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Comparison of Collaboration and Performance in Groups of Learners Assembled Randomly or Based on Learners' Topic Preferences

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ABSTRACT

Teachers and instructional designers frequently incorporate collaborative learning approaches into their e-learning environments. A key factor of collaborative learning that may affect learner outcomes is whether the collaborative groups are assigned project topics randomly or based on a shared interest in the topic. This is a particularly important question for adults, whose performance can depend strongly on how closely the project topic relates to their professional goals. In this study involving an on-line course for 103 professionals we divided the learners into two parallel sections that differed in how they would be assigned to groups to perform collaborative tasks on different topics. In one section, learners were assigned randomly into groups and were given task topics randomly as well. In the other section, they were assigned to a group based on whether they shared a common interest in the topic given to that group. We used Social Network Analysis and Content Analysis to assess the level of collaboration in quantitative and qualitative terms (knowledge construction). Both groups showed a low level of knowledge construction and similar levels of centrality degree and learning performance. However, more learners participated in the collaborative tasks if groups had been assigned based on learners' topic preferences. Our findings suggest that forming groups of adult learners based on topic preferences in on-line environments can increase the number of learners that collaborate, but it does not necessarily improve learner performance.

Keywords

Collaborative learning, Learner preference, SNA, Content analysis, eLearning

Introduction

Designed to mimic the fact that collaboration is an everyday activity, the collaboration approach has been widely used since the 1970s (Strijbos, Martens, & Jochems, 2004), and it has taken on particular prominence in education within the last decade (Laal & Ghodsi, 2012). eLearning environments typically incorporate several tools and communication channels to support collaboration among learners (Koschmann, Kelson, Feltovich, & Barrows, 1996).

The term "collaboration" has been widely applied and studied in many fields with the aim of optimising and exploiting the synergies made possible by collective intelligence (Levy, 2007). Collaboration supports corporate success by fostering the transfer of knowledge within multidisciplinary teams (Skyrme, 2013). Olson, Olson, Carter, and Storrosten (1992) analysed how different members of one organisation collaborated during meetings, and they found that a significant amount of time was spent designing the format of the discussion. Robson and Bennett (2000) found that collaborative modes of interaction between small businesses and their suppliers were critical to increasing turnover.

Collaboration in education has been widely studied (Dillenbourg, Baker, Blaye, & O'Malley, 1995). In one seminal study, Dewiyanti, Brand-Gruwel, Jochems, and Broers (2007) found that group satisfaction with collaborative work varied directly with group cohesion, and that most learners enjoyed working on collaborative projects. So and Brush (2008) found that students who participated more in collaborative learning projects were more satisfied with the learning experience than learners who participated less. Educational technology in general and eLearning in particular exploit a range of platforms and communication tools to harness the learning power of collaboration. Evidence suggests that 3D immersive environments, in which learners interact in a virtual learning world, are particularly effective at catalysing collaboration among learners (Lorenzo, Sicilia & Sánchez, 2012).

One of the key questions when designing collaborative tasks is how to assign learners to collaborative groups. This is particularly important when the target audience is adult learners, since they often exhibit strong preferences about what topics they wish to learn and which learning strategies and tactics they wish to use (Knowles, 1970). Thus designing collaborative tasks according to learner's preferences may provide strategic insights into instructional design for adult learners in on-line courses.

Surprisingly, little is known about how learner's preferences influence collaborative learning outcomes in eLearning. The present study adopts the relatively new and underexploited approach of combining content analysis (CA) and Social Network Analysis (SNA) to examine the effects of learner preferences on participation in collaborative projects and on learning performance.

Here we compare collaboration in quantitative and qualitative terms and in terms of learning performance between groups of on-line learners organised randomly and groups containing only members interested in the assigned topic. We wanted to know whether learners who work only on their preferred topics collaborate differently than learners who are assigned topics randomly. To gain insights into how learners collaborate under each type of group composition, we took a combined approach of SNA and CA. These complementary techniques provide insights into, respectively, the quantity and quality of interaction (Erlin, Yusof, & Rahman, 2008; Erlin, Yusof, & Rahman, 2009; Rabbany k., Takaffoli, & Zaïane, 2012).

Theoretical background

Collaborative learning

Collaborative learning is an instructional approach in which students work in groups to solve a problem (Dillenbourg & Schneider, 1995). In learning environments, collaboration can promote critical thinking (Gokhale, 1995), lead to better learning outcomes than traditional methods under certain conditions (Terenzini, Cabrera, Colbeck, Parente, & Bjorklund, 2001), develop social interaction skills and help students develop a sense of responsibility towards one another (Laal & Ghodsi, 2012), and develop social competencies (Bruffee, 1995) cognitive skills (Lê, 2002) and problem-solving abilities (Blaye et al., 1991).

One of the advantages of eLearning is that it can facilitate learning among students living far apart. Indeed, collaborative learning is an integral part of most eLearning environments, and it has become more prominent as a result of technological advances that support communication via chat, email, and forums. At the same time, any collaborative learning strategies adopted in eLearning should be well focused in order to maximise outcomes and avoid learner drop out that plagues many virtual learning initiatives.

Numerous factors should be taken into account when designing collaborative activities. These factors include the nature of the content, technological support available, and competence of course tutors (Dillenbourg, 1999). These factors can strongly influence the probability that learners will isolate themselves or collaborate, complete the course or drop out (Frankola, 2001).

Another key factor potentially important in learner outcomes is how learners are organised into groups to work on collaborative tasks (Kumar, 1996; Dillenbourg, 1999; Chidambaram, 2005). Instructors often ask themselves, should the groups be assigned randomly or according to some criterion, such as learners' current knowledge of the assigned topic or preference for that topic?

Despite the importance of this issue, relatively few studies have examined it. Webb, Nemer, Chizhik, and Sugrue (1998) found that below-average students working in heterogeneous groups in which they were grouped with above-average students performed better than below-average students working only with other below-average learners. Popov, Biemans, Brinkman, Kuznetsov, and Mulder (2013) found that collaborative groups comprising culturally homogeneous members were more effective at solving assigned tasks than were culturally mixed groups. Alfonseca et al. (2006) studied the effects of grouping learners according to learner style and concluded that some dimensions of learning styles affect the quality of collaborative work. Savicki, Kelley, and Lingenfelter (1996) found that female-only groups used more words per message and reported greater satisfaction with the collaborative process than did male-only groups or mixed groups.

It is also possible to organise groups based on learner preferences for topics, such that a group receiving one topic comprises only those learners interested in that topic. To date, this type of group composition has not been studied in eLearning environments, despite its potential importance for adult learners, who are generally autonomous learners, capable of deciding what knowledge or skills will be useful for their lives and therefore what they are interested in learning (Knowles, 1970; Aretio, 1988; Wlodkowski, 1986). Therefore we set out to analyse group composition based on the topic preferences of learners in order to see whether it affects how adult learners interact and how they perform in the learning task overall.

Social Network Analysis

Social Network Analysis (SNA) aims to study social relationships among actors in a network, where each actor is represented as a node connected to other actors (Wasserman & Faust, 1994). Actors may be persons, organisations, countries, or communities, and they may be connected through social bonds, kinship, economic interests, or personal interests (Haythornthwaite, 1996).

The ability of SNA to handle large data sets involving complex interactions makes it ideal for analysing eLearning systems (Scott & Carrington, 2011; Cela et al., 2014). In a typical eLearning study, data on interactions among learners and between learners and teachers are continuously gathered during the course. SNA identifies patterns in the data and builds a picture of the social structures operating in the eLearning environment (De Laat, 2002). Learning management systems (LMS) widely used today incorporate a range of communication channels, including forums (Bentivoglio, 2009; Erlin et al., 2008; Gottardo & Noronha, 2012), microblogs (Stepanyan, Borau, & Ullrich, 2010) and wikis (Barth, 2010; Kepp & Schorr, 2009). SNA can analyse the extent of knowledge sharing on all of these channels using graphical and mathematical methods.

SNA has proven effective for evaluating social structures in collaborative learning (Nurmela, Lehtinen, & Palonen, 1999). For example the method has provided an overview of how interactions among learners change over time (De Laat, Lally, Lipponen, & Simons, 2007), how students work in a self-taught course (Laghos & Zaphiris, 2006), how learners and teachers interact in on-line courses (Gottardo & Noronha, 2012), and how high- and low-performing students interact (Dawson, 2010).

Content analysis

Content Analysis (CA) makes inferences from texts (Berelson, 1952). CA has been widely used to complement SNA to obtain deeper insights into learners' interactions in on-line environments (De Laat, 2002; Erlin et al., 2008; Erlin et al., 2009; Yang, Yoo, Lin, & Moon, 2010). Researchers have drawn on CA to develop several models to analyse interactions in eLearning courses. For example, Henri (1992) proposed classifying textual features into five categories, two of which capture critical phases of knowledge construction. Newman, Webb, and Cochrane (1995) proposed an analytical model to measure critical thinking. Their model comprised a set of approximately 46 indicators organised into 10 categories.

Gunawardena's CA-based model focuses on co-construction of knowledge (Gunawardena, Lowe, & Anderson, 1997). This model stipulates five phases of knowledge co-construction; the learner is expected to pass through the phases progressively. The first phase involves sharing and comparing information; the second phase, discovering and exploring dissonance (inconsistency) among ideas, concepts or statements; the third phase, negotiation of meaning and construction of knowledge; the fourth phase, testing and modifying synthesised or co-constructed knowledge; and the last phase, agreeing on newly constructed meaning and applying it (Gunawardena et al., 1997, p. 412). Each phase comprises several subphases involving such actions as corroborating, stating, asking, and clarifying (Table 1).

Gunawardena's model has been used in several studies assessing the knowledge-building of learners in on-line environments (Aviv, Erlich, Ravid, & Geva, 2003; De Laat, 2002). Gunawardena et al. (1997) originally developed and validated the model using data on the interactions among 554 undergraduates in a global forum. De Laat (2002) later used the same model to analyse the online discourse of 46 participants in an online community, while Sing and Khine (2006) analysed knowledge-building among 11 teachers and 1 tutor in an on-line forum. Zhang and Zhang (2010) studied the discourse of 120 participants and one teacher in a blended learning course. Therefore we chose Gunawardena's model to analyse collaboration quality in terms of knowledge-building. We combined the conceptual depth of the qualitative Gunawardena model with the quantitative measures of SNA in order to gain the most complete possible picture of network interactions.

Table 1. Phases and subphases of knowledge co-construction in Gunawardena's model and the corresponding actions or textual indicators*

Phase I Sharing/comparing of information	
Subphase	Action or textual indicator
IA	Statement of observation or opinion
IB	Announcement of understanding
IC	Corroborating examples
ID	Making inquiries to clear up subtleties of explanations
IE	Definition, illustration, or fleshing-out of a problem
Phase II Discovery and exploration of dissonance or inconsistency	
IIA	Recognising differences
IIB	Asking and answering questions to identify the source and degree of difference
IIC	Adopting the position of the participants and supporting arguments or opinions on the basis of data collected, documentary references, etc.
Phase III Negotiation of meaning/Co-construction of knowledge	
IIIA	Negotiating or clarifying the meaning of terms
IIIB	Negotiating how arguments should be weighted
IIIC	Identifying overlap among conflicting opinions
IIID	Statements embodying compromise or co-construction
IIIE	Statements that integrate or accommodate metaphors or analogies
Phase IV Testing and modifying proposed knowledge synthesis or co-construction	
IVA	Testing and verifying proposals
IVB	Testing against existing cognitive schemata
IVC	Testing against formal data collected
IVD	Testing against contradictory evidence in the literature
Phase V Agreement about, and application of, newly constructed meaning	
VA	Summarising agreements
VB	Applying new knowledge
VC	Statements that demonstrate participants' awareness of their own learning and understanding of knowledge.

Note. *Adapted from Gunawardena, Lowe, & Anderson (1997), p. 414.

Methodology

Research questions

The goal of this study was to assess the collaboration and performance of learner groups engaged in a collaborative task as part of an eLearning course, and to examine whether these factors depended on whether learners were placed in groups randomly or according to whether they had a preference for the task assigned to the group:

- *Random* condition (control group): Learners were assigned randomly to groups, and groups were randomly assigned topics.
- *Preference-based* condition (intervention group): Learners sharing a preference for a given topic were assigned to the same group, and the group was asked to work on that topic.

These two groups were analysed separately and compared in order to address the following research questions:

- *RQ1:* Does grouping learners by topic preference instead of randomly affect their performance?

- *RQ2:* Does grouping learners by topic preference instead of randomly affect their collaboration in terms of quantity and/or quality?

Context and participants

This study was conducted in two sections of the same 5-week course entitled "Creation of learning objects using eXeLearning" during the fall semester 2012. This course is one of many optional, free courses offered to professionals and other interested adults by the University of Armed Forces (ESPE) in Sangolquí, Ecuador. The course was offered via the Moodle LMS.

At the start of the course, the 103 participants, all graduate-level professionals from Sangolquí, were randomly assigned into two sections. Both sections were given the same content and activities by the same instructor. Course content was organised into four modules, each of which lasted 1 week, except the third module, which lasted 2 weeks. Module 1 was an introduction intended to ensure that all students shared the same minimal level of computer skills going into Module 2. The first module introduced students to tools of communication and collaborative working, such as internal messaging, forums and wikis. Module 2 presented background on learning objects, while Module 3 allowed participants to practice creating learning objects using eXelearning software. Finally, Module 4 was a practical section in which students worked in groups to configure and publish learning objects in the Moodle LMS. For this final task, groups were asked to create a wiki covering a topic that they were assigned. In the *random* condition, teacher created groups randomly and assigned them topics randomly as well; in the *preference-based* condition, teacher assigned topics to groups based on topic preferences that group members had expressed during previous forum discussions.

Students were provided documents to read to help them complete the Module 4 collaborative assignment, and students could access their group's forum to discuss and debate ideas. The final wiki was graded based on the quality of the content and how well it fulfilled the teacher's guidelines and expectations, which were provided to students at the start of the course.

The main characteristics of both sections of participants are presented in Table 2.

Table 2. Participant characteristics

	Random group (control)	Preference-based group (intervention)
Men, *n*	31	33
Women, *n*	22	17
Age range (yr), *n*		
20-30	4	2
31-40	17	25
41-50	20	13
51-60	10	9
>60	2	1
Educational level, %		
Undergraduate degree (engineering)	79	78
Master's degree	20	22
No previous knowledge related to the on-line course material, %	98	98

Data collection and analysis

Content for analysis was taken from the logs of each group's forum during the Module 4 collaborative task, where members communicated with one another to perform the collaborative task. We analysed the logs using a combination of SNA to capture quantitative characteristics of learner collaboration, and Gunawardenas's (1997) approach to assess quality of collaboration. All data arose from interactions between learners; no information was collected regarding interactions between learners and instructors.

The *random* and *preference-based* conditions were compared using the SNA measures of density and centrality degree, as well as Gunawardena's phases; comparisons were made using Student's *t*-test or the Mann-Whitney U test.

Results and discussion

Learning performance

Learning performance in the on-line course in this study was assessed through individual grades on a final test, as well as a final group grade on the wiki project. This approach is similar to that in several previous studies that have used final grades to assess learning performance (Cho, Gay, Davidson, & Ingraffea, 2007; Loomis, 2000; Parker & Gemino, 2001).

The final grade did not differ significantly between the *random* condition (M = 7.94, SD = 1.92, N = 53) or the *preference-based* condition (M = 7.70, SD = 1.73, N = 50).

Social network analysis

Centrality degree and density provide an overview of how nodes in a network interact (Wasserman & Faust, 1994; Scott & Carrington, 2011). In our study, the nodes were the students and the paths between nodes were the forum posts produced during the Module 4 collaborative task.

Centrality

The centrality degree of a node is the number of its adjacent nodes (Freeman, 1979): the higher the degree of centrality, the greater the proportion of nodes adjacent to the node in question, and the more access that node has to information. In this way, the centrality degree of a network (centralisation) assesses how balanced is the participation in a network (Borgatti, Everett, & Johnson, 2013). A high centralisation degree indicates that a few actors control or significantly influence on-line interactions in the network. In the extreme case of a "star network," for example, centralisation is 100%. In a directed network, two types of centrality degree are often calculated: the "out degree," which assesses the inequality of participants based on sent messages; and the "in degree," which assesses the concentration of contributions based on messages received. For the *random* condition, in degree centralisation was M = 17.60 (SD = 9.82) and out degree centralisation was M = 49.80 (SD = 34.78); the corresponding values for the *preference-based* condition were M = 17.83 (SD = 18.68) and M = 60.77 (SD = 32.69). Table 3 shows the in and out degrees of centrality for each learner group under both conditions.

Table 2. Centrality degree and density in random and preference-based learner groups.

Condition	Group no.	No. members	In centrality	Out centrality	Density
Random	1	6	33.33	33.33	0.548
	2	5	18.75	18.75	0.1
	3	5	6.25	100	0.2
	4	5	25	25	0.3
	5	5	12.5	75	0.15
	6	4	8	80	0.15
	7	5	31.25	31.25	0.5
	8	6	16	16	0.067
	9	5	18.75	18.75	0.1
	10	5	6.25	100	0.2
Preference-based	11	5	62.5	6.25	0.95
	12	5	6.25	100	0.2
	13	5	0	31.25	0.75
	14	6	16	64	0.267

15	5	18.75	50	0.6
16	5	31.25	93.75	0.25
17	5	0	62.5	0.5
18	5	12.5	75	0.8
19	5	25	25	0.8
20	5	6.25	100	0.2

Among the groups under the *random* condition, group 1 showed the highest in degree of centrality (33.3%). This is substantially lower than the 100% of a star network, suggesting that interactions in all the groups in this condition were quite dispersed among the nodes. The groups with the smallest in degrees were 3 (6.25%) and 10 (6.25%), and these groups also had the highest out degrees (100%). This means that only one learner in the group received posts in response to posts that he or she had sent, akin to a star network. In other words there was no reciprocal dialogue among the members of these groups.

Under the *preference-based* condition, group 11 had the highest in degree of centrality (62.5%), closer to the star-network maximum of 100% than the corresponding maximum under the *random* condition. The groups with the smallest in degrees were groups 13 (0%) and 17 (0%). An in degree of 0% means that all learners in the group received a message in the forum; in other words, the network was not like a star. Groups 12 and 20 showed the maximum out degree of 100%, while group 11 showed the smallest out degree of 6.25%.

Density

Density expresses the level of connectivity in a network as a proportion of the maximum possible connectivity (Wasserman & Faust, 1994); it is calculated by dividing the number of observed ties by the maximum possible number of ties (Scott & Carrington, 2011). Thus it varies from 0 to 1, where 1 (100%) refers to a situation in which all nodes are interconnected. The network density was significantly different between the *random* condition (M = 0.23, SD = 0.17) and the *preference-based* condition (M = 0.53, SD = 0.289).

Density values for individual groups under both conditions are shown in Table 3. Group 1 in the *random* condition showed the highest density (0.548), while groups 2 and 9 showed the smallest (0.1). Most groups showed densities much smaller than the highest of 0.548. Under the *preference-based* condition, in contrast, several groups showed high density: Group 11, 0.95; Group 13, 0.75; Group 15, 0.6; and Groups 18 and 19, 0.8.

Quality of collaboration

In order to assess quality of collaboration, forum logs were codified according to Gunawardena's model in order to assign learners to the appropriate phase and subphase of knowledge construction. Although the unit of analysis was a single forum post, some posts were assigned to multiple phases because they contained statements consistent with more than one phase. This codification was performed twice in order to detect any inconsistencies in the classification of occurrences. Most posts from groups under the *random* condition were assigned to phases IA-IE. Most posts from the *preference-based* groups also belonged to phases IA, IB, and ID, but nearly none to phase IE, which corresponds to the definition, description or identification of a problem; and none to phase IC, in which the learner corroborates examples cited by other learner(s).

Groups in both the *random* and *preference-based* conditions made one statement belonging to phase IIA, which corresponds to discovering and exploring dissonance or inconsistency among ideas, concepts or statements. Groups in the *random* condition made two statements belonging to phase IIB, while those in the *preference-based* condition made none; this subphase involves asking and answering questions to clarify the source and extent of disagreement.
Groups under the *random* condition made more phase IIIA contributions than groups in the *preference-based* condition; this phase includes negotiating or clarifying the meaning of terms. Conversely, the *preference-based* groups made more phase IIID contributions, which involves proposing and negotiating new statements embodying compromise and co-construction. These same groups made nearly as many phase IIIE contributions, which involve

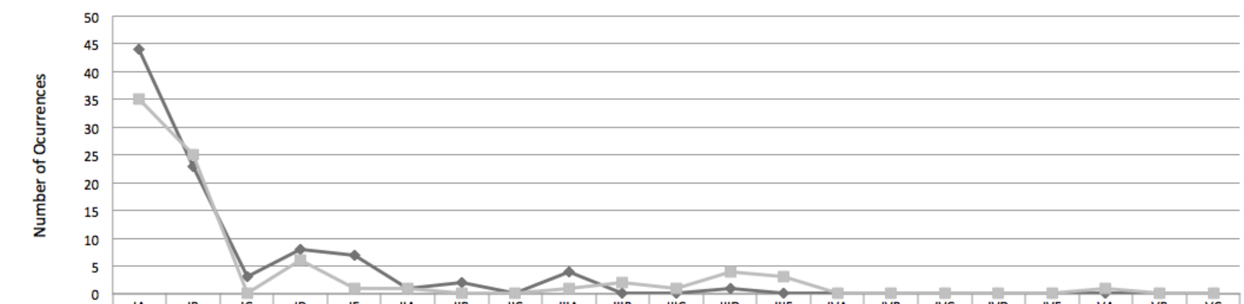
proposing or integrating metaphors or analogies. Groups did not make Phase IV contributions under either condition, and only one phase V contribution was recorded (in *preference-based* groups).

Together, these results show that learners under both conditions showed a relatively low level of knowledge construction: 88% of forum posts were in phase I, which involves comparing and sharing information. These results echo those of other studies with participants in other countries and with different ages from our students. In Gunawardena's study of messages from 554 list subscribers of a global debate, 93% of posts belonged to the first phase. In De Laat's (2002) study of 46 professionals in Europe, 72% of messages were assigned to phase I, and Zhang and Zhang's (2010) study of 120 university students in China found 85% of posts in the first phase.

Most forum posts focused on comparing and sharing information, which suggests that these elementary actions are the priority for learners in order to achieve a collaborative task (Sing & Khine, 2006). This finding also suggests the difficulty of achieving a higher level of knowledge in this eLearning environment.

Statistical results

We performed statistical tests to compare group collaboration under the *random* and *preference-based* conditions in terms of the SNA measures of centrality degree and density, as well as to compare knowledge construction under the two conditions according to the relative frequency of forum posts assigned to different phases of Gunawardena's model based on content analysis. Figure 1 shows these data for each group under the two conditions.



	IA	IB	IC	ID	IE	IIA	IIB	IIC	IIIA	IIIB	IIIC	IIID	IIIE	IVA	IVB	IVC	IVD	IVE	VA	VB	VC
Random	44	23	3	8	7	1	2	0	4	0	0	1	0	0	0	0	0	0	0	0	0
Preference	35	25	0	6	1	1	0	0	1	2	1	4	3	0	0	0	0	0	1	0	0

Phase code

Figure 1. Assignment of forum posts to different phases in Gunawardena's model of knowledge construction for random and preference-based learner groups (Phase codes are defined in Table 1)

The assumption of homogeneous variance was accepted based on Lévene's test for centrality in degree, centrality out degree, and Gunawardena's phases I-IV. We used Student's *t*-test to compare group means for these variables under the *random* and *preference-based* conditions. The results showed no significant difference for any of the variables between the two conditions.

Since the assumption of homogeneous variance was not accepted for the SNA measure density, we compared group results under the two conditions using the Mann-Whitney test. The test indicated that mean density under the *preference-based* condition was significantly higher ($p = 0.009$).

Together, these results suggest that arranging learners into groups based on their preference for the assigned topic may increase the number of learners who get involved in discussions to complete a collaborative task (the SNA measure of density), but it does not necessarily alter the numbers of messages received by learners (centrality in degree), the number of messages posted (centrality out degree), or the overall level of knowledge construction achieved.

In this way, our study extends the literature on how learner characteristics influence the way that they collaborate. Previous work has already emphasised the importance of gender (Savicki et al., 1996), learning styles (Alfonseca et al., 2006) and below- and above-average performance (Webb et al., 1998). These findings have so far been obtained in adult learners, who adopt a more goal-oriented focus than younger learners (Wolfgang & Dowling, 1981). It would be interesting to see whether similar results are obtained with other types of eLearning courses in other countries or cultures with learners of different educational backgrounds.

Conclusions

In this study, we assess whether grouping learners by topic preference instead of randomly affects their performance (RQ1) as well as the quantity and quality of collaboration (RQ2).

We combined the quantitative power of SNA to examine centrality degree and density of learner-learner interactions, with the richness of CA to assess the level of knowledge co-construction. Our results show that groups who were assembled and assigned topics randomly showed similar centrality in and out degrees as groups who were assembled and assigned topics based on member preferences. However, more members of *preference-based* groups participated in forum discussions than did members of *randomly assigned* groups. Nevertheless, groups under both *random* and *preference-based* conditions showed similarly low levels of knowledge co-construction according to Gunawardena's (1997) model. Most learner contributions were limited to sharing and comparing information through the actions of making remarks, presenting opinions, clarifying information, or citing evidence to corroborate other learners' examples. Our results suggest that taking into account learner preferences when assigning topics for collaborative projects to adults in an eLearning course may increase the number of learners who participate in discussions, but it may not make any difference to the performance achieved. A major limitation of this study is the small population. These results should be verified and extended in studies conducted in other countries with other types of topics, learners, and collaborative tasks.

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