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Exploring Conditions for Enhancing Critical Thinking in Networked Learning: Findings from a Secondary School Learning Analytics Environment

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Abstract: Networked learning provides opportunities for learners to develop their critical thinking, an important 21st century competency, through dialogue with fellow learners to consider other perspectives and negotiate and critique ideas and arguments. However, much extant literature has not examined networked learning environments among younger learners nor the optimal conditions for enhancing critical thinking. Therefore, a study was carried out to investigate these conditions. A learning analytics networked learning environment was designed and 264 secondary three students participated in the 10-week long intervention as part of their English curriculum. Individual and collective social network metrics, critical reading scores, and self-reported survey data were used to quantitatively evaluate students' critical reading performance in relation to their participation in networked learning. Results highlight several optimal conditions, notably that it is not just participation of the learner that enhances critical thinking but the learners' reciprocity in replying and the distance of those posts in the network. Discussions and implications of the findings follow to provide insightful understanding of how the rich and complex settings of networked learning can enhance critical thinking capacities in secondary schooling.

Keywords: networked learning; critical thinking; secondary school; learning analytics

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1. Introduction

Critical thinking is one of the core competencies for learners in the 21st century and beyond. Networked learning provides opportunities for learners to develop their critical capacities through dialogue with fellow learners, to consider other perspectives, and negotiate and critique ideas and arguments [1]. While online learning forums are important predecessors of networked learning, technological and pedagogical developments in learning analytics point to the importance of dynamic visual learning analytics in computer-mediated learning environments [2], as well as multimodal social dialogic learning spaces [1,3]. Participation in such social dialogic spaces can dispose networked learners toward higher criticality [4].

Many existing networked learning environments have been implemented in post-secondary educational settings, such as distance education and higher education. Besides originating from the higher education context, it may be relatively easier to enact such networked learning with older learners as compared to younger learners due to the learner agency and self-regulation required [5]. A related issue is that existing pedagogical models for younger learners tend to focus on information or knowledge accumulation rather than productive interactions for learning [6]. Consequently, the research-informed empirical understandings of younger learners' (e.g., adolescents) participation in social dialogic learning and the extent to which this affects their learning outcomes is limited [7,8]. As networked learning environments and pedagogy are increasingly being extended to K-12 educational settings [9], it is important to explore and examine the optimal application of such learning environments with younger learners.

Since social and intellectual interactions are key aspects of networked learning [10], examining interaction patterns to examine participants' activities and relationships in the learning network have the potential to uncover insights into the interactions in networked learning and their association with learning outcomes [11]. Exploring collaborative and technology-dependent processes in networked learning through social network analysis (SNA) can potentially uncover the conditions necessary for effective learning and characterize productive interaction patterns for optimising networked learning environments [12].

Toward identifying the optimal conditions for developing critical thinking in secondary schooling, a 10-week intervention was carried out using WiREAD, a networked learning environment with affordances of multimodal social dialogic learning and dynamic visual learning analytics. A total of 264 secondary three (grade 9) students from a mainstream secondary school in Singapore participated in the intervention as part of their English language (EL) curriculum.

Our research aims to contribute to addressing some of the above-mentioned issues by: (1) presenting a web-based collaborative critical reading and learning analytics environment that was designed and implemented in schools; and (2) reporting individual and collective social network metrics, critical reading scores, and self-reported survey data to quantitatively evaluate students' critical reading performance in relation to their participation in networked learning.

This paper starts with a literature review on networked learning environments and critical thinking, including advanced techno-pedagogical designs of learning network environments; this is followed by a review of quantitative methods for networked learning, primarily SNA for analyzing interactions. We then present the networked learning environment that was implemented. Next, the methods and materials used in the study are described. SNA was used together with multiple regression analysis (MRA) and t-tests to analyse the data. The results are shown and discussed with implications for theory, pedagogy, and design. Lastly, we end with a conclusion with contributions of the study and future ways forward.

2. Literature Review

2.1. Networked Learning Environments and Critical Thinking

The design of networked learning and computer-supported collaborative learning (CSCL) environments is often informed by socio-constructivist theories whereby knowledge is seen as socially negotiated and co-constructed [13,14]. Social and intellectual interactions between people are an integral process of learning [15–17] and key to networked learning [10]. These interactions are primarily carried out through dialogue, highlighting the crucial role of dialogic interaction for knowledge co-construction and learning in networked learning environments [1,18]. Accordingly, new theorizations of literacy, such as multiliteracies [19], have reconceptualized literacy as a social practice that is "increasingly multiple, multimodal and mediated through new technology" [20] (p. 1). These new literacies emphasise higher-order learning outcomes, such as the critical and collaborative evaluation and understanding of multiple forms of texts [19,21]. Students' interactions with peers and instructors have been positively associated with student learning in general [22,23] and with higher-order learning outcomes in online collaboration [24,25]. In the context of networked learning, online discussions have been shown to enhance critical thinking capacities by engaging students in more constructive interactions [26,27].

Although critical thinking can be embedded in the curriculum and taught in various ways, the lesson materials and task criteria will influence students' critical thinking performance [28]. Correspondingly, Johnson et al. [29] emphasize the importance of intentionally designing interaction into the learning context for high-quality interactions to occur. Aviv et al. [30] found that a higher level of critical thinking was achieved during knowledge construction in a structured learning network than in an unstructured learning network. To provide more structure, scripts can be built into the networked learning environment to scaffold students' interaction. Schellens et al. [4] found that students using thinking or knowledge types scripts to tag their contributions displayed a greater depth of critical thinking as compared to the control group. These findings stress the importance of structuring interactions in networked learning environments to foster students' criticality thinking.

Another key aspect of the design of networked learning and CSCL environments is the integration of learning analytics dashboards to support teaching and learning. Learning analytics dashboards can be used as a formative feedback tool to provide opportunities for learners to gain awareness of and reflect on their learning, and subsequently modify their learning behaviours [2]. In networked learning, social learning analytics can also be harnessed to generate insights on learning patterns and behaviors, based on learners' participation and interactions in the learning environment [18]. The use of learning analytics dashboards has been associated with more opportunities for students to reflect on their learning and to provide greater motivation [2,31] and improved academic achievement [32]. In other words, well-designed dashboards can create a networked learning environment conducive to building students' critical thinking capacities.

2.2. Quantitative Networked Learning Metrics

To understand learning in a network, there are many methods and measures. While acknowledging the importance of qualitative and mixed method approaches, this research uses a quantitative method with measures and metrics that help to account and control for the scale of networks. Individual measures of learners' characteristics, such as their participation, achievement, and perceptions, together with collective measures that provide insight into the specific context the learner is situated in, can be useful for understanding networked learning. Understanding the social aspects of learning is gaining focus in education research [33], particularly with the growing use and applicability of SNA in educational settings [30,34]. SNA seeks to identify underlying relationships between actors in a social network based on their interactions with one another [35]. In networked learning environments, system log data can be used to map out interaction patterns to examine participants' activities and relationships in the learning network [11]. SNA is an effective technique for understanding collaborative and technology-dependent processes [11,12] that has been applied to identify well-connected learners and learners who require more support and to design more effective learning environments [34,36]. SNA has also been used to monitor and assess the effectiveness of virtual learning groups [37,38].

SNA can examine network-level metrics (e.g., density, reciprocity) and individual-level metrics of networks (e.g., degree centrality) [39]. At the network level, SNA metrics provide more information about the network structure and network-level participation patterns. Network structure in terms of density and tie strength was found to influence social learning [40], and network centrality and reciprocity are correlated with grades [41]. Instructor's presence has been found to influence network density [42], and information flow was highly influenced by instructors [43]. However, in networks with no instructor present, learners took on central roles [44]. Central actors are also influential as research shows that participants are more likely to follow central actors' recommendations compared to less central actors in the network [45,46].

At the individual level of network metrics, "centrality" measures the extent of an individual's interactions with other participants in the network [35]. In higher education, low participation in a learning network was identified as a possible predictor of low achievement [47] and low in-degree centrality was predictive of underachievement [48]. Out-degree centrality and interacting with tutors was associated with better grades in a problem-solving course [49], although this effect of out-degree was not significant for students in a medical course [48]. The inconclusive findings for out-degree centrality indicate that further examination of out-degree centrality is needed to understand its relationship to learning.

3. Study Context

The study was carried out using WiREAD, a web-based collaborative critical reading and learning analytics environment that was implemented in a secondary three (grade 9) EL subject in a Singapore secondary school. WiREAD was designed with the aim of fostering critical thinking in the EL domain as a socially generative practice by motivating and scaffolding students' collaborative knowledge construction around multimodal texts. The techno-pedagogical design of WiREAD focused on two key learning affordances: (i) multimodal social dialogic learning (Figure 1), and (ii) dynamic visual learning analytics (Figure 2). These key affordances are in turn underpinned by four embedded learning and pedagogical frameworks: (i) multiliteracies pedagogical framework [19], (ii) dialogic learning [50], (iii) assessment for learning (AfL) [51], and (iv) CSCL [52]. The key principles of these four interconnected and nested learning and pedagogical frameworks are visually represented in Figure 3.

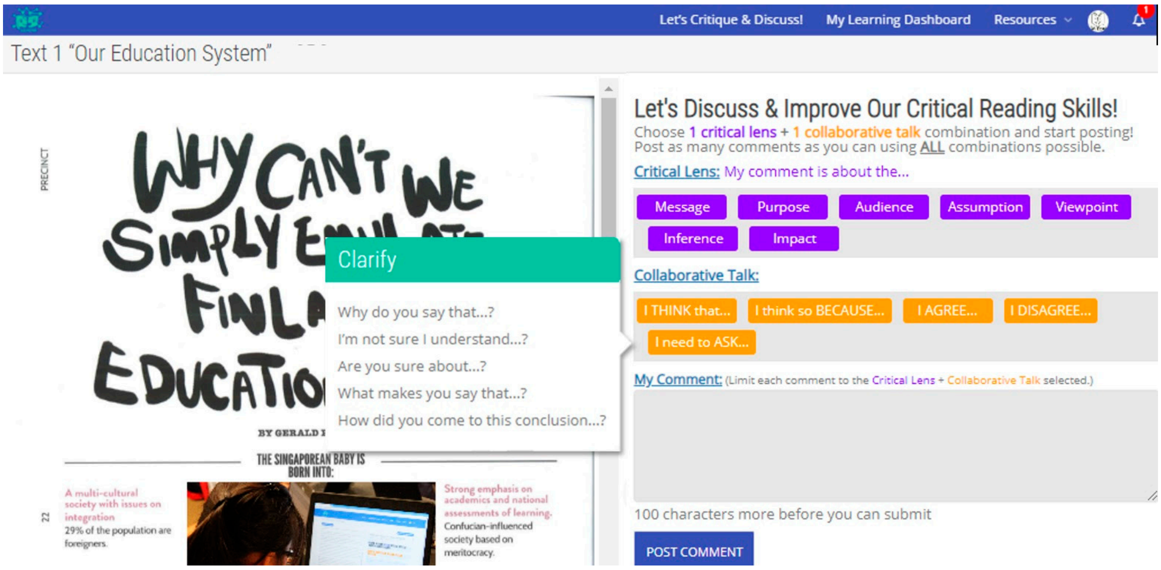

Figure 1. Multimodal social dialogic learning space of WiREAD.

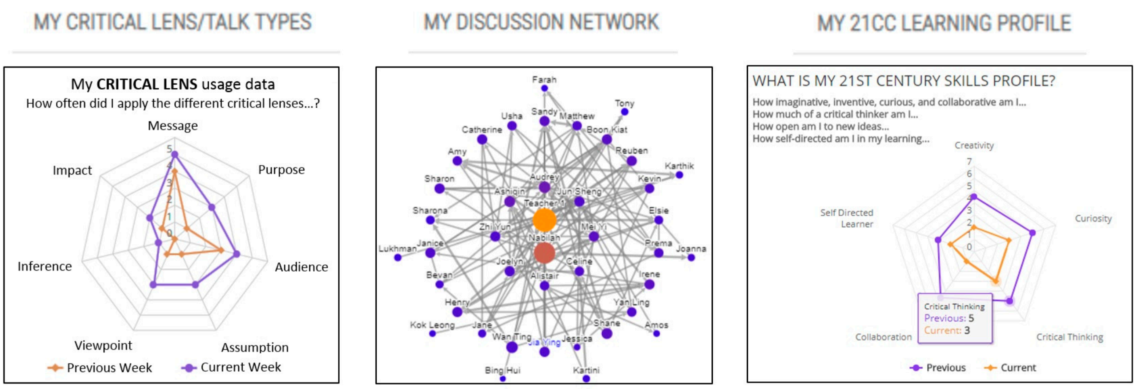

Figure 2. Dynamic learning analytics visualizations of WiREAD (selected only).

The multimodal social dialogic learning space allowed teachers to embed multimodal textual resources around social, moral, and/or ethical dilemmas for students to read and collaboratively critique with their peers during and beyond formal class time (see [53]). Critical reading pedagogical scaffolds based on the multiliteracies pedagogical framework [21,54], Paul–Elder's "wheel of critical reasoning" [55], as well as dialogic indicators of collective creativity and criticality [56], guided students' reading and discussions of the texts. The pedagogical scaffolds were comprised of seven critical lenses and five critical talk types, which are listed in Table 1. Students had to select one critical lens and one critical talk type for every comment or reply that they posted on WiREAD. Students' participation on WiREAD was captured and visualized to them through a learning analytics dashboard, enabling them to track their critical reading engagement and progress in terms of: (i) the number of comments and replies posted, (ii) the number of critical lenses and critical talk types used, and (iii) sociograms visualizing their involvement and interactions within their WiREAD learning network.

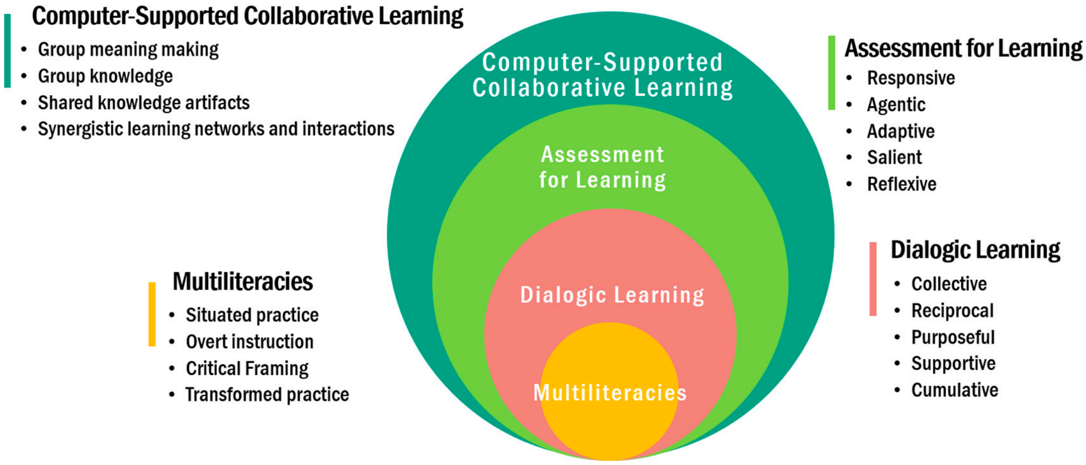

Figure 3. Learning and pedagogical principles underlying techno-pedagogical design of WiREAD.

Table 1. Critical reading pedagogical scaffolds.

Critical Lenses	Critical Talk Types
Message: What is the text/author telling the reader?	Ideate: I think that ...
Purpose: What is the objective of the text/author?	Justify: I think so because ...
Audience: Who are the target readers?	Validate: I agree ...
Assumption: What presuppositions does the author make?	Challenge: I disagree ...
Viewpoint: Whose perspective is the text written from?	Clarify: I need to ask ...
Inference: What conclusions did I draw from the text and why?	
Impact: How effective are the language/visuals used?	

Typically, a new teacher-nominated text would be uploaded to WiREAD every 1–2 weeks. Students would read and respond to texts on WiREAD using one-to-one devices for one EL lesson (around one hour) every 1–2 weeks in their classrooms or in computer labs, as well as in their own time out of class. During the lesson, teachers would set aside some time for students to read the text before posting comments and replies. The critical lenses acted as questions for students to respond to. Students were encouraged to use a range of critical lenses and critical talk types, as well as engage with their classmates' comments. To this end, teachers often provided guidelines on the minimum number of comments and replies students should aim to post (e.g., at least three comments and three replies), to ensure that they are engaging sufficiently with the text and classmates' responses. Although most of the lesson would be spent engaging online on WiREAD, teachers may pause the lesson at critical junctures to provide instructions and feedback to the class or highlight key points.

Previous research on WiREAD documented its impact on students' critical reading fluency, cognitive reading engagement, and EL self-efficacy [57], and students' and teachers' qualitative accounts of its usefulness [53]. In this study, we focus on the conditions for promoting critical reading as generated by the network metrics. To examine and identify conditions for effective critical thinking in WiREAD, a networked learning environment, this paper asks, what are the conditions for promoting critical thinking of students in a networked learning environment?

4. Methods and Materials

4.1. Research Design and Procedure

The paper is situated in a larger study that employs design-based research with multiple trials to develop a techno-pedagogical networked learning environment with multimodal social dialogic learning and dynamic visual learning analytics in the secondary school context. The trial concerned was conducted in 2016 at the participating school, a mainstream secondary school. Seven secondary three classes participated in the 10-week long WiREAD intervention. During the intervention, WiREAD was used as part of the secondary three EL curriculum, with almost weekly WiREAD sessions during curriculum time, as well as out-of-class usage. Seven multimodal texts adapted from newspaper or magazine articles and online posts were embedded in WiREAD for students' collaborative critique. The topics covered included education systems, abortion, filial piety, and euthanasia.

For this study, quantitative data at the start, during, and at the end of the trial were gathered. Quantitative data were in terms of the pre- and post-tests and log data on WiREAD. Informed consent was obtained from the students and their parents in accordance with the institutional review board's research ethics requirements. One student opted not to participate in the study and was thus excluded from the data collection and analysis, although the student used WiREAD as part of the curriculum.

4.2. Participants

Consenting participants consisted of 263 students in the seven classes. These classes were taught by a total of five EL teachers. A breakdown of the participants is provided in Table 2 below. All the classes were of similar size, except for Class C, which had 23 participants. There were slightly more female students in the study (53.2%) as compared to male students (46.8%).

Table 2. Breakdown of participants by class, gender, and English language (EL) teacher.

Class	*n*	% Males	% Females	EL Teacher
Class A	40	67.5%	32.5%	Teacher 1
Class B	40	42.5%	57.5%	Teacher 2
Class C	23	34.8%	65.2%	Teacher 3
Class D	39	30.8%	69.2%	Teacher 1
Class E	39	51.3%	48.7%	Teacher 4
Class F	40	42.5%	57.5%	Teacher 5
Class G	42	52.4%	47.6%	Teacher 2
Total	263	46.8%	53.2%	5 Teachers

4.3. Measures

4.3.1. Social Network Metrics

Social network measures were computed to identify individual (node) and collective (network) characteristics that are optimal for fostering critical reading. On WiREAD, log data on whose posts a student had replied to and who had replied to a student's posts was captured. This data was then fed into UCINET 6.0 [58] as seven separate matrices, one matrix per class. Node-level and network-level metrics were generated separately for each class of students since each class was a closed network on WiREAD and interactions were restricted to students and teachers within each class.

Several network metrics were calculated in relation to the context and research question:

- Out-degree centrality: As students were encouraged to post replies to their classmates' posts, out-degree centrality was computed to measure how many participants a student had out-going ties with (i.e., how many people they sent replies to).
- Out k-step reach centrality: To measure how closely connected a student was to other participants in the class, out k-step reach centrality was used. Out k-step reach centrality refers to "the

proportion of actors that a given actor can reach in k steps or less" [59] (p. 178). It was used instead of closeness centrality as it is more suited to directed networks.

- Arc reciprocity: This was used as a network- or class-level metric to measure the extent to which replies from a student to another participant was matched by replies from that participant to the student. By default, UCINET dichotomizes the data in order to generate these metrics, meaning that the analysis focused on whether ties/interactions existed between two participants rather than how many ties there were between two participants.

Additionally, the metrics generated for each class of students were normalized so as to allow between-class comparisons.

4.3.2. Engagement in Collaborative or Networked Learning

At the start of the intervention, a self-report questionnaire was used to measure students' perception of their engagement in collaboration using a five-item scale adapted from Tan and Nie's [60] group engagement scale. The items are on a seven-point Likert-type scale ranging from "strongly disagree" to "strongly agree." The scale demonstrated excellent internal reliability, with a Cronbach's alpha coefficient of 0.94. Items from the scale are listed below:

- I try my best to contribute to group discussions in EL;
- I share my ideas during group work in EL;
- I try my best to get involved in discussions during EL;
- I try my best to contribute to group work in EL;
- I enjoy discussions with my classmates in EL.

During the intervention, students' posting behaviour on WiREAD was captured through the log data. The total number of words each student posted on WiREAD was used to quantify the extent of their participation. The word count of posts is a more meaningful measure as it reflects the depth of students' participation and contribution compared to a frequency count of the number of posts, which can be inflated by a high frequency of very short posts.

4.3.3. Critical Reading Score

Students' critical reading competency was measured using an objective critical reading test that was co-designed with the EL teachers. The test aimed to assess students on two dimensions: (i) critical reading quality and (ii) critical reading fluency. Critical reading quality pertains to the accuracy of students' answers to the test questions. The questions were drawn from the critical lenses (e.g., Message: "What is the text telling you?"). Answers were scored on their accuracy, with 0 for irrelevant responses and up to 3 for responses with deeper inference/insight. Critical reading fluency pertains to the breadth of critical reading sub-skills demonstrated in each answer (idea/claim, agreement/validation, justification, etc.). These sub-skill dimensions were drawn from the critical talk types. Critical reading quality and fluency scores were combined to obtain an overall critical reading competency score for each student. Students completed the critical reading test at the start of the intervention, and again at the end of the intervention. The tests were graded by the EL teachers.

4.4. Data Analysis

SNA data and pre- and post-test variables were collated and descriptive statistics were generated to determine the characteristics of the sample and the variables examined. To identify the optimal conditions for fostering effective critical reading, a standard multiple regression analysis (MRA) was conducted using the enter method. The independent variables were the students' pre-test critical reading score, self-reported engagement in collaboration, word count of posts, out-degree centrality, out 2-step reach centrality, and class' arc reciprocity. The dependent variable was the students' post-test critical reading score. The results are reported in the next section of this paper.

5. Results

5.1. Multiple Regression Analysis

Prior to interpreting the results of the MRA, several assumptions were evaluated. An analysis of standard residuals was carried out, which indicated that the data contained no outliers (std. residual min. = −2.39, std. residual max. = 3.10). To check for influential cases that could bias the model, Cook's distance and the Mahalanobis distance were examined. Although Cook's distance was less than 1 for all cases, the Mahalanobis distance exceeded the critical χ^2 for df = 6 (at α = 0.001) of 22.458 for four cases in the sample, indicating that these cases could be exerting undue influence over the parameters of the model. A total of 11 potentially influential cases were examined and removed iteratively until a maximum Mahalanobis distance of less than 22.458 was achieved in the final model. Descriptive statistics for the original model (model 1) and the final model (model 2, after the 11 cases were removed) are summarized in Table 3.

Table 3. Descriptive statistics for students' critical reading scores, self-reported engagement in collaboration, and online participation on WiREAD.

	Model 1			Model 2		
Variable	***n***	***M***	***SD***	***n***	***M***	***SD***
Post-test critical reading score	263	18.82	5.88	252	18.94	5.91
Pre-test critical reading score	263	17.49	4.91	252	17.55	4.93
Pre-test engagement in collaboration	263	5.30	1.07	252	5.36	0.96
Word count of posts	263	1012	674.79	252	979.52	583.22
Out-degree centrality	263	0.24	0.15	252	0.23	0.13
Out 2-step reach centrality	263	0.83	0.22	252	0.83	0.22
Class arc reciprocity	263	0.52	0.07	252	0.52	0.07

Multicollinearity was not a concern in either model as the variance inflation factor (VIF) was below 4 and the tolerance level was above 0.2 for all the independent variables [61,62]. The data met the assumption of independent errors (Durbin-Watson value$_{\text{model1}}$ = 2.04; Durbin-Watson value$_{\text{model2}}$ = 2.04). Inspection of the normal probability plots of standardized residuals and scatterplots of standardized residuals against standardized predicted values indicated that the assumptions of normality, linearity, and homoscedasticity of residuals were met for both models.

In model 1, the six predictor variables explained 38.8% of the variance in the post-test critical reading score, F (6, 256) = 28.652, $p < 0.001$, $R^2 = 0.402$, adjusted $R^2 = 0.388$. By Cohen's [63] conventions, an effect of this magnitude can be considered "large" ($f^2 = 0.67$). The pre-test critical reading score (β = 0.30, $p < 0.001$), word count of posts (β = 0.16, $p = 0.011$), out-degree centrality (β = −0.17, $p = 0.013$), out 2-step reach centrality (β = 0.17, $p = 0.007$), and class arc reciprocity (β = 0.32, $p < 0.000$) were statistically significant predictors of post-test critical reading score, while engagement in collaboration was not a significant predictor (β = 0.06, $p = 0.252$).

This pattern was also seen in model 2, where the six predictor variables explained 38.8% of the variance in post-test critical reading score, F (6, 245) = 27.505, $p < 0.001$, $R^2 = 0.402$, adjusted $R^2 = 0.388$, with a "large" effect size ($f^2 = 0.67$). Pre-test critical reading score (β = 0.27, $p < 0.001$), word count of posts (β = 0.21, $p = 0.003$), out-degree centrality (β = −0.20, $p = 0.009$), out 2-step reach centrality (β = 0.17, $p = 0.008$), and class arc reciprocity (β = 0.33, $p < 0.001$) were statistically significant predictors of post-test critical reading score, while engagement in collaboration was not a significant predictor (β = 0.05, $p = 0.371$). The regression coefficients, standard errors, and t-values are reported in Table 4.

Table 4. Summary of Multiple Regression Analysis.

	Model 1				Model 2			
Predictor	**B**	**SE_B**	**B**	***t***	**B**	**SE_B**	**β**	***t***
Pre-test critical reading score	0.362	0.067	0.302	5.431 ***	0.329	0.069	0.275	4.751 ***
Pre-test engagement in collaboration	0.319	0.278	0.058	1.148	0.284	0.317	0.046	0.896
Word count of posts	0.001	0.001	0.158	2.560 *	0.002	0.001	0.208	2.966 **
Out-degree centrality	−6.670	2.679	−0.166	−2.490 *	−9.251	3.495	−0.202	−2.647 **
Out 2-step reach centrality	4.426	1.638	0.168	2.702 **	4.617	1.736	0.170	2.660 **
Class arc reciprocity	27.174	4.458	0.324	6.096 ***	28.045	4.609	0.335	6.085 ***

Note: B—unstandardized regression coefficient; SE_B—Standard error of the coefficient; β—standardized coefficient; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Comparing the two models, the predictors explained 38.8% of the variance in both models. Only engagement in collaboration was not a statistically significant predictor of post-test critical reading score in both models, while pre-test critical reading score, word count of posts, out 2-step reach centrality, and class arc reciprocity were positively-related significant predictors, and out-degree centrality was a negatively-related statistically significant predictor. Given that neither the presence nor absence of the influential cases changes the conclusions that can be drawn from the results, we focus our discussion on the original model, model 1.

5.2. Further Analysis

Out k-Step Reach

To further examine what level of connections in the network out k-step reach centrality were optimal for fostering effective critical reading, the post-test critical reading scores of students with different levels of out k-step reach were examined. To perform this test, we computed a median split for four measures of out k-step reach, where k = 1, k = 2, k = 3, and k = 4, and used a series of independent samples t-tests with the out k-step reach variable as the independent variable and post-test critical reading score as the dependent variable. The results are reported in Table 5.

Table 5. Out k-step reach centrality: descriptive data, independent samples t-test results and effect sizes.

	Below-Median Group		Above-Median Group			
Variable	***n***	**Mean *(SD)***	***n***	**Mean *(SD)***	***t***	**Cohen's *d* (Effect size)**
Out-degree centrality	136	18.77 (6.54)	127	18.88 (5.11)	−0.15	−0.02 (Small)
Out 2-step reach centrality	136	17.58 (5.80)	127	20.15 (5.71)	−3.62 ***	−0.45 (Medium)
Out 3-step reach centrality	135	17.21 (4.67)	128	20.52 (6.54)	−4.69 ***	−0.58 (Medium)
Out 4-step reach centrality	167	19.40 (6.36)	96	17.82 (4.83)	2.27 *	0.28 (Medium)

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. SD—standard deviation.

For out-degree centrality (equivalent to out 1-step reach), preliminary assumption testing indicated that scores for both groups were relatively normally distributed, but Levene's test was significant as there was substantially more variance in the below-median-group's scores. Consequently, Welch's t-test was used to compare the two groups' post-test critical reading scores. The results indicated that there was no significant difference in scores for students with below median out-degree centrality ($n = 136$, $M = 18.77$, $SD = 6.54$) and students with above median out-degree centrality ($n = 127$, $M = 18.88$, $SD = 5.11$), $t\ (253.20) = -0.15$, $p = 0.877$.

For out 2-step reach centrality, preliminary assumption testing indicated that scores for both groups were relatively normally distributed, and Levene's test was also non-significant. Thus, equal variances can be assumed. The results indicated that there was a significant difference in scores for students with below median out 2-step reach centrality ($n = 136$, $M = 17.58$, $SD = 5.80$) and students with above median out 2-step reach centrality ($n = 127$, $M = 20.15$, $SD = 5.71$), $t\ (261) = -3.62$, $p < 0.001$.

For out 3-step reach centrality, preliminary assumption testing indicated that scores for both groups were relatively normally distributed, but Levene's test was significant as there was substantially more variance in the above-median-group's scores. Consequently, Welch's t-test was used to compare the two groups' post-test critical reading scores. The results indicated that there was a significant difference in scores for students with below median out 3-step reach centrality (n = 135, M = 17.21, SD = 4.67) and students with above median out 3-step reach centrality (n = 128, M = 20.52, SD = 6.54), t (228.88) = −4.69, p < 0.001.

For out 4-step reach centrality, preliminary assumption testing indicated that scores for both groups were relatively normally distributed, but Levene's test was significant as there was substantially more variance in the below-median-group's scores. Consequently, Welch's t-test was used to compare the two groups' post-test critical reading scores. The results indicated that there was a significant difference in scores for students with below median out 4-step reach centrality (n = 167, M = 19.40, SD = 6.36) and students with above median out 4-step reach centrality (n = 96, M = 17.82, SD = 4.83), t (241.53) = 2.27, p = 0.024.

6. Discussion

This paper examines the conditions for promoting critical thinking among grade 9 students in a techno-pedagogical designed networked learning environment. The MRA results show that class arc reciprocity, out 2-step reach centrality, pre-test critical reading score, and word count of posts were significantly positive predictors of higher post-test critical reading score, while out-degree centrality was a significantly negative predictor of post-test critical reading score. Pre-test engagement in collaboration was not found to significantly predict post-test critical reading score. The results are discussed in the following paragraphs and provide some insight into optimal conditions for enhancing the critical thinking capacities of learners.

Starting with students' prior achievement in terms of pre-test critical reading scores, this was found to be a strong significant predictor of post-test critical reading scores in the networked learning environment. Past studies have shown that individual factors, such as prior achievement and knowledge, can influence knowledge comprehension and construction, with high-achieving students performing better on various thinking skills [64], as well as participating more actively in online discussion tasks [65]. The result implies that students with lower prior critical reading ability levels still require more teacher support and guidance in order to participate adequately in networked learning environments [66,67].

Examining the SNA metrics, the results strongly show that class arc reciprocity predicts students' post-test critical reading scores. This was the highest unstandardized regression coefficient in the MRA and shows a clear alignment with existing research indicating the positive association between reciprocity and students' grades [41]. Facilitating a culture of reciprocity at the network-level could contribute toward students' critical thinking by ensuring that they are interacting sufficiently with other students' responses, as well as contributing ideas of adequate quantity and quality for others to respond to their contributions, as shown by other studies, e.g., Saqr et al. [48,68].

Although out-degree centrality and out 2-step reach centrality are both measures of active outward interactions, findings from our MRA revealed that out 2-step reach centrality was a significant predictor of higher post-test critical reading scores, whereas out-degree centrality was predictive of lower post-test critical reading scores. These contrasting findings reflect the inconclusive findings around out-degree centrality in the literature [48,49]. One possible interpretation of these results is that maintaining a high out-degree centrality, i.e., interacting with a large number of participants in the network, requires considerable time and effort. Larger discussion threads are important for continuous discussion to develop [69], but a high volume of interactions can result in information overload [70]. Being engaged in a high number of discussions might result in a trade-off between breadth and depth of connections in the learning network. Students with high out-degree centrality could be engaged in many short and disconnected discussions without developing ideas with sufficient depth [70], thus not developing their critical thinking capacities despite their high participation.

In this case, the finding that out 2-step reach centrality was a significant predictor of critical reading scores suggests that forming indirect connections with the entire network through deeper interactions with a smaller number of participants might have been more beneficial for developing students' critical reading compared with forming direct but shallow connections with all participants in the learning network. As mentioned, we performed further analysis to probe this finding. Further analysis comparing the scores of students with above median and below median out k-step reach centrality revealed that students of above median out 2-step reach centrality and out 3-step reach centrality had significantly higher post-test critical reading scores as compared to their below median peers. For out-degree centrality (out 1-step reach centrality), there was no significant difference in post-test critical reading scores for students above and below the median.

The findings from the further analysis provided more evidence that being able to reach the rest of the learning network through two or three other indirect or intermediary connections is optimal for fostering critical thinking capacities, such that students can easily be connected to the ideas of many different participants in the network without having to directly interact (i.e., reply) with all of them. This implies that effective strategies for fostering interactions and guiding students toward achieving a conducive balance between breadth and depth of interactions in order to develop their critical thinking capacities are needed. For instance, in the design or pedagogical instruction of networked learning environments, learners should be guided to steer away from replying to many posts, but instead to concentrate on certain ones that pique their interest and that allow them to engage deeply in the discussion.

We note that the results were reversed for the further analysis of out 4-step reach centrality; students below the median had significantly higher post-test critical reading scores than students above the median. In this case, the results for out 4-step reach centrality should be interpreted with caution as students in the above-median group were exclusively from three of the seven classes. Teachers in these three classes were highly involved and connected in the network, with extremely high normalized out 2-, 3-, and 4-step reach centralities of 1. Correspondingly, it is likely that these students had high out 4-step reach centrality because of their connection to the teacher rather than their own interactions in the network. Additionally, there was at most only a difference of 0.05 between the out 4-step reach centrality of 98% of the sample whereas there was a greater variation among students for out-degree, out 2-step reach, and out 3-step reach centralities. This suggests that out 4-step reach centrality and beyond might not be useful metrics for analyzing small networks such as the classes in our study.

Lastly, the study also examined conditions related to individual participation. While greater participation in terms of the word count of posts was a significant predictor of students' post-test critical reading scores, students' self-reported pre-test engagement in collaboration in EL had no influence over their critical reading scores. Quantity of words can be indicative of the depth of students' contributions and interactions [71], and could be a proxy for whether students are sufficiently engaged in the process of critical and collaborative evaluation and knowledge co-construction to develop their critical thinking capacities. Greater participation levels in networked learning are associated with achievement [47]. This implies that due to the potential inaccuracy of self-reported measures of participation or collaboration, it is likely more useful to focus on word count of posts and other behavioral measures in examining participation in networked learning environments [72].

Looking at the findings overall, it does suggest that while it is important to have learners participate individually in the network to develop their critical thinking, the extent of that participation matters. Specifically, what seems to matter is the reciprocity between learners' replies and the distance or nearness between learners' replies. This means that optimal conditions for learner's critical thinking in the networked learning environment include learners' ability to respond to a reply and going deeply into a few posts rather than many. A pedagogical implication, therefore, is that facilitating critical thinking in such environments requires several instructional guidelines for students' interactions. It should not be “random” replies or posts but thoughtful dialogues between learners clarifying and exchanging perspectives, as well as intentional discussions on various topics/posts that learners can deeply engage in.

7. Conclusions

In this paper, an empirical investigation of the optimal networked learning conditions for enhancing critical thinking capacities among grade 9 students as part of the EL curriculum was conducted. The networked learning environment WiREAD integrated multimodal social dialogic learning and dynamic visual learning analytics to foster students’ 21st century competencies including critical thinking. We found that higher prior achievement in critical reading and greater participation in terms of word count of posts were optimal factors. More importantly, the findings utilized network metrics to highlight that it was not just participation in the network, but also the reciprocity between learners’ replies and the distance between learners’ replies that enhanced students’ critical thinking. There is a need to balance the breadth with the depth of interactions to cultivate students’ critical thinking capacities.

Implications of these results are that the design of the networked learning environment and pedagogical instruction should provide more structure and support for students in developing their critical thinking in terms of both the quantity and quality of interactions. Students should be guided toward greater participation in the learning network. However, this should be done in combination with strategies to help students engage deeply and critically with others in the network so as to encourage higher quality interactions [70,73].

Students with lower prior achievement can also benefit from more teacher support and guidance to optimize their meaningful participation in networked learning environments [66,67]. To meet diverse students’ needs, teachers should be adaptive in their teaching strategies [74] while leveraging contemporary technologies, such as networked learning environments, to provide support and structure for students’ interactions while allowing sufficient agency for students to develop their critical thinking capacities. We acknowledge that the role of the teacher is important in networked learning, as also seen in other learning networks [43] and will be examined in future studies.

This study was not without its limitations and we highlight them and suggest ways forward. First, overall network metrics were used and there was no breakdown of students’ participation for different teacher-nominated texts or by the discussion thread. This resulted in slightly coarse-grained findings with a broad overview that cannot resolve participation levels that can differ across texts and threads. Future studies can look into examining finer-grained metrics to provide more information about interaction behaviors for each text and thread in the network. Second, although this study examined the quality of students’ critical reading through their critical reading scores, our analysis of students’ participation in networked learning involved metrics related to the quantity of their participation. Combining content analysis with SNA can provide a more comprehensive understanding of the type and quality of interactions in networked learning that might be optimal for enhancing students’ critical thinking [11,34] and are future steps for the research team. Another limitation is related to the log data available on the technical system. There was no indicator for whether a post was read, which limited the kind of inferences we could draw. This lack of data is partly due to the current technological limitations that although post clicks can be detected, it cannot accurately inform if a post was read. Examining reading in networks, e.g., requiring eye trackers for each student, is practically and technically challenging at this point in time. Lastly, we acknowledge that the study can be further strengthened through the use of a quasi-experimental design with a control group.

In conclusion, this paper has identified several key conditions for enhancing critical thinking in a collaborative critical reading and learning analytics networked learning environment. While several of the study’s findings support existing research, this is one of a few studies on networked learning that focus on grade 9 learners. In that sense, it helps to widen and extend the optimal conditions. Besides contributing to the broader application of networked learning, the study also showcases a networked learning environment designed with advanced affordances, and provides design, pedagogical, and theoretical implications. It is our hope that the findings and discussion presented here contribute toward identifying optimal networked learning conditions for enhancing critical thinking capacities. By presenting how conditions such as students' prior achievement, and their participation reciprocity and distance in networked learning affects critical reading scores, we provide a more insightful understanding of how the rich and complex settings of networked learning can enhance critical thinking capacities in secondary schooling.

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