Dynamic Online Interaction Analysis Based on Social Presence and Social Network

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ABSTRACT

Social presence and interaction are closely related. Social network analysis of network structure analysis and other parameters can faithfully characterize the characteristics of online interaction. This research combines the two methods to build an interactive conceptual model of online interactions in a blended learning classroom. The social telepathy measurement data was collected in three stages and then they were analyzed quantitatively and visually based on the online interaction data.

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1. **INTRODUCTION**

With the acceleration of knowledge updating and the increasing demand for lifelong learning, online learning has become the most pervasive distance learning method at present. Nevertheless, online learning is mostly implemented in a human-computer interaction virtual learning environment. Some social clues of face-to-face interaction is virtually filtered out in this process, resulting in the lack of online exchange of emotions. So, learners may feel lonely and tired while learning, or even just give up[1]. Studies have found that loneliness is relevant to low social presence[2]. Social presence can not only alleviate the loneliness of online learners, but also help them improve learning outcomes, and learning satisfaction of online learners as well as allow learners to form a network of mutual support [3][4]. The establishment of social presence cannot be separated from the social interaction among participants[5]. Therefore, understanding how social interaction promotes the formation of social presence plays a significant role in determining the social nature of online learning and providing practical approaches for online teachers to cope with loneliness.

Many researchers have analyzed the interactions in online education and underlined its importance to the success of online learning. However, the majority of the current research methods mainly give priority to understanding individual learners' opinions and views, and exploring less interaction among group learners[6]. Online learners are generally divided into groups to discuss, so it is necessary to analyze the method of group interaction pattern when studying interaction for understanding the nature and types of the interaction in online learning[7]. Social network analysis provides a quantitative analysis method to characterize the network membership model. It can visualize the relational model among members and quantitatively compare the similarities and differences between different network groups, which can effectively solve the problems existing on current interaction research[7]. This research is to construct a dynamic interaction model that focuses on a course of using blended learning mode in the interactive mode between teachers and students. We combines social presence scale and dynamic social network analysis of social network relational data generated by interactive activities between forums and WeChat groups to find out that whether social network analysis is related to social interaction. The results shows that there is a significant difference in learners' social presence at different periods. Adding the WeChat class into online course can significantly improves the social presence of learners and promote the online interaction effect.

2. **MODEL BUILDING**

Dynamic network is a group of networks composed of a limited number of static networks according to a certain time series. Each static network is a snapshot of the
interaction between all individuals and individuals in the network at a certain time. The
dynamic network describes the evolution process of the network over a period of
time[8]. As is shown in figure 1, the first 3 graphs represent the connection between
time series $T_1$ to time series $T_3$ and interconnection between nodes ① to ⑤, finally
formed a static network composed of time slices $T_1$, $T_2$ and $T_3$. However, the edge of
nodes ① to ⑤ in the upper and lower part of time series $T_1$, $T_2$, $T_3$ are different, but the
synthesis of the static network is the same. Thus, it can be seen that synthetic static
network will lose the timing information of network evolution.

![Figure 1. A time series based synthesis network.](image)

We define an online interactive network graph $G(V, E)$, the model is regarded as a
directed graph $G$ of interactive online with $n$ nodes and $m$ edges. By adding time $t$, it
forms a static online interactive graph $G_t(V, E)$ at time $t$, where $V_t$ denotes all
interacting individuals or nodes in the online interaction observed at time $t$, $E_t$ denotes
all the directed edges between nodes observed in the online interaction at time $t$, these
directed edges represent the interaction between nodes. Then:

$$G_t = \left\{ (V_1, V_2, \ldots, V_t), \right. \left. (V_t, V_1) \right\}$$

(1)

$$\left\{ (E_1, E_2, \ldots, E_t), \right. \left. (E_t, E_1) \right\}$$

(2)

The online interactive network $G(V, E)$ represents a time slice network composed of
t static networks in the online interaction process, which satisfies $V=U_t V_t, E=U_t E_t \cup U_v$
and $U_t (V_t, V_{t+1})$, where $(V_t, V_{t+1})$ represents the self directed edge of the node from $t$ time
series to $t+1$ time series. Then:

$$G=\{G_1, \ldots, G_t\}$$

(2)
We propose a dynamic online interactive conceptual model based on social network theory and characteristics of dynamic social network. The model includes three main elements: interaction subject, interaction media and interaction analysis indicator, in order to deconstruct individual interaction process and then expand the research on dynamic online interaction.

The main part of the interaction includes the originator of the interaction and the recipient of the interaction, the interaction channel which mainly includes the WeChat group of the online course forum and the corresponding course. The selection of interaction analysis index can reflect the center, density, center potential, cohesion subgroup and social presence questionnaire of dynamic online interaction. With the change of learning contents and requirements in different stages of online learning, the role of the interactive subject conversion, interactive subjects through the forum and WeChat group to carry out a variety of interactive activities to promote the rise of online interactive frequency.

3. DATA ANALYSIS

3.1 Questionnaire Analysis

This research is based on the analysis of the blended learning course, "Public English Speaking" is attended by the author, which involved a total of 48 undergraduates. Social presence scale source was developed in Garrison's study of community social presence sub-scale, including 9 Richter 5 point item[9]. We
conducted a survey of online interactive social presence questionnaires for students participating in online interactions three times in the early, middle and late stages. The alpha coefficients of the questionnaire were 0.921, 0.854 and 0.897 at different stages, and the scale had high reliability. One-way ANOVA was used to analyze the questionnaire. The results show that there is a significant difference in the social presence of students in different stages of the course, F(2,139)=3.918, P=0.019<0.05. The social presence measurement questionnaire score for the previous were 3.72 (early stage), 4.32 (mid stage), 4.09 (later stage). Mid-term social presence scores were significantly higher than the early and late stage. Thus it can be seen that understanding of the interaction between different stages is conducive to understanding the social presence in the course of change and development.

3.2 Social network analysis

This research aims to explain the differences in social presence at different stages through social network analysis of interactive activities at different stages.

3.2.1 CENTRALITY COMMUNITY ANALYSIS OF DYNAMIC ONLINE INTERACTION

This research uses the social network analysis software Gephi0.9.1 and Ucinet6 to analyze and process the interaction data of forum and WeChat group to get the interactive community graph of the course, as shown in figure 3. Using the FR algorithm (fruchterman-reingold) to visualize the interactive activities of the course.
In the overall situation of figure 3, early stage activities are conducted by teachers with fewer students participating in the online interaction and more marginal participants. Mid stage students are the most active in interactive activities, have frequent interaction, the number of marginal participants are smaller, and teachers are not the core of interaction. In the later stage, interaction frequency are less than mid-term’s, marginal participants increased, the teacher is still not the core of interaction. The interaction of WeChat group is consistent with the overall situation, but there is little difference in the interaction in different periods of the forum, and it is all about the teacher.

### 3.2.2 DEGREE CENTRALITY ANALYSIS OF DYNAMIC ONLINE INTERACTION

The degree centrality is represented by the number of other nodes that are directly connected to a node, because the interaction is directional, the out-degree centrality of the exit point represents the information sent by the learner, in-degree centrality represents the response information received by learners[10].
### TABLE 1. THE AVERAGE DEGREE CENTRALITY STATISTICS.

<table>
<thead>
<tr>
<th></th>
<th>Forum in-degree</th>
<th>Forum out-degree</th>
<th>WeChat Group in-degree</th>
<th>WeChat Group out-degree</th>
<th>All Stage in-degree</th>
<th>All Stage out-degree</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early stage</td>
<td>6</td>
<td>6</td>
<td>15.40</td>
<td>15.40</td>
<td>20.52</td>
<td>20.52</td>
</tr>
<tr>
<td>Mid stage</td>
<td>6.09</td>
<td>6.09</td>
<td>52.90</td>
<td>52.90</td>
<td>58.60</td>
<td>58.60</td>
</tr>
</tbody>
</table>

In table 1, the interactive activities in the mid stage of the course are the most active, the average in-degree and out-degree are higher than early stage and later stage. The overall differences of in-degree and out-degree at three stages are analyzed by one-way ANOVA. In terms of overall in-degree, $F(2,141)=3.105$, $P=0.047$, while, in terms of overall out-degree, $F(2,141)=15.273$, $P=0.0002$, there is a significant difference in the in-degree and out-degree of each individual in different stages of interaction. The variance analysis of the in-degree and out-degree centrality of WeChat group shows that in terms of in-degree, $F(2,141)=4.140$, $P=0.018<0.05$, while, in terms of out-degree, $F(2,141)=19.20$, $P=0.0001$, there is also have significant difference in the in-degree and out-degree of each individual at different stages in WeChat group. But the analysis of in-degree and out-degree centrality difference in different stages of the forum shows that in-degree, $F(2,141)=0.023$, $P=0.98>0.05$, out-degree, $F(2,141)=0.340$, $P=0.71>0.05$, there is no difference in the in-degree centrality and out-degree centrality in the forum. The research found that the interactive activities in the forum is closely related to the teacher, so the individual of in-degree and out-degree centrality are not significantly different in each stage of the forum. Offer class in WeChat, task-driven approaches such as role-play providing cognitive scaffolding for learners' online interactions. It makes learners clearer about their responsibilities in the process of interaction, and the learning activities are more specific, so that learners' overall participation is higher, interaction is more balanced, and then get higher social presence. In the WeChat class, the teacher is only in the interactive core position in the early stage. In the mid and later stage, with the students presiding over the WeChat class, the interactive core is occupied by multiple students in turns, and the learners still maintain a high interactive frequency when the teachers are less involved.

### 3.2.3 DENSITY ANALYSIS OF ONLINE INTERACTION

Network density is used to reveal the extent to which nodes in the network are connected to each other. The greater the density is, the more the edges among the nodes are connected, indicating that the closer the nodes in the network are to each other[11].

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TABLE 2. THE AVERAGE NETWORK DENSITY STATISTICS.

<table>
<thead>
<tr>
<th>Stage</th>
<th>Forum Density</th>
<th>WeChat Group Density</th>
<th>All Stage Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early stage</td>
<td>0.15</td>
<td>0.451</td>
<td>0.601</td>
</tr>
<tr>
<td>Mid stage</td>
<td>0.138</td>
<td>1.125</td>
<td>1.247</td>
</tr>
<tr>
<td>Later stage</td>
<td>0.146</td>
<td>0.476</td>
<td>0.566</td>
</tr>
</tbody>
</table>

As the table 2 shown, the overall density state of the course shows that the interactivity density in the mid stage is much higher than in the early and later stage. The variance analysis of individual interaction density at different stages is presented, F(2,128)=6.713, P=0.034<0.05, the individual interaction density is significantly different at each stage. The variance analysis of individual interaction density in different stages of the forum shows that F(2,128)=0.013, P=0.96>0.05, there is no significant difference in individual interaction density at each stage of the forum. The variance analysis of individual interaction density in different stages of the WeChat group shows that F(2,128)=5.132, P=0.003<0.01, there is a significant difference in individual interaction density at each stage of the WeChat group. The overall interaction density is low, the density difference in each stage is small due to the small number of interaction among the students in the forum. However, the density in the later stage is increased, which is caused by some students who wants to get credits from the forum. The interaction density in the WeChat group is much higher than that in the forum, with significant differences in different periods and the mid-term role-playing mechanism being conducted in the WeChat community, the enthusiasm of students is improved and the social presence is enhanced. Students are always the core of the interactive network. Affected by the WeChat group, the overall mid stage interaction density is significantly different from that of the early and later stage, indicating that learners are connected with more individual learners in the mid stage, making the mid stage individual interaction networks more dense.

3.2.3 DEGREE CENTRALIZATION ANALYSIS OF DYNAMIC ONLINE INTERACTION

Degree centralization is a concept used to characterize the overall compactness of a graph and describes to what extent the cohesion of a graph is organized around certain points[11].
Table 3 reflects the overall in-degree centralization of the course is higher than the out-degree centralization more than 100% in the early stage, indicating that the interaction is relatively unbalanced. This interaction imbalance is due to the beginning of the interactive information flows mostly to the teacher, whom is the core of the interactive network, this feature is reflected in the forum and WeChat group. In the mid stage, the overall out-degree centralization is higher than the in-degree, indicating that the active population in this stage is relatively concentrated, while the mid stage in-degree centralization is the lowest compared with the early stage and the later stage, indicating that the mid stage group information flow is more balanced, and the core participation groups are more than the other stage. In the WeChat group, in-degree centralization is higher than out-degree centralization in the early stage, and out-degree centralization is higher than in-degree centralization in the mid and later stage. It shows that in the WeChat group, teacher have a greater influence in early stage, the influence of students in the core position of social network are enhanced in the mid and later stage. It can be seen that the general analysis of the influence of individuals in online interactions may not accurately reflect the actual changes in online interactions. However, In accordance with the dynamic analysis of different periods, the evolution of online interaction over time can be reflected more accurately.

### 3.2.4 COHESIVE SUBGROUP ANALYSIS OF DYNAMIC ONLINE INTERACTION

Cohesive subgroup analysis is the most typical analysis method of social network substructure, the simplification of complex networks the social network structure with more succinct and more powerful visual representation can be obtained from the simplification of complex networks. This research uses the factional method to analyze cohesive subgroups. Factions are the largest interlinked sub-networks. Factions are not isolated. There may also be some form of connection between external actors and their
members, but not with all members of the faction have contact[12]. In order to ensure
to ensure more frequent interactions among members of the faction, we require a minimum of 5
members in each faction during the analysis and no less than 2 interactions between
each other.
Figure 4. Factions diagram at different stages.

Figure 4 shows that in the early stage, teacher 1 and student 10 appeared in 44 factions, indicating that they are a bridge and core participants of the class. And student 4, 15, 22 and other 10 people did not appear in any faction, indicating that they belonged to the marginal participants. In the Mid stage, with the increase of WeChat class, the interaction was strengthened, the frequency of participants in different factions increased, and the factions also raised. Among the most factions were student 30 and 43, which appeared in all 73 factions. They were the core participants of the mid stage interaction, and all members appeared in the factions, reflecting the good interaction of WeChat class. It shows that with the increase of WeChat class, the interaction between different members increase but some members quit the interaction, and the average number of late members participating in the faction was less than the mid stage, and the member interaction frequency was also less than that in the mid stage. The ANOVA was used to analyze the average factions of the three stages in this course. The result showed that F(2,141)=26.137, P=0.0014<0.01. There was significant difference among the average factions of participants in the three stages. The mid stage's average number of members participating in factions and the frequency of interaction was the highest, the later stage was the second, the least was the early stage and the frequency of interaction was the lowest. It confirms the fact that social presence increases with the increase of interaction and decreases with the decrease of interaction.

4. DISCUSSION ON DATA ANALYSIS RESULTS

Variance analysis of social presence in different learning stages of blended learning course “Public English Speaking” shows that there are significant differences in learners’ social presence at different stages of learning. The differences are mainly reflected in the early and mid stage, mid and later stage, but not significant in the early
and later stages. On the whole, the social network analysis of community diagram and quantitative analysis show that the mid stage’s learners are more active and the in-degree and out-degree of penetration centrality, individual network density, and average factions of individuals are significantly higher than other two stages. The interaction between participants in the intermediate curriculum is more frequent and balanced. The results of social network analysis and social presence questionnaire collected at this stage are consistent, that is learners perceive a higher level of social presence in the mid stage, and learners interact online more closely. It can be seen that interactive social network analysis can reveal the development and change of social presence. The results of community diagram analysis show that the phase in period, along with the development of the WeChat class, more students through role-playing form to organize interactive activities, learners are more closely contact with each other, teachers' influence on group interaction is reduced, the learners become the core interactive.

5. SUMMARY

The result confirms that interaction playing an important role in the formation of learners' social presence during online learning. It indicates that social network analysis community diagram can reveal whether students are isolated in the community diagram, and lead teachers to adopt more targeted interactive strategies, and finally promote a better online learning. Secondly, teachers should design and organize online collaborative learning activities in appropriate ways. In the mid stage, students are at the core of the social diagram of in-degree and out-degree, which shows that online collaborative activities provide students with more opportunities to communicate with each other, and to learn from each other. Finally, teachers should provide students with experience humanistic care, find out the backward learners as soon as possible, understand the difficulties these students may face with and solve them in time.

The WeChat class used in this research is an effective tool to improve students' social presence and enhance the interactive frequency and quality of online courses. The results provide the researchers who are interested in this area and who put online learning into practice with a theoretical and methodological reference. Based on quantitative analysis and social network analysis, this paper presents new ideas for understanding online interaction and social presence. But there are also some limitations which need to be figured out. In the further study, we should combine the content analysis method, focus group interviews method, individual differences of quantitative analysis method and social network analysis method to conduct a multiple analysis of interaction, for a better understanding of the social character of online learning experience.
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