek out degrees. Traditionally, the academic response has been to focus on building and maintaining improved curriculum; however, this often does not address the unique needs of non-traditional students. Thus, to be sustainable, higher educational institutions must create environments that will encourage student retention.

We suggest that sense of community and connectedness with the educational institution will help improve retention. We base this supposition on research by Tinto (2005), who suggests that the following factors will influence student retention:

1. A commitment to success must include monetary resources and not just words.
2. A high expectation of student performance begins with the first year.
3. Develop support programs for navigating the new college environment.
4. Utilize student feedback and assessments of the learning environment.
5. Foster student involvement both academically and socially.
6. Focus on the development of a setting that encourages learning.

These conditions are all attainable based on the characteristics of community and are not discipline specific. With a strong community, the results will include increased involvement in learning, promotion of social and academic involvement, and academic support for the student's motivation to persist (Tinto, 1997, 1998, 2003; Stefanou & Salisbury-Glennon, 2002; Zhao & Kuh, 2004).

To increase student persistence through active involvement, a successful online program will encourage computer supported collaborative learning that brings together technology, interaction, and learning in a manner similar to what is encouraged in learning communities (Stahl, Koschmann, & Suthers, 2006). An active learning environment through collaborative learning techniques has been encouraged in higher education as a means of improving student engagement (Freeman, Eddy, McDonough, Smith, Okoroafor, Jordt, & Wenderoth, 2014; Slavich & Zimbardo, 2012; Prince, 2004), but there is a gap in the literature when it comes to connecting the two areas of research. Thus, the purpose of this study is to create and test a model that will measure the factors that significantly influence a student's persistence in higher education. The proposed model can be utilized to measure the impact of community and connectedness found in collaborative learning activities on student intentions to persist and can be used to evaluate the effectiveness of online programs and the likelihood of student retention in these programs.

2. Background

In this section we discuss several of the factors that are important in influencing student participation in and success with collaborative learning. We begin by discussing collaborative learning environments. We then discuss several of the factors that are used in our model such as usability, connectedness, sense of community, commitment, and turnover intention. During this discussion, we present the hypotheses that are predicted by our model.

2.1 Computer Supported Collaborative Learning

The expectation that employers have for employees in the workplace is to be able to adapt to change, use critical thinking skills, and collaborate professionally (Jerald, 2009). These skills have been called "21st century skills" and they are defined as "being able to solve complex problems, to think critically about tasks, to effectively communicate with people from a variety of different cultures and using a variety of different techniques, to work in collaboration with others, to adapt to rapidly changing environments and conditions for performing tasks, to effectively manage one's work, and to acquire new skills and information on one's own" (The National Research Council, 2011, p. 1). Collaborative teams are more effective because of the diversity of ideas generated and this is particularly important because many types of jobs are becoming too multifarious for just one person to complete effectively.

Just as the workplace in the 21st century requires effective teamwork, higher education is following suit and is moving to engage with active learning techniques (Freeman, Eddy, McDonough, Smith, Okoroafor, Jordt, & Wenderoth, 2014). In fact, active learning techniques, such as collaborative learning teams, don't only benefit employees when they graduate and take jobs, they have also been found to improve student persistence in college. For example, collaborative learning has been found to play a significant role in retention of first-year students (Freeman et al., 2014; Tinto, 1997; Tinto, 1998). Collaborative learning is achieved when individual strengths are combined so that all members of the group participate in the collaborative construction of knowledge (Stahl, Koschmann, & Suthers, 2006). Collaborative learning fosters a diversity of thought and allows for others to experience differing ideas for discussion. Each member brings a unique perspective to the group that is based on prior experiences, which can collectively add to the knowledge gained. Collaborative learning also involves a community of learners and teachers that share experiences or knowledge through social interaction (Zhu, 2012). The focus of learning is not limited to the knowledge of just the instructor but, rather, the instructor acts as a facilitator of the interaction among all involved parties. Members of the group control the collaboration process with input from the instructor, and it is the responsibility of the entire group to participate in all aspects of the process, including the diffusion of conflicts, contribution of ideas, and the achievement of learning goals (Dewiyanti, Brand-Gruwel, Jochems, & Broers, 2007).

When collaborative learning is transferred online, it is often referred to as *computer-supported collaborative learning* (CSCL). This domain emerged as a research field in the 1990s in response to new software innovations that were meant to bring students together to learn (Stahl, Koschmann, & Suthers, 2006). Kirschner and Erkens (2013) developed a framework for CSCL research that is divided into three main elements: pedagogical, the level of learning, and the unit of learning. The *pedagogical* element pertains to the learning portion of the collaborative learning environment and the tools used to support and guide the individual, team, and/or community through a set of learning goals. The *level of learning* element pertains to the skills that students use to work collaboratively in a team. This element includes the communication process that students navigate when working on a team task, the level of motivation that a student puts forth to be successful and engaged in a task, and the social aspects involved in student-to-student interaction and student-to-teacher interactions. The third element, the *unit of learning* element, pertains to the technological needs of the activity depending on the makeup of the environment. Most CSCL environments have the basic communication, productivity, and support tools for individual, group, and/or community use, but how the CSCL tools are presented and encouraged for use will determine the way the technology is used and the effectiveness of the activity. Kirschner and Erkens (2013) suggest that more research is needed concerning the social aspects of CSCL. Specifically, they identify sense of community and feelings of belonging as two important elements of a solid group structure and factors that need to be examined in collaborative learning environments.

Collaborative techniques of online learning have been influenced by the theory of social constructivism, which is based on the idea that an individual can enhance his or her own construction of knowledge by negotiating meanings with other individuals (Bernard, Rojo de Rubalcava, St. Pierre, 2000; So & Brush, 2008; Zhu, 2012). Bernard, Rojo de Rubalcava, and St. Pierre (2000) offer several design considerations for collaborative online learning: proper assessment of student needs, communication of expectations, creation of a positive social environment, establishment of collaborative small group projects, promotion of information sharing, availability of technology, and technology readiness of participants. Beyond the social aspect of CSCL, our research investigates how collaborative learning, when supported by technology, can enhance how students work in groups interactively and how technology can facilitate shared knowledge among the members of a group (Wang, 2009; Dewiyanti, Brand-Gruwel, Jochems, & Broers, 2007). While collaborative learning involves using technology to work in a group to collectively complete a task, each individual needs to also be accountable for his or her share of the work (Wang, 2009). The presence of individual accountability encourages ownership of the learning task, and special attention to the meaningfulness of the task, equality among group members, and added instructional strategies can help to foster this atmosphere of learning (Wang, 2009; Brandon & Hollingshead, 1999). The level of a group's sense of community can affect the positive interdependence among the team members and whether they pull their own weight during group tasks. Wang (2009) suggests that both individual accountability and positive interdependence require coordination if a collaborative learning environment is to be successful.

This review of the role and design of technology for collaborative learning suggests that technological characteristics are important but the literature also suggests that technology in and of itself is not sufficient. As with most technological applications, how the technology is applied and used by both the instructor and the students will influence success and success is influenced by several factors such as the usability of the technology and how this influences perceptions that students develop such as sense of community and commitment (Brandon & Hollingshead, 1999). We review these factors and discuss our hypotheses in the following sections.

2.2 Usability

Usability is a core concept in the study of human-computer interaction, and it is the measurement of how easy an interface is to use based on factors such as learnability, efficiency, memorability, errors, and satisfaction (Nielsen, 1993). Usability is measured against the context in which it is currently being used (Phang, Kankanhalli, & Sabherwal, 2009; Brooke, 1996). For example, Fischer notes, "A fundamental objective of human-computer interaction research is to make a system more usable, more useful, and to provide users with experiences fitting their specific background knowledge and objectives" (2001, p.65). In this study, students utilized a course management system to collaborate inside and outside of the classroom. The students were also supported using a virtual learning community (VLC) that was designed to tie these students together by utilizing the same course management system. An important assumption in our model is that for students to be successful in using a collaborative learning system, they have to be willing and able to do so. Prior research in technology adoption has shown that ease of use is important in user decisions regarding whether or not to use a system; therefore, we include usability in our model as an antecedent of involvement in group activities. This suggests the following:

H1*: The perceived usability of a CSCL system will have a positive influence on collaborative learning involvement.*

2.3 Connectedness

In research pertaining to the measurement of belonging, Lee and Robbins (1995) propose that the notion of belongingness is composed of three main constructs – companionship, affiliation and connectedness. While companionship is the act of bonding with another human being and affiliation is the establishment of peer relations of similar values, connectedness is a feeling of relatedness and identification of differences. Townsend and McWhirter (2005) conducted a literature review specifically on the construct of connectedness to identify a common definition of the construct as well as an appraisal of the many dimensions of connectedness. They promoted a definition that was first proposed by Hagerty and colleagues, who defined the occurrence of connectedness as "…when a person is actively involved with another person, object, group, or environment, and that involvement promotes a sense of comfort, well-being, and anxiety-reduction" (Hagerty, Lynch-Sauer, Patusky, & Bouwsema, 1993, p. 293).

As noted earlier, Tinto (2005) stresses the responsibility of an institution to develop an environment of success if improved student persistence is to be realized. Most of the conditions that foster success - institutional level student support, commitment to both academic and social involvement, and programs for navigating the college environment – lie beyond the scope of a collaborative learning group. On the other hand, connectedness is something that can be fostered in collaborative learning groups. Specifically, if a student feels that he or she has a connection with his or her group, that student will likely participate effectively in the group's activities and feel more involved in the academic program. Thus, connectedness, and particularly feelings of connectedness with the campus and the students on the campus, should have a positive effect on retention and persistence.

Campus connectedness is the study of social connectedness in the context of a college environment (Lee, Keough, & Sexton, 2002). In a study of the social connectedness in university settings, Lee and colleagues (Lee, Keough, & Sexton, 2002) modified the original Social Connectedness Scale (Lee & Robbins, 1995) to study interpersonal closeness and factors that influence perceptions of closeness. The study found that women who experience low connectedness reported a negative campus climate and higher level of stress. Interestingly, this relationship was not seen for men given that a negative view of climate did not result in significantly greater stress or negative views of campus climate.

Freeman, Anderman, and Jensen (2007) conducted a study to examine the association between the sense of belonging in a single class and belonging at the university level using two variables, faculty-student interaction and sense of social acceptance, that together are designed to cultivate a sense of belonging. The results suggest that there is no relationship between the sense of belonging that a student has for a single class and the sense of belonging that the student has with the university as a whole. The authors suggest that a student's sense of social acceptance by peers and instructors might be the most important factor in an overall sense of belonging with the institution.

Summers and colleagues (Summers, Beretvas, Svinicki, & Gorin, 2005) evaluated collaborative learning methods based on feelings of campus connectedness, academic classroom community, and effective group processing. An important objective of their study was to develop a survey that would quantitatively capture outcomes of instructional methods for the development of learning communities. Their findings suggest a positive relationship between classroom community and positive attitudes about campus connectedness.

While some of the findings from prior research offer mixed results, the literature, when considered in aggregate, does seem to point to the likelihood that connectedness is influenced by a number of factors that pertain to the degree of involvement expressed by a student in courses and team activities. Thus, we offer the following pertaining to connectedness:

H2: *Students with greater involvement in collaborative team learning will have a greater sense of campus connectedness.*

2.4 Sense of Community

McMillan and Chavis (1986) define the construct of *sense of community* as "a feeling that members have of belonging, a feeling that members matter to one another and to the group, and a shared faith that members' needs will be met through their commitment to be together" (p. 9). Sense of community is defined as having four sub-constructs: membership, influence, integration, and shared emotional connection. The element of *membership* pertains to the boundaries of belonging to the group and how this determines whether an individual is likely to make a personal investment in team activities. *Influence* occurs on two levels. A member of the group may be attracted to participation if there is an opportunity to influence others. On the other hand, the community will seek to influence conformity among members. The third element is *integration* or, alternatively, *reinforcement* (McMillan & Chavis, 1986). Members will ultimately participate when it serves their needs to do so and this often occurs when their behavior is reinforced with positive rewards. Finally, the element of *shared emotional connection* is based on the bond that occurs from shared events by the membership.

Commonly used scales for measuring sense of community include the Sense of Community Index (SCI) (Chavis, Hogge, McMillan, & Wandersman, 1986) and the Sense of Community Index 2 (SCI2) (Chavis, Lee, & Acosta, 2008). Unlike the original SCI, the revised SCI2 scale has shown greater reliability and validity across different cultures and is able to measure each of the attributes presented in the original theory. Furthermore, SCI2 has been used in a number of studies examining sense of community. For example, Abfalter, Zaglia, and Mueller (2012) utilized the SCI2 to better understand the dynamics of virtual communities and to improve the measurement of a sense of virtual community (SOVC). In their study, a comparison of the original SCI measure to the revised SCI2 was made and the results showed that the revised scale performed better than the original. Thus, we use the SCI2 measure but, per the recommendations of Abfalter and colleagues, we modified the scale to focus on the work team with which the student has participated (see Abfalter, Zaglia, & Mueller, 2012).

The original sense of community model offered by McMillan and Chavis (1986) as well as research using the SCI2 and SCI scales both suggest that sense of community will be positively related to involvement in collaborative learning and to connectedness (Abfalter, Zaglia, & Mueller, 2012; Chavis, Hogge, McMillan, & Wandersman, 1986; Chavis, Lee, & Acosta, 2008). Based on this, we offer the following hypotheses:

H3: *Students with greater involvement in collaborative learning will have a greater sense of community.*

H4: *Students with a greater sense of community will have a greater sense of campus connectedness.*

2.5 Commitment

Meyer and Allen (1991) identify three general themes associated with organizational commitment. First, commitment can be described as effective when an individual has an emotional attachment to an organization because the more that the individual connects with the organization, the stronger will be the commitment he or she experiences. A second factor is the perceived cost of leaving an organization. An individual will weigh the cost of leaving and when there is a greater cost, the individual will be less likely to leave. The third theme relates to the obligation that an individual feels toward an organization, with a greater sense of obligation leading to greater commitment.

Based on these themes, Allen and Meyer (1990) developed a three-component model to analyze affective, continuance, and normative commitment levels. They designed the model so that the three components are linked together in such a way that the model decreases turnover rates, but each factor has a unique role to play in the act of commitment toward an organization. Individuals who stay in an organization because they want to stay experience a level of affective commitment, those who stay because they need to stay experience a level of continuance commitment, and normative commitment exists when individuals stay because they feel obligated to the organization. They further suggest that the antecedents of affective commitment fall into three categories – demographics, structure, and work experiences. The first category pertains to personal characteristics, which include demographics (e.g., age, sex, ethnicity, etc.) and personality characteristics (e.g., desire to succeed, academic honesty and ethics, desire for belonging, etc.). The second category, o*rganizational structure*, pertains to the relationship between commitment and the preference for how an organization operates. For students, this would pertain to how classes are offered, the length of each semester, and the plan of study. The third category, work experiences, suggests that experiences garnered both prior to and in the course will influence attitudes about commitment to the organization.

Only a few researchers have explored how organizational commitment influences student retention. For example, Meyer, Allen, and Smith (1993) performed a study utilizing the three-component commitment model (Meyer & Allen, 1991) to examine student commitment. In this study, students were surveyed on the satisfaction they had with their program and the level of commitment they had to continue and they found that satisfaction with the program correlated with affective commitment early in the program but this relationship was not significant as students spent more time in the program.

In another research study, Larkin, Brasel, and Pines (2013) conducted a study in organizational commitment across domains to investigate student retention factors. The purpose was to investigate how organizational commitment and embeddedness are related to intention to persist. They concluded that an individual's level of commitment predicted graduation likelihood.

McNally and Irving (2010) also sought to extend organizational commitment research into the study of student behavior. A portion of their study utilized prior research in workplace commitment to analyze the effects of affective, normative, and continuance commitment on a student's commitment to his/her university. The results of the study supported prior research that affective commitment leads to lower turnover intention. They suggest that future research could identify antecedents of commitment so that higher education administration can improve student retention programs.

These results, when considered collectively, suggest that organization commitment will be influenced by factors such as connectedness and sense of community. Thus, we suggest the following:

H5: *Campus connectedness will positively influence affective organizational commitment.*

H6: *Sense of community will positively influence affective organizational commitment.*

2.6 Turnover intention

The focus of most research examining student attrition from educational settings involves examining turnover intention. Bean's (1980) foundational work in this area culminated in a model of student attrition that examines how organizational determinants impact two intervening variables, satisfaction and institutional commitment, and how these mediating variables, in turn, influence dropout intention. Bean's definition of student attrition is "the cessation of individual student membership in an institution of higher education" (Bean, 1980, p. 157). Bean's model reflects its origins in research examining workplace turnover (Price, 1977) in that just as employees may be unhappy or dissatisfied with their place of employment and choose to leave, students too may have similar reasons for leaving their chosen institution of higher learning. In subsequent work, Bean and Metzner (1985) proposed a model that focuses on attrition among non-traditional student populations. To achieve a better understanding of high dropout rates by non-traditional students, the authors proposed four variables thought to influence a student's intention to leave: a student's demographics, the academic environment, environmental factors, and psychological outcomes. These variables are based on the obstacles that non-traditional students face when attempting to persist through a higher education degree.

Subsequent research has examined these variables in a variety of settings. For example, Meyer, Allen, and Smith (1993) studied the dropout intention of nursing students and found that the level of commitment determined the level of turnover. Similarly, Kelloway, Gottlieb, and Barham (1999) studied employees that may or may not be experiencing work-family conflict and again found that the level of commitment determined the level of turnover. Given these findings and the predictions offered in Bean's model, we offer the following hypothesis related to turnover intention:

H7: *Affective organizational commitment will negatively influence turnover intention*

2.7 Research Model

Our research model is based on the literature and is offered to frame the discussion by outlining the factors that are significant for student persistence (see Figure 1). Based on prior theoretical research, the model is developed to analyze how collaborative learning influences campus connectedness and a sense of community, and subsequently how it impacts student persistence. The model presents each theoretical construct and our hypothesized predictions about how each factor contributes to student persistence.

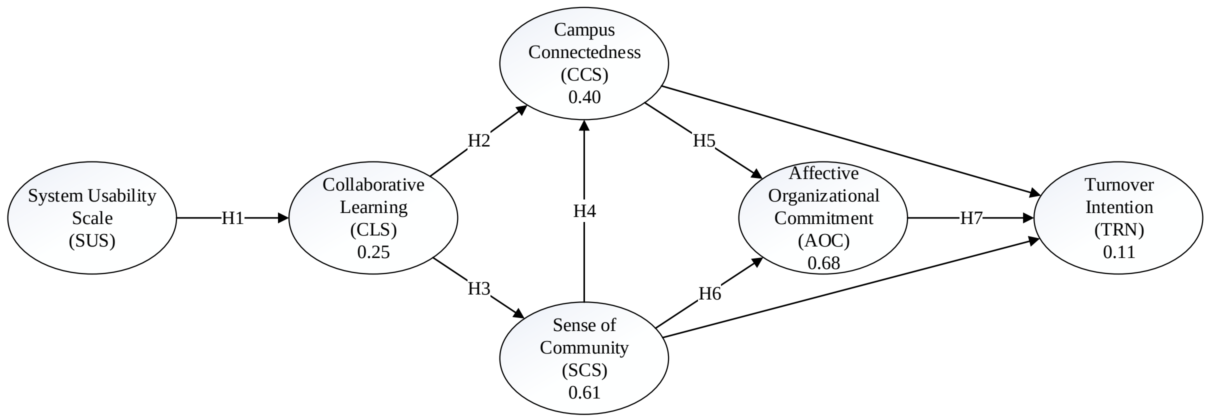

Fig 1. A Model of Collaborative Learning Commitment

3. Methods

The following section details the processes and methodologies used in this research. Responses were collected via a voluntary online survey via Qualtrics. The participants were allowed to opt out at any time as stated in the consent materials. In addition to the collected survey data, participation data were gathered based on voluntary involvement in a virtual learning community.

3.1 Participants and Learning Community Structure

The participants of this study included primarily first year college students attending commuter campuses from two different academic institutions: a community college and a 4-year state university located in the Midwest U.S. The ten participating campuses are geographically dispersed across the state, but are bound by a partnered pathway curriculum. The pathway concept is based upon an articulated college curriculum in the field of technology. To accommodate the demographic variety and diverse expectations of today's college student, the pathway has a significant number of enrollment milestones and graduation options so as to give students multiple entry and advancement opportunities.

As part of the partnership, a virtual learning community between the institutions was implemented as an intervention method for student success. A cohort of students across the partnering institutions was invited to participate in this learning community based upon enrollment in an affiliated course within the pathway curriculum. A total of 223 students voluntarily enrolled in the learning community.

The cohort of students participating in the partnering pathway program used a course management system called Blackboard Learn™ for regular course activities, including collaborative group assignments and individual assignments. The online learning community space that was made available to the same students was also housed within Blackboard Learn™. As for the learning community, activities were designed to encourage socialization among students and to offer mutual coursework related to their technology program. The participants in the learning community were part of a common first year experience based upon an introduction to the major and discipline. These students were located across a broad geographic region within the state.

Learning community activities were designed to encourage socialization among students and included selected coursework. The participants in the learning community were part of a common first year experience based upon an introduction to the major and discipline. To support the student through peer understanding, the students' initial learning community activity was to get to know their peers across the VLC by posting biographies and initial discussion of common interests, background, and general understanding. The rest of the activities were based upon common coursework. While the specific Associate's degree and Bachelor's degree students differed, the overall learning objectives were the same: an introduction to Engineering Technology and the program. The main student learning experience for the introduction course was a common design project. Students were expected to utilize the ideation process and come up with a solution to a problem of student design and effort. A subsequent activity was to support the teaching of the problem solving and design process where students would watch a number of subject matter expert (SME) videos on the topic and collaborate on the problem design process. Students were asked to reflect on the process and respond to other posts in other student groups also working on the design process. The third activity was later in the semester and timed to class progression: the students were asked to post their design project and gather feedback from other students in the discussion boards. The final activity was to bring the students face to face at an Engineering Technology summit. Industry advisors, faculty, and the VLC students were invited to attend the summit to socialize and discuss the discipline, their learning experiences, and industry career pathways.

3.2 Research Instruments

The survey instrument consisted of 64 questions that were designed to measure the factors of collaborative learning (CLS or Collaborative Learning Scale) (So & Brush, 2008), campus connectedness (CCS or campus connectedness scale) (Summers, et al., 2005), sense of community (SCS or Sense of Community Scale) (Chavis, Lee & Acosta, 2008), affective organizational commitment (AOC or Affective Organizational Commitment Scale) (Meyer, Allen, & Smith, 1993), turnover intention (TRN or Turn Over Intention) (Kelloway, Gottlieb, & Barham, 1999), and system usability (SUS or System Usability Scale) (Brooke, 1996; Bangor, Kortum, & Miller, 2008; Unal & Unal, 2011). The instrument was tailored to the terminology used for communities and academia, and questions used a 5-point Likert-type scale with the following possible responses: *strongly disagree, disagree, neutral, agree, and strongly agree*. The validation and statistical evaluation of the instruments is discussed in detail in the Results Section.

3.3 Data Collection Procedures

Within 2 weeks of the conclusion of the semester, students were asked to complete an online survey, which included the collaborative learning scale, sense of community scale, campus connectedness scale, commitment scale, turnover scale and usability scale. Participation data from the virtual learning community was also gathered, as well as demographic and context information such as major, classification, academic institution, and academic status. The participation data includes time spent in the system and how often it was accessed.[1]

4. Results

4.1 Preliminary Data Examination

To test the entire model, partial least squares structural equation modeling (PLS-SEM) was used. PLS was chosen for several reasons. First, the primary purpose of this research is to predict and explain the endogenous variables in the model as opposed to testing a theoretical model (Hair, Hult, Ringle, & Sarstedt, 2014). Second, the small sample size as

[1] Previous research has discussed some of the problems with self-report measures as the sole method of observation. Many of these issues relate to the exclusive use of these measures and the potential for common method bias. Research has demonstrated that the unmeasured latent method construct approach to assessing common method bias in PLS is not able to detect nor control for common method bias (Chin, Thatcher, & Wright, 2012) and researchers should instead use a measured latent marker variable approach (Chin et. al., 2013). This research was collected without incorporating a latent marker variable and therefore should be interpreted with this in mind.

compared to the large number of indicators per construct makes PLS-SEM a good choice as compared to the more traditional covariance-based structural equation modeling (CB-SEM) (Reinartz, Haenlein, & Henseler, 2009), with the large number of indicators and complexity of the model actually helping to lessen the effects of PLS-SEM bias (Lohmoller, 1989; Reinartz et al., 2009; Ringle, Gotz, Wetzels, & Wilson, 2009).

Preliminary data examination found no missing values. Furthermore, no outliers were found and skewness and kurtosis measures for all indicator variables were within the -1 to 1 range, indicating good data properties for use in the model. A power analysis for the entire model shows that the sample size of n = 103 is well above the 10-indicator rule (Barclay, Higgins, & Thompson, 1995), which says the sample size should be 10 times the maximum arrowheads pointing to any one construct in the model. In the case of our model, this maximum number of arrows is 3, which indicates the sample size should be above 30. Using Cohen's more differentiated sample size recommendations (Cohen, 1992), our sample is above the 59 subjects needed to achieve a statistical power of 80% for detecting R^2 values of at least 0.25 at $p = 0.05$. For the group-based analyses, the subjects are split into two groups according to the amount of time spent in the online virtual learning community. A split was made at 5 hours of usage based on the activities presented to the subjects, and the amount of time that the subjects voluntarily spent online in the system. For the group-based analyses, group1 (n = 58) and group2 (n = 45) both meet the requirements of the 10-indicator rule which indicates the sample size should be above 30. Group1 is also close to the 59 subjects needed to achieve a statistical power of 80% for detecting R^2 values of at least 0.25 at $p = 0.05$. Group2, while not above the 59 sample size needed to achieve a statistical power of

80% for detection R^2 values of at least 0.25 at $p = 0.05$, is above the 38 subjects needed to achieve a statistical power of 80% for detecting R^2 values of at least 0.5 at $p = 0.05$.

4.2 Measurement Model

The measurement model was first evaluated to assess the psychometric properties of the constructs used in the model (see Table 1. for a listing of the measurement model statistics). All constructs in the model were specified reflectively, as per previous research in the area for each construct, with the SCS construct specified as a second-order construct with four lower order factors. Reliability/internal consistency was assessed using both Cronbach's alpha and composite reliability. Both the first order factors as well as the second order factor of SCS were evaluated. The values for the latent constructs for both Cronbach's alpha and composite reliability were above the 0.7 cutoff and below 0.95, as is satisfactory (Nunnally & Vernstein, 1994). The second-order factor of SCS was slightly above the 0.95 cutoff, but given the correlated nature of the error terms of the lower-order factors, this was deemed acceptable (Drolet & Morrison, 2001; Hayduk & Littvay, 2012). Indicator reliability was assessed by evaluating the outer loadings of each indicator on its respective construct (see Table 2. for the loadings and cross loadings of each item on its respective construct). All loadings were above the 0.7 cutoff (Hair et al., 2014), except for one item in AOC (0.60), but the removal of this item did not produce a noticeable increase in composite reliability or average variance extracted (Hair, Ringle, & Sarstedt, 2011).

Table 1. Cronbach's alpha, composite reliability, average variance extracted, and correlations of the latent constructs, with the square root of the AVE along the diagonal (square root of the AVE not included for lower order factors)

				Correlations and Square Root AVE									
	Cronbach	CR	AVE	SUS	CLS	CCS	SCS	SCSFN	SCSINF	SCSMEM	SCSSEC	AOC	TRN
Usability (SUS)	0.92	0.94	0.76	0.87									
Collaborative Learning (CLS)	0.94	0.95	0.72	0.53	0.85								
Connectedness (CCS)	0.84	0.89	0.68	0.28	0.36	0.82							
Sense of Community (SCS)	0.97	0.98	0.64	0.50	0.73	0.40	0.80						
SCS Fulfillment of Needs	0.94	0.96	0.78	0.55	0.73	0.35	0.92	LOF					
SCS Influence	0.90	0.93	0.68	0.51	0.69	0.41	0.96	0.83	LOF				
SCS Membership	0.90	0.93	0.68	0.39	0.63	0.32	0.94	0.81	0.89	LOF			
SCS Shared Emotional Connection	0.93	0.95	0.74	0.45	0.70	0.41	0.94	0.80	0.90	0.84	LOF		
Affective Organizational Commitment (AOC)	0.89	0.92	0.65	0.32	0.48	0.34	0.49	0.45	0.52	0.44	0.44	0.81	
Turnover Intention (TRN)	0.88	0.91	0.72	0.14	0.25	0.13	0.29	0.25	0.26	0.27	0.29	-0.05	0.85

Both convergent and discriminant validity were assessed for the measurement model. Convergent validity was assessed using the average variance extracted (AVE). All latent constructs had an AVE well above the recommended cutoff of 0.5 (Bagozzi & Yi, 1988; Bearden, Netemeyer, & Mobley, 1993; Fornell & Larcker, 1981), indicating good convergent validity. Discriminant validity was assessed using both the cross loadings and the square root of the AVE. No loading of an item on a construct was found to be greater than the indicator's loading on its associated construct, providing evidence of discriminant validity (Hair, Ringle, & Sarstedt, 2011). Also, the square root of the AVE for each latent construct, was higher than its correlation with any other construct, again providing evidence of discriminant validity (Chin, 1998; Gefen & Straub, 2005; Majchrzak, Beath, Lim, & Chin, 2005). This does not apply to the lower-order factors belonging to the second-order construct of SCS.

Table 2. Squared loadings and cross loadings of items on constructs[2]

	SUS	CLS	CCS	SCS	SCSFN	SCSMEM	SCSINF	SCSSEC	AOC	TRN
SUS1	0.52	0.23	0.22	0.34	0.29	0.22	0.32	0.39	0.17	0.06
SUS2	0.86	0.19	0.15	0.17	0.17	0.09	0.21	0.13	0.18	0.03
SUS3	0.87	0.19	0.14	0.21	0.25	0.12	0.22	0.17	0.20	0.01
SUS4	0.83	0.22	0.11	0.14	0.16	0.07	0.19	0.10	0.17	0.00
SUS5	0.84	0.16	0.11	0.15	0.17	0.09	0.18	0.10	0.12	0.02
CLS1	0.05	0.60	0.15	0.37	0.27	0.29	0.28	0.47	0.19	0.05
CLS2	0.16	0.86	0.31	0.52	0.51	0.41	0.41	0.49	0.30	0.06
CLS3	0.18	0.70	0.17	0.32	0.32	0.23	0.33	0.26	0.21	0.05
CLS4	0.26	0.84	0.45	0.56	0.50	0.41	0.59	0.48	0.48	0.03
CLS5	0.21	0.80	0.33	0.53	0.54	0.38	0.44	0.50	0.29	0.03
CLS6	0.22	0.90	0.36	0.56	0.54	0.40	0.51	0.51	0.42	0.04
CLS7	0.14	0.67	0.17	0.38	0.40	0.33	0.27	0.33	0.28	0.09
CLS8	0.38	0.83	0.38	0.51	0.47	0.40	0.52	0.40	0.41	0.00
CCS1	0.06	0.09	0.67	0.14	0.10	0.10	0.14	0.18	0.30	0.06
CCS2	0.25	0.30	0.62	0.37	0.25	0.26	0.37	0.43	0.41	0.01
CCS3	0.09	0.31	0.73	0.22	0.25	0.13	0.19	0.21	0.56	0.04
CCS4	0.16	0.39	0.85	0.24	0.23	0.14	0.23	0.24	0.58	0.09
SCSFN1	0.09	0.43	0.20	0.68	0.80	0.54	0.50	0.54	0.18	0.06
SCSFN2	0.22	0.31	0.23	0.59	0.76	0.47	0.51	0.37	0.25	0.02
SCSFN3	0.27	0.52	0.25	0.79	0.88	0.73	0.63	0.55	0.30	0.01
SCSFN4	0.14	0.46	0.31	0.66	0.80	0.56	0.55	0.42	0.26	0.04
SCSFN5	0.21	0.48	0.18	0.67	0.67	0.63	0.49	0.55	0.15	0.01
SCSFN6	0.35	0.44	0.17	0.60	0.69	0.51	0.50	0.40	0.26	0.01
SCSMEM7	0.21	0.54	0.26	0.74	0.75	0.75	0.57	0.54	0.25	0.04
SCSMEM8	0.10	0.38	0.16	0.74	0.67	0.84	0.61	0.52	0.21	0.04
SCSMEM9	0.06	0.29	0.12	0.70	0.56	0.84	0.60	0.48	0.22	0.02
SCSMEM10	0.12	0.23	0.16	0.58	0.49	0.64	0.42	0.52	0.08	0.09
SCSMEM11	0.08	0.25	0.15	0.51	0.42	0.64	0.46	0.31	0.23	0.08
SCSMEM12	0.11	0.35	0.09	0.65	0.43	0.69	0.65	0.56	0.18	0.04
SCSINF13	0.08	0.24	0.14	0.63	0.40	0.61	0.70	0.53	0.27	0.08
SCSINF14	0.26	0.28	0.18	0.60	0.55	0.54	0.65	0.40	0.23	0.03
SCSINF15	0.12	0.30	0.21	0.66	0.42	0.62	0.69	0.61	0.25	0.07
SCSINF16	0.22	0.25	0.24	0.49	0.30	0.42	0.67	0.39	0.24	0.01
SCSINF17	0.17	0.65	0.25	0.58	0.52	0.44	0.66	0.44	0.38	0.02
SCSINF18	0.37	0.53	0.27	0.64	0.61	0.41	0.64	0.61	0.32	0.01
SCSSEC19	0.15	0.41	0.19	0.58	0.33	0.43	0.59	0.76	0.22	0.04
SCSSEC20	0.07	0.34	0.22	0.46	0.30	0.32	0.42	0.61	0.14	0.09
SCSSEC21	0.15	0.41	0.27	0.68	0.45	0.55	0.63	0.80	0.28	0.04
SCSSEC22	0.09	0.37	0.23	0.57	0.44	0.43	0.40	0.75	0.16	0.06
SCSSEC23	0.25	0.41	0.35	0.68	0.54	0.57	0.56	0.72	0.17	0.12
SCSSEC24	0.27	0.52	0.34	0.85	0.71	0.68	0.73	0.86	0.35	0.02
AOC1	0.19	0.21	0.32	0.14	0.14	0.09	0.17	0.11	0.60	0.04
AOC2	0.27	0.13	0.11	0.17	0.14	0.10	0.20	0.16	0.36	0.00
AOC3	0.19	0.41	0.59	0.32	0.29	0.23	0.36	0.27	0.83	0.01
AOC4	0.08	0.32	0.52	0.26	0.16	0.18	0.34	0.24	0.77	0.05
AOC5	0.23	0.28	0.52	0.27	0.26	0.20	0.32	0.19	0.74	0.01
AOC6	0.10	0.37	0.60	0.32	0.26	0.27	0.35	0.26	0.85	0.04
TRN1	0.00	0.03	0.04	0.03	0.01	0.02	0.02	0.05	0.00	0.88
TRN2	0.00	0.04	0.04	0.07	0.05	0.10	0.05	0.07	0.01	0.89
TRN3	0.02	0.08	0.10	0.07	0.03	0.08	0.04	0.10	0.05	0.72
TRN4	0.00	0.01	0.02	0.00	0.00	0.01	0.00	0.01	0.00	0.67

[2] Squared loadings are recommended for presentation purposes. See (Esposito Vinzi, et. al., 2010).

4.3 Structural Models

For this research, the hypothesized model was analyzed. First, one model was analyzed for all subjects. Next, two separate models were analyzed using samples of individuals who highly utilized the virtual learning community environment (greater than 5 hours of usage) and those who underutilized the virtual learning community environment (less than 5 hours of usage). The following frequency table provides a representation of how many hours were spent in the VLC (Table 3).

Table 3. Hours of participant usage in the VLC.

Number of hours	Frequency
Less than 1 hour	30
1-2 hours	8
2-3 hours	6
3-4 hours	6
4-5 hours	8
5-6 hours	8
6-7 hours	3
7-8 hours	2
8-9 hours	4
9-10 hours	5
Greater than 10 hours	23

Each separate model and its results are described below. The means and standard deviations for the entire sample as well as those for the two separate groups can be seen in Table 4.

Table 4. Means and standard deviations for the entire sample, as well as the two groups separated by the amount of hours in the VLC.

	combined		Group 1: VLC < 5		Group 2: VLC > 5	
	mean	std	mean	std	mean	std
SUS	3.38	0.91	3.47	0.93	3.27	0.89
CLS	3.33	0.93	3.41	0.90	3.24	0.96
CCS	3.22	0.88	3.28	0.92	3.14	0.84
SCS	2.30	0.73	2.34	0.75	2.24	0.70
AOC	4.63	1.22	4.73	1.18	4.51	1.27
TRN	2.42	0.99	2.56	1.00	2.24	0.95

Before beginning, given that multiple indicators were used to predict CCS (CLS and SCS), AOC (CCS and SCS), and TRN (CCS, SCS, and AOC) a collinearity assessment was run. Results did not indicate collinearity with variance inflation factor (VIF) scores below the suggested cutoff of 5 (Hair, Ringle, & Sarstedt, 2011) for CLS/SCS (VIF = 2.22), CCS/SCS (VIF = 1.19), and CCS/SCS/AOC (VIF = 1.77, 1.36, 2.01).

4.3.1 Combined model

The first model included all subjects. Structural path coefficients were first evaluated (see Figure 2 and Table 5). The model showed significant ($p < 0.01$) path loadings of SUS on CLS ($\beta = 0.54$) – supporting H1, CLS on SCS ($\beta = 0.74$) – supporting H3, CCS on AOC ($\beta = 0.54$) – supporting H5, SCS on AOC ($\beta = 0.29$) – supporting H6, and SCS on TRN ($\beta = 0.39$); significant ($p < 0.05$) path loadings of SCS on CCS ($\beta = 0.29$) – supporting H4 and AOC on TRN ($\beta = -0.36$) – supporting H7; and a significant ($p < 0.1$) path loading of CCS on TRN ($\beta = 0.21$). Further examination of indirect effects found that an indirect effect of SCS on AOC ($\beta = 0.16$) produces a significant ($p < 0.01$) total effect of 0.45, and an indirect effect of SCS on TRN ($\beta = -0.10$) produces a significant ($p < 0.05$) total effect of 0.29. Also, while the direct effect of CLS on CCS is not significant ($\beta = 0.15$), when combined with the indirect effect ($\beta = 0.22$) of CLS on CCS via SCS this produces a significant ($p < 0.01$) total effect of 0.37.

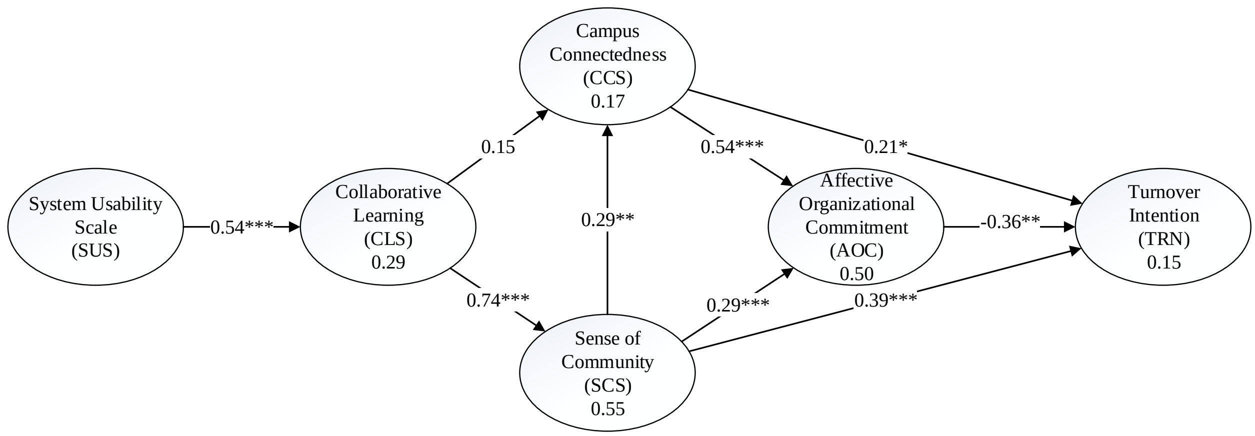

Fig 2. Combined structural model with standardized path loadings (*p < 0.1, **p < 0.05, ***p < 0.01)

Table 5. Path loadings of combined structural model, including effects.

	β	SE(β)	t-value	indirect	total	SE(total)	t-value
SUS -> CLS	0.54	0.10	5.19 ***	-	0.54	0.10	5.19 ***
CLS -> SCS	0.74	0.04	16.70 ***	-	0.74	0.04	16.70 ***
CLS -> CCS	0.15	0.15	1.06	0.22	0.37	0.12	2.96 ***
SCS -> CCS	0.29	0.14	2.01 **	-	0.29	0.14	2.01 **
CCS -> AOC	0.54	0.07	7.18 ***	-	0.54	0.07	7.18 ***
SCS -> AOC	0.29	0.08	3.71 ***	0.16	0.45	0.10	4.67 ***
CCS -> TRN	0.21	0.13	1.65 *	-0.19	0.02	0.12	0.14
SCS -> TRN	0.39	0.11	3.63 ***	-0.10	0.29	0.12	2.42 **
AOC -> TRN	-0.36	0.15	2.37 **	-	-0.36	0.15	2.37 **

Further assessment of the model used R^2 values, f^2 effect size measures, and q^2 predictive relevance measures (see Table 6). To evaluate the model's predictive accuracy, R^2 values were examined. The analysis showed the proportion of variance explained was 0.29 for CLS, 0.55 for SCS, 0.17 for CCS, 0.50 for AOC, and 0.15 for TRN. The f^2 effect size measure was used to assess the contribution of the exogenous constructs on their respective endogenous latent variable's R^2 value. The effect of CLS on CCS (0.01), SCS on CCS (0.04), CCS on TRN (0.04), and AOC on TRN (0.04) were found to be small, SCS on AOC (0.14) and SCS on TRN (0.12) to be medium, and CCS on AOC (0.44) to be large (Cohen, 1988). The q^2

effect size measure was used to assess the predictive relevance of the exogenous constructs on their respective endogenous construct. The effect of CLS on CCS (0.01), SCS on CCS (0.03), SCS on AOC (0.07), CCS on TRN (0.03), SCS on TRN (0.08), and AOC on TRN (0.06) were found to be small while the effect of CCS on AOC (0.22) was found to have a medium effect.

Table 6. R^2, f^2, and q^2 values for the AOC structural model

	R^2	R^2 excluded	f^2 effect	Q^2	Q^2 excluded	q^2 effect
SUS -> CLS	0.29	-	-	0.21		
CLS -> SCS	0.55	-	-	0.35	-	-
CLS -> CCS	0.17	0.16	0.01	0.12	0.11	0.01
SCS -> CCS		0.14	0.04		0.09	0.03
CCS -> AOC	0.50	0.28	0.44	0.31	0.16	0.22
SCS -> AOC		0.43	0.14		0.26	0.07
CCS -> TRN	0.15	0.12	0.04	0.11	0.08	0.03
SCS -> TRN		0.05	0.12		0.04	0.08
AOC -> TRN		0.12	0.04		0.06	0.06

4.3.2 Group-based models

To gain a greater understanding of the effectiveness of the model, two separate sub-models were estimated by separating individuals based on low (less than 5 hours) and high (greater than 5 hours) levels of virtual learning community use throughout the semester.[3] This provides evidence that the model can differentiate between heterogeneous groups (Hair et al., 2014), thereby providing greater credence to the effectiveness of the model overall. Differences in structural path coefficients are shown in Figure 3, Figure 4, Table 7, and Table 8. A significant ($p < 0.1$) difference is seen between groups (Sarstedt, Henseler, & Ringle, 2011) with the relationship of CLS on CCS where the impact of CLS on CCS is significant

[3] Previous studies have split data for group analysis based on the nature of how the particular group under study actually used the system. While many studies use either the median or mean to split the sample into groups, the median number of hours for all subjects for this study was found to be 4.34 while the mean was found to be 6.07. Given this two-point difference, the midpoint of 5 was chosen as a conservative estimate to split the difference between these two values.

(β = 0.42) for the high VLC use group and not significant (β = -0.04) for the low VLC use group, with a total effect that is also significantly different ($p < 0.05$) between the high and low VLC groups (β = 0.61 vs. β = 0.19 respectively). This shows that while the path from CLS to CCS is not significant in the combined model, there is actually a significant interaction effect present for this relationship, providing partial support for H2. Another noticeable difference is seen with regard to the effects on TRN between the two groups. In the low VLC group both AOC (β = -0.48) and SCS (β = 0.45) have a significant relationship on TRN whereas none of the three variables leading to TRN in the high VLC group have a significant relationship with TRN.

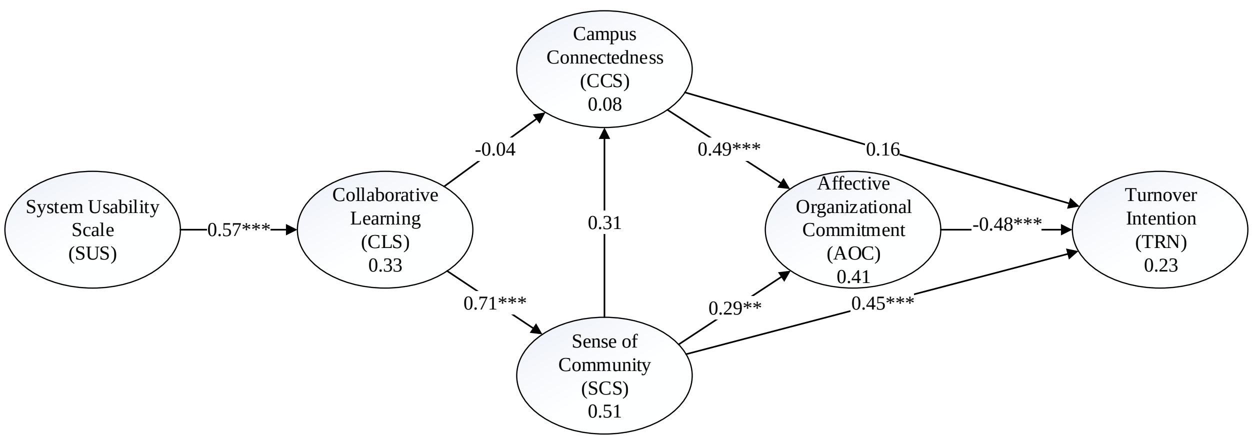

Fig 3. Structural model with standardized path loadings (*p < 0.1, **p < 0.05, ***p < 0.01) for low VLC group

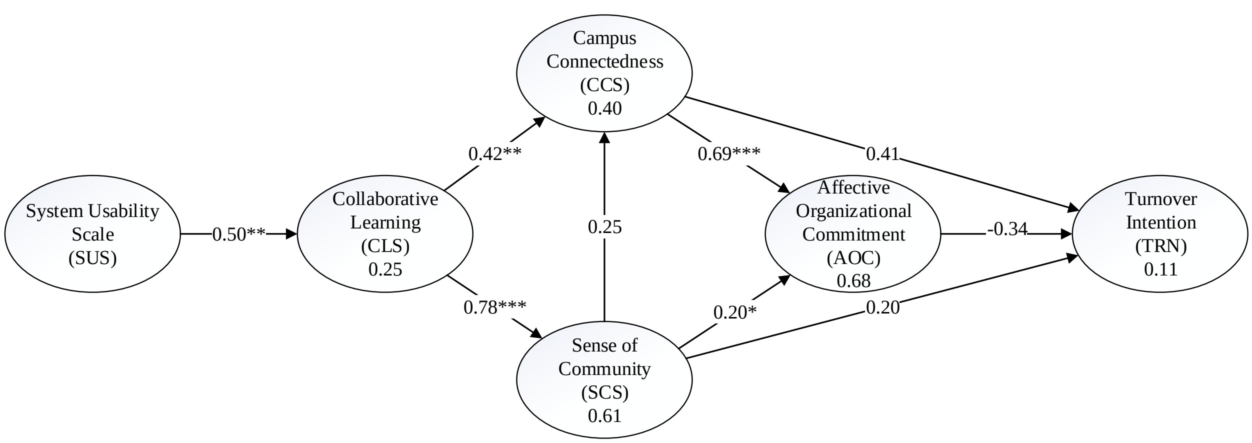

Fig 4. Structural model with standardized path loadings (*p < 0.1, **p < 0.05, ***p < 0.01) for high VLC group

Table 7. Path loadings of structural model for low VLC group, including effects.

	Group 1: VLC < 5						
	β	SE(β)	t-value	indirect	total	SE(total)	t-value
SUS -> CLS	0.57	0.11	5.15 ***	-	0.57	0.11	5.15 ***
CLS -> SCS	0.71	0.06	11.65 ***	-	0.71	0.06	11.65 ***
CLS -> CCS	-0.04	0.21	0.18	0.23	0.19	0.19	0.99
SCS -> CCS	0.31	0.21	1.49	-	0.31	0.21	1.49
CCS -> AOC	0.49	0.12	4.14 ***	-	0.49	0.12	4.14 ***
SCS -> AOC	0.29	0.14	2.05 **	0.15	0.44	0.18	2.52 **
CCS -> TRN	0.16	0.15	1.02	-0.24	-0.08	0.17	0.47
SCS -> TRN	0.45	0.14	3.16 ***	-0.16	0.29	0.19	1.49
AOC -> TRN	-0.48	0.19	2.59 ***	-	-0.48	0.19	2.59 ***

Table 8. Path loadings of structural model for high VLC group, including effects.

	Group 2: VLC > 5						
	β	SE(β)	t-value	indirect	total	SE(total)	t-value
SUS -> CLS	0.50	0.21	2.44 **	-	0.50	0.21	2.44 **
CLS -> SCS	0.78	0.07	11.90 ***	-	0.78	0.07	11.90 ***
CLS -> CCS	0.42	0.18	2.34 **	0.19	0.61	0.10	6.29 ***
SCS -> CCS	0.25	0.18	1.41	-	0.25	0.18	1.41
CCS -> AOC	0.69	0.10	6.73 ***	-	0.69	0.10	6.73 ***
SCS -> AOC	0.20	0.10	1.93 *	0.17	0.37	0.14	2.60 ***
CCS -> TRN	0.41	0.27	1.53	-0.24	0.17	0.20	0.85
SCS -> TRN	0.20	0.20	1.00	-0.03	0.17	0.17	1.00
AOC -> TRN	-0.34	0.27	1.25	-	-0.34	0.27	1.25

Differences are also seen with regard to effect sizes of the model between the two groups (see Table 9 and Table 10). First, the R^2 value of CCS in the low VLC group (0.08) is much lower than the same R^2 value in the high VLC group (0.40). Also, the R^2 value of AOC in the low VLC group (0.41) is lower than the same R^2 value in the high VLC group (0.68). Conversely, the R^2 value of TRN in the low VLC group (0.23) is double the same R^2 value in the high VLC group (0.11). Second, the f^2 effect size is larger for CLS on CCS in the high VLC group (0.12) as compared to the low VLC group (0.00), is substantially larger for CCS on AOC in the high VLC group (0.98) as compared to the low VLC group (0.34), and is larger for SCS on AOC in the low VLC group (0.14) as compared to the high VLC group (0.05). Third, the q^2 effect size is again substantially larger for CCS on AOC in the high VLC group (0.34) as compared to the low VLC group (0.15) and is larger for SCS on TRN in the low VLC group (0.13) as compared to the high VLC group (0.00).

Table 9. R^2, f^2, and q^2 values for the structural model for the low VLC group.

	Group 1: VLC < 5					
	R^2	R^2 excluded	f^2 effect	Q^2	Q^2 excluded	q^2 effect
SUS -> CLS	0.33	-	-	0.23	-	-
CLS -> SCS	0.51	-	-	0.32	-	-
CLS -> CCS	0.08	0.08	0.00	0.04	0.04	0.00
SCS -> CCS		0.03	0.05		0.01	0.03
CCS -> AOC	0.41	0.21	0.34	0.21	0.09	0.15
SCS -> AOC		0.33	0.14		0.17	0.05
CCS -> TRN	0.23	0.22	0.01	0.16	0.15	0.01
SCS -> TRN		0.15	0.10		0.05	0.13
AOC -> TRN		0.16	0.09		0.09	0.08

Table 10. R^2, f^2, and q^2 values for the structural model for the high VLC group.

	Group 2: VLC > 5					
	R^2	R^2 excluded	f^2 effect	Q^2	Q^2 excluded	q^2 effect
SUS -> CLS	0.25	-	-	0.20	-	-
CLS -> SCS	0.61	-	-	0.38	-	-
CLS -> CCS	0.40	0.33	0.12	0.28	0.24	0.06
SCS -> CCS		0.38	0.04		0.26	0.03
CCS -> AOC	0.68	0.36	0.98	0.42	0.22	0.34
SCS -> AOC		0.66	0.05		0.41	0.02
CCS -> TRN	0.11	0.07	0.04	0.07	0.04	0.03
SCS -> TRN		0.09	0.02		0.07	0.00
AOC -> TRN		0.08	0.03		0.05	0.02

5. Discussion

The primary purpose of this study is to develop and test a model of collaborative learning commitment. Specifically, we developed our model to measure the effectiveness of an institution’s collaborative learning environment by basing the model on prior theory and research in the domains of community and organizational commitment. In this study we set about to evaluate this model in an online educational setting where it was expected that factors such as sense of community, perceptions of campus connectedness, and organizational commitment would influence turnover intention. To do so, we used structural equation modeling to examine our data and model and we found support for most of the predictions specified in our model. Not only were most relationships found to be significant, but the model was also able to discern between two separate groups of students, which supports the generalizability of the model's structure.

While a sense of community and commitment to an institution can materialize from a number of situations, our model focuses on the impact of collaborative learning on these factors. The focus on collaboration is due, in part, to the fact that employers are seeking graduates who possess not only task-specific skills and knowledge, but also skills with working collaboratively in online settings. Our model builds on prior research in usability, collaborative learning, community, and organizational commitment and while the factors examined in the model have been considered in prior studies, our research is the first to combine these constructs into one model to measure the effect of collaborative learning on student turnover intention. Thus, an important contribution of this research is the model itself, which represents an important tool for understanding the factors that influence student retention.

Nevertheless, several specific findings are also important to highlight. For example, our results suggest that the level of usability that students perceive about an online educational system has a significant influence on their collaborative learning experience. The ease of use in a system can set a tone for the way students interact, which has an important influence on the outcomes of the collaborative learning activity. If the system is perceived as usable, there will be an increased likelihood of a positive collaborative learning experience. Further, an easy to use system not only encourages active learning, but also is likely to result in a convergence of knowledge among participants. The concept of collaborative learning is derivative of the theory of social constructivism, which is based on the premise that individual knowledge can be acquired through the negotiation of meanings with others (Bernard, Rojo de Rubalcava, St. Pierre, 2000; So & Brush, 2008; Zhu, 2012). These interchanges of information and participation within a group reduce feelings of isolation and foster a sense of community (Rovai, 2001); therefore, the usability of a system can influence whether these exchanges occur and whether knowledge transfer and convergence is possible.

Prior research suggests that both sense of community and connectedness should be considered when examining collaborative learning settings. As a result, we include both of these variables in our model (McMillan & Chavis, 1986; Chavis, Lee & Acosta, 2008; Lee, Keough, & Sexton, 2002). We hypothesized that a high level of sense of community and connectedness would both positively influence a student to stay with his or her academic institution. Our results suggest that, had all students in the sample used this system, the collaborative learning environment would significantly influence the student’s sense of community, but we also found that it would not have a direct effect on campus connectedness. This is likely because a collaborative learning system will generally be designed to have a greater focus on establishing and maintaining relationships within and between group members and it will have a lesser goal associated with building a rapport between a student and the institution as a whole. Nevertheless, the results do show that there is an indirect effect between the learning environment and connectedness because sense of community significantly influences connectedness. These results are similar to those found by Summers and colleagues (Summers et al., 2005) where these two factors complement each other.

An important implication of this finding is that if a student can be encouraged to develop a perception of connectedness with his or her classmates, this will transfer to creating perceptions of connectedness with the academic institution as a whole. This is important because if collaborative learning is a means for preparing students for the workplace environment, it is appropriate to measure a student's commitment to an institution much like a firm would measure an employee's workplace commitment and subsequent turnover intention (Allen & Meyer, 1990; Bean, 1980). If a student feels connected to the university, it would suggest a commitment to persist out of loyalty. If a student has a lower level of connectedness, the level of commitment is not strong due to apathy toward the university. As with connectedness, if a sense of community is not acquired, there is less likelihood of commitment toward the institution.

We also consider turnover or dropout intention in our model. The measure of a student's intention to drop out is based on the prior research by Meyer and colleagues (Meyer, Allen, & Smith, 1993) and Kelloway and colleagues (Kelloway, Gottlieb, & Barham, 1999) where the level of commitment was found in both studies to determine the level of turnover. As with prior research, commitment was shown to significantly impact turnover intention, with higher commitment being associated with lower turnover intention and, importantly, lower likelihood of actually dropping out.

The results of the VLC study used to test the model demonstrate that the model can provide insight on what changes must be made in a VLC environment in order to increase student persistence and lessen student attrition concerns. A better understanding of where the VLC needs improvement was obtained through the use of our model. All of the relationships suggested significance except one (collaborative learning did not have a significant effect on campus connectedness), and all items were in the right direction. The non-significant relationship between collaborative learning and connectedness may imply that more emphasis should be put on adding curriculum to the collaborative learning environment that fosters a feeling of relatedness to the institution and not just a feeling of belonging to a group.

We sought to examine how robust the model is by performing a more nuanced analysis of the data by doing a split sample analysis. Our objective with this analysis is to evaluate the validity of the model by examining whether the factors hold up when the model is applied to examine two sets of data. Our approach follows the advice of MacKenzie and colleagues (MacKenzie, Podsakoff, & Podsakoff, 2011) who suggest that one of the most effective ways of assessing validity is to compare groups that are expected to differ on the constructs either through experimental manipulation or splitting samples based on a defined criterion (also see Hair et al., 2014). As a result, we split the sample based on the level of use made by students of the virtual learning community. When comparing the two groups, low VLC usage versus high VLC usage, the low VLC usage group reported means of higher community, connectedness, and commitment. We also saw a statistically significant impact of affective organizational commitment on turnover intention in the low VLC group while, at the same time, we did not find these relationships to be significant in the high VLC group. Our examination of the models show that the models do demonstrate differences between these groups, which supports the validity of the model overall and point to the robust nature of this model for examining VLC participation and intentions in different contexts.

The analysis shows that, when considering the effect of collaborative learning on campus connectedness, there is a significant difference between the low and high usage groups. An inspection of the relationship shows that collaborative learning has a significant impact on campus connectedness in the high VLC group but this relationship is not significant in the low VLC group. So, while the combined model suggests that this relationship is non-significant, a between group analysis shows that there is a moderating relationships between these variables based on VLC usage. The implication is that with more emphasis on the appropriate collaborative learning curriculum and encouragement of faculty to participate, students who are willing to participate may be more influenced in their relatedness to the institution. Of course, this also shows that this model is useful in examining a variety of factors that influence student retention.

We have demonstrated that our model is useful in explaining the relationship between collaborative learning and turnover intention. The model and our research have implications for examining student persistence and turnover intention. Chief among these implications is the finding that our model is effective in measuring turnover intention for a collaborative learning environment in an educational context. The trend in higher education is to increase collaborative learning in the classroom and in online settings; therefore, more research on the impact that collaborative learning can have on student persistence is warranted and we have shown that our model is useful in defining and measuring the factors that influence these outcomes. While collaborative learning is an important 21st century skill, there is a need for assessing its impact on students beyond the acquisition of new knowledge. Despite prior research examining student attrition, the issue of turnover (i.e., dropout) still remains high as tuition costs rise and technical skills are required for employment. Understanding the impact community and connectedness have on commitment in a collaborative learning environment is important to student attrition research; thus, future research should apply our model to examine these issues in other educational contexts. .

When considering the implications of this study on virtual learning community research, this model approaches student persistence from a different perspective. The students who participate in a VLC are encouraged to participate in community driven activities and ultimately find a connection to the institution in the process. This study looks at that process through participation in collaborative learning activities. Our model measures the impact of collaborative learning activities that are designed to foster community and, consequently, student persistence. As collaborative learning activities are tested and implemented in a virtual learning community in an attempt to encourage participation, this model contributes to research in how well the activities impact a student's feelings toward persistence.

While our model was shown to be valid and useful, it does not explain all of the variance. Thus, a logical extension to this research is to not only examine the model in different contexts (e.g., in traditional classroom settings, in executive education, in flipped courses, etc.), but also to identify other variables that should be considered in examining collaborative learning.

While we primarily focus our discussion on the model development and the results of the model validation and testing, we also think that our model has practical implications for administrators and faculty seeking to evaluate the effectiveness of learning environments.

When institutions invoke collaborative learning activities into the first year experience, as students are new to the institution and have not had a chance to develop relationships, a sense of community and connectedness to the institution should be made explicit within collaborative learning activities because this will reduce turnover intention. Furthermore, the model provides a basis for developing student surveys that could be used to evaluate student intentions and, thereby, offer practical guidance to educators about student intentions and the condition of those factors that are influencing these attitudes.

While we think our analysis demonstrates the validity of the model, the study does include several limitations that should be considered in interpreting these results. First, this study was conducted in the Midwestern United States and involved only two institutions. Plus, the student population from which the study sample draws upon is predominately white, male, non-traditional, and rural. While self-selecting, the nature of this sample and the size of the sample used in this evaluation may limit the generalizability of the results. Additionally, the VLC program included a small number of activities designed to engage students, not all students participated equally. Thus, some of the variance in the results may reflect differences in participation. While manipulations of the contents and structure of the VLC program is outside of the scope of our analyses, these characteristics are important to consider when interpreting results.

Another limitation of the study involves turnover intention measures. The turnover intention scale is traditionally utilized in an organizational setting and concepts related to turnover, while positioned as dropping out of the program, might need refinement to distinguish between different ways that someone might exit a program. All students inevitably leave academic institutions, so future research could look at the different ways that people exit other than “dropping out.” Finally, while turnover intention was the focal dependent measure in this study, we did not measure whether the student does, in fact, persist in the program. Prior research has shown that intentions and behaviors are highly correlated, but our model could be improved by measuring actual behaviors in addition to intentions.

While the sample sizes of the usage groups were relatively small in this initial test of the model, it provided enough power to show significant results in the analysis of the new model. There are many possibilities with the proposed model when it comes to future research, including group comparisons. This study had a notable limitation as it was not contrasted with a group that did not participate in the virtual learning community, so future research would benefit from a comparison group. Further research in learning domains, demographics, delivery techniques in the classroom, and graduate courses are all appropriate research paths. The impact of collaborative learning on student turnover intention may be different based on demographics. As for delivery methods in the classroom, the flipped classroom can entail a sizable amount of collaborative group work. It would be beneficial to measure the impact it has on community, connectedness, and commitment among the participants in the course. While this study focuses on undergraduate education, it would be of interest to measure the impact of collaborative learning in graduate student persistence. Further research in student persistence is still important as the problem continues to plague academic institutions, and this model is an appropriate contribution to the research domain.

6. Conclusion

Institutions of higher education are being called upon to provide a more robust pathway to a college degree and improve upon the advanced workforce for the needs of the 21st century. As 21st century skills call for employees to successfully work collaboratively in groups, an increase in technology adoption, globalization, and increased competition are among the factors that make collaboration one of the most important skills that employers insist that individuals obtain today. The purpose of this study is to create and evaluate a model that will measure the factors that significantly influence a student's persistence in a computer supported collaborative learning environment. Utilizing prior theoretical research as a foundation, we developed and tested a model to analyze how collaborative learning is mediated by campus connectedness and a sense of community and how these factors impact student persistence. We tested the model using structural equation modeling and found that the relationships between all factors but one were statistically significant. Additionally, we showed that the model can be used to discern between two separate groups, adding to the model's versatility. An important outcome of this research is the demonstration of an effective model that can be used to research the impact of collaborative learning on turnover intention.

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