Leveraging Techniques of Epistemic Network Analysis to Discover Behaviors of Student Learning Reflections in Online Learning Environments

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ABSTRACT

In the domain of learning analytics, reflective writing has introduced trends to enhance the learning and teaching experience. Epistemic Network Analysis (ENA), is a recent development in the techniques of learning analytics regarding handling huge amounts of text and visualizing learners' interactions in the form of network graphs. In this context, 43 students participated in 10 tasks over a 16-week semester on a blended course. The current article aims to explore their reflective behaviors through this new learning methodology and establish via the ENA technique whether there is any relationship between such behaviors and course performance. The findings show the effectiveness of ENA in investigating students' overall learning reflection patterns and revealing the frequencies of each reflection type for both high- and low-performing students. The group of high performers demonstrated a stronger connection with positive feelings regarding the learning experience, whereas the low performers exhibited a negative attitude toward the learning process. The obtained results provide insights into students' impressions of specific teaching or learning methods. Linking the reflection behavior to the level of student performance enables teachers to improve course design and provide appropriate interventions, which may be reflected in enhanced student performance.

Keywords-Epistemic Network Analysis (ENA); model graph-based analysis; learning reflection; reflective practice; reflective writing

I. INTRODUCTION

Reflection is an intrinsic component of learning that is determined by a student's learning experience in a specific learning environment. Studies have demonstrated that reflection is helpful in learning and teaching, as it gives both teachers and students the ability to think critically about learning and professional development. Reflection is used to detect any barriers to the success of a learning and teaching method and find solutions for the future. Various definitions of the reflection concept have their basis in context. The most common one is that reflection is an idea that occurs during meditation on and consideration of a previous experience or action [1]. Regarding learning, authors in [2] defined reflection as an activity that enables students to recapture, deeply think and evaluate their experience. Reflection is a term given to emotional and intellectual activities in which learners investigate their experiences to reach new understanding and future directions [2]. Thus, to practice reflecting on an experience is vital to learning, as the former leads to an increase in awareness, enabling students to evaluate it and begin to make decisions. For instance, giving students the opportunity to consider what they have gained from a scientific experiment increases their learning, thus improves achievement and develops stronger critical thinking skills [3]. Methods of implementing reflection vary, and the most common one is the Reflective Writing (RW) task [4, 5]. Instructors rely on it to capture and understand students' learning experiences in numerous settings. It is effective if it is instruction-directed and linked to a course's specific learning objectives [4]. For example, students may be asked to recall their experience of the course, assess both the experience and the knowledge gained, and suggest adjustments for their future learning [2, 6]. Letting students plan, manage, evaluate, and reflect on their learning and progress means that they take an active role in achieving their academic goals and are aware of their cognitive processes [7–9].

A prominent topic of research and practice in the field of learning analytics is learners' data analytics, in terms of strategically directing their behaviors and environment towards their goals [10-13]. In this context of learning analytics, RW has introduced new trends that enhance the learning and teaching experience. Studies typically build on techniques of data analytics that are already established in fields, such as machine learning, statistics, network science, and Natural Language Processing (NLP). Recently there has been a development in such techniques able to analyze huge amounts of data and visualize a learner's interaction in the form of network graphs, the Epistemic Network Analysis (ENA) [14].

ENA was developed in [15], and is defined as a quantitative ethnographic technique [17] that assesses epistemic frames, like the skills, knowledge, identity, values, and epistemology of a Community of Interest (CoI) [16-18]. These epistemic frames, or meaningful patterns, are identified by coding, then constructing network models to analyze the connections between the codes [14]. ENA measures the associations among coded elements through quantifying co-occurrences of those elements in data [14, 16-20]. While ENA was originally used mostly for the analysis of discourse in computer-supported collaborative learning, its use has recently spread to other phenomena (e.g. RW and self-regulated learning) and other data types (e.g. trace and eye-tracking data). Previous studies of RW varied in the way they use it, how they examine its content, and its purpose, as can be seen in the literature review section. In a novel approach to the exploration of students' reflection behaviors, this research aims to analyze students' RW with a networked ENA model.

II. LITERATURE REVIEW

The use of ENA in the online learning environment has been the focus of several researchers worldwide and their applications of ENA widely differed. The ENA technique requires data to be encoded by performing content analysis to determine epistemic frames through the relationship between codes [14]. Authors in [21] made use of NLP techniques to encode students' online discussions according to the topics defined in the course syllabus, and then performed ENA analysis. Their approach provides novel and important insights into the epistemic frame of students' knowledge concerning the various course topics. Similarly, authors in [22] performed ENA analysis of students' discussions to investigate how students' social presence was associated across the various course topics. Topic modelling – an NLP technique – was also implemented in combination with ENA to identify and analyze the connections between the topics discussed in students' psychology chats [23]. Authors in [23] demonstrate the significantly different connections among topics in epistemic networks between low- and high-learning gain student groups. From another point of view, researchers have revealed seven types of knowledge-creation practice in student discourse. Deploying ENA, the interaction between these types was shown to differ between low- and high-learning-outcome groups in terms of students' engagement in such practices [24].

ENA has also been employed to understand students' social interactions in online discussions relating to a specific problem. For instance, in [25], the differences between epistemic networks regarding the problem-based learning tasks of dentistry students across five courses were compared through ENA. Similarly, collaborative problem-solving patterns associated with students' successful learning were examined by comparing high-quality and low-quality solutions developed during social interaction [26]. ENA has proven to be valuable for measuring and modelling students' deliberative discourse patterns on similar issues at contrasting universities [27]. Also, using ENA, the audio transcripts of teams during collaborative problem-solving activities were converted to discourse to determine the connections between the scientific practices, communication responses, and the language style of the students' groups [28].

Furthermore, students' social interactions through online verbal problem-solving were compared by modelling the temporal co-occurrences of social-cognitive activities in discourse [29]. The results suggest that, compared to a traditional coding-and-counting approach, ENA provides greater insight into students' socio-cognitive learning activities. In [30], the authors compared the purely conversation-based segmentation method with affordances of temporal segmentation for modelling connections in discourse using ENA. They found that ENA can make real-time updates to the group and individual discourse models every time that a student chats in an online discussion. Thus, the ability to model an individual's contributions to group discussions in the last temporal context of the chat may allow the teacher to assess student's performance in the real-time online environment. Several researchers have utilized ENA for the analysis of online discussions [20]. This approach provides teachers with insights into the factors that may increase students' interactions in communities of inquiry under varying instructional conditions. Furthermore, this study exhibit how ENA can track the development of CoI over time. The proposed approach may lead to course design improvements and so enhance student performance.

ENA has been employed in studies to explain differences in learning behaviors and to assess the effectiveness of the educational support in online learning environments. For instance, authors in [31] studied students' engagement behavior to maintain enthusiasm during a learning game by designing appropriate interventions at the right time. They modelled the ENA with specific event logs of students' interaction with the game. Other researchers demonstrated how differences in learning behaviors during Active Video Watching (AVW-Space) reflect students' performance [32]. Based on event logs, they compared the interactions and performance of students who started late with those of the earlier starters. Other authors aimed to evaluate the assignments of a group of students through the ENA, based on the keywords of the essay related to the assignment topic [33] or concentrating on the type of participation (i.e. text, video, or interactive) in the assignment [34]. Their analyses indicate that ENA can visually confirm the quality of assignments, analyze their complexity, and provide the teacher with a helpful tool. In a completely different way, authors in [35] assessed students' knowledge according to their gaze coordination while solving a multiple-choice assignment. They used eye-tracking data and identified gaze coordination to construct and analyze each student's epistemic network. ENA presented the differences between the gaze patterns of those who solved the assignment correctly and those who did not. The above mentioned studies suggest that ENA can address analytic challenges of gaze coordination and facial expressions, gestures, discourse, and other data correlated with collaborative learning.

In other exploratory studies, researchers have demonstrated ENA's potential to explain the impact of instructional interventions on student behavior. For instance, authors in [36] applied ENA to compare students' collaborative and exploratory speech of "intervention and control" groups across specific interventions. The quality of students' in depth cognitive engagement in online discussions was the subject in [37]. The authors examined the impact of instructional interventions on the relationship between the extracted speech acts and phases of cognitive presence in online discussions. This examination found that speech acts can reasonably be used to provide feedback in relation to cognitive presence. In another way, authors in [38] examined the impact of instructional interventions by integrating multiple quality measures for asynchronous online discussions. They combined cognitive presence (CoI) and cognitive engagement (the ICAP framework). The ICAP framework defines four modes of cognitive engagement, based on four observable student behaviors: Interactive, Constructive, Active, and Passive [39]. It was disclosed how student behavior was affected by the type of instructional intervention and the introduced method can be applied to other situations where multiple indicators interact in potentially complex ways.

Regarding learner reflection, the literature reports that ENA has been applied in conjunction with self-reported reflection to explore the metacognitive differences between learners in cooperative learning, on the basis of performance data and demographic information [40]. The development of learners' reflection has also been explored by ENA in online collaborative scriptwriting [41]. From another point of view, RW has been widely studied regarding its impact on learning. For instance, the investigation of metacognitive activities in reflection has been the focus of much research. Authors in [42, 43] conducted manual examinations of reflection features, and aligned these features with student metacognition. Recent advances in NLP computational methods have expanded the scope of RW analysis and the efficient understanding of reflective texts of students. In this context, NLP's potential to identify the quality of students' metacognitive reflective responses is revealed [44, 45]. Furthermore, the reflective tasks, either written, oral, or video, have been examined to identify whether reflective-writing skill relates to students' academic success [46]. Studies demonstrate that RW, in its various forms, can be a predictive measure of students' academic success. Recently, authors in [47] studied the engagement behaviors of two student groups in an RW task using time series analysis. This study aimed to identify the effect of a behavioral feedback intervention on students' engagement with RW tasks. The group that received analytical feedback engaged in the RW task significantly more than the group that received no feedback. In [48], an RW task on a specific course was designed, implemented, and evaluated to give insights into how RW practice increases learning. It was demonstrated that RW tasks promote course enjoyment and may help teachers to assess how effectively students apply the knowledge obtained from the course.

RW's impact on critical reflection skills and reflection levels was examined in [3] through quasi-experimental research. It was found that the use of RW improved critical thinking skills. Investigating the level of reflection was the focus in [49], which automatically analyzed the content of RW through the adoption of machine learning and NLP methods. The extracted reflection features were based on the conceptual Reflective Writing Framework (RWF) and pointed to the following indicators: future action, new learning; perspective, reasoning, feelings, understandings, and description of an experience. In the current study, students' RW essays were analyzed by ENA to model their learning reflection patterns regarding a specific learning experience. The coding schemes to these learning reflection elements of the Boud reflection model were customized. After coding, ENA was undertaken to find and interpret the connections and interactions between these codes and explore the students' reflection behaviors towards a new learning methodology delivered in a specific blended course at King Abdulaziz University in Saudi Arabia. Another aim was to investigate the ENA technique's potential to identify how differences in students' reflective behaviors might provide insights into their performance on the course.

III. METHOD

This study raises two Research Questions (RQs) attempting: to capture the students' reflection behaviors; and to investigate how differences in such behaviors are reflected in their performance in course activities. These RQs are:

RQ1: What reflective behaviors of undergraduate learners are demonstrated in a reflective writing assignment?

RQ2: To what extent does prior performance in the course affect students' reflective behaviors?

To address the research questions, ENA was utilized to provide analytical insights into the various reflective behaviors of students' learning in relation to their performance. The steps of the analytical procedure are displayed in Figure 1.

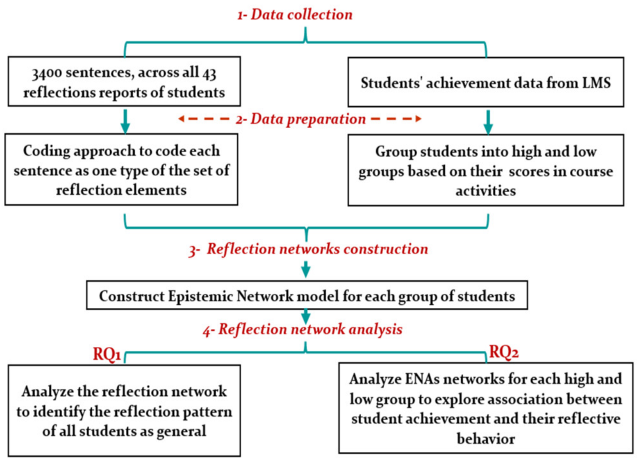


Fig. 1. Network analytical approach to students' reflection behaviors.

A. *Participants and Context*

The analysis presented in this study builds upon the data from the fall of semester 2021, for 43 male computing students enrolled on the Technical Communication course at King Abdulaziz University, Saudi Arabia. This is a blended course organized on Blackboard, an online learning environment, and is rather task-based than exam-based. The aims of the course are centered on three areas: effective oral and written communication, efficient functioning in teams, and professional responsibilities recognition. The course consists of 10 tasks, as revealed in Table I.

TABLE I. DESCRIPTION OF COURSE TASKS

Week	Task	Name	Score	Description
1	1	Don't Be Shy, and Say Hi	No grade	This task comes as a surprise to students in their first class. It introduces the concept of the comfort zone. Students are asked to introduce themselves in a video and to tweet it using the hashtag #CPIT221_intro.
2	2	YouTube Video	3	All students are required to introduce themselves and express what they expect to learn in this course, within one week, in a 2 minute video. Then they are to submit the video on their YouTube channel and share it on the course discussion board.
3–11	3	Weekly Task	20	Every student is required to write reflectively about a learning material or any relevant topic/event that occurred in one of the previous weeks or about the topics suggested each week.
12	4	Group Online Conversation	5	Groups of 5 randomly chosen students are required to conduct an online meeting and hold conversations on given topics.
13	5	Make Me Buy	10	Students are requested to find something that they like/are passionate about, such as a product, service, idea, or hobby, and to record a 3–5-minute video to express convincing messages to a targeted audiences to buy, do, or act.
14	6	Peer Review Assessment	10	Two stages: submission and evaluation. Students are requested to consider a given scenario and write a convincing message of about 400 words, and then submit it. At the evaluation stage, every student is given two submissions by peers to evaluate on the basis of a provided rubric.
15	7	CV Writing Latex	10	LaTeX is introduced to students.
16	8	Group Proposal	12	Groups of 5 students are required to write an effective proposal to target a decision-maker.
16	9	Group Proposal Presentation	10	Each group is requested to present and highlight the main outcomes of their written proposal.
17	10	Final Reflective Writing Report	20	At the end, students are required to write a report about their experience on this course in approximately 1500 words.
Total			**100**	

B. Epistemic Network Analysis (ENA) Method

In this step, epistemic networks of students' reflections were constructed and a network analysis was conducted to address the RQs following the ENA technique. The critical concepts of ENA are codes, the unit of analysis, and the stanza [18]. In the current study, the codes are the reflection elements described in Table II, represented as nodes in the network model. The student is the unit of analysis that allows the estimation of the code co-occurrence in a specified stanza. A stanza is a collection of sentences in the unit of analysis.

TABLE II. REFLECTION CODES

Code	Reflection Type	Description
Returning.E	Returning to Experience	Recollection of the salient events. Replaying the initial experience in the mind of the learner. Recounting to others the experience features. **Ex**. A group was randomly formed and had to choose a topic to talk about in video recording.
Positive.F	Utilizing Positive Feelings	Positive feelings about learning and the experience which is subject to reflection. Recollection of good experiences. Attention to pleasant aspects of the immediate environment. Anticipation of the possible benefits to be derived from the processing of events. **Ex**. Having to chat with classmates was a wonderful experience.
R.Obstructing	Removing Obstructing Feelings	Expressing one's feelings when recounting an event to others, such as: Laughing through the tale of an embarrassing incident, any other form of catharsis, whatever needs to be done in order to remove impediments to a thorough examination of the experience. **Ex**. At first, I had some difficulties in weekly writing but in the end, I managed my time and practiced more to have very good work results.
Evaluate.E	Re-Evaluating Experience	Re-examining experience in the light of the learner's intent. Associating new knowledge with the one already possessed. Integrating the new knowledge into the learner's conceptual framework. **Ex**. It helped me build my character and transformed me into a more confident person than I ever was.
Negative.E	Recollecting Negative Feeling	Negative feelings about learning and the experience which is subject to reflection. Recollection of bad experiences. Anticipating no benefit to be gained from event processing. **Ex**. The disadvantage this course has is that the task time is in crowd with other subjects at the end of the semester.
Others	Others	Recollection of the learning experiences not related to the course. **Ex**. During the last semester, we also had a presentation that had to be performed by a group, I said to my professor that I would like to do it bymyself.
NA	Not Applicable	The text does not apply to different proposed types of reflection. **Ex**. When I was in high school, I always wondered what to do after finishing college.

In detail, if two codes co-occur within the specified stanza, ENA creates a connection between those codes. The saturation and thickness of the connections reflect the relative frequency of co-occurrence between each pair of codes. Furthermore, ENA creates a projection space that centers the data into low-dimensional space through Singular Value Decomposition (SVD) [14]. Like Principal Component Analysis (PCA), SVD maximizes the explained variance in the data, yet in contrast the analysis is on the basis of the co-occurrence in cumulative adjacency matrices, but not concentrated on the code's strengths or counts. Moreover, ENA applies a cosine or sphere norm to the original data and places them at the center, yet it does not rescale the dimensions individually [18]. ENA can quantify and visualize the structure of connections among the reflection codes, making it possible to characterize students' connection-making patterns in their reports. For RQ1, an epistemic network was created for all the students to provide insights into their reflective behaviors about their experience on the course. For RQ2, two epistemic networks of the high- and low-performance student groups were created to investigate the reflection pattern of each group and to explore the association between students' reflective behaviors and their performance.

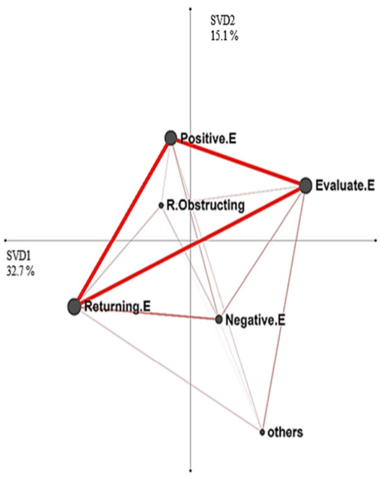
IV. RESULT

In this section it is described how the cognitive networks representing the structure of the connections between the six reflection codes were constructed and analyzed using methods from the field of ENA. ENA produces three graphical outcomes: (1) projection graphs, which represent the positions of epistemic networks of each student (dots) known as centroids in the network projection space, (2) epistemic network graphs, which show the structure of students' reflection connections when they reflect on their learning experience on the course, and (3) subtraction/difference network graphs, which compare two epistemic networks and show their differences, calculated by subtracting the weight of each connection in one network from the corresponding connection in the other. The network weights the links between nodes, so thicker links represent stronger connections, while thinner ones represent weaker connections. The links' thickness is proportional to the number of stanzas (i.e. collection of sentences) co-occurring between two codes. This means that the connection's width reflects the relative frequency of co-occurrence, or association, between two codes.

For network visualization, ENA uses SVD to reduce the dimensionality needed to contain all the unique co-occurrences of codes summed across all the stanzas in each analysis unit. So, with SVD, ENA achieves visualization in an analytic space composed of two dimensions (x and y axes), facilitating the interpretation and modeling of the variance among the data.

A. *RQ1: Capturing Learning Reflection Patterns among Students*

The epistemic network of all students is presented in Figure 2, where SVD1 accounts for 33% along the x-axis and SVD2 accounts for 15% along the y-axis. This graph gives an aggregated view of the structure of the network connections made by the students when they reflected on their learning experience on the course. The nodes indicate the type of reflection, while the strength of connections between them is based on their co-occurrence. On the lower right side the weak connections between Negative.E and all the other codes can be found, whereas there are strong connections on the left and upper part of the plane between Returning.E, Positive.E, and Evaluate.E. In detail, students made reflection connections mostly among Returning to Experience, Utilizing Positive Feelings, and Re-Evaluation Experience. Connections to Recollecting Negative Feelings and Removing Obstructing Feelings are not prominent in the network graph, and no strong links between them were discovered. Students reflected on their learning experience on the course more positively and recalled notable events, listed the features of the pleasant experience to others, and anticipated the potential benefits. The salient features of this network are easier to identify than in other networks, as is detected in the following research question.



Code	Reflection Type
Rreturning.E	Returning to Experience
Positive.E	Utilizing Positive Feelings
Negative.E	Recollecting Negative Feeling
R.Obstructing	Removing Obstructing Feelings
Evaluate.E	Re-Evaluating Experience
O	Others

Fig. 2. Students' epistemic (reflection) network.

B. *RQ2: Association between Students' prior Performance in Course Tasks and their Reflective Behavior*

To address the second research question, two epistemic network models were constructed, one for the high-performance group and one for the low-performance group. The groups were identified by students' scores in the weekly tasks prior to the RW task. Figure 3 presents the projection graphs for each group in a two-dimensional projection space, where the first and second dimensions account for 17% and 22%, respectively, presenting the maximum variance for network visualization.

In this graph, each centroid (blue and red dots) corresponds to the mean location of the weighted epistemic network of a student in the network projection space. The two blue and red squares mark the positions of the mean networks of the high- and low-performance groups, correspondingly. The surrounding rectangle represents the confidence interval of each group at the 95% level interval. The graph depicts the significant difference between the locations of the means of the plotted points of the high-performance and the low-performance groups along the ENA space x-axis.

To understand how the low- and high-performers differently reflected on their past experience in the course, this study generated the epistemic (reflection) network graphs of each group (low and high), in Figures 4 and 5, respectively.

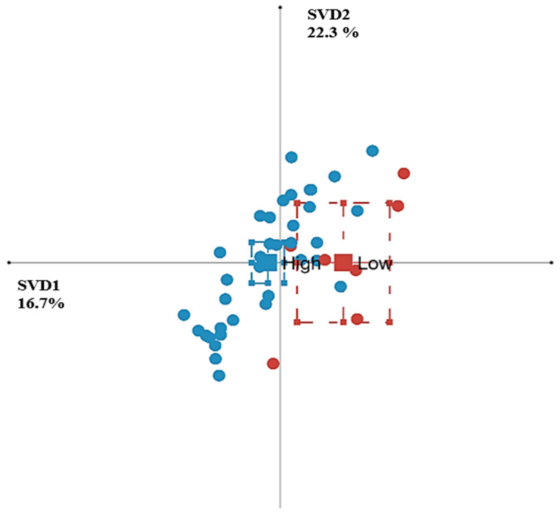


Fig. 3. Centroids of the epistemic network of the high-performance group (blue) and the low-performance group (red) in the projection space.

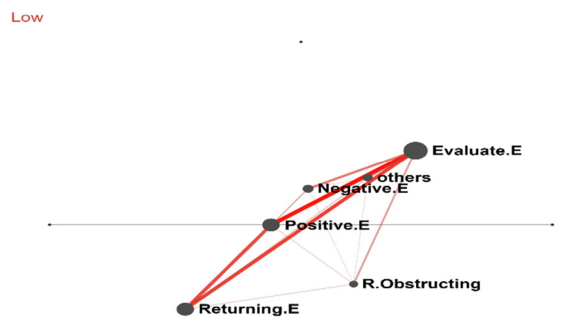


Fig. 4. Epistemic (reflection) network graph of the low-performance group.

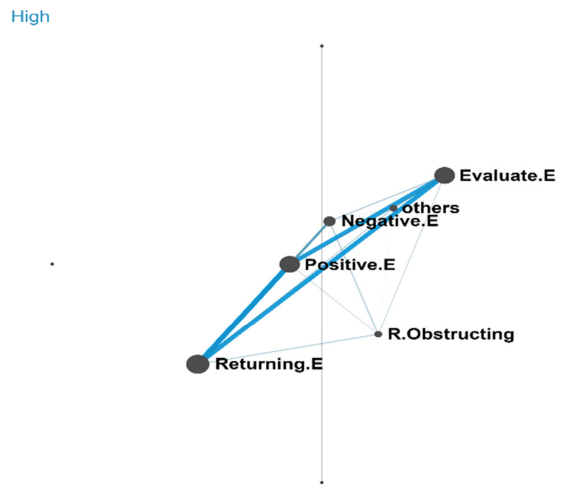


Fig. 5. Epistemic (reflection) network graph of the high-performance group.

Some of the connections among the reflection elements in the low-performance group, in Figure 4, are thicker than in the high-performance group, in Figure 5. For example, the link among Recollecting Negative Feelings, Re-Evaluation Experience, and Removing Obstructing Feelings appears more clearly in the low-performance group than in the high-performance group. In contrast, the high-performing students formed stronger connections between Utilizing Positive Feelings and Returning to Experience. Subtracting the two mean network graphs in Figures 4 and 5 creates a difference network graph that clearly manifests the contrast between the low- and the high-performance groups, as seen in Figure 6.

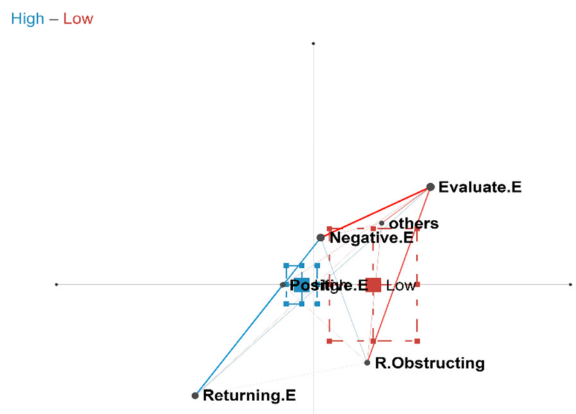


Fig. 6. Network difference graph.

As observed in Figure 6, the Returning to Experience and Utilizing Positive Feelings are on the left of the graph, meaning that they are closely related to the centroid of the high-performing group. By contrast, Recollecting Negative Feelings, Re-Evaluating Experience, and Removing Obstructing Feelings are on the right, meaning that they are more closely related to the centroid for the low-performing group. The graph also indicates that the high-performing group (in blue) focused more on the connection between reflection elements on the left, namely Returning to Experience and Utilizing Positive Feelings, whereas the low-performing group (in red) concentrated more on the right, containing Recollecting Negative Feelings, Re-Evaluation Experience, and Removing Obstructing Feelings. This contrast between the two regions (left and right) confirms the significant differences between the two groups, whereby students who achieved lower grades in the weekly tasks reflected negatively on their learning experience and were trying to over-come the obstructive feelings holding them back. On the contrary, the high performers in the weekly tasks reflected positively on their learning experience, and tended to return and re-examine their good learning experience, utilizing positive feelings and anticipating its potential benefits.

V. DISCUSSION

The literature demonstrates ENA's value for studying the aforementioned topics in several ways: as an instructional approach [50, 51, 36-38], as self-regulated learning [52–56], as learning design [57–606], and as eye-tracking patterns [35].

The results of the current study indicate that ENA might yield valuable insights into the reflection behaviors of student learning. ENA has been proved through this study to be an effective method to reveal connections and distinguish between high and low learning performance by means of students' RW. The findings obtained agree with previous studies in that ENA provides a rich, analytical insight into learners' behaviors by comparing the epistemic networks generated via low and high performance in specific learning activities [23, 24, 52].

The result of RQ1 was the construction of an analytical network model, using ENA, which depicts the relative frequencies of the reflection code co-occurence in students' RW reports. The performed analysis developed six elements (codes) of learning reflection that were expressed in students' RW reports, namely Returning to Experience, Utilizing Positive Feelings, Removing Obstructing Feelings, Re-Evaluating Experience, Recollecting Negative Feelings, and Other. The first four are derived from the theoretical learning reflection process proposed by Boud [2], while the last two are recommended on the basis of the content of students' reflection reports in the current study.

The ENA graph exhibits an aggregated view of the overall co-occurrence patterns of the reflection codes that the students made when reflecting on their course's learning experience. The most dominant learning reflections were Returning to Experience, Utilizing Positive Feelings, and Re-Evaluating Experience, as seen in the strong connections developed among them on the network. Reflection on Recollecting Negative Feelings and Removing Obstructing Feelings are not prominent on the network graph, as no strong links were found to exist among them. ENA investigated the overall learning reflection pattern of all students, and this may help those interested in finding out the learners' thoughts on the course experience.

In the RQ2, ENA was employed to compare the co-occurrence of six elements of the learning reflection of the two student groups. This comparison provides insights into the relationship between students' RW and their learning performance. The ENA analysis displays how the students reflected differently on their past course experience in terms of their prior performance in the earlier course activities. For instance, low-performing students tended to connect to Recollecting Negative Feelings and Removing Obstructing Feelings more than the high-performing students, who made stronger connections between Utilizing Positive Feelings and Returning to Experience. This confirms the findings of [61, 62] according to which, the RW can be used to predict students' academic success and provide more insightful feedback on their learning outcomes.

VI. CONCLUSION

In this research, ENA has been proved to be an effective method to investigate students' overall learning reflection pattern, which reveals their views regarding a new learning methodology delivered in a specific blended course at King Abdulaziz University in Saudi Arabia. ENA was an effective tool for revealing the difference between high- and low-performing students in terms of the frequency of the various connections between the reflection types. The high performers showed stronger connections relating to positive feelings to both learning and experience, while the low performers recalled negative feelings about their experience.

The current research confirms ENA's ability to capture and model students' reflective behaviors in a writing task (text), in addition to its effectiveness in distinguishing between the reflections of disparate students in terms of performance. The results provide instructors with knowledge of students' impressions of specific teaching or learning methods, students' satisfaction with the learning experience, and whether students were able to overcome obstacles during the learning processes. Linking these results to the level of student performance, enables a teacher to improve course design and provide appropriate interventions, which may be reflected in enhanced student performance.

Although the proposed approach seems promising in addressing important issues concerning the association of students' written reflections on a particular learning experience with their achievement in course activities, the current study has several limitations that must be acknowledged: First, it relied on data a particular course during just one semester in a single educational institution, and this may negatively affect the generalizability of the results and the broader application of this approach. Second, due to the peculiarities of the course design in this study, the results obtained are somehow limited. To address these issues, this study recommends applying the proposed analytical approach to a further course setting and using other datasets in a language other than English. Also, as future work, the proposed approach could be taken in conjunction with existing approaches to automatically classify (code) the reflection report transcripts. This would ease the adoption of the proposed analytic approach since there would be no need to manually code the transcripts, as it had to be done in the current study.

REFERENCES

[1] D. A. Schon, *The Reflective Practitioner: How Professionals Think In Action*, 1st edition. New York, NY, USA: Basic Books, 1983.

[2] D. Boud, R. Keogh, and D. Walker, "Promoting reflection in learning a model," in *Boundaries of Adult Learning*, Routledge, 2013, pp. 32–56.

[3] K. R. Murphy, "The effect of reflective practice on high school science students' critical and reflective thinking," Ph.D. dissertation, Western Connecticut State University, Danbury, CT, USA, 2014.

[4] R. G. Bringle, P. H. Clayton, and J. A. Hatcher, "Research on Service Learning: An Introduction," in *Research on Service Learning*, 1st Edition., London, UK: Routledge, 2012, pp. 3–25.

[5] J. Eyler and D. E. Giles, *Where's the Learning in Service-Learning?* Jossey-Bass, Inc, 1999.

[6] K. D. Tanner, "Promoting Student Metacognition," *CBE—Life Sciences Education*, vol. 11, no. 2, pp. 113–120, Jun. 2012, https://doi.org/10.1187/cbe.12-03-0033.

[7] T. A. Mesbah, R. A. R. Abed, A. S. Al-Sagheer, and M. S. Ghaly, "Relationship between Metacognitive Awareness and Reflective Learning of Medical Students at the Faculty of Medicine, Suez Canal University," *Journal of Education, Society and Behavioural Science*, vol. 32, no. 4, 2019, Art. no. JESBS.53452, https://doi.org/10.9734/jesbs/2019/v32i430187.

[8] B. Eilam and S. Reiter, "Long-Term Self-Regulation of Biology Learning Using Standard Junior High School Science Curriculum,"

Science Education, vol. 98, no. 4, pp. 705–737, 2014, https://doi.org/10.1002/sce.21124.

[9] G. Schraw and R. S. Dennison, "Assessing Metacognitive Awareness," *Contemporary Educational Psychology*, vol. 19, no. 4, pp. 460–475, Oct. 1994, https://doi.org/10.1006/ceps.1994.1033.

[10] C. Lang, G. Siemens, A. F. Wise, D. Gašević, and A. Merceron, Eds., *Handbook of Learning Analytics*, 2nd ed. Society for Learning Analytics and Research, 2022.

[11] A. B. Rashid, R. R. R. Ikram, Y. Thamilarasan, L. Salahuddin, N. F. A. Yusof, and Z. B. Rashid, "A Student Learning Style Auto-Detection Model in a Learning Management System," *Engineering, Technology & Applied Science Research*, vol. 13, no. 3, pp. 11000–11005, Jun. 2023, https://doi.org/10.48084/etasr.5751.

[12] A. B. Altamimi, "Big Data in Education: Students at Risk as a Case Study," *Engineering, Technology & Applied Science Research*, vol. 13, no. 5, pp. 11705–11714, Oct. 2023, https://doi.org/10.48084/etasr.6190.

[13] M. Alsuwaiket, A. H. Blasi, and R. A. Al-Msie'deen, "Formulating Module Assessment for Improved Academic Performance Predictability in Higher Education," *Engineering, Technology & Applied Science Research*, vol. 9, no. 3, pp. 4287–4291, Jun. 2019, https://doi.org/10.48084/etasr.2794.

[14] D. W. Shaffer, W. Collier, and A. R. Ruis, "A Tutorial on Epistemic Network Analysis: Analyzing the Structure of Connections in Cognitive, Social, and Interaction Data," *Journal of Learning Analytics*, vol. 3, no. 3, pp. 9–45, Dec. 2016, https://doi.org/10.18608/jla.2016.33.3.

[15] D. W. Shaffer *et al.*, "Epistemic Network Analysis: A Prototype for 21st-Century Assessment of Learning," *International Journal of Learning and Media*, vol. 1, no. 2, pp. 33–53, May 2009, https://doi.org/10.1162/ijlm.2009.0013.

[16] D. W. Shaffer, *Quantitative Ethnography*. Madison, WI, USA: Cathcart Press, 2017.

[17] D. W. Shaffer, "Epistemic frames for epistemic games," *Computers & Education*, vol. 46, no. 3, pp. 223–234, Apr. 2006, https://doi.org/10.1016/j.compedu.2005.11.003.

[18] D. W. Shaffer and A. R. Ruis, "Chapter 15 - Epistemic Network Analysis: A Worked Example of Theory-Based Learning Analytics," in *Handbook of Learning Analytics*, 2nd ed., C. Lang, G. Siemens, A. F. Wise, D. Gašević, and A. Merceron, Eds. Society for Learning Analytics and Research, 2022.

[19] D. W. Shaffer, "Formatting Data For Epistemic Network Analysis," GAPS, Technical Report 2014-1, 2014.

[20] V. Rolim, R. Ferreira, R. D. Lins, and D. Gasevic, "A network-based analytic approach to uncovering the relationship between social and cognitive presences in communities of inquiry," *The Internet and Higher Education*, vol. 42, pp. 53–65, Jul. 2019, https://doi.org/10.1016/j.iheduc.2019.05.001.

[21] R. Ferreira, V. Kovanovic, D. Gasevic, and V. Rolim, "Towards Combined Network and Text Analytics of Student Discourse in Online Discussions," in *International Conference on Artificial Intelligence in Education*, London, United Kingdom, Jun. 2018, pp. 111–126, https://doi.org/10.1007/978-3-319-93843-1_9.

[22] V. Rolim, R. Ferreira Leite de Mello, V. Kovanovic, and D. Gasevic, "Analysing Social Presence in Online Discussions Through Network and Text Analytics," in *19th International Conference on Advanced Learning Technologies*, Maceio, Brazil, Jul. 2019, pp. 163–167, https://doi.org/10.1109/ICALT.2019.00058.

[23] Z. Cai, B. Eagan, and N. M. Dowell, "Epistemic Network Analysis and Topic Modeling for Chat Data from Collaborative Learning Environment," in *10th International Conference on Educational Data Mining*, Wuhan, China, Jun. 2017, pp. 104–111.

[24] J. Oshima, R. Oshima, and S. Saruwatari, "Analysis of students' ideas and conceptual artifacts in knowledge-building discourse," *British Journal of Educational Technology*, vol. 51, no. 4, pp. 1308–1321, 2020, https://doi.org/10.1111/bjet.12961.

[25] M. H. Khan, "Epistemic Network Analysis in Problem-Based Learning," M.S. thesis, University of Eastern Finland, Joensuu, Finland, 2020.

[26] V. Nachtigall and H. Sung, "Students' Collaboration Patterns in a Productive Failure Setting: An Epistemic Network Analysis of Contrasting Cases," in *International Conference on Quantitative Ethnography*, Madison, WI, USA, Oct. 2019, pp. 165–176, https://doi.org/10.1007/978-3-030-33232-7_14.

[27] P. Levine, B. Eagan, and D. W. Shaffer, "Deliberation as an Epistemic Network: A Method for Analyzing Discussion," in *International Conference on Quantitative Ethnography*, Copenhagen, Denmark, Oct. 2022, pp. 17–32, https://doi.org/10.1007/978-3-030-93859-8_2.

[28] D. M. Bressler, A. M. Bodzin, B. Eagan, and S. Tabatabai, "Using Epistemic Network Analysis to Examine Discourse and Scientific Practice During a Collaborative Game," *Journal of Science Education and Technology*, vol. 28, no. 5, pp. 553–566, Oct. 2019, https://doi.org/10.1007/s10956-019-09786-8.

[29] A. Csanadi, B. Eagan, I. Kollar, D. W. Shaffer, and F. Fischer, "When coding-and-counting is not enough: using epistemic network analysis (ENA) to analyze verbal data in CSCL research," *International Journal of Computer-Supported Collaborative Learning*, vol. 13, no. 4, pp. 419–438, Dec. 2018, https://doi.org/10.1007/s11412-018-9292-z.

[30] A. L. Siebert-Evenstone, G. A. Irgens, W. Collier, Z. Swiecki, A. R. Ruis, and D. W. Shaffer, "In Search of Conversational Grain Size: Modeling Semantic Structure using Moving Stanza Windows," *Journal of Learning Analytics*, vol. 4, no. 3, pp. 123–139, Dec. 2017, https://doi.org/10.18608/jla.2017.43.7.

[31] S. Karumbaiah, R. S. Baker, A. Barany, and V. Shute, "Using Epistemic Networks with Automated Codes to Understand Why Players Quit Levels in a Learning Game," in *International Conference on Quantitative Ethnography*, Madison, WI, USA, Oct. 2019, pp. 106–116, https://doi.org/10.1007/978-3-030-33232-7_9.

[32] N. Mohammadhassan and A. Mitrovic, "Discovering Differences in Learning Behaviours During Active Video Watching Using Epistemic Network Analysis," in *International Conference on Quantitative Ethnography*, Copenhagen, Denmark, Oct. 2022, pp. 362–377, https://doi.org/10.1007/978-3-030-93859-8_24.

[33] S. S. Fougt, A. Siebert-Evenstone, B. Eagan, S. Tabatabai, and M. Misfeldt, "Epistemic network analysis of students' longer written assignments as formative/summative evaluation," in *8th International Conference on Learning Analytics and Knowledge*, Sydney, NSW, Australia, Mar. 2018, pp. 126–130, https://doi.org/10.1145/3170358.3170414.

[34] H. Wang, C. Wang, and F. Wu, "How Multimedia Influence Group Interaction in STEM Education An Epistemic Network Analysis for Online Synchronous Collaborative Learning," in *International Symposium on Educational Technology*, Bangkok, Thailand, Aug. 2020, pp. 303–306, https://doi.org/10.1109/ISET49818.2020.00072.

[35] S. Bruckner, J. Schneider, O. Zlatkin-Troitschanskaia, and H. Drachsler, "Epistemic Network Analyses of Economics Students' Graph Understanding: An Eye-Tracking Study," *Sensors*, vol. 20, no. 23, Jan. 2020, Art. no. 6908, https://doi.org/10.3390/s20236908.

[36] J. Vandenberg *et al.*, "Prompting collaborative and exploratory discourse: An epistemic network analysis study," *International Journal of Computer-Supported Collaborative Learning*, vol. 16, no. 3, pp. 339–366, Sep. 2021, https://doi.org/10.1007/s11412-021-09349-3.

[37] S. Iqbal *et al.*, "Uncovering Associations Between Cognitive Presence and Speech Acts: A Network-Based Approach," in *12th International Learning Analytics and Knowledge Conference*, Mar. 2022, pp. 315–325, https://doi.org/10.1145/3506860.3506908.

[38] E. Farrow, J. Moore, and D. Gasevic, "A network analytic approach to integrating multiple quality measures for asynchronous online discussions," in *11th International Learning Analytics and Knowledge Conference*, Irvine, CA, USA, Apr. 2021, pp. 248–258, https://doi.org/10.1145/3448139.3448163.

[39] M. T. H. Chi and R. Wylie, "The ICAP Framework: Linking Cognitive Engagement to Active Learning Outcomes," *Educational Psychologist*, vol. 49, no. 4, pp. 219–243, Oct. 2014, https://doi.org/10.1080/00461520.2014.965823.

[40] L. Wu, Q. Liu, G. Mao, and S. Zhang, "Using epistemic network analysis and self-reported reflections to explore students' metacognition differences in collaborative learning," *Learning and Individual Differences*, vol. 82, Aug. 2020, Art. no. 101913, https://doi.org/10.1016/j.lindif.2020.101913.

[41] Y. Yi, X. Lu, and J. Leng, "Exploring the Development of Reflection Among Pre-service Teachers in Online Collaborative Writing: An Epistemic Network Analysis," in *International Conference on Quantitative Ethnography*, Madison, WI, USA, Oct. 2019, pp. 257–266, https://doi.org/10.1007/978-3-030-33232-7_22.

[42] T. D. Ullmann, "Reflective writing analytics: empirically determined keywords of written reflection," in *Seventh International Learning Analytics & Knowledge Conference*, Vancouver, BC, Canada, Mar. 2017, pp. 163–167, https://doi.org/10.1145/3027385.3027394.

[43] Y. Cui, A. F. Wise, and K. L. Allen, "Developing reflection analytics for health professions education: A multi-dimensional framework to align critical concepts with data features," *Computers in Human Behavior*, vol. 100, pp. 305–324, Nov. 2019, https://doi.org/10.1016/j.chb.2019.02.019.

[44] W. Luo and D. Litman, "Determining the Quality of a Student Reflective Response," in *Twenty-Ninth International Florida Artificial Intelligence Research Society Conference*, Key Largo, FL, USA, Dec. 2016, pp. 226–231.

[45] A. Gibson, K. Kitto, and P. Bruza, "Towards the Discovery of Learner Metacognition From Reflective Writing," *Journal of Learning Analytics*, vol. 3, no. 2, pp. 22–36, Sep. 2016, https://doi.org/10.18608/jla.2016.32.3.

[46] C. Tsingos-Lucas, S. Bosnic-Anticevich, C. R. Schneider, and L. Smith, "Using Reflective Writing as a Predictor of Academic Success in Different Assessment Formats," *American Journal of Pharmaceutical Education*, vol. 81, no. 1, Feb. 2017, Art. no. 8, https://doi.org/10.5688/ajpe8118.

[47] W. Suraworachet, Q. Zhou, and M. Cukurova, "Impact of combining human and analytics feedback on students' engagement with, and performance in, reflective writing tasks," *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, Jan. 2023, Art. no. 1, https://doi.org/10.1186/s41239-022-00368-0.

[48] O. Ezezika and N. Johnston, "Development and Implementation of a Reflective Writing Assignment for Undergraduate Students in a Large Public Health Biology Course," *Pedagogy in Health Promotion*, vol. 9, no. 2, pp. 101–115, Jun. 2023, https://doi.org/10.1177/23733799211069993.

[49] H. Alrashidi, N. Almujally, M. Kadhum, T. Daniel Ullmann, and M. Joy, "Evaluating an Automated Analysis Using Machine Learning and Natural Language Processing Approaches to Classify Computer Science Students' Reflective Writing," in *Pervasive Computing and Social Networking*, G. Ranganathan, R. Bestak, and X. Fernando, Eds. New York, NY, USA: Springer, 2023, pp. 463–477.

[50] K. Q. Fisher, L. Hirshfield, A. Siebert-Evenstone, G. A. Irgens, and M. Koretsky, "Network Analysis of Interactions between Students and an Instructor during Design Meetings," in *ASEE Annual Conference & Exposition*, New Orleans, LA, USA, Jun. 2016, pp. 1–13, https://doi.org/10.18260/p.25782.

[51] S. Zhang, Q. Liu, and Z. Cai, "Exploring primary school teachers' technological pedagogical content knowledge (TPACK) in online collaborative discourse: An epistemic network analysis," *British Journal of Educational Technology*, vol. 50, no. 6, pp. 3437–3455, 2019, https://doi.org/10.1111/bjet.12751.

[52] L. Paquette, T. Grant, Y. Zhang, G. Biswas, and R. Baker, "Using Epistemic Networks to Analyze Self-regulated Learning in an Open-Ended Problem-Solving Environment," in *International Conference on Quantitative Ethnography*, Nov. 2021, pp. 185–201, https://doi.org/10.1007/978-3-030-67788-6_13.

[53] N. Melzner, M. Greisel, M. Dresel, and I. Kollar, "Using Process Mining (PM) and Epistemic Network Analysis (ENA) for Comparing Processes of Collaborative Problem Regulation," in *International Conference on Quantitative Ethnography*, Madison, WI, USA, Oct. 2019, pp. 154–164, https://doi.org/10.1007/978-3-030-33232-7_13.

[54] J. Saint, D. Gasevic, W. Matcha, N. A. Uzir, and A. Pardo, "Combining analytic methods to unlock sequential and temporal patterns of self-regulated learning," in *10th International Conference on Learning Analytics and Knowledge*, New York, NY, USA, Mar. 2020, pp. 402–411, https://doi.org/10.1145/3375462.3375487.

[55] Y. Fan, W. Matcha, N. A. Uzir, Q. Wang, and D. Gasevic, "Learning Analytics to Reveal Links Between Learning Design and Self-Regulated Learning," *International Journal of Artificial Intelligence in Education*, vol. 31, no. 4, pp. 980–1021, Dec. 2021, https://doi.org/10.1007/s40593-021-00249-z.

[56] S. Zhang, J. Chen, Y. Wen, H. Chen, Q. Gao, and Q. Wang, "Capturing regulatory patterns in online collaborative learning: A network analytic approach," *International Journal of Computer-Supported Collaborative Learning*, vol. 16, no. 1, pp. 37–66, Mar. 2021, https://doi.org/10.1007/s11412-021-09339-5.

[57] M. Ferreira, R. F. Mello, R. D. Lins, and D. Gasevic, "Analytics of Emerging and Scripted Roles in Online Discussions: An Epistemic Network Analysis Approach," in *International Conference on Artificial Intelligence in Education*, Utrecht, The Netherlands, Jun. 2021, pp. 156–161, https://doi.org/10.1007/978-3-030-78270-2_28.

[58] M. A. D. Ferreira, R. Ferreira Mello, V. Kovanovic, A. Nascimento, R. Lins, and D. Gasevic, "NASC: Network analytics to uncover socio-cognitive discourse of student roles," in *12th International Learning Analytics and Knowledge Conference*, Mar. 2022, pp. 415–425, https://doi.org/10.1145/3506860.3506978.

[59] W. Matcha *et al.*, "Detection of Learning Strategies: A Comparison of Process, Sequence and Network Analytic Approaches," in *European Conference on Technology Enhanced Learning*, Delft, The Netherlands, Sep. 2019, pp. 525–540, https://doi.org/10.1007/978-3-030-29736-7_39.

[60] N. A. Uzir, D. Gasevic, J. Jovanovic, W. Matcha, L.-A. Lim, and A. Fudge, "Analytics of time management and learning strategies for effective online learning in blended environments," in *10th International Conference on Learning Analytics and Knowledge*, Frankfurt, Germany, Mar. 2020, pp. 392–401, https://doi.org/10.1145/3375462.3375493.

[61] H. YuekMing and L. A. Manaf, "Assessing Learning Outcomes through Students' Reflective Thinking," *Procedia - Social and Behavioral Sciences*, vol. 152, pp. 973–977, Oct. 2014, https://doi.org/10.1016/j.sbspro.2014.09.352.