Social media in the classroom: examining the effects of social influence mechanism on peer learning

Fang-Ling Lin*
Department of Information Management, Lunghwa University of Science and Technology, 300, Sec.1, Wanshou Rd., Guishan District, Taoyuan City, Taiwan
Email: fangling@mail.lhu.edu.tw
*Corresponding author

Chen-Ya Wang
Department of Management and Information, National Open University, 172, Zhongzheng Rd., Luzhou District, Xinbei City, Taiwan
Email: ntuimgrace@gmail.com

Abstract: Social media is popular in college students' life. However, there are only a few studies exploring the impact of social media on student relationship, and none of them studied the prevalence of social media by dynamic network analysis. This study developed OpenSlide, a teaching system combining the social function of SlideShare and Youtube as an after-school auxiliary learning tool and analysed the impact of this tool on peer interaction in a classroom by using the advantage of multimedia database management. One of the most widely discussed issues in social network analysis is that both the interaction between individual and network formation comprises two processes: social selection and social influence. This study used the stochastic actor-based model to model the network dynamics of students interact recorded in the system and their face-to-face knowledge discussion networks. Our findings demonstrated that similar social media tools can enhance learning effectiveness, allow knowledge construction across the boundary of class and improve students' academic achievement while identifying successful strategies for social media development at an early stage.

Keywords: social network analysis; social media; stochastic actor-based model; peer learn.


Biographical notes: Fang-Ling Lin is an Assistant Professor in Department of Information Management at the Lunghwa University of Science and Technology. She received her PhD from the National Taiwan Normal University and she also holds a first degree in Computer Science from the Tamkang University and MS in Information Engineering from the Tatung University. She has been involved in a number of national science funded
research projects with emphasis on e-learning and social network analysis. Her research interests include the adoption and impact of ICT on education, social media, social network analysis and methodology of data analysis.

Chen-Ya Wang is an Assistant Professor at the Department of Management and Information, National Open University, Taiwan. She received her PhD in Information Management from the National Taiwan University. She has worked as a System Analyst and Product Manager. Her current research interests are user behaviour, service innovation, electronic commerce, recommendation systems, data analytics, and knowledge management.

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1 Introduction

Content delivery is the key part to success in social media websites. Scholars believe that diffusion of multimedia content through social media websites is beneficial to assist in learning. Students know how to use the advantage of social media to actively interact with friends, post short articles or access a great deal of online media resources (Wasko and Faraj, 2005). With these social media, learning can take place anywhere, anytime. Various types of social media (Hung and Yuen, 2010), such as blogs, wikis, podcasts and chat-room can support independent learning, participation learning or peer learning. They provide platforms for students to illustrate their works, share experience, build confidence (Crook and Harrison, 2008), help students be familiar with the presence of the audience and strengthen their learning motives (Hemmi et al., 2009). However, some scholars have different views. They argue that social media was not originally designed for educational use. The function of making public in the social media was essentially created for writing to audiences or to gain the impression (Hemmi et al., 2009).

Moreover, most students have the tendency to copy their classmates’ works or find quick solutions in order to get their assignments done. Such fast-food learning style may impede students’ opportunities to develop deep learning and has created a lot of repetitive and meaningless multimedia content (Crook and Harrison, 2008; Hemmi et al., 2009). Selwyn (2009) believed that increased integration of social mechanism in the application of information and communication technology on campus will compromise formal pedagogic methods.

Learning is a process of social interaction and social interaction support knowledge building and enhance students’ learning achievement (Dewey, 1963; Vygotsky, 1978). Social media connect participants and extend their relationship, accelerate information exchange and facilitate content delivery (Crook and Harrison, 2008). However, learning is a complex process. Factors affect learning strategies include students’ values, motivations, course materials, assessments and classroom environment (Xie et al., 2008). Marton and Saljo (1976) developed a learning-oriented concept from their study on students’ cognition on homework. For example, students may pass assessments by pure memorisation, but sometimes they need to apply deep learning strategies in order to get
the assignments done. A student who usually can make deep conversation might
determine to use a surface strategy to pass less constructive tests which consisting of
multiple choice questions. Deep learning and surface learning are different learning
approached. Usually, students use certain learning methods on certain courses or work
(Biggs et al., 2001).

This study explored the successful strategies for social media development by
applying a social media website in the classroom, investigated how students share
knowledge, and then discussed how to develop learning strategies by effective use of
social media. This study developed a learning system combining the social networking
function of SlideShare and Youtube as an after-school auxiliary learning tool by using the
advantage of multimedia database management. It also investigated the impact of this
tool on the interaction between students with different learning approaches. When this
system was applied to after-school peer learning activities, students had to upload their
homework when they finish it and freely browse, collect or discuss others’ homework.
This study used the stochastic actor-based model to model the interaction of students
recorded in the database system and the face-to-face discussion relationships, explore the
reasons why students interact and investigate whether there is a social influence on the
selection of discussion relationship. This study also used social network analysis to show
whether the evolution of students’ online interactive has direct or indirect disseminative
effect on the content of social media websites. By understanding the network dynamics
behind peer learn this study probed into the efficiency of content delivery on social media
websites.

2 Literature review

2.1 Social selection and social influence

The base of a social network is that people tend to make friends with similar interests or
personalities. The process of social influence (Friedkin, 1998) makes people adopt
behaviours of people they interact with. For example, new concept can be spread through
word of mouth or social network (Strang and Soule, 1998). On the other hand, people
tend to establish a relationship with people who are very similar to themselves. This is the
social selection theory in sociology (McPherson et al., 2001). Social influence and social
selection are two forces affecting our daily life. We often act according to the behaviour
of the people around us and create new interaction from current activities. It requires a
long process to study these two forces and their interaction. Zappa (2011) applied the
theory of social selection to model knowledge sharing among clinicians, describe how
knowledge flows and identify individual habits and environmental factors that can
facilitate voluntary contribution. With the development of social media technology,
Crandall et al. (2008) tried to model the social interaction of online communities and
developed an analysis program with the social selection and social influence in their
study on Wikipedia, and found clear interactive effects between these two factors.
Overall, when the similarity of two individuals increases, it can be used as an indicator to
predict future interaction. However, after a long period of time, similarity will reach a
stable level at a slow rate from the first interaction.

The selection process of peers may be due to the similarity of behaviour,
characteristics or personality, for example, selection of friends. During the pairing
process, the relationship might be established according to the similarity between two people. It is called preferential attraction (McPherson et al., 2001). It might also be due to social condition (Blau, 1977; George and Hartman, 1996; Verbrugge, 1977). For example, in school, everybody has the similar social-economic condition, intelligence or belongs to the same race. Similar social condition enhances the chance to meet or connect with similar peers. The concept of ‘chance to connect’ provides another explanation for the similarity among the people who are connected to a network. There is an influence process where actors accept and adopt the behaviour and attitude of peers in the network (Veenstra and Dijkstra, 2011). The influence process involves observation that an individual changes his/her behaviour or personality because of the people who he/she has a close connection with. In other words, it is a process of assimilation. Socially connected individuals become more and more similar as the time they spend together increases.

Because both pairing and assimilation result in the same empirical phenomenon, i.e., connected individuals are similar. Studies on social influence must consider the process of social selection, and vice versa. If selection process results in similarity, it also may mean that behaviour remains the same but the relationship is dissolution. On the contrary, the process of influence means that the relationship remains stable but the behaviour is changed. This continuous change in network and behaviour reacts with each other, creating an interdependent relationship (Veenstra and Dijkstra, 2011). The studies on co-occurring networks and the behavioural process must obtain all information about the subject and his/her peers. This will be confronted by many constraints. Moreover, the limitation of the methodology will affect the judgement on the underlying phenomena of peer similarity.

2.2 Network dynamic of stochastic actor-based model

In order to overcome the aforementioned limitations, Snijders et al. (2007a) design a program for the stochastic actor-based modelling. Such system, called SIENA which stands simulation investigation for empirical network analysis, can simultaneously evaluate behavioural change and network change through simulation. Therefore, it allows researchers to test the effect of selection and influence by control one aspect. A simple example is provided here to explain such limitation and introduce the stochastic actor-based model.

As shown in Figure 1, it is assumed that actor i believes j is his friend in the initial stage, but their behaviour is not similar. During the second observation, actor i still think j is his friend and his behaviour are similar to j, i.e., the transition (a) in the figure. In earlier studies, such change may be categorised as a social influence because actor i changed his behaviour to be similar to j. However, such conclusion is premature because it is under the assumption that the relationship remains unchanged during the interval of the two observations. Due to the limitation to data collection, we could not know what happened in this period. In fact, it is possible that transitions (b), (c) and (d) occurred resulting in the same outcome as (a). In other words, in the initial stage, the relationship between i and j no longer exists, like in transition (b), and i might change his behaviour without being in any relationship with j, like in the transition (c). After the change, i and j have similar behaviour. Then, their relationship might begin again, resulting in the outcome of the second observation. Since both actors have no connection at the transition (b), it is not considered as the result of social influence. On the contrary, the transitions (b) and (d) demonstrate that social selection plays an important role in the establishment
of their relationship. The general statistical approach ignores the unobserved changes, leading to biased conclusions. If we were to comprehensively inspect the effect of social selection and social influence, we need a method to account for the unobserved changes.

Figure 1  The basic change process of similarity and friendship pairing

Therefore, we need a continuous time model. The stochastic actor-based model was a tool designed for this purpose. It allows data of discrete time span to be analysed and explained continuously. It requires at least two observations on the social network and behavioural variables. Time steps $t_1, t_2, ..., t_m$ represent observations on a set of actors. A tie means directional relationship, which is controlled by the sender. The tie variable $x_{ij}$ is a binary variable. 1 means actor $i$ and $j$ are related and 0 means they are not related. A set of tie variables that make up the entire network can be represented by an $n \times n$ matrix, $x = (x_{ij})$, wherein $n$ is the number of actors. It must be assumed that dependent behaviour variables are discrete and ordinal. For example, the data obtained from measurement by Likert scales can be expressed as a vector $z = (z_i)$. In the stochastic actor-based model, dependent variables are the time series of the matrix and behaviour vector of observation, $(x, z)(t_1), (x, z)(t_2), ..., (x, z)(t_m)$.

The stochastic actor-based model interprets the unobservable changes in discontinuous data based on the decision of the actors observed in a cumulative matter. The unobservable underlying changes can only be inferred from the model. Therefore, two important assumptions must be made. One is a division of changes into the unit as small as possible; the other is conditional sequential independence. In other words, at any point in time, a certain state of the evolution process has sufficient information to move to the next state. This is Markov hypothesis that past relevant information must be included as an external predictor.

The core of the stochastic actor-based model is an operation called objective function, which will determine the probability of change of actors’ tie. The objective function will consider various network dynamic parameters, including reciprocity, popularity alters, activity ego and so on as shown in Figure 2. Meanwhile, the objective function also takes into account the covariant effects of the actors’ attributes and various behavioural effects (Snijders et al., 2010).
2.3 Social network benefit of knowledge sharing

The main phase of knowledge acquisition is to know who owns the knowledge and make a connection to the knowledge owner (McDermott, 1999; Cross et al., 2001; Borgatti and Cross, 2003). Therefore, knowing who is an expert is an important factor influencing the effectiveness of information search (Lin and Chiou, 2008). Who is the prestigious expert in knowledge exchange? A person who has positive recognition in a group during knowledge exchange or dissemination must be a prestigious person (Lin 2001). Because the prestigious person has a great deal of direct connection with others, he will be the main information-sharing channel in this group, i.e., the dominator of content dissemination (Burt, 1992).

Greenberg (1964) pointed out that when a person is in the centre of the social network, it is easy for him to find others and for others to find him. In the internet era, studies also showed that the more a person is engaged in group activities on the internet, the more he will move to the centre (Bradner et al., 1998). Lai and Wong (2002) believed that the participants in group centre appear to be active and efficient in disseminating information. Therefore, researchers proposed that what determines one’s social status online is based on what one contributes rather than what one controls (Kollock, 1999). Prestige becomes a measure of success online. The a person who often contributes knowledge in an online community can be viewed as the centre of the community (Wenger, 2002).

From another perspective, the social network of an individual represents the person’s potential impact (Stefanone et al., 2004). Social network scholars have long used the ego-centre network to study information transaction and exchange (Burt, 1992), service and feelings (Degenne and Forse, 1999). They also demonstrated that work interactions can predict the effectiveness of information search (Cross et al., 2001, Binder et al., 2012), job search (Marsden and Hurlbert, 1988), status acquisition (Lin, 2001) and knowledge exchange (Nahapiet and Ghosha, 1998). At the same time, scholars also suggested that mobile characteristics of the social network include occupants, location, resources and procedure (Lin, 2001). In the study of knowledge sharing, the authors also found that the critical social relation that facilitates knowledge sharing of members of the community of practice are a linkage between members and members with high
knowledge prestige or knowledge brokers. The strength of knowledge sharing indirectly affects the knowledge competitiveness of knowledge workers (Lin and Chiou, 2012).

This study uses social media to assist classroom activities. It aims to create an interactive environment for students to form an efficient social network through knowledge sharing and dissemination among peers. Students of different learning approach can receive new content through the new relationship established (like a popular alter), extend their relationship through the dissemination of content (as an activity ego), and form a classroom knowledge system to achieve learning outcomes. Understanding the social selection and social influence that affect students’ formation of the social network can assist teachers in developing useful strategies of social media-assisted learning.

3 Methods

This study developed the OpenSlide multimedia database, replacing SlideShare or Youtube, to record the interaction and relationship among students. Students were required to upload their work or videos to Openslide, and share and discuss them with their classmates. They were encouraged to learn from others’ homework, discuss important concepts and give comments and suggestions.

Figure 3  Open slide system functions (see online version for colours)
3.1 System design

The features of the OpenSlide system are listed below:

1. **Dynamic playback of visualised slideshow**: the uploaded files can be converted to slide files. An embedded player can be easily used for browsing (Figure 3).
2. **Video playback**: the embedded player can play the uploaded videos (Figure 4).
3. **Personal folder**: a personal folder in which a member can save personal files.
4. **Upload and downloader**: users can upload files in the aforementioned format. If the public download option is ticked during upload, others can download the original file.
5. **Feedback**: anyone can comment on the presentation files.
6. **Tag cloud**: users can set up several tags for the file when uploading the file. The system will show the tags in different size based on their popularity. Click a tag and relevant files will be displayed.
7. **Search text**: search relevant videos or slides with title keywords.

![Dynamic playback of visualised slideshow (see online version for colours)](image)

3.2 Research design

The subjects of this study were juniors taking the elective course, introduction to operation system, in the Department of Information Management, School of Management. Students were asked to use OpenSlide system in teaching activities. The
instructor uploaded videos of teaching materials and supplementary materials and encouraged students to watch the videos. Meanwhile, the instructor assigned homework, and students participated in the same teaching activities. Students shall upload the assignments when they were done, and share their knowledge online. At the end of the semester, students were asked to fill out a questionnaire about the study process of learning approach. The study process questionnaire includes items of deep learning motivation, deep learning strategy, surface learning motivation, and surface learning strategy. The items can be seen in appendix of Biggs’s et al. (2001) article. Figure 6 gives an overview of the research design.

**Figure 5**  Video playback (see online version for colours)

![Video playback](image)

**Figure 6**  Research design (see online version for colours)

![Research design](image)

The manipulated variables of this study are defined in Table 1 as follows.
Table 1  Definition of the manipulation variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Data type and value range</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA</td>
<td>Score of deep learning approach</td>
<td>Decimal, 1–30</td>
</tr>
<tr>
<td>SA</td>
<td>Score of surface learning approach</td>
<td>Decimal, 1–30</td>
</tr>
<tr>
<td>Pre-test</td>
<td>Pre-test</td>
<td>Decimal, 1–100</td>
</tr>
<tr>
<td>Midterm</td>
<td>Midterm score</td>
<td>Decimal, 1–100</td>
</tr>
<tr>
<td>Final</td>
<td>Final exam score</td>
<td>Decimal, 1–100</td>
</tr>
<tr>
<td>Online</td>
<td>Interaction in the OpenSlide system</td>
<td>Social network (matrix)</td>
</tr>
<tr>
<td>Class</td>
<td>Relationships with the same class</td>
<td>Social network (matrix)</td>
</tr>
<tr>
<td>ds1</td>
<td>Social network of knowledge discussion before this semester</td>
<td>Social network (matrix)</td>
</tr>
<tr>
<td>ds2</td>
<td>Social network of knowledge discussion in the end of this semester</td>
<td>Social network (matrix)</td>
</tr>
<tr>
<td>pr1</td>
<td>Academic achievement</td>
<td>0: regress, 1: same, 2: progress</td>
</tr>
</tbody>
</table>

3.3 Data collection

Among 39 students taking this course, 36 students completed the course. Two types of social network data were collected for analysis in the four-month course. One is ego-centred social network survey. Each student was given a questionnaire with the name of all classmates on it in the beginning and the ending of semester respectively. Students shall select relevant people when answering the question in the social network questionnaire. The social network questionnaire can be referred in Table 2. The collective answer of each question of the social network questionnaires was converted to a relational matrix. This study also evaluated students’ learning effectiveness in accordance with their performance in midterm and final exams. The second type of network data was collected from the OpenSlide system. This system recorded all peer-to-peer comments and interaction for the assignment. The interactive data were converted to a relational matrix. This study used RSiena software (Snijders et al., 2007b) to analyse stochastic actors in the dynamic social network.

Table 2  The social network questionnaires of knowledge sharing

<table>
<thead>
<tr>
<th>Id</th>
<th>Name</th>
<th>Please identify the people from whom you have ever discussed with to solve problems related to homework</th>
</tr>
</thead>
<tbody>
<tr>
<td>xxxx</td>
<td>xxxx</td>
<td>□</td>
</tr>
<tr>
<td>xxxx</td>
<td>xxxx</td>
<td>□</td>
</tr>
</tbody>
</table>

4 Data analysis

Table 3 shows the behavioural variables, including a statistical description of different learning approaches, pre-test score, and midterm score and final exam score. This study used the method of multivariate analysis of variance to test the difference in the
performance of learners between surface learners and others with the pre-test score as a covariate. To classify their type of learning approach, this study compared the students’ scores on their tests of the study process questionnaire. Thirteen students were classified as surface learners (indicated by variable SL) as their scores of surface learning approach were greater than their scores of deep learning.

The first step of the analysis of covariance is to test the homogeneity of the variance-covariance matrices among these two different groups of learning approach. The authors examined the univariate homogeneity of variance across the two groups and test the equality of the covariance matrices between the groups for the dependent variables collectively. The Levene’s test for midterm and final exam variables are non-significant (0.776 and 0.509). The Box’s M test for equality of the covariance matrices shows a non-significant value (0.838). These two measures indicated no significant difference between the two groups on the two different variables collectively. The author also examined the between-subjects effect of SL*pre-test interaction on the midterm and a final exam. The F-test (0.469 and 0.586) and p-test (0.498 and 0.450) indicated no significant to reject the assumption. Therefore, the assumption of homoscedasticity is met for each individual variable separately and the two variable collectively.

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Statistical description of behavioural variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables (N = 36)</td>
<td>Min</td>
</tr>
<tr>
<td>DA (deep learning approach)</td>
<td>20.00</td>
</tr>
<tr>
<td>SA (surface learning approach)</td>
<td>15.00</td>
</tr>
<tr>
<td>Pretest</td>
<td>15.00</td>
</tr>
<tr>
<td>Midterm</td>
<td>27.00</td>
</tr>
<tr>
<td>Final</td>
<td>41.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 4</th>
<th>Analysis of covariance on the effect of learning approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factors</td>
<td>Variables</td>
</tr>
<tr>
<td>Pretest</td>
<td>Midterm</td>
</tr>
<tr>
<td>Final</td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>Midterm</td>
</tr>
<tr>
<td>Final</td>
<td></td>
</tr>
</tbody>
</table>

Notes: a R-square = 0.232 (adjusted R-square = 0.186).
b R-square = 0.007 (adjusted R-square = –0.054).

The second step is to examine the pairwise comparison. Table 4 summarises the difference in midterm score and final exam score of students with different learning approaches. We can draw from Table 4 that when the influence factors of pre-test were excluded, students’ midterm scores were significantly different, while the differences in final exam scores were not significant. In general, students’ performance was better on the final exam than in the midterm exam, but the difference was not significant. Students with surface learning approach and students with deep learning approach had a significant difference in their performance in the midterm scores, but their performance had no difference in the final exam scores.
4.1 Description of network statistics

Table 5 describes the statistics of various social networks. This course was an elective course. Students were from three different classes. Each student had about ten directly connected alters on average. However, every student, on average, only interacted with 1.5 alters on the OpenSlide system. Figure 7 shows the drawing of knowledge sharing network surveyed in the beginning of the semester (dsl) using software NetDraw (Borgatti, 2002). The purple lines in Figure 8 represent the knowledge sharing network surveyed at the end of the semester (ds2). Each point in the figure represents a student and the colour of the node indicates the different class to which they belonged.

Table 5  Statistical description of various social networks

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Std.</th>
</tr>
</thead>
<tbody>
<tr>
<td>dsl (network size of knowledge discussion before the course)</td>
<td>3</td>
<td>16</td>
<td>9.11</td>
<td>3.1</td>
</tr>
<tr>
<td>ds2 (network size of knowledge discussion after the course)</td>
<td>6</td>
<td>16</td>
<td>10.70</td>
<td>2.4</td>
</tr>
<tr>
<td>Online (connections in the OpenSlide system)</td>
<td>0</td>
<td>9</td>
<td>1.56</td>
<td>2.3</td>
</tr>
</tbody>
</table>

Figure 7  Knowledge discussion network dsl (see online version for colours)

Figure 9 is the interactive network on the OpenSlide system, with only about half of the students participating in the online interaction. Among which, the purple lines represent the overlap between knowledge sharing network ds1 and knowledge sharing network ds2. The red lines indicate the new relationship existed only in online interaction. Figure 10 illustrates the intersection of the online interaction and knowledge sharing network ds2 of the second survey.

4.2 Network dynamic analysis

Table 6 shows the characteristics of actors, dual covariance and dual independent model (i.e., reciprocal model) of network dynamics. Parameter estimation shows a strong tendency to the selection of reciprocity and transitivity (which may be calculated by a tendency toward triangular transitivity, and few actors would be at a distance two steps
away in socio metrics). The use of OpenSlide has a positive and significant impact on network change. The performance improvement (pr1) had a significant impact on network change, wherein the progress of deep learners had a significant effect on network change.

**Figure 8** Knowledge discussion network ds1 and ds2 (see online version for colours)

**Figure 9** An online interactive network of the OpenSlide system (see online version for colours)

Table 7 illustrates relevant characteristics of actors in network dynamic. The characteristics of actors include personal learning approach (sender of the relationship: activity ego) (Snijders et al., 2010) and impact of others’ learning approaches (receiver of the relationship: popular alter) (Snijders et al., 2010). Dual characteristics include the convergence effect of network selection based on individual learning approach. In Table 7, the sending relationship of surface learners is significant and negative, which means they do not actively contact with people often. The receiving relationship of the students who made an improvement is positive in Table 6, but not significant.
Table 6  Network variables and model adaptation

<table>
<thead>
<tr>
<th>Effect name</th>
<th>Parameter value</th>
<th>Standard error</th>
<th>P-value</th>
<th>T-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic rate parameter network</td>
<td>14.528</td>
<td>1.812</td>
<td>&lt; 0.001</td>
<td>0.038</td>
</tr>
<tr>
<td>Out degree (density)</td>
<td>−0.591</td>
<td>0.084</td>
<td>&lt; 0.001</td>
<td>0.029</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>0.15</td>
<td>0.146</td>
<td>0.306</td>
<td>−0.017</td>
</tr>
<tr>
<td>Online</td>
<td>0.634</td>
<td>0.270</td>
<td>0.018</td>
<td>−0.018</td>
</tr>
<tr>
<td>Class</td>
<td>1.2</td>
<td>0.127</td>
<td>&lt; 0.001</td>
<td>0.013</td>
</tr>
<tr>
<td>Rate prl period 1</td>
<td>29.099</td>
<td>3.981</td>
<td>&lt; 0.001</td>
<td>−1.44</td>
</tr>
<tr>
<td>Behaviour prl linear shape</td>
<td>−0.172</td>
<td>0.203</td>
<td>0.398</td>
<td>−0.186</td>
</tr>
<tr>
<td>Behaviour prl quadratic shape</td>
<td>−0.428</td>
<td>0.198</td>
<td>0.030</td>
<td>−0.166</td>
</tr>
<tr>
<td>Behaviour prl: effect from SA</td>
<td>−0.045</td>
<td>0.035</td>
<td>0.202</td>
<td>0.163</td>
</tr>
<tr>
<td>Behaviour prl: av.sim. (network) × SA</td>
<td>−0.276</td>
<td>0.367</td>
<td>0.453</td>
<td>−0.025</td>
</tr>
<tr>
<td>Behaviour prl: effect from DA</td>
<td>0.076</td>
<td>0.033</td>
<td>0.022</td>
<td>0.049</td>
</tr>
<tr>
<td>Behaviour prl: av.sim. (network) × DA</td>
<td>0.239</td>
<td>0.281</td>
<td>0.394</td>
<td>−0.018</td>
</tr>
</tbody>
</table>

4.3 Analysis of learning approaches and academic achievement

In order to predict what factors affected the progress of progress, this study used regression analysis to test the predictability of behavioural variables. Among all behaviour variables, deep learning approach has the best positively significant prediction whereas surface learning approach has the negative prediction (referred in Table 8). The negative predictive power of the pre-test variable shows that the students with higher academic achievements in the beginning of the course were not necessarily had higher achievement than other students. Namely, it indicated that the learning effectiveness in the end of this course enhanced the academic achievement of students who have low academic achievement in the last semester.
Table 7  Behaviour variables and the model’s goodness of fit

<table>
<thead>
<tr>
<th>Effect name</th>
<th>Parameter value</th>
<th>Standard error</th>
<th>P-value</th>
<th>T-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic rate parameter network</td>
<td>1.165</td>
<td>0.106</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Out degree effect on rate network</td>
<td>0.049</td>
<td>0.032</td>
<td>0.136</td>
<td>0.15</td>
</tr>
<tr>
<td>In degree effect on rate network</td>
<td>0.15</td>
<td>0.063</td>
<td>0.018</td>
<td>0.018</td>
</tr>
<tr>
<td>Reciprocity effect on rate network</td>
<td>0.008</td>
<td>0.101</td>
<td>0.936</td>
<td>0.055</td>
</tr>
<tr>
<td>Out degree (density)</td>
<td>−0.598</td>
<td>0.151</td>
<td>&lt; 0.001</td>
<td>0.023</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>0.834</td>
<td>0.153</td>
<td>&lt; 0.001</td>
<td>0.026</td>
</tr>
<tr>
<td>Online</td>
<td>0.782</td>
<td>0.339</td>
<td>0.021</td>
<td>−0.01</td>
</tr>
<tr>
<td>SA alter</td>
<td>0.02</td>
<td>0.014</td>
<td>0.172</td>
<td>0.014</td>
</tr>
<tr>
<td>SA ego</td>
<td>−0.173</td>
<td>0.030</td>
<td>&lt; 0.001</td>
<td>−0.02</td>
</tr>
<tr>
<td>prl alter</td>
<td>0.119</td>
<td>0.150</td>
<td>0.432</td>
<td>−0.015</td>
</tr>
<tr>
<td>prl ego</td>
<td>−0.267</td>
<td>0.341</td>
<td>0.434</td>
<td>−0.019</td>
</tr>
<tr>
<td>DA alter</td>
<td>−0.019</td>
<td>0.026</td>
<td>0.464</td>
<td>0.001</td>
</tr>
<tr>
<td>DA ego</td>
<td>−0.049</td>
<td>0.084</td>
<td>0.562</td>
<td>−0.054</td>
</tr>
</tbody>
</table>

Table 8  Learning effectiveness predicted by behavioural variables

<table>
<thead>
<tr>
<th>Model</th>
<th>Beta</th>
<th>t</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td>1.54</td>
<td>0.133</td>
<td></td>
</tr>
<tr>
<td>DA</td>
<td>0.352**</td>
<td>2.30</td>
<td>0.028</td>
</tr>
<tr>
<td>SA</td>
<td>−0.226</td>
<td>−0.145</td>
<td>0.157</td>
</tr>
<tr>
<td>Pre-test</td>
<td>−0.289</td>
<td>−0.186</td>
<td>0.072</td>
</tr>
</tbody>
</table>

Note: p** < 0.05.

5  Discussions

This study explored the factors that influence the effectiveness of knowledge discussions and developed strategies to enhance students’ learning by understanding how the content of social media is shared among students and how the sharing changes students’ knowledge sharing network. Several important findings can be summarised from the results.

5.1 Network change of peer knowledge discussion

There were 328 relationships in the pre-course knowledge discussion network ds1 and 385 relationships in knowledge discussion network ds2, which is a significant increase. Based on the record of the OpenSlide system, there were only 56 online interactions. Most students only chose to press the ‘like’ button.

Figure 7 presents students’ discussion network before the class visually. Because the students are from different classes, it was easier for them to form different clusters based on their classes. Figure 8 illustrates both ds1 and ds2 knowledge discussion networks. We
can see that many new inter-class networks were built. Figure 9 is based on the online discussion and interaction about the multimedia assignment recorded by the OpenSlide system. Although about half of the class had never participated in online interaction, many new inter-class relationships were built. Figure 10 illustrates the discussion relationship with online interaction in ds2 but not in dsl, i.e., these relationships might be established and sustained by online interactions. Although the number of these relationships is small, the online interactive relationship has a significant impact on the change of knowledge discussion network \( p < 0.05 \), as demonstrated by the stochastic actor-based model analysis in Table 6. The online interaction through sharing of social media content has a direct impact on establishing a relationship.

5.2 The process of social selection of peer interaction

In this study, students used social media in after-school peer learning activities. They had to upload homework slides and browse, collect or comment their classmates’ homework. This is a knowledge sharing process. Based on sociologists’ theory, the least costly way to acquire knowledge is to know who owns the knowledge and connect to the knowledge owner directly. Based on the friendship transfer theory proposed by Veenstra and Dijkstra (2011), the reciprocal communication increased because of social selection. Table 6 demonstrates that the same class relationship has a significant impact on network dynamic change. Without the same class network factor, Table 7 demonstrates that reciprocal communication has a significant impact on network dynamic change. Therefore, it is believed that reciprocal communication is significantly important in the process of social selection.

As shown in Table 7, those with improved academic achievement have negative factor loading in activity ego relationship, which means that students with improved academic achievement perceived they did not send out much relationship during the network dynamic, that is, they perceived they seldom made initiatives to establish discussion relationship. However, the students with improved academic achievement had a positive factor loading in receiving relationship (i.e., popular alters). In other words, more students said that they had discussion relationship with the students who made improvement in their academic achievement. As a person who has positive recognition in a group during knowledge sharing would be a prestigious person (Lin, 2001), this the prestigious person will be the main information-sharing channel in this group (Burt, 1992). Although it was not statistically significant, it still demonstrated that students were more willing to establish knowledge discussion relationship with their peers with improved academic performance. This is in line with the saying, “one takes the behaviour of one’s company”. Moreover, these students with improved academic achievement have potential to be the dominators of content dissemination.

The results also showed that surface learners’ factor loading of active ego relationship is significantly negative, i.e., they rarely established knowledge discussion relationship with others. Deep learners’ active ego relationship and receiver’s relationship were both negative. It is not significant and the load is small. Obviously, this factor of learning approach has no social selection effect on the network dynamic change. It may mean that the main purpose students shared and engaged in disseminating social media content are for academic performance. Therefore, when using social media for learning, the content must have a clear benefit and academic goal so that the community members are more willing to take part in.
5.3 Process of social influence of peer interaction

In a semester of classroom development, peer interaction gradually changed in the entire learning community. It began with a class-based discussion. However, through OpenSlide, peer interaction resulted in collective change. Figure 11 displays the second discussion network alone. We can see that more students appear in the middle and more inter-class relationships are established which makes class boundaries less clear. Scholars suggested the mobile characteristics of occupants and location in the social network (Lin, 2001). Brokers are professional manipulators of people and information who obtains the benefits of linking persons who would not otherwise be communicable (Burt, 1992). They have opportunities of bridging critical resources and “have effects of network structure on influence in dyadic exchanges” (Burt, 1992; Fernandez and Gould, 1994).

Social media system allows members to continue to expand social relationship through online activities and accelerate information exchange. However, such interaction has a certain form of limitation. OpenSlide allows users to develop new online connection quickly through specifically designed system functions, such as click, like collection or comment, so that learners can choose different strategies based on their learning approaches. Although online interaction has a significant impact on the change of knowledge discussion network, it still requires longer development to understand the impact of different learning approaches on network change.

Figure 11 Knowledge discussion network ds2 (see online version for colours)

There is a changing process in peer interaction by using social media for discussing and sharing content in after-school activities. Most of the students’ interactions are greatly influenced by this social symbol called ‘class’. The OpenSlide System is useful to affect the change of knowledge discussion network. The achievement-oriented strategy is beneficial in the early stage. Table 8 illustrates that the learning effectiveness of deep learners is improved significantly. Moreover, the significant negative predictability of the pre-test on the final grade of this course indicates that students with lower academic achievement improved their academic performance greatly. However, it still needs a
longer period of development to change students’ learning approach through social media interaction.

6 Conclusions

This study explored the use of social media in class and attempted to develop strategies that can effectively use social media to facilitate learning by understanding the way students share knowledge. This study proposed OpenSlide, a teaching system combining the social function of SlideShare and Youtube, as an after-school learning assistance tool for students by using the advantage of multimedia database management. Students can use this system in after-school peer learning activities. They have to upload homework and freely browse, collect or discuss their classmates’ homework. This study used social network analysis and stochastic actor-based model to analyse students’ interaction recorded in the system and explored the change of knowledge discussion networks in class and the interaction of students with different learning approach.

The study found that students’ knowledge discussion network was significantly influenced by the OpenSlide online sharing network. It also demonstrated that such social media-like tool can enhance learning effectiveness in class, knowledge was able to be built across the class boundary, and deep learners were able to improve their learning outcome. Because of social influence, there was no obvious difference in the network behaviour among actors of different learning approach. Although the mechanism of its transformation still needs further study, the academic achievement-oriented strategy is beneficial at an early stage.

This study, combining the archive function of the multimedia database system, conducted dynamic network analysis on the students’ interaction recorded in the system and explored the effectiveness of dissemination of social media content by understanding network dynamics behind peer learning. The stochastic actor-based model was used to explore social influence patterns between different learning approaches so as to understand more social behaviours hidden in the peer interaction and build a foundation for the next stage of research.

References


