Modeling Performance in Asynchronous CSCL: An Exploration of Social Ability, Collective Efficacy and Social Interaction

Wanli Xing, So Mi Kim and Sean Goggins,
wxdg5@mail.missouri.edu, kimsomi@missouri.edu, Gogginss@missouri.edu
School of Information Science and Learning Technologies, University of Missouri-Columbia

Abstract: Previous studies have invested effort in understanding the factors affecting student learning from isolated perspectives. Based on social cognitive theory, this study proposes two dynamic CSCL models of learning using understudied factors – system functionality, social ability, collective efficacy and social interaction – to examine mediation and causal relationships among these constructs and their influence on learning. The models are tested using data collected from a large US university. Specifically, while the predictive constructs are operationalized through the survey instruments, outcome measures are modeled using electronic trace data and actual evaluation information. Data is analyzed via the Partial Least Squares method. Results demonstrate close relatedness among the constructs and a different influencing mechanism on learning for each. The addition of social interaction as a factor to the learning model increases predictability of student learning as compared to models without this factor. The paper concludes with discussion of the implications of this study.

Keywords: CSCL, social ability, collective efficacy, social interaction, PLS

Introduction

Researchers have taken considerable effort to understand the factors affecting student achievement in computer supported collaborative learning (CSCL). Previous studies, however, have investigated these factors from more or less isolated perspectives. Kirschner and Erkens (2013) classified these perspectives into three categories: pedagogy, technology, and human factors. From pedagogical point of view, Shaw (2013) studied group sizes and the impact on programming language learning. Jackson et al. (2013) explored the effect of interactive tabletops on elementary students' mathematical achievement. From a human factors perspective, Joksimovic et al. (2014) reported how individual differences (e.g., working memory) influenced perceived cognitive presence in communities of inquiry. These approaches, despite their contributions to our understanding of CSCL to date, have overlooked emergent dynamics created by multiple factors across categories. For example, one might question how groups perceive pedagogies and technologies to experience of agency, social interaction, and learning. Given that CSCL builds on person-environmental reciprocity in socio-technical systems (c.f., Bandura, 1986), it is important to examine internal forces and synergies that result from interactions among multiple factors, including pedagogy, technology, and human factors.

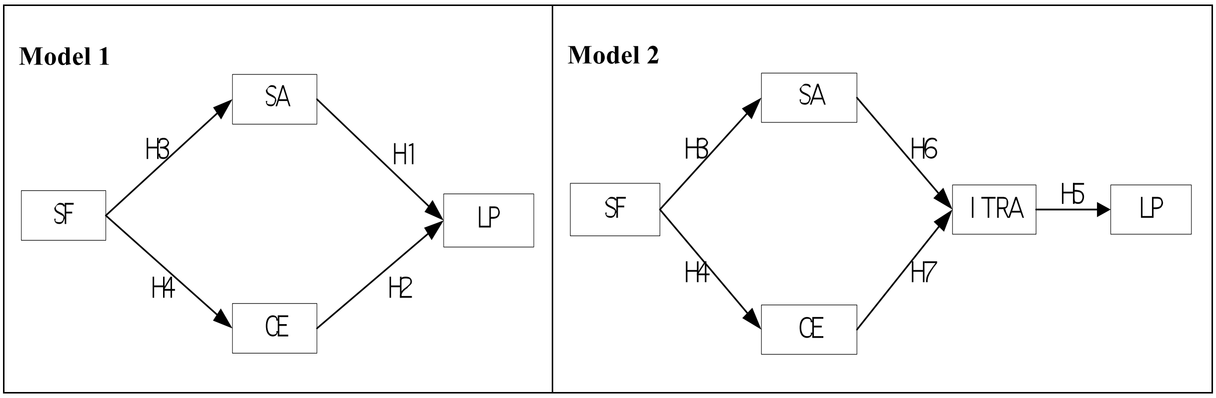
The current study, therefore, proposes and validates a model of learning that sheds light on dynamics across several factors that are particularly understudied in CSCL. Specifically, with inspiration from social cognitive theory, we examine how cognitive factors—social ability and collective efficacy—influence student learning while mediating the impact of technological environments—system functionality—on learning outcomes. Social ability, the perceived individual capacity to perform well within social-technical systems, is a fitness measure among task, technology and people (Yang et al., 2006). It is a factor not captured by previous approaches isolating pedagogy, technology and human factors. Few studies have investigated how social ability correlates with other factors to influence CSCL. Similarly, Bandura (2000) suggested that collective efficacy, the group's shared belief that it can execute a task successfully, has positive impact on various aspects of group learning and performance. There is, however, little research examining the role of collective efficacy in CSCL. Introducing social ability and collective efficacy and constructing a dynamic model of learning with them has the potential to improve our understanding of how learning takes place in CSCL.

We further build an alternative model to examine how these factors (system functionality, social ability, and collective efficacy) are ultimately embodied as social interaction behavior influencing student learning outcomes. This model specifies social cognitive theory's triadic reciprocity of environment-cognition-behavior in CSCL. For example, system functionality is measured as task-specific support. Social ability is measured as the fit between person, task, and tools in CSCL. The second model aims to illustrate the influencing process of these factors on social behavior and learning, and outperforms the first model in predicting and explaining learning.

Theoretical background and research models

Social cognitive theory (Bandura, 1986) builds on reciprocal determinism, which indicates that environments and persons influence and shape each other. Environmental factors refer to social and physical characteristics—system functionality in our study. Human factors represent 1) psychological characteristics such as knowledge, beliefs, and emotion and 2) their involvement in cognitive and social events. With inspiration from social cognitive theory, we consecutively built two CSCL models of learning to explore and elaborate CSCL dynamics. System functionality (SF), social ability (SA), collective efficacy (CE) and social interaction (ITRA) are exogenous or/and mediation variables. Learning performance (LP) is an endogenous variable. Table 1 presents each model.

Table 1: Research models



Model 1

Previous CSCL studies rarely considered psychological characteristics among human factors (Joksimovic et al., 2014). Our first model highlights how environmental impact is mediated by beliefs related to ability at both individual and group levels to influence student learning. First, the construct of social ability is a synthetic representation of individuals' beliefs about their capacity to learn within a surrounding environments' social affordances. Yang et al. (2006) suggested a social ability measure for online group learning contexts comprised of five factors: social navigation, peer social presence, instructor social presence, written communication, and comfort in sharing personal information. Social navigation indicates that students can perform well due to the visibility of actions of other students in the online system (c.f., Dourish, 1999). Social presence reflects student confidence in social interaction. Clear communication through writing is an especially crucial factor for student success in asynchronous online learning. Finally, in a less private space, learners may feel uncomfortable in sharing some types of information, which in turn affects the interaction between group members. Instead of being a single dimension measure, social ability captures intricate effects of the interaction between person, task and tool. Social ability is previously shown to be a significant predictor of online learning satisfaction and participation pattern change; students with higher social ability move from peripheral to central roles in an online CSCL courses (Tsai et al, 2008). We therefore assume a positive relationship between social ability and learning outcome:

H1: Social ability has a significant positive effect on student learning.

Social cognitive theory posits efficacy, belief in one's own ability to complete tasks, as an important factor that guides human behavior. Research on efficacy has been essentially confined to self-efficacy exercised individually. However, this is not the only way in which a person can bring an impact on learning. Bandura (2000) suggested extending the notion of self-efficacy to collective efficacy. It is a notion that exits in the mind of group members, or group's shared beliefs in its conjoined capabilities to execute the actions required to achieve common goals (Bandura, 2000). Perceived collective efficacy is particularly relevant when the goal achievement requires a massive amount of interdependent efforts, which is usually the case in CSCL. Lent, Schmidt and Schmidt (2006) conducted an experiment to show that collective efficacy is even a stronger predictor of team performance than self-efficacy. Hence, collective efficacy is held to be an important determinant of student learning in CSCL:

H2: Collective efficacy has a significant positive effect on student learning.

The quality and usefulness of the technological systems is a fundamental determinant of effective online learning (Schwier, 2002). Therefore, system functionality is considered as a base factor influencing learning. System functionality in our case is the perceived ability of the environment to provide task-specific support, problem solving, and collaboration. Without quality system provisions (e.g., communication channels), students may feel isolated and depowered to accomplish the scheduled tasks. In Schwier (2002)'s study, therefore, system functionality was crucial to building online learning communities. As a foundational infrastructure for students to be social, we assume system functionality will affect students' perceived social ability:

H3: System functionality significantly influences social ability

Similarly, the technological environment serves as a determinant of collective efficacy. Social cognitive theory posits that past success, vicarious experience, verbal persuasion, and physiological cues (c.f., Bandura, 1986). We assume that system functionality can promote collective efficacy by providing effective communication channels, which make visible other students' success traces, support group regulation, and enable peer encouragements (c.f., Kirschner & Erkens 2013) :

H4: System functionality has a significant positive effect collective efficacy.

Model 2

Social cognitive theory also emphasizes that the person behavior (i.e., involvement in cognitive and social events) embodies psychological characteristics to influence the social environment. In the same vein, our second model adds social interaction to the first model to mediate paths between belief in ability and student learning. Social interaction in the current study is modeled as individual contribution to in-group dialogues encompassing peer interaction and student-to-instructor interaction. First, social interaction is important process mechanisms in CSCL (Stahl, 2006). As a key factor of success in CSCL, we assume that social interaction not only promotes cognitive processes in collaboration (e.g., reasoning, critical thinking, and reflection) but also develop positive affective relationships, which directly influence learning (c.f., Yang et al., 2006):

H5: Social interaction has a significant positive influence on student learning.

As a behavioral factor, social interaction also mediates social ability and collective efficacy to influence learning. As a positive learning climate encourages exchanges of opinions and information (Wu, Tennyson & Hsia, 2010), we assume strong ability beliefs reflecting positive social affordances will contribute to efforts invested by students to collaborate and interact during CSCL:

H6: Social ability has a significant positive influence on interaction.

H7: Collective efficacy has a significant positive influence on interaction.

This second model is expected to outperform the first model in explaining student learning variances in the CSCL context.

Methods

Research context

The data reported in this paper represent a subset of data gathered in a larger study conducted in the context of an online graduate student course on Computer Support for Collaborative Learning, offered in a large mid-western US university. Twenty-four students were divided into eight small groups at the end of the first week of an eight week summer session and completed all course activities in the context of that small group for the remaining seven weeks of the course. The collaborative environment that supported the CSCL course was Sakai. The CANS (http://www.cansaware.org) system was also applied to provide activity awareness information. When a student logged into Sakai and posted a message or read a message, CANS logged the information automatically. Specifically, the data we analyzed from Week 5 and Week 6, where the group activity is to design a two day online learning module consisting of three parts: scenario, script and assessment. Survey data were collected before Week 5 and the log data from CANS were gathered after week 6 when the module was completed.

Measures

All instruments were adapted from existing literature to increase validity. Social ability is measured via the social ability survey composed of 5 constructs developed by Yang et al. (2006). Collective efficacy was operationalized through a 4-item survey constructed by Hardin et al (2006) for virtual teams. System functionality was informed by Sonnenwald's (2005) information horizons concept about how a person perceives the usefulness of an environment that was adapted to Sakai including 5 items. The system functionality was presented to students with a five-point Likert scale, and the other two are with a seven-point Likert scale.

Most previous studies applied self-reported questionnaires to reflect student learning performance construct (e.g. Yang et al., 2006; Wu, Tennyson & Hsia, 2010). However, a common bias exists if independent variables (social ability, collective efficacy, system functionality) and dependent variables (social interaction and student learning performance) are reported by the same individuals. To avoid such a bias, this study applied actual assignment and evaluation data to generate measures for student learning. The purpose of the module analyzed was for group members to develop an online module that can be implemented in a real-life environment. Two raters proceeded to evaluate the three work products – scenario, script, and assessment – and generate a group grade based on the rubric. Each individual student was then asked to rate and nominate their group members and the whole class. The frequency of rating from other group members or other students is considered a reflection of the individual grade. Therefore, student learning performance is represented by two indicators – group and individual grade.

In this study, social interaction is approached from a network theory perspective. Individuals must socialize to form a group which shares goals and values. The way individuals are situated in social networks, i.e., the structure of groups, significantly affects the creation of social capital (Cho et al., 2007). Students occupying structurally advantageous positions have a better opportunity to influence others, and thus play a more important role in the social space. In network analysis, degree centrality has been used to examine the advantageous positions of individuals. Persons with high degree centrality are assumed to be more active and influential due to the many ties and connections they have with others in the social structure (Freeman, 1979). From the perspective of graph theory, degree centrality is a quantification of the relative importance of a node within the graph. It indicates the number of links the student has with other students in the course.

Partial least squares (PLS) modeling

PLS method is a multivariate statistical modeling technique used to test the relationships between a set of independent variables and dependent variables. It is considered to be the second generation of multivariate analysis (Fornell & Larcker, 1982), integrating multiple regression, path analysis, principle component analysis, and multiple discriminant analysis. As a component-based structural equation modeling technique, PLS is particularly suitable for predicative applications, while the linear structure relationships (LISREL) model is more oriented towards theory testing and development.

Normality assumption is not required for PLS, and the technique shows utility even with small sample sizes (Chin Marcolin & Newsted, 1996). By conducting a Monte Carlo simulation study on PLS with small samples, Chin, et al. (1996) found that the PLS approach can offer information about the appropriateness of indicators for sample sizes as low as 20 and even under the condition that the number of variables surpasses the number of observations. Fornell and Bookstein (1982) states that "PLS involves no assumptions about the population or scale of measurement and consequently works without distributional assumptions and with nominal, ordinal, and interval scaled variables" (p. 443). Considering the relatively small sample size and the explanatory nature of the study, the PLS method is preferred for model testing in this study.

Results

Measure models

This study applied two-step analysis. The measurement model was first estimated and re-specified and then the structural model. Tables 2 and 3 demonstrate the results for the measurement models. In terms of individual item reliability, Chin (1998) indicated that items should load highly (greater than 0.7) on their intended constructs. Loadings with 0.5 or 0.6 are still acceptable on the condition that there are additional indicators in the construct for comparison analysis (Chin, 1998). As a result, items such as Item 4 in system functionality, Item 2, 3, 7 in social ability, and Item 1 in collective efficacy were removed according to the criteria. Then all the factor loadings of the measurements (Table 2) met the suggested condition.

To evaluate the internal consistency and construct reliability, composite reliability was calculated. As suggested by Nunnally (1978), composite reliability should be greater than 0.7, which most of constructs in this study satisfied (Table 2). The learning performance construct was close to 0.7 and is generally considered acceptable in social science. Regarding convergent validity, it was suggested that the average variance extracted (AVE) for each factor should be larger than 0.5. Table 2 shows the values of AVEs meet the recommendation. Discriminant validity is valid if the squared root of AVE is greater than the correlations between latent variables (Fornell & Larcker, 1982). Table 3 indicates that all the scales meet the suggested requirements to indicate an adequate level measurement validity.

Table 2: Item loadings, construct reliability and convergent validity

Construct	Composite reliability	AVE	Item	Loading
System Functionality	0.88	0.73	SF1	0.93
			SF2	0.78
			SF3	0.82
			SF5	0.88
Social Ability	0.92	0.57	SA5	0.80
			SA6	0.79
			SA9	0.74
			SA14	0.69
			SA15	0.90
			SA16	0.64
			SA18	0.88
			SA19	0.70
			SA21	0.79
			SA28	0.58
Collective Efficacy	0.73	0.64	CE2	0.89
			CE3	0.78
			CE4	0.73
Interaction	1.00	1.00	INTR	1.00
Learning Performance	0.66	0.55	LP1	0.99
			LP2	0.79

AVE = Average Variance Extracted

Table 3: Discriminant validity.

Construct	SF	SA	CE	INTR	LP
System Functionality	**0.85**				
Social Ability	0.47	**0.76**			
Collective Efficacy	0.28	0.22	**0.80**		
Interaction	0.53	0.37	0.31	**1.00**	
Learning Performance	0.69	0.28	0.29	0.58	**0.74**

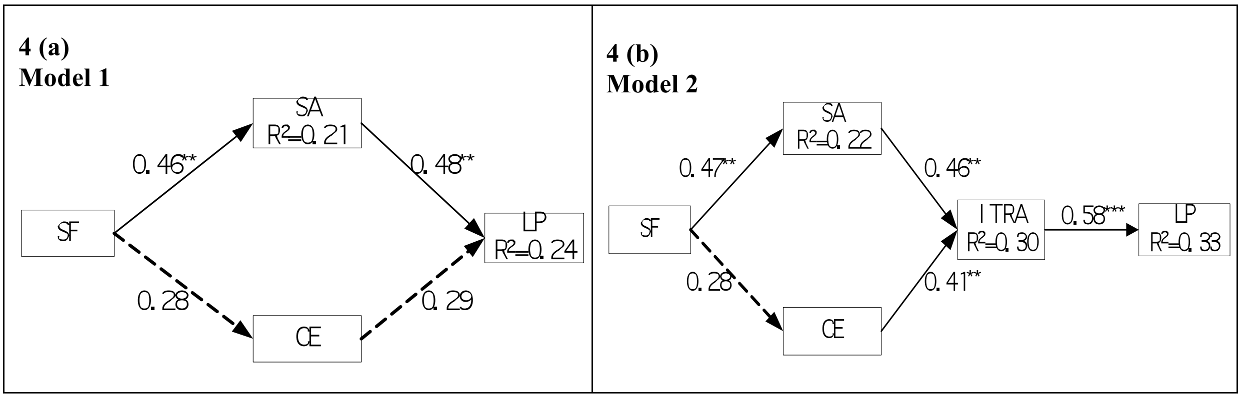
Diagonal elements (bold) are the square root of the AVE of each construct.

Structural models: Direct effects

The explained variance (R^2) in the endogenous variables and the significance of the coefficients are the indicators of model performance (Chin, 1998). For Model 1, as shown in Table 4 (a), social ability had a positive relation to learning performance (0.48, $p < .05$) and therefore supported H1. However, H2 was not supported since collective efficacy had no significant relationship with student learning. Again, system functionality had a significantly association with social ability but not with collective efficacy. The explained R^2 for student learning in Model 1 was 0.24.

In terms of Model 2, H3 and H4 obtained the same results as in Model 1 showing that system functionality significantly influenced social ability but not collective efficacy. However, both social ability (0.46, $p<.05$) and collective efficacy (0.41, $p<.05$) had significant associations with social interaction supporting H5 and H6. Social ability was a more influential factor on social interaction than collective efficacy. Again, social interaction influenced learning performance significantly (0.58, $p<.01$). The social interaction factor was more influential than social ability on learning performance when we compared path coefficients across Model 1 and 2. Moreover, the R^2 in Model 2 was 0.33, which was higher than 0.24 in Model 1. Therefore, Model 2 has better predicting performance of student learning than Model 1.

Table 4: Model performance



Dashed lines represent no significant relationship. **p < .05, ***p < .01.

Structural models: Mediation analysis

We further examined indirect, mediation effects in Model 2. Baron and Kenny (1986) suggested three steps to examine mediation effects: a) the independent variable must be significantly correlated with the mediator; b) the independent variable must be significantly correlated with the dependent variable; c) both the independent variable and mediator should be employed to predict the dependent variable. If both independent value and mediator significantly explain the dependent variable, then this mediator partially mediate the effect of the independent variable on the dependent variable. If only the mediator is significant, then the mediator fully mediated the independent variable effect on dependent variable. Table 5 presents the experiment results.

Table 5: Mediation effects tests

IV	M	DV	IV -> DV	IV -> M	IV + M -> DV		Mediating Effect
					IV	M	
SF	SA	LP	0.56**	0.64***	0.26	0.49**	Fully Mediated
SA	INTR	LP	0.46**	0.76***	0.32	0.29	Not Supported
CE	INTR	LP	0.32	0.32	0.15	0.54**	Not Supported

*p < .05, **p < .01, ***p < .001

As shown in Table 5, the direct link between system functionality and social ability was significant and hence satisfied the first condition. Then the link between system functionality and learning performance was significant meeting the second condition. The direct link between system functionality and learning performance becomes insignificant when controlling for the link between social ability and learning performance. Therefore, social ability fully mediated the relationship between system functionality and student learning performance. Using the same logic, social interaction did not mediate the relationship between social ability and learning performance. Again social interaction did not mediate the relationship between collective efficacy and learning performance.

Conclusions and implications

Informed by social cognitive theory, this study built two different CSCL models of learning especially contributing to the understanding of the role of social ability, collective efficacy and social interaction in CSCL. The results revealed that system functionality significantly influenced students' social ability, which again fully mediated the system functionality effect on student learning. Social ability also showed a significant effect on student learning. However, system functionality did not affect collective efficacy significantly, and collective efficacy had no significant influence on student learning. Both social ability and collective efficacy had significant effects on social interaction, but social ability was a more influential predictor for social interaction. Finally, social interaction significantly impacted student learning performance and served as a stronger predictor than social ability in explaining student learning. Social interaction, however, did not mediate the influence of social ability and collective efficacy on learning.

To sum up, the addition of the social interaction factor (Model 2) increased the predictive power of our model of student learning over the model without it (Model 1). Social interaction alone had the strongest impact on student learning, which is well supported by CSCL literature. In addition, when students were supported by well functioning environments, which also impacted on social ability, students were more likely to interact with each other and tended to have higher learning performance. Technology designs focused on supporting learning activities as well as fluid social interaction, therefore, appear to enhance learning overall.

However, linkage between beliefs about ability and learning was not evident. Though beliefs about ability had significant direct effects on social interaction, results failed to prove beliefs about ability can reach far to impact student learning outcomes. The results may be explained by two reasons. First of all, CSCL studies frequently report free-rider effects when some students do not contribute to group works. It might be the case when students believe their group members outperform themselves, they may not be willing to exert their best efforts (Piezon, 2005); therefore, collective efficacy may not guarantee successful student learning outcomes. Also, it should be noted this study utilized degree centrality as a social interaction measure. Though degree centrality impacts learning significantly, different attributes of interaction might be considered to mediate ability beliefs and impact on student learning. For example, a student in a central role may or may not be contributing to the learning of others. In this case, how one student disseminates important information and how other members rely on this student (i.e., betweenness centrality) may be a critical indicator of quality interaction. Future research may examine how to build a social interaction measure that integrates both the quantitative and qualitative aspects of information and incorporates it into the proposed model of learning and test its effect.

The findings of this study are important in that previous studies found the direct effects of social ability, collective efficacy, and system functionality on student learning mostly not controlling for or explaining other factors. But it seems that dynamics among these factors are far more complex than reported. The reported study enriches literature on student learning in CSCL by providing new insights into the influencing mechanisms of these factors. Methodologically, previous studies have only used self-reported data to measure all the constructs used in the model. However, self-reported participation or evaluation instrument may not address the student performance appropriately and can be different from the actual case (Tsai et al, 2008). Moreover, the potential of common method bias exists if both independent and dependent variables are self-reported by the same persons. Unlike those works, the present study applied actual evaluation of the student works as the learning performance indicator, in alignment with Goggins' (2009, 2013a, 2013b, in press) and Xing's (2014a, 2014b, 2014c, 2014d, 2015a, 2015b) data analytics approaches to the examination of trace data, "Group Informatics". In addition, this study took advantage of the advancement of information systems by modeling student social interaction using electronic trace data informed by network theory. Our study demonstrates a potential approach to measure the constructs in CSCL studies and possibly with more validity and objectivity.

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