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

1. 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 collaborative learning, its use has recently spread to other mostly for the analysis of discourse in computer-supported educational spaces (CoI) 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.

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 (Co) 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 (RFW) 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

<table>
<thead>
<tr>
<th>Week</th>
<th>Task</th>
<th>Name</th>
<th>Score</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>Don't Be Shy, and Say Hi</td>
<td>No grade</td>
<td>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.</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>YouTube Video</td>
<td>3</td>
<td>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.</td>
</tr>
<tr>
<td>3-11</td>
<td>3</td>
<td>Weekly Task</td>
<td>20</td>
<td>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.</td>
</tr>
<tr>
<td>12</td>
<td>4</td>
<td>Group Online Conversation</td>
<td>5</td>
<td>Groups of 5 randomly chosen students are required to conduct an online meeting and hold conversations on given topics.</td>
</tr>
<tr>
<td>13</td>
<td>5</td>
<td>Make Me Buy</td>
<td>10</td>
<td>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 audience to buy, do, or act.</td>
</tr>
<tr>
<td>14</td>
<td>6</td>
<td>Peer Review Assessment</td>
<td>10</td>
<td>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.</td>
</tr>
<tr>
<td>15</td>
<td>7</td>
<td>CV Writing Latex</td>
<td>10</td>
<td>LaTeX is introduced to students.</td>
</tr>
<tr>
<td>16</td>
<td>8</td>
<td>Group Proposal</td>
<td>12</td>
<td>Groups of 5 students are required to write an effective proposal to target a decision-maker.</td>
</tr>
<tr>
<td>16</td>
<td>9</td>
<td>Group Proposal Presentation</td>
<td>10</td>
<td>Each group is requested to present and highlight the main outcomes of their written proposal.</td>
</tr>
<tr>
<td>17</td>
<td>10</td>
<td>Final Reflective Writing Report</td>
<td>20</td>
<td>At the end, students are required to write a report about their experience on this course in approximately 1500 words.</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td>100</td>
<td></td>
</tr>
</tbody>
</table>
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 quantitively 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.

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.

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.

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 overcome 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-occurrence 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 of 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 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.

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