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Using topic modeling-based network visualization and generative AI in online discussions, how learners' perception of usability affects their reflection on feedback*

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This study aims to analyze the impact of learners' usability perceptions of topic modeling-based visual feedback and generative AI interpretation on reflection levels in online discussions. To achieve this, we asked 17 students in the Department of Korean language education to conduct an online discussion. Text data generated from online discussions were analyzed using LDA topic modeling to extract five clusters of related words, or topics. These topics were then visualized in a network format, and interpretive feedback was constructed through generative AI. The feedback was presented on a website and rated highly for usability, with learners valuing its information usefulness. Furthermore, an analysis using the non-parametric Mann-Whitney U test based on levels of usability perception revealed that the group with higher perceived usability demonstrated higher levels of reflection. This suggests that well-designed and user-friendly visual feedback can significantly promote deeper reflection and engagement in online discussions. The integration of topic modeling and generative AI can enhance visual feedback in online discussions, reinforcing the efficacy of such feedback in learning. The research highlights the educational significance of these design strategies and clears a path for innovation.

Keywords : Online discussions, Topic modeling, Generative AI, Learner reflection, Feedback usability.

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Introduction

As the development of information technology has increased the demand for online learning environments, online discussions have become a popular way to improve learners' engagement and critical thinking skills. Online discussions, which are mainly text-based in an online environment such as an LMS, are a teaching and learning method in which learners freely organize their knowledge and share their opinions on a specific topic. In this process, learners can critically accept diverse opinions and information, think deeply about a topic, and reflect on their values and attitudes by promoting problem solving and logical thinking (Kim, 2023; Tudge & Rogoff, 1999).

However, the asynchronous nature of online learning environments presents challenges for fostering active participation in discussions. Donna Smith and Katy Smith (2014) noted that these environments, by being separated by time and space, impede interactive engagement. Fung (2004) observed that learners often contribute only the bare minimum of threaded posts necessary to fulfill grading requirements. Moreover, Hewitt (2005) identified a tendency in threaded discussions to prioritize the most recent contributions, with posts arranged in sequential order of submission. This structure, coupled with the cognitive burden associated with comprehending the full scope of discussions, limits effective interaction (Wise et al., 2013).

Online discussions facilitate collaborative knowledge construction through social interaction among learners. Therefore, it is important for instructors to intervene and provide appropriate feedback (Im & Jin, 2021; Dennen, 2005). Instructors should monitor the discussion's progress by connecting each thread and providing feedback based on knowledge and insight. This will help learners recognize the flow of the discussion and increase their level of reflection (Rohfeld & Hiemstra, 1995). However, when the number of discussion participants increases, the instructor's burden to provide qualitative feedback also increases, requiring a significant investment of time and effort (Lao, 2002).

In this context, prior research has underscored the benefits of employing learning analytics to visualize participation metrics and discussion content, thereby enabling learners to comprehend the dynamics and outcomes of discussion activities more effectively and to engage in reflective learning practices. Jin and Yoo (2018) introduced a 'keyword dashboard' that visualizes the frequency of discussion-related terms, alongside a 'message type dashboard' that categorizes threads by type using a radial graph, as a means of content analysis for discussion activities. Their findings suggest that these dashboards were perceived by learners as instrumental in enhancing motivation and enriching the quality of their contributions to discussions. Similarly, Jeon et al. (2023) implemented a graphical organizer that includes a T-chart for juxtaposing arguments, a tree chart for organizing ideas under broad themes, and a map to illustrate the interconnections between arguments. This approach was found to significantly enhance learners' comprehension and engagement in discussions.

According to prior research, providing visual feedback on the content of online discussions can enhance engagement by making learners perceive the information as useful and promoting intrinsic motivation. However, some forms of feedback have been found to be less comprehensible or easy to understand. The visualization and interpretation of material become more challenging as the discussion becomes more complex and informative.

To enhance the comprehensibility and usability of visual feedback, it is crucial to extract essential information from the discussion and provide feedback that is intuitively visualized. Topic modeling, a text mining technique, can accomplish this. It is a machine learning-based text analysis method that automatically extracts key topics from large amounts of textual data (Blei, 2012). Summarizing complex discussion data into key topics and visualizing their connections can help learners understand results quickly. Additionally, generative AI can interpret calculated values and important words from topic modeling to aid content comprehension.

Therefore, this study aimed to design user-friendly visual feedback by visualizing online discussion activities and investigating the impact of feedback using generative AI on learners' reflection levels. To do this, we analyzed threads using topic modeling, a text mining method, to visualize learners' discussion content and provide feedback interpreted by generative AI. Additionally, we conducted a usability evaluation to examine the effect of visual feedback on reflection levels.

The research questions are:

1) What is the perceived usability of feedback using topic modeling-based content visualization and generative AI in online discussion activities?

2) Is there a difference in the level of reflection based on the perceived usability of feedback using topic modeling-based content visualization and generative AI in online discussion activities?

Literature Review

Online discussions and reflection

Online discussion is a teaching and learning activity where learners interact with the instructor or other learners by sharing their opinions through text (Dillon & Morris, 1996). As discourse-based learning, online discussions allow learners to examine opinions from different perspectives and reflect on their own opinions to expand their thinking. Non-real-time online discussions offer learners the opportunity to gather quality data and engage in in-depth thinking about the topic, promoting higher-order thinking (Kwon & Park, 2017).

According to the social constructivist perspective, effective online discussions occur when learners' social and cognitive engagement are combined, with the formation of a learning community and collaborative knowledge construction being key factors (Abawajy, 2012). Social interaction and cognitive thinking lead to the development, integration, and elaboration of individual opinions, as well as the construction of community-shared knowledge (Lin et al., 2014). Therefore, it is crucial for learners to be reflective and critically accept perspectives that differ from their own, to develop their own opinions based on them (Nussbaum & Schraw, 2007).

Previous research has indicated that in online learning environments where learners are physically separated from their instructors, it is important to emphasize the need for reflection and to employ a variety of strategies to promote reflective thinking. Yilmaz and Keser (2016) discovered that incorporating reflective questions and tasks in learning materials, such as podcasts, had a positive impact on learner motivation. Roskos et al. (2001) suggested several methods to promote reflection, including debriefing and reorganizing learning activities, keeping a reflection journal, and using prompts and feedback.

The purpose of reflection in discussion activities is not only to evaluate one's behavior and identify areas for improvement, but also to shift one's existing perspective (Abdul & Badlishah, 2020; Mezirow, 1991). In other words, learners can reflect on their opinions, experiences, beliefs, and arguments through interaction with others and to potentially alter their perspective (Im & Jin, 2021). Kember et al. (2008) proposed four levels of learner reflection: non-reflective, understanding, reflection, and critical reflection.

The highest level, 'critical reflection', involves presuppositional reflection, where the learner is aware of unconscious thoughts and behaviors that have been shaped by past experiences and critically examines them to change their perspective (Mezirow, 1978). 4 levels of reflection can be used as a guide to assess the level of reflection in a learner's writing (Kember et al., 2008). The highest level of reflection observed in the writing is considered the learner's level of reflection. In this study, reflective writing activities were conducted using visual feedback that summarizes and reorganizes the results of online discussion activities to assess learners' level of reflection.

Visual feedback

From a learning analytics perspective, visualized feedback provides a representation of learners' learning outcomes to facilitate future activities (Yoo, 2017). Learning analytics serves as the foundation for appropriate teaching and learning support by collecting and analyzing various learning data, such as learners' participation frequency, learning time, and behavior patterns (Siemens & Long, 2011). The text mainly reports or predicts learners' activities through quantitative data that is easy to collect and record. This data is then visualized in an easy-to-understand form to provide meaningful information to both instructors and learners (Lim & Kim, 2017).

However, judging the quality or effectiveness of learning activities based solely on numerical learning data is challenging. Therefore, qualitative analysis of learning activities is necessary (Malheiro et al., 2008). In online discussion learning environments, understanding the content of learners' discussions is crucial for reflection on their learning process and outcomes (Kim, 2023). Previous studies have confirmed the learning effect by analyzing learners' discourse content during discussions, the frequency of key words set by the instructor, or visualizing social connections between learners (Jin & Yoo, 2018; Lim et al., 2014; Matsuzaw et al., 2011).

Qualitative analysis and visualization of online discussions can help reduce the cognitive burden on learners who must read multiple texts and follow the discussion flow (Jyothi et al., 2012). However, previous studies have shown that providing visual feedback alone can make it difficult to comprehend complex discussion content (Jang & Lee, 2023). Therefore, it is necessary to provide explanatory or prescriptive feedback to aid in understanding the visual feedback. Generative AI is expected to enhance the understanding of visual feedback by interpreting qualitative data and simplifying the complexity of visual feedback into a language that is easy for learners to comprehend, and even automate it. However, to ensure educational significance, it is crucial to investigate how new tools and strategies are perceived from the learner's perspective (Cho et al., 2015).

When learners perceive visual feedback as useful, it is more likely to result in actual changes in their learning plans and behaviors. Sun and Vassileva (2006) suggest that visual feedback should be designed for intuitive presentation and usability, without requiring significant effort to understand and recognize the information. Additionally, previous studies on dashboards that visually display online learning information have found that learners' perceptions of usability have a positive impact on their ability to self-direct their learning and change their behavior (Park & Jo, 2019; Rohloff et al., 2019).

Considering the purpose of reflection, which is for learners to reflect on their learning process to improve and change their perspectives and behaviors, the usability perceptions of visual feedback are crucial in helping learners develop self-directed learning skills, increase self-awareness of learning, and ultimately improve learning outcomes.

LDA Topic modeling

Topic modeling is an analytical technique that groups words in individual or sets of documents into topics based on their similarity (DiMaggio et al., 2013). A topic is a collection of words with comparable meanings within a set of documents. Topic modeling extracts these topics and analyzes them by calculating the percentage of each document that contains a topic. Therefore, meaning can be extracted from text by analyzing the distribution of words by topic. This method can be used to analyze qualitative data, such as public opinion through social media analysis, by examining multiple topics in a document (Park et al., 2022). Latent Dirichlet Allocation (LDA) is the most used technique among topic modeling methods. LDA is a technique for extracting topics by generating a document-word matrix based on a generative probabilistic model and calculating the probability of the correlated distribution of documents and words (Lee & Yi, 2021; Blei & Lafferty, 2006).

The LDA results can be presented as a network of connections among the words that form a topic. Topic modeling can summarize the content of online discussions by extracting subtopics from learners' comments on the discussion topic. By visualizing the frequency of words that make up a topic and the connections between them, the collaborative knowledge base that learners have built becomes apparent.

However, it is necessary to determine the appropriate number of topics for LDA-based topic modeling, as the results can vary depending on the number of topics set in the analysis (Grün & Hornik, 2011). To find the optimal number of topics, Coherence Value and UMass Measure are commonly used to measure the coherence of the model. Coherence Value is a metric that measures the cohesion of a topic based on the mutual information between words and takes a value from 0 to 2. A higher coherence value indicates a more balanced distribution of words within a topic, which means that the topic has a clear, coherent theme (Syed & Spruit, 2018). Conversely, UMass Measure is a metric based on the frequency of co-occurrence of word pairs within a document, with lower values indicating better topic coherence (Mimno et al., 2011).

Topic modeling only produces a set of words, so it is necessary to manually assign names to the topics. This can be done by identifying the context of a topic based on the top words assigned to it and interpreting the results by assigning appropriate names based on the common meanings or topics of the words (Park et al., 2022; Lim et al., 2021). However, it is important to note that subjective judgment cannot be eliminated when interpreting information (Chang et al., 2009). Generative AI can analyze the words and numbers extracted from topic modeling results and generate a summary of the topic or provide related example sentences to aid in understanding. This AI-based automated interpretation can help reduce reliance on human subjective judgment in naming topics and increase the consistency and accuracy of results.

Method

Participants

The study was conducted on a sample of 17 junior students in the Department of Korean language education who were taking the course 'Educational Methods & Educational Technology' at A University in Seoul. The sample consisted of 11 female and 6 male students who were all attending a teachers' college.

Research Procedures and Instruments

A. Online discussion

This study examined the impact of visual feedback, based on topic modeling, on the level of reflection in online discussions. An online discussion activity was conducted on the topic of 'What do I think learning is?' After watching a video lecture on learning theories, students wrote a definition of learning based on their own experiences and uploaded it to the LMS bulletin board in approximately 300 words. During the week-long discussion period, students had five days to upload their own posts and two days to comment on other learners' posts. Learners were able to view other learners' posts after writing their own and could also reply to comments on their own posts, which encouraged lively discussion.

B. LDA Topic modeling

We analyzed 89 threads of thread data collected from online discussion activities using NetMiner 4. To preprocess the data, we excluded the formal words 'thanks', 'comment', and 'classmate' from the analysis. We also excluded the word 'learning', which occurred in all posts, and single-letter words that were difficult to understand. To consider the significance of words in the text, we calculated TF-IDF, which is the relative frequency of words in each text and removed words with a value of 0.3 or less.

To determine the suitable number of topics and parameter values for topic modeling, we analyzed the model fit indices Coherence Value and UMass Measure using the ‘Evaluation of Topic models’ extension of NetMiner 4. The number of topics and parameters were set to five topics, alpha .07, and beta .02, which were determined to be the optimal values for Coherence Value (0.627) and UMass Measure (-1.197) through simulation.

A network was created to visualize the five topics and the words that make them up. This visualization shows the frequency of word occurrence and the order of word pairs based on the size of the nodes and the direction of the connected lines.

We utilized generative AI to interpret the visual feedback. The report file and information were organized in a table with the probability of occurrence of the constituent words of each topic, which resulted from topic modeling. This was then entered ‘Chat with any PDF’. The network image of each topic was also entered to explain the topic of the online discussion and output the definition and interpretation of each topic. (Prompt: It was generated through an LDA analysis of the students' discussions on the topic of ‘How I think about learning’. The report presents the top keywords distributed by topic, the number of documents assigned to each topic, and the probability of distribution of the keywords by topic. Please use the distributed keywords to generate topic names and interpretation sentences).

The discussion on the definition of learning resulted in the formation of five topics: ‘Memory and recall’, ‘Study methods and information retention’, ‘Student learning and self-direction’, ‘Behavior change and cognitive perspectives’, and ‘Knowledge acquisition and application’. The website provides feedback results of LDA topic modeling and generative AI.

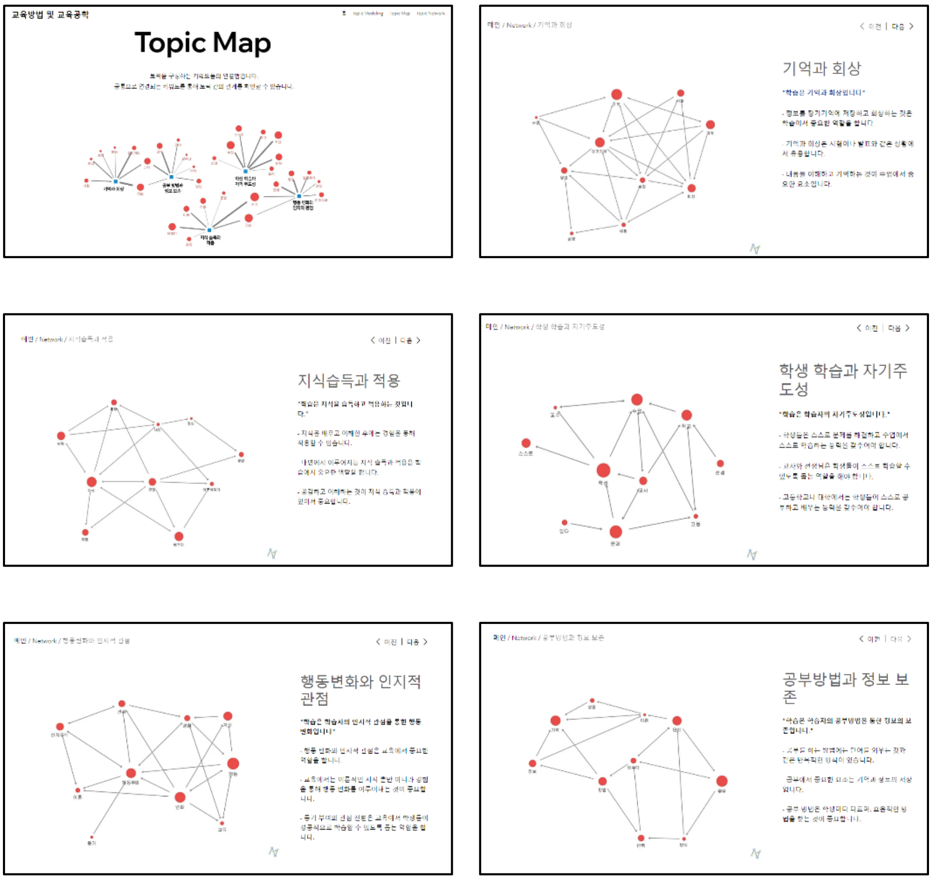

Figure 1. Providing visual feedback screen

C. Online discussion reflection & Feedback usability evaluation

On the website, students can view the network of topics and words resulting from the discussion activity. They can click on topics to view the interpretations generated by the generative AI and freely explore the feedback. The instructor then asked students to write a reflection on their discussion, comparing the results of the entire discussion activity to their own writing. After the reflection activity, the students took part in a usability evaluation of the visual feedback and interpretation information resulting from the discussion activity.

The evaluation was based on the online discussion visual feedback usability evaluation factors and items developed in the studies by Lim et al. (2020) and Park & Jo (2019). These were modified to fit the context of this study, and the final items were reviewed by a PhD in Educational Technology. Additionally, we included open-ended questions soliciting opinions on each usability subareas (refer to Table 1).

Table 1
Usability Evaluation Factors

Usability Subarea	Item
Visual Attraction	• Was the amount of information provided by the visual feedback appropriate? • Was the material presented in a clear and concise manner? • Was it easy to find the information you needed? • Was the visual feedback presented on one screen?
Understanding	• Was the visual feedback clear in helping you understand the results of the discussion activity? • Was the network image easy to comprehend? • Was the network description clear?
Perceived usefulness	• Would monitoring the outcome and process of a discussion activity be useful if I use visual feedback in my class? • Can visual feedback provide me with the necessary information?
Behavioral changes	• Would the visual feedback you received during the semester motivate you to participate in online discussions? • Would you use the information provided by the visual feedback to guide your level of engagement in the discussions?

In this study, we used Kember et al. (2008) four-step model of reflection to analyze students' reflective thinking about online debates, and we reviewed each students' final level of reflection by a pedagogical engineer, as shown in Table 2.

Table 2
Reflection Level Measurement Metrics

Reflection Level	Description	Example of Reflective Writing
Level 1. Non-reflection	The text lacks subjective evaluations and personal opinions, focusing solely on habitual feelings, facts, and experiential benefits of discussion activities.	It was exciting to discuss online and express opinions, empathize, and rebut in a casual manner.
Level 2. Understanding	The text mentions the discussion topics and methods used during the activity and acknowledges what was learned but refrains from providing personal opinions or evaluations of individual participation.	It was enlightening to discover new perspectives that I had not considered before.⋯ I learned that it is possible to disagree with someone who holds the same position, and that there are aspects that can resonate with someone who holds a different position.
Level 3. Reflection	Evaluates the thought process on the topic and the content of the final opinion objectively, and seeks ways to improve thinking in the future, without forming or changing a new perspective.	After comparing my definition of learning to those of my classmates, I realized that I was limited by my own perspective. ⋯ Recognizing this as a problem, I resolved to overcome it and strive towards becoming an adult capable of initiating change beyond the confines of a given framework.
Level 4. Critical reflection	Examined their own perspectives and beliefs about the topic of discussion or gained an understanding of social and ethical issues related to the topic.	I think we should have thought more about what learning is in essence, and I think we've overemphasized the role of the instructor. ⋯ Instructors need to help learners learn correctly, that is, to master something fully.

Analysis methods

This study aimed to investigate whether there is a difference in the level of reflection based on the usability of topic modeling-based visual feedback. To achieve this, a non-parametric Mann-Whitney U test was performed, with usability perception as the independent variable and reflection level as the dependent variable. The Mann-Whitney U test is used to compare differences between two independent groups when the data distribution is non-normal or when the sample size is small. In this study, we used a non-parametric test due to the small sample size of 17 subjects.

Additionally, we categorized the participants into high and low usability awareness groups based on the mean value of usability awareness. We examined the differences in reflection levels between groups across sub-domains that comprise usability perceptions, such as visual attraction, understanding, perceived usefulness, and behavioral changes. This provides detailed considerations and empirical evidence for designing visual feedback that represents the outcome of online discussions.

Results

Awareness of usability in visualized feedback

Table 3 presents the descriptive statistics of learners' perceptions of usability and reflections on the visual feedback of online discussions based on topic modeling. The learners perceived the visual feedback to be somewhat highly usable (M=4.219), with the highest perceived level of usability being Perceived usefulness (M=4.500). The average reflection level of all learners was 2.2, which corresponds to the level of understanding.

The normality assumption was satisfied as the skewness and kurtosis of each variable ranged from -.712 to .960 and did not exceed the absolute value of 3 (Kline, 2005). However, due to the small sample size, a nonparametric Mann-Whitney U test was performed.

Table 3
Metrics Topic Modeling-based Visual Feedback Usability Awareness & Reflection Level Descriptive Statistics (N=17)

Factors		*M*	*SE*	*SD*	Skewness	Kurtosis
Usability awareness	Usability awareness	4.219	.100	.412	-.109	-.012
	Visual attraction	4.221	.115	.475	-.182	.011
	Understanding	3.961	.143	.588	.200	-.211
	Perceived usefulness	4.500	.129	.530	-.712	-.635
	Behavioral changes	4.324	.142	.585	-.535	-.038
Reflection Level		2.206	.122	.502	-.567	.960

Regarding feedback on usability, learners found the visual feedback helpful in understanding the outcome of the discussion. The network visualization, where the size of the circles represented the mentions and importance of topics, aided in comprehending the content. It is important to note that this feedback is subjective and not necessarily representative of all learners.

> "I think it would be useful to see the results of the discussion summarized like this rather than having to read through the threads." (Participant B)

> "It was easy to understand because it was drawn like a mind map. However, I would like to see more images for each main topic." (Participant D)

During the discussion, I observed that opinions and information were identifiable through visual feedback. This suggests that LDA topic modeling effectively represents the collaborative knowledge formed during the activity.

> "It was well organized by topic, and when I read other people's posts, I found it

easy to see that the parts that I felt were similar were tied together and organized well, so I think it was presented in the right way in that respect." (Participant G)

"It was nice to be able to visibly see how many people had similar opinions to me, and to intuitively grasp the key points of the discussants who thought differently." (Participant F)

Nonparametric test results

A. Level of reflection based on perceptions of usability feedback

To determine if there is a difference in learners' reflection based on the usability level of visual feedback in online discussion activities using topic modeling, a non-parametric Mann-Whitney U test was conducted. The high and low groups were divided into two based on the mean of usability perception (M=4.219). The results are presented in Table 4. There is a significant difference in the level of reflection between the groups with high and low usability perceptions. Learners who perceived good usability of visual feedback had a higher level of reflection than those who perceived poor usability (z=-2.707, p<.01).

Table 4
Level of learner reflection based on perceived usability of visual feedback

Group	N	Mean Rank	Sum of Rank	Mann-Whitney U	z
high	9	11.94	107.50	9.50	-2.71**
low	8	5.69	45.50		

**p <.01

B. Level of reflection based on perception of usability subareas in visual feedback

To determine if there is a difference in learners' reflection based on the level of awareness in each subarea of visual feedback usability, we conducted a non-parametric Mann-Whitney U-test on the mean awareness in each subarea. The results are presented in Table 5.

In all subareas, the group with high awareness exhibited a higher level of reflection than the group with low awareness. Significant differences were observed between the groups in terms of understanding (z=-2.020, p<.05), perceived usefulness (z=-3.367, p<.01), and behavioral change (z=-2.196, p<.05), except for visual attraction (z=-1.243, p>.05). In summary, if online learners find the visual feedback based on topic modeling and the interpretive feedback from generative AI easy to understand and useful, and if they are willing to use the feedback to improve their future learning activities, then higher levels of reflection can be achieved.

Table 5
Level of learner reflection based on perceptions of usability subareas of visual feedback

Usability subarea	Group	N	Mean Rank	Sum of Rank	Mann-Whitney U	z
Visual attraction	high	10	10.20	102.00	23.00	-1.24
	low	7	7.29	51.00		
Understanding	high	10	10.95	109.50	15.50	-2.02*
	low	7	6.21	43.50		
Perceived usefulness	high	7	13.64	95.50	2.50	-3.37**
	low	10	5.75	57.50		
Behavioral changes	high	9	11.39	102.50	14.50	-2.20*
	low	8	6.31	50.50		

$^{*}p$ <.05 $^{**}p$ <.01

Conclusion

The aim of this study was to examine how learners' perceptions of usability affect their reflection on topic modeling-based visual feedback and interpretation of generative AI. The researchers analyzed texts from online discussion activities to identify key topics, presented them in a network format, and generated interpretive feedback using generative AI. The analysis revealed the following results regarding learners' perceptions of feedback usability and their level of reflection.

First, it was found that learners rated the usability of the network visualization, which was based on topic modeling and interpretive feedback from generative AI, quite highly. Among the different aspects of usability, learners rated information usefulness the highest. The subtopics extracted from the shared opinions, along with the network and interpretive feedback, were perceived by learners to be a good representation of the main content of the discussion activity. Learners can establish a sense of social presence through the process of seeing and interpreting the collaborative knowledge formed by the interactions between members of the learning community (Joksimović et al., 2015).

However, the subdomain of interpreting nodes and links in the network had the lowest perceived level of information comprehension. To improve this, it is necessary to provide direct explanations and information about each element when providing visual feedback. Yoo (2017) developed a visualization principle for online discussion activities based on learning analytics. The author found that for visual feedback based on nodes and links, it is necessary to design the user experience so that the size or color of the node, the thickness of the link, and the detailed information or related discussion opinions appear when the learner clicks on the element.

The study's second research question analyzed the relationship between learner reflection and usability perception of network visualization based on topic modeling and interpretive feedback from generative AI. The results showed that students with higher usability perception of the feedback demonstrated higher levels of reflection. This suggests that design measures should be taken to improve the usability of visual feedback using topic modeling and interpretation of generative AI.

Design should focus on the usability subdomains of “Understanding”, “Perceived usefulness” and “Behavioral changes” which were found to have significant differences in the level of reflection based on perception. For instance, learners can be presented with meaningful information more concisely through selection and filtering features that enable them to obtain the desired information (Dabbebi et al., 2017). Furthermore, learners can compare and develop their opinions by indicating the relative position of their posts within the learning community. Unlike the other subareas, "Visual attraction" did not show a difference in reflection levels, suggesting that individual learners' preferences for how visual feedback is provided and their perceptions of the amount and ease of information do not influence reflection.

Content analysis of online discussions aims to extract new meanings that may not be immediately apparent. De Wever et al. (2006) propose this method as a means for learners to reflect on and evaluate their learning activities by visualizing the shared knowledge of online discussion participants using topic modeling. Compared to Kolb's (2014) reflection model based on experiential learning, it serves as information for learners to reflect and evaluate their learning activities because it extracts new meanings by visualizing the shared knowledge of online discussion participants using topic modeling. Based on this, learners can set goals for their next learning, which means that they change as they practice (Kolb, 2014).

The diversification of data analytics and advances in generative AI technologies are increasing the feasibility of automating visual feedback and building systems for user-friendly design of online discussion environments, and there is a need to explore their empirical effectiveness from data design and learner perspectives. From this perspective, this study is significant in that it explored learners' perceptions of text analysis and network visualization using LDA topic modeling and interpretive feedback from generative AI to improve the quality of pedagogical interaction in online discussions and how to promote learners' deep reflection and knowledge construction. This study differs from previous research, which focused on visual feedback development and usability, by exploring how learners' perceptions of usability affect their reflective thinking. Additionally, it examines strategic feedback design approaches that aim to enhance learning outcomes and increase cognitive engagement in online discussions.

However, future research should consider conducting empirical studies with larger sample sizes to identify more specific ways to construct feedback in online discussions. This approach would lay an important foundation for maximizing the effectiveness of online discussions and enhancing learner reflection. By exploring a broader range of data and applying these findings in various learning environments, we can deepen our understanding of how visual and interpretive feedback from generative AI, as presented in this study, contributes to deeper learner reflection in online discussions.

References

Abawajy, J. (2012). Analysis of asynchronous online discussion forums for collaborative learning. *International Journal of Education and Learning, 1*(2), 11–21.

Abdul Rabu, S., & Badlishah, N. (2020). Levels of students' reflective thinking skills in a collaborative learning environment using Google docs. *TechTrends, 64*, 533-541.

Blei, D. (2012). Probabilistic topic models. *Communications of the ACM, 55*(4), 77-84.

Blei, D., & Lafferty, J. (2006). Correlated topic models. *Advances in neural information processing systems, 18*, 147.

Chang, J., Gerrish, S., Wang, C., Boyd-Graber, J., & Blei, D. (2009). Reading tea leaves: How humans interpret topic models. *Advances in Neural Information Processing Systems, 22*.

Cho, Y., Park, H., Kim, J., Seok, Y., & Lee, S. (2015). Exploring roles of feedback to facilitate online discussion, *Asian Journal of Education, 16*(2), 289-313.

Dabbebi, I., Iksal, S., Gilliot, J. M., May, M., & Garlatti, S. (2017). Towards adaptive dashboards for learning analytic: An approach for conceptual design and implementation. In *9th international conference on computer supported education* (pp. 120–131).

De Wever, B., Schellens, T., Valcke, M., & Van Keer, H. (2006). Content analysis schemes to analyze transcripts of online asynchronous discussion groups: A review. *Computers & education, 46*(1), 6-28.

Dillon, A., &Morris, M. G. (1996). User acceptance of new information technology: theories and models. In M. Williams (ed.) *Annual Review of Information Science and Technology* (Vol. 31, pp. 3-32). Informtion Today.

DiMaggio, P., Nag, M, & Blei, D. (2013). Exploiting affinities between Topic modeling and the sociological perspective on culture, *Poetics, 41*(6), 570-606.

Fung, Y. (2004). Collaborative online learning: Interaction patterns and limiting factors. *Open Learning: The Journal of Open, Distance and e-Learning, 19*, 135–149.

Grün, B., & Hornik, K. (2011). Topic models: An R package for fitting topic models.

Journal of statistical software, 40, 1-30.

Hewitt, J. (2005). Toward an understanding of how threads die in asynchronous computer conferences. *Journal of the Learning Sciences, 14*(4), 567–589.

Im, K., & Jin, S. (2021). Students' reflection levels by feedback type in asynchronous online group discussion activities, *Korean Journal of Educational Research, 59*(4), 31-62.

Jang, M., & Lee, H. (2023). Analyzing learners' intention to use topic modeling-based visual feedback: Focusing on reflection activities in online discussion learning, *The Korean Journal of Educational Methodology Studies, 35*(1), 155-174.

Jeon, M., Kwon, K., & Bae, H. (2023). Effects of different graphic organizers in asynchronous online discussions. *Educational technology research and development, 71*(2), 689-715.

Jin, S., & Yoo, M. (2018). Dashboard development and usability test to support contents analysis of team-based online discussion, *Journal of Educational Technology, 34*(3), 587-616.

Joksimović, S., Gašević, D., Kovanović, V., Riecke, B., & Hatala, M. (2015). Social presence in online discussions as a process predictor of academic performance. *Journal of Computer Assisted Learning, 31*(6), 638-654.

Jyothi, S., McAvinia, C., & Keating, J. (2012). A visualization tool to aid exploration of students' interactions in asynchronous online communication. *Computers & Education, 58*(1), 30–42.

Kember, D., McKay, J., Sinclair, K., & Wong, F. (2008). A four-category scheme for coding and assessing the level of reflection in written work. *Assessment & Evaluation in Higher Education, 33*(4), 369-379.

Kim, H. (2023). *A Developmental Study on a Dashboard-based Chatbot for Reflection on Online Discussion*, [Master's thesis, Seoul National University].

Kline, T. (2005). *Psychological testing: A practical approach to design and evaluation*. Sage publications.

Kolb, D. (2014). *Experiential learning: Experience as the source of learning and development*. FT press.

Kwon, K., & Park, S. (2017). Effects of discussion representation: Comparisons between social and cognitive diagrams. *Instructional Science, 45*, 469-491.

Lao, T. (2002). *A description of the experiences, perceptions, and attitudes of professors and graduate students about teaching and learning in a web-enhanced learning environment at a Southwest border institution*. New Mexico State University.

Lee, D., Yi, H. (2021). Exploring methods for determining the appropriate number of topics in LDA: Focusing on perplexity and harmonic mean method, *Journal of Educational Evaluation, 34*(1), 1-30.

Lim, J., Oh, Y., & Ahn, M. (2021). An analysis of research trends on maker education using LDA-based topic modeling, *Journal of Korean Association for Educational Information and Media, 27*(3), 1189-1219.

Lim, K., Kim, H., Choi, J., & Kim, Y. (2020). Usability test of learner dashboard: Visualization of multi-dimensional interaction information, *Journal of Korean Association for Educational Information and Media, 26*(2), 395-424.

Lim, K., Park, H., & Kim, H. (2014). Effects of social network-based visual feedback on learning in online discussion, *Journal of Educational Technology, 30*(3), 443-466.

Lim, S., & Kim, E. (2017). The design of dashboard for instructor feedback support based on learning analytics, *The Journal of Korean Association of Computer Education, 20*(6), 1-15.

Lin, K., Hong, H., & Chai, C. (2014). Development and validation of the knowledge-building environment scale. *Learning and Individual Differences, 30*, 124–132.

Malheiro, S., Morgado, L., & Mendes, A. (2008). Analysis of engaged online collaborative discourse: A methodological approach. In A. J. Mendes, I. Pereira, & R. Costa (Eds.), *Computers and education: Towards educational change and innovation (pp. 33-43)*. UK: Springer.

Matsuzaw, Y., Oshima, J., Oshima, R., Niihara, Y., & Sakai, S. (2011). KBDeX: A platform for exploring discourse in collaborative learning. *Procedia-Social and Behavioral Sciences, 26*, 198-207.

Mezirow, J. (1978). Perspective transformation. *Adult education, 28*(2), 100-110.

Mezirow, J. (1991). *Transformative dimensions of adult learning*. Jossey-Bass.

Mimno, D., Wallach, H., Talley, E., Leenders, M., & McCallum, A. (2011, July). Optimizing semantic coherence in topic models. *Proceedings of the 2011 conference on empirical methods in natural language processing (pp. 262-272).*

Nussbaum, E., & Schraw, G. (2007). Promoting argument-counterargument integration in students' writing. *The Journal of Experimental Education, 76*(1), 59-92.

Park, J., Park, H., Jung, S., & Lim, K. (2022). An analysis of research trends on personalized learning: Using TF-IDF, LDA based text mining, *The Korean Journal of Educational Methodology Studies, 34*(4), 711-739.

Park, Y., & Jo, I. (2019). Factors that affect the success of learning analytics dashboards. *Educational Technology Research and Development, 67*, 1547-1571.

Rohfeld, R., & Hiemstra, R. (1995). Moderating discussions in the electronic classroom. *Computer Mediated Communication and the Online Classroom, 3*, 91-104.

Rohloff, T., Sauer, D., & Meinel, C. (2019, December). Student perception of a learner dashboard in MOOCs to encourage self-regulated learning. In *2019 IEEE international conference on engineering, technology and education (TALE)* (pp. 1-8). IEEE.

Roskos, K., Vukelich, C., & Risko, V. (2001). Reflection and learning to teach reading: A critical review of literacy and general teacher education studies. *Journal of Literacy Research, 33*(4), 595-635.

Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review, 46*(5), 30.

Smith, D., & Smith, K. (2014). Case for 'Passive' learning–the 'Silent' community of online learners. *European Journal of Open, Distance and E-Learning, 17*(2), 86-99.

Sun, L., & Vassileva, J. (2006). Social visualization encouraging participation in online communities. In *Groupware: Design, Implementation, and Use: 12th International Workshop, CRIWG 2006, Medina del Campo, Spain, September 17-21, 2006. Proceedings 12* (pp. 349-363). Springer.

Syed, S., & Spruit, M. (2018, January). Selecting priors for latent Dirichlet allocation. In *2018 IEEE 12th International Conference on Semantic Computing (ICSC) (pp. 194-*

202). IEEE.

Tudge, J., & Rogoff, B. (1999). Peer influences on cognitive development: Piagetian and Vygotskian perspectives. In P. Lloyd, & C. Fernyhough (Eds.), *Lev Vygotsky: Critical assessments (pp. 32-56)*. Routledge.

Dennen, V. (2005). From message posting to learning dialogues: Factors affecting learner participation in asynchronous discussion. *Distance education, 26*(1), 127-148.

Wise, A., Speer, J., Marbouti, F., & Hsiao, Y. (2013). Broadening the notion of participation in online discussions: Examining patterns in learners' online listening behaviors. *Instructional Science, 41*(2), 323–343.

Yilmaz, F., & Keser, H. (2016). The impact of reflective thinking activities in e-learning: A critical review of the empirical research. *Computers & Education, 95*, 163-173.

Yoo, M. (2017). *Development of Visualization Principles for Online Discussion Activities based on Learning Analytics*, [Doctoral dissertation, Seoul National University].

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