A NETWORK ANALYTICS APPROACH TO EXAMINE THE RELATIONSHIP BETWEEN LEARNING REFLECTION AND SELF-REGULATED LEARNING SKILLS

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ABSTRACT

Previous studies have demonstrated the effectiveness of Epistemic Network Analysis (ENA) to explain students' epistemic interaction with specific learning activities or tasks. However, the potential of ENA has not been widely explored in investigating the relationship between students' self-regulated learning skills and their reflective behaviors in a new learning experience. This paper demonstrates how ENA and cluster analysis can reveal and analyze differences in the reflective behaviors of groups of students with varying self-regulated learning constructs. The results of this study show that the most prominent reflections among students with a high level of self-regulation use positive feeling about their good experience and try to overcome their obstructing feelings that hinder their learning process. The following are the learning constructs: intrinsic/extrinsic goal orientation, task value, expectancy beliefs, self-efficacy, test anxiety, metacognitive awareness and metacognitive writing strategies. By contrast, students with low self-regulation in these learning constructs more frequently reflected by recollecting their negative feelings and examining the knowledge obtained from the course. The analytical approaches proposed in this study reveal that the reflective behaviors among students with both high and low motivation to learn through “intrinsic goal orientation”, “expectancy beliefs” and “self-efficacy contain no negative feelings towards their learning experience.

Keywords: *Epistemic Network Analysis, Model Graph-Based Analysis, Self-Regulated Learning, Reflection, Reflective Writing, Reflective Practice.*

1. INTRODUCTION

To keep pace with the shift towards effective digital learning, rapid developments in information and communication technologies have led to changes in teaching and learning curricula in the field of education. Modern teaching and learning methods ensure student engagement in scholarly practices where teachers can demonstrate, support, and continuously assess students' conceptual understanding [1,2]. There is increasing evidence that creating interactive online learning environments and using active learning methods can ensure students’ interaction with both the content, teachers, and peers and also advance students’ learning and reduce achievement gaps [3-5]. Students who take an active role in achieving their academic goals and are able to take control of their own learning processes are referred to as self-regulated learners [6,7]. The theory of Self-Regulated Learning (SRL) is an umbrella term for many factors affecting learning, such as the cognitive, metacognitive, behavioral, motivational, and affective aspects [8]. For instance, Zimmerman states that self-regulated learning occurs when students actively enact to plan, monitor, control, or evaluate their learning processes in order to adapt or maintain certain aspects such as motivation, metacognition, cognition, context, and affect [9]. However, Winne and his colleague describe the concept of SRL as four regulation phases that occur in any learning process: “defining tasks”; “setting and planning goals”; “enacting strategies”; and “reflecting and adapting” [10]. In this context, reflective writing is one of the learning processes used in higher education to promote thoughtful reflection on events, and thus stimulate transformative practice and learning [11]. Reflective writing is a demanding task, because it requires an ability to regulate one’s learning [12]. Students with skills in self-regulation of learning are able to reflect on their own learning process and their progress, thus obtain new knowledge that can guide future actions of learning [13,14].

The literature has many studies demonstrating that learners who engage in writing reflection practices are more accurate in evaluating their own learning and better at understanding what can be improved in future [15,16]. Learners' data analytics in terms of strategically regulating their behaviors and environment towards their goals has been a prominent topic of research and practice in the field of learning analytics [17]. Researcher have analyzed the reflection essay by several learning analytics techniques already established in fields such as machine learning, statistics, network science, and natural language processing. Lately there have been developments in learning analytics techniques to analyze huge amounts of text and visualize a learner's interactions in form of network graphs, such as Epistemic Network Analysis (ENA). ENA has attracted much attention in the field of learning analytics. It can be used to analyze the discourse generated by communication between students [18]. ENA was developed by Shaffer et al. (2009), and is defined as a quantitative ethnographic technique (2017) that assesses epistemic frames such as the skills, knowledge, identity, values, and epistemology of a community of practice [19,20]. The data's epistemic frames, or meaningful patterns, are identified by coding and then constructing network models to analyze the connections between the codes [21]. Previous studies have demonstrated ENA's effectiveness in explaining students' epistemic interactions through specific learning activities or tasks. However, the potential for using ENA to investigate the relationship between students' reflective behavior and their self-regulated learning skills has not been widely explored. Our study aims to investigate whether there is a relationship between the reflective behaviors and the self-regulated learning skills observed in students on a specific blended course run by King Abdulaziz University in Saudi Arabia.

2. RELATED WORK

Self-Regulated Learning (SRL) theory holds that high-competence students in SRL tend to approach the tasks of learning timely and strategically to attain their learning goals [22]. In this context, Suraworachet et al.'s study is consistent with this theory, as it examined by time-series and correlation analysis the associations between students' behaviors on reflective writing tasks and their self-regulated learning competence. The results show that the ones who made frequent and regular visits to the reflective writing tasks were the high-performing and high-competence SRL students. Thus, the level of regulation of behavior in reflective writing is better among students with high efficiency in SRL [23]. This evidence aligns with the findings of Robbins and colleagues about the effect of reflective writing on self-regulated learning strategies in the context of the flipped classroom. Students' SRL was assessed on the six subscales of the Motivated Strategies for Learning Questionnaire (MSLQ). The study shows that students who participated in reflective writing tasks showed greater motivation in their intrinsic and extrinsic goal orientation, task value; expectancy beliefs, self-efficacy for learning and performance, and test anxiety than those who did not. As a result, the reflective writing practice appeared to mitigate any decreased motivation for self-regulated learning during the semester [24].

In a study by Raković et al., reflective writing was used to determine the relationship between students' evaluations and their planning for learning adaptation to their self-regulated learning processes. Students' evaluations and adaptations were extracted from their reflective writing texts, using natural language processing and digital traces of their learning behaviors, to measure their actual adaptation to their use of learning resources. This study provides evidence of how students' evaluations of their own learning can guide their changes to planning and behavior in future learning; moreover, enacting the effective learning strategies may result in their improved performance in learning tasks [25]. Recently, evidence has emerged of the potential effectiveness of reflective writing tasks to enhance students' self-regulatory writing strategies [26]. The qualitative results of Zhang's study indicate a significant difference in levels of SRL writing proficiency, as low-efficiency students applied goal-setting significantly more than high-efficiency students, who instead used resource management, feedback handling, and idea planning. Furthermore, qualitative research by Sani et al. proved the effectiveness of reflective writing in improving general writing skills, along with the level of critical thinking. In detail, students' general writing improved in its mechanics, vocabulary, grammar, organization, and content, while reflective writing raised the level of reflection [27]. Students' level of writing was also assessed through the use of a reflective writing task. In this context, quantitative descriptive research was conducted to measure students' reflective writing on the basis of reliability, organization, language proficiency, key points, and comprehension [28].

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In another exploratory study, Zareski et al.'s research evaluated a specific course design of a flipped classroom and included reflective writing exercises, examining the students’ experiences. This qualitative analysis indicates that incorporating reflective writing activities into course design helps to develop students’ critical thinking and problem-solving skills, self-regulated learning behaviors, and metacognitive awareness [29]. As in the Platt study [30], Reflective Writing Prompts (RWP) were designed to stimulate students' reflective thinking through writing. This latter study reports that RWP developed students’ self-regulated learning and metacognitive skills, which may enable them become independent learners who practice reflective journaling effectively [30]. Incorporating reflective writing activities in the course design serves as a model for educators wishing to develop students' metacognitive and SRL skills. Moreover, implementing reflective writing activities online has been shown to be more effective in facilitating self-regulated learning than doing so by paper-based portfolios [31].

Previous studies have shown that ENA might yield valuable insights related to the cognitive, metacognitive, motivational, emotional, and performance dimensions of student learning in an online learning environment [32-34]. Using ENA and cluster analysis, several studies have detected and analyzed the roles that learners take up in online discussions in a variety of settings. For example, a proposed method highlights the differences and similarities between emerging and scripted roles on the basis of the social and cognitive phases present in the online discussion [35]. Researchers have automatically detected these emerging roles and compared them to the scripted roles by tracking the development of social knowledge construction over time [36]. Furthermore, both learning tactics and strategies have been investigated by the ENA technique, and a correlation was found between the diversity of tactics and strategies adopted by learners and their academic performance [37,38]. Recently, many researchers have investigated the regulation patterns of student learning [39-43]. ENA provides a rich insight into learners’ self-regulated behaviors by comparing the epistemic networks generated by low and high performances, both in an open-ended problem-solving environment [39] and, in particular, in online collaborative learning activities [43]. Analysing how groups of learners regulate their collaboration variously at the many stages of online learning activities has provided insights into effective learning design [43].

In this context, Fan et al. revealed links between learning design and self-regulated learning in contrasting performance groups. Their analysis of the use of learning tactics across learning sessions showed that learners from different performance groups had different priorities [42]. The combination of process mining and ENA seems warranted to investigate how students regulate their motivational problems and comprehension-related problems [40]. This proposed complementary method is also used to compare both qualitatively and quantitatively the sequential and temporal patterns of self-regulated learning across learner groups [41]. The combination of analyses provides a richer insight into SRL behaviors than any single method. The literature reports that ENA has been applied in conjunction with self-reported reflections to explore metacognitive differences among learners in cooperative learning, based on performance data and demographic information [44]. Also, a study has used ENA to explore the development of learners’ reflection in online collaborative scriptwriting [45]. In contrast to previous studies, our study uses a mixture of analytical approaches to leverage state-of-the-art ENA and cluster analysis to obtain analytical insights into how differences in students' reflective behaviors are associated with their self-regulated learning skills.

3. METHOD

Using ENA, this study aims to investigate the extent to which students' reflective behaviors relate to their motivational learning strategies of goal orientation, task value, expectancy beliefs, self-efficacy, and test anxiety, as well to as their metacognitive awareness and metacognitive writing strategies. To achieve our research objective, written transcripts were collected of the reflective writing tasks on a specific blended course run by King Abdulaziz University in Saudi Arabia. At the beginning of the course the students were asked to complete a questionnaire to measure their self-regulated learning skills. The questionnaire uses three popular scales: Motivated Strategies for Learning Questionnaire (MSLQ) [46]; Metacognitive Awareness Inventory (MAI) [47]; and Language Learners’ and Metacognitive Writing Strategies in Multimedia Environments (LLMWSIME) [48]. MSLQ includes six constructs: intrinsic and extrinsic goal orientation; task value; expectancy beliefs; self-efficacy; and test anxiety. MSLQ, MAI, and LLMWSIME were

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adapted to fit the characteristics and instructional requirements of the course that was observed. It is worth noting that, of the 77 students enrolled on the course, only 43 students submitted both their reflection and questionnaire, so our analysis for our research objectives was limited to those data. As the key prerequisite for ENA is coding raw data and identifying nodes, we took the coding scheme approach to the reflective writing texts and coded the sentences (3,400) with a specific set of epistemic (reflection) elements. Next, the SRL questionnaire data underwent cluster analysis to identify the groups of students with varying levels of SRL. The steps of our analytical procedure are described in Figure 1.

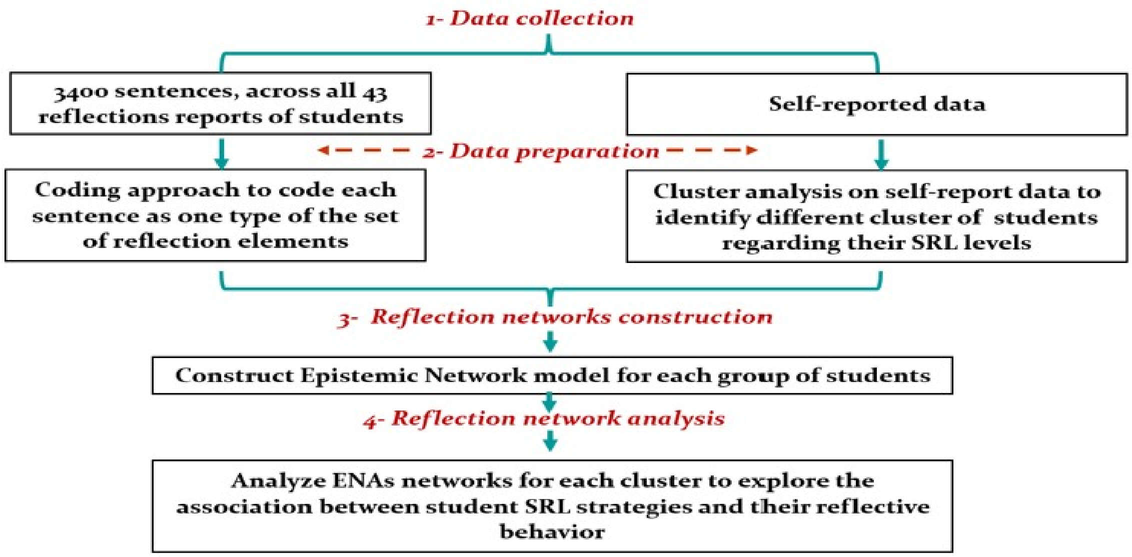

Figure 1: Network analytical approach to students' reflection behaviors

3.1 Coding approach

Each reflective writing report's transcript was coded, sentence by sentence, to convert it into codified data on which we could later conduct ENA. For the coding schema, the set of reflection elements was chosen according to the reflective process elements of learning in Boud's reflection model: Returning to experience; Utilizing positive feelings; Removing obstructing feelings; and Re-evaluating experience [49]. Boud et al. believed that these four elements are vital to learners' reflective process. In this context, we examined the 43 texts to identify the epistemic elements of reflection. Through examining their content, we proposed two elements of reflection additional to the four in Boud's reflection model: Recollecting negative feelings; and Other learning experience. Sentences that could not be categorized any of these six reflection elements were coded as NA and were ignored in our analysis as there were only a small number. As result, the 43 reports consisting of approximately 3,400 sentences were coded to one of the developed reflection elements. The explanation and description of seven reflections elements in our study's coding scheme are shown in Table 1.

Table 1: Reflection Codes.

Code	Reflection Type	Description
Returning.E	Returning to Experience	Recollection of the salient events. Replaying of the initial experience in the mind of the learner. Recounting to others of the features of the experience. **Ex**. We randomly formed a group and had to choose a topic to talk about in video recording as a group.
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.

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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 do more practices to have a very good work.
Evaluate.E	Re-Evaluating Experience	Re-examining experience in the light of the learner's intent. Associating new knowledge with that which is already possessed. Integrating the new knowledge into the learner's conceptual framework. **Ex**. It helped me build my character and made 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 that I hate in this course is that the task time is in crowd with another subject at the end of the semester.
Others	Others	Recollection the learning experiences that not related to the course. **Ex**. In the last semester, we have also a presentation that must do with a group, I talk to my professor I like to do it by myself.
NA	Not Applicable	The text does not apply to different proposed types of reflection. **Ex**. When I was in high school before entering college, I have been always lost on what to do after finishing college.

3.2 Cluster Analysis

To answer the third research question, cluster analysis was conducted on the self-report data collected on the questionnaires. This identified groups of students who with contrasting levels in the eight learning constructs; that is, students' intrinsic/extrinsic goal orientation, task value, expectancy beliefs, self-efficacy, writing anxiety, metacognitive awareness, and writing strategies. Cluster analysis is popularly used to identify groups with similar behaviors under contrasting perspectives [50]. Clustering algorithms are unsupervised machine learning techniques, and among all possible clustering algorithms, the k-means algorithm has been adopted in several previous studies to uncover patterns in questionnaire data. In k-means method, the iterative process of classification minimizes variance within each cluster that ensure a maximum of intra-cluster homogeneity. K-means usually performs well in a short processing time [51] and requires selecting the number of clusters (k) as an input parameter. The literature recommends the use of the 'elbow' method to establish the optimal number of clusters (K) by calculating the sum of squared errors between data points [52]. For each learning construct we implemented the 'elbow' method and select the value of K when the graph starts to take the shape of elbow. This clustering algorithm was used in our study to segment students into groups, where similar SRL levels are grouped into a cluster on the basis of similarity of their questionnaire responses. After preparing our data through the clustering method, ENA was undertaken to examine whether the resulting groups of students, on average, differ systematically in their course reflection.

3.3 Epistemic Analysis

In the previous step, our data were prepared by coding transcripts of students' reflective reports, then grouping students on the basis of their SRL's level in the eight learning constructs. In this step, methods from the field of ENA were employed to construct epistemic networks to model reflection connections between students, considering their self-regulated learning, and then to analyze the extracted networks to examine and compare the groups. The critical concepts of ENA are codes, the unit of analysis, and the stanza [21]. In our study, the *codes* are the reflection elements described in Table 1, represented as nodes in the network. The *student* is the unit of analysis that allowed us to measure the co-occurrence of the code in a specified stanza. The *stanza* is the collection of sentences in the unit of analysis. In detail, if two codes co-occur within the specified stanza, ENA creates a connection between the codes. The saturation and thickness of the connections refer to the relative frequency of co-occurrence between each pair of codes. ENA can quantify and visualize the structure of connections among the reflection codes of clusters of students for each learning construct: 1) goal orientation; 2) task value; 3) expectancy beliefs; 4) self-efficacy; 5) test anxiety; 6) metacognitive awareness inventory; and 7) metacognitive writing strategies.

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In each construct, the ENAs are compared to explore the association between the various levels of students' SRL strategies and their reflective behavior. For instance, for each task value construct, the network of students with low task value is compared to the network of students with high task value.

4. RESULTS

This study aims to investigate and analyze the differences in reflection behavior of groups with varying levels of SRL. SRL was assessed, through questionnaires, on specific learning constructs. The six motivational strategies for student learning are (intrinsic/extrinsic) goal orientation, task value, expectancy beliefs, self-efficacy, and test anxiety, alongside students' metacognitive awareness inventory and metacognitive writing strategies. The k-mean clustering algorithm determined the groups of students in each learning construct. The clusters identified in each learning construct are shown in Table 2. As captured by cluster analysis on the questionnaire data, students differed in their level of self-regulation of their learning. The learning reflections of the student groups in these self-regulated learning constructs were analyzed by ENA.

Table 1: Clusters In Each Construct Of Self-Regulation Of Student Learning

Learning Construct	Cluster Name	Elbow Test
Intrinsic Goal Orientation (IGO)	High-IGO Low-IGO	K=2
Extrinsic Goal Orientation (EGO)	Medium-EGO High-EGO Low-EGO	K=3
Task Value (TV)	High-TV Low-TV	K=2
Expectancy Beliefs (EB)	High-EB Low-EB	K=2
Self-Efficacy for Learning and Performance (SE)	High-SE Low-SE	K=2
Test Anxiety (TA)	High-TA Low-TA	K=2
Metacognitive Awareness Inventory (MAI)	High-MAI Low-MAI	K=2
Metacognitive Writing Strategies (MWS)	Medium-MWS High-MWS Low-MWS	K=3

ENA, visualized in analytic space, comprises two dimensions at a time (X and Y axes) through using Singular Value Decomposition (SVD), which facilitates interpretation and models the variance among the data. ENA uses SVD to reduce the dimensionality that contains all unique co-occurrences of the codes that are summed across all the stanzas in each analysis unit. ENA produces many graphical outcomes: a *projection graph* that represents the positions of epistemic networks of each student (dots) called centroids in analytical space; and an *epistemic network graph* that shows the structure of reflection connections that the students make when they reflect on their learning experience in the course. Furthermore, ENA calculates a *subtraction/difference network graph* that is used to compare two epistemic networks and clearly show the difference between them. It is calculated by subtracting the weight of each connection in one network from the corresponding connections in another. The network weights the links between nodes, so the that thicker ones represent stronger connections and the thinner ones represent weaker connections. The links' thickness is proportional to the number of stanzas (i.e., collection of sentences) between which two codes co-occur, meaning that the connection width reflects the relative frequency of co-occurrence, or association, between two codes. The resulting reflection networks of groups of students in each self-regulated learning construct are analyzed in the following section.

4.1 Students' Intrinsic Goal Orientation (IGO) and their course reflection

Figure 6 presents the projection graph for high-IGO and low-IGO clusters of students in two-dimensional projection space, where the maximum variance explained by the first- and second-dimensions accounts for 14% and 30%, respectively. The graph shows differences in the location of the mean of the plotted points in the projected ENA space for units (students) in each cluster. To understand how the students in the two clusters reflected differently on their past experience in the course, we generated the reflection network graph for each cluster in Figure 7, and the difference network graph of both clusters in Figure 8. As shown in Figure 7, there are some connections between reflection elements in the high-IGO that do not exist in low-IGO. For example, the link between (R.Obstructing and Positive.E) appears only in the high-IGO group. Furthermore, the connection between Evaluate.E and Others in the high-IGO appears to be stronger than in the low-IGO, while the connection between Negative.E and Returning.E in low-IGO is the strongest. The strong connection indicates that the reflections codes appear more frequently in pairs of students' reflection reports.

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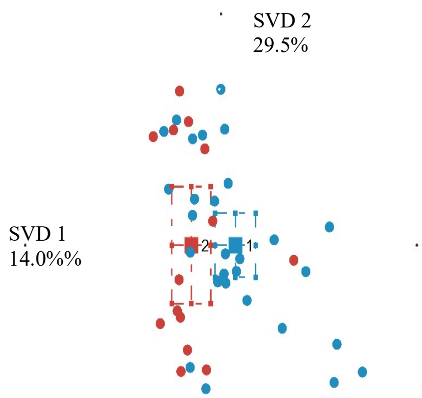

Figure 6. Centroids of epistemic network of each cluster in Intrinsic Goal Orientation (IGO) construct in projection space.

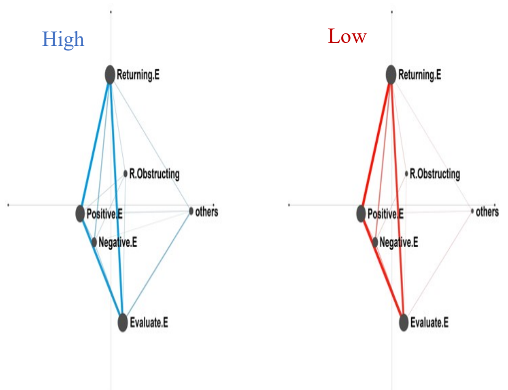

Figure 7. Epistemic network graph of high-IGO (blue on the left) and low-IGO (red on the right)

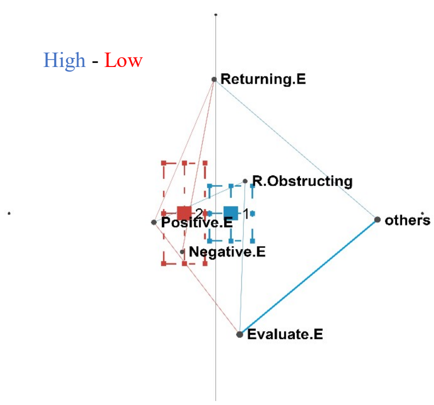

Figure 8. Difference network graph between high-IGO and low-IGO groups of students.

By subtracting the weight of each connection in the network of high-IGO cluster from the corresponding connections in the network of the low-IGO cluster, we created a difference network graph. The difference network in Figure 8 clearly shows the differences between the groups of students' reflections on their past learning experience in relation to their intrinsic goal orientation. As can be seen from Figure 8, "Removing Obstructing Feelings", "Re-Evaluation Experience", and "Others" are located on the right side of the graph, meaning that they have a closer relation with the centroid for the high-IGO group. By contrast, "Utilizing Positive Feelings" is located on the left side, meaning that it is closely related to the centroid of the low-IGO group. "Returning to Experience" is located between the two centroids as it has connections with both groups of students. The graph also shows that the students with low-IGO (in red) are more likely to have a strong connection between "Returning to Experience", "Utilizing Positive Feelings" and "Re-Evaluation Experience". This indicates that low-IGO students tended to revisit and re-examine their learning experience in combination with "Utilizing Positive Feelings", whereas students with high-IGO (in blue) focused more on the right side, as they have a strong connection between "Returning to Experience", "Others", Re-Evaluation Experience and "Removing Obstructing Feelings". This indicates that the high-IGO students tended to revisit and re-examine their learning experience in combination with "Removing Obstructing Feelings". This difference between the two regions (left and right) confirms our conclusion that there are significant differences between the two clusters.

4.2 Students' Extrinsic Goal Orientation (EGO) and their Course Reflection

Three clusters of students (high-EGO, low-EGO, and medium-EGO) were projected in two-dimensional space, as shown in Figure 9, with a maximum variance that accounts for 15% in dimension-Y and 33% in dimension-X. The graph presents the centroid of medium-EGO in red, high-EGO in blue, and low-EGO in green. Where the confidence intervals (squares) for high-EGO and low-EGO groups overlap it means that there is a similarity between the two groups in terms of their reflection on the course. Through ENA, we created difference network graphs to understand how these groups of students differed in their reflective behavior on the course. Figure 11 presents the difference network graph between the high and low EGO groups, where most links were very thin, indicating that there was little difference between the groups in terms of their reflections. Only high-IGO students showed a strong connection between Positive.E and Returning.E.

Regarding the difference between students in the medium-EGO cluster and in the other two

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clusters, we constructed the difference networks graphs shown in Figure 12. The two graphs in this figure show that the medium-EGO group (in red) has a strong connection between "Re-Evaluation Experience", "Others", and "Returning to Experience". On the right graph, the high-EGO students (in blue) have a strong connection between "Returning to Experience" and "Utilizing Positive Feelings", while the left graph shows that the low-EGO students (in green) have more connection between "Returning to Experience" and "Recollecting Negative Feelings". As a result, students tended to revisit their learning experience with "Utilizing Positive Feelings" in the high-EGO group and with "Recollecting Negative Feelings" in the low-EGO group. The medium-EGO students tended to revisit and re-examine their learning experience with reflections in the category of "Others".

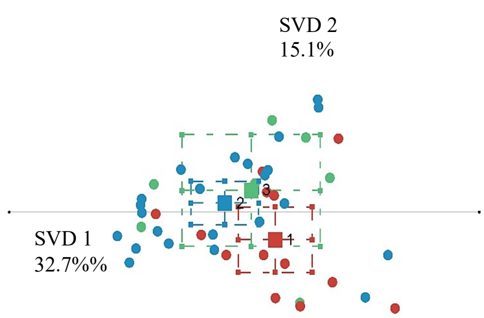

Figure 9. Centroids of epistemic network of each cluster in Extrinsic Goal Orientation (EGO) construct in projection space.

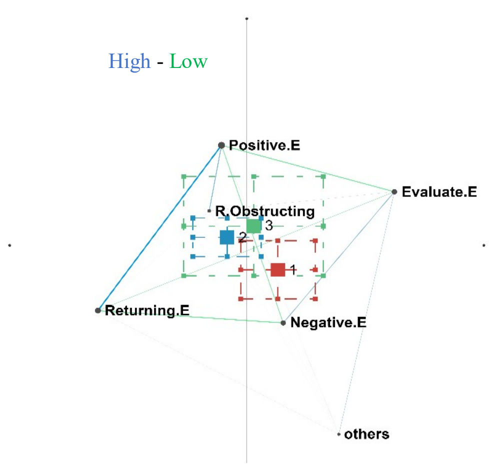

Figure 11. Difference network graph between high-EGO and low-EGO groups of students.

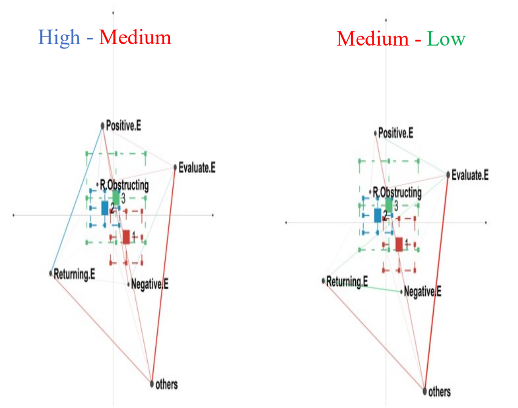

Figure 12. Difference network graph of medium-EGO cluster with high-EGO (on right) and with low-EGO cluster (on left).

4.3 Students' Task Value (TV) and Their Course Reflection

The projection graph of the students with high task value (high-TV) and low task value (low-TV) is presented in Figure 13, where there is partial overlap in the confidence intervals (squares) for both groups, indicating a similarity between the two groups in terms of their course reflection. Figure 14 shows that the reflection networks of both groups seem similar in structure. For more understanding, we created the difference network graph between high-TV and low-TV groups in Figure 15. The weakness of the links shown in the graph indicates that there are only minor differences between the two groups. The students with high TV have more connection between Returning.E and Positive.E, on the left side of the graph, while the students with low TV have more connection between Negative.E and Evaluate.E, on the right side. This means that students who have a high task value tend to revisit their learning experience with positive feelings when they reflect, while students with low task value tend to reexamine their learning experience with negative feeling about their course.

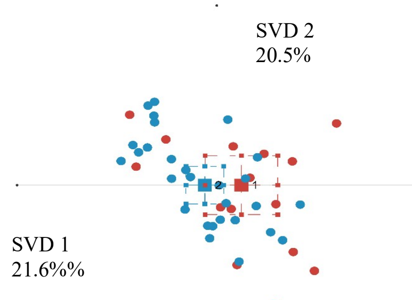

Figure 13. Centroids of epistemic network of each cluster in Task Value (TV) construct in projection space.

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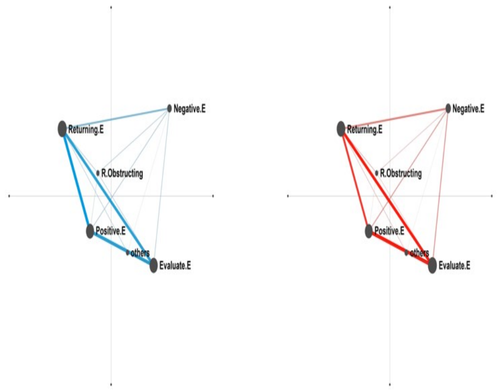

Figure 14. Epistemic network graph of high-TV cluster (blue, on left) and low-TV cluster (red, on right).

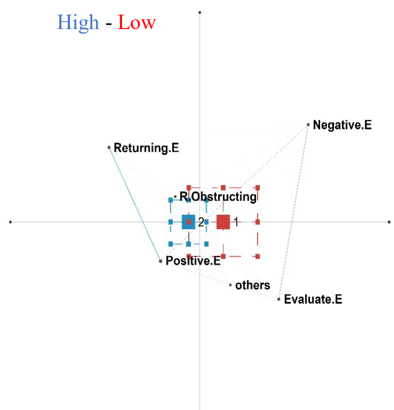

Figure 15. Difference network graph between high-TV and low-TV clusters

4.4 Students' Expectancy Beliefs (EB) and their Course Reflection

The two clusters of students, in terms of their Expectancy Beliefs (EB) for the course, were projected into two-dimensional projection space as shown in Figure 16, where blue centroids indicate the high-EB group and red the low-EB group. Figure 17 shows the reflection network graph for the high-EB group (blue, in the left graph) and the low-EB group (red, in the right graph). To understand how the students reflected differently, we generated the difference network graph shown in Figure 18. The graph shows that low-EB group (in red) has strong connections between "Re-Evaluation Experience" and "Others", on the right of the graph. This means that this group of students tends to revisit their learning experience to re-examine the knowledge obtained. Students with high-EB (in blue) tend to reflect with "Removing Obstructing Feelings", "Returning to Experience" and "Re-Evaluation Experience".

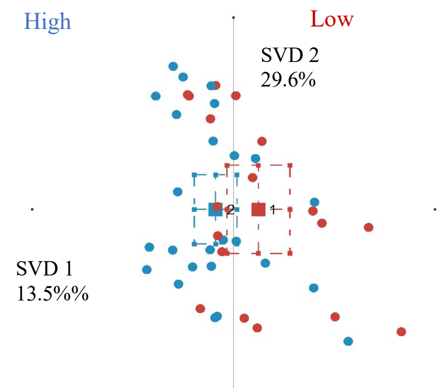

Figure 16. Centroids of epistemic network of each cluster in Expectancy Beliefs (EB) construct in projection space.

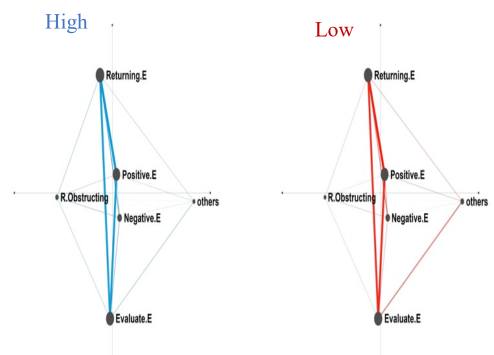

Figure 17. Epistemic network graph of high-EB cluster (blue, on left) and low-EB cluster (red, on right).

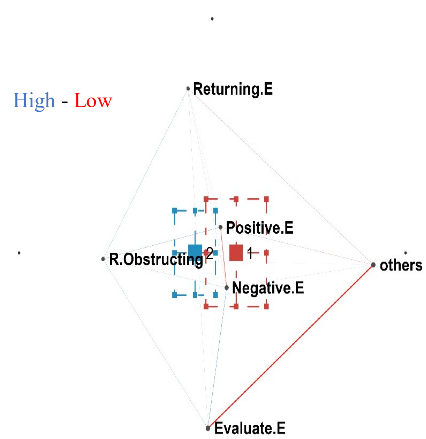

Figure 18. Difference network graph between the high-EB and low-EB clusters.

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4.5 Students' Self-Efficacy for Learning and Performance (SELP) and Their Course Reflection

The projection graph of the groups with high and low Self-Efficacy for Learning and Performance (SELP) is presented in Figure 19, where blue dots represent the high-SELP group and red the low-SELP group. The reflection networks made by both groups are displayed in Figure 20. To discover the differences in the reflection of students in the high-SELP and low-SELP groups, we generated the difference network graph shown in Figure 21. Clearly, the thickness of most links is very thin, indicating little difference between the two groups. At the right of the graph, the low-SELP group (in red) has more connections between "Re-Evaluation Experience" and "Utilizing Positive Feelings". Therefore, the low-SELP group differed from the high-SELP group in that the students tended to re-examine their learning experience with positive feelings.

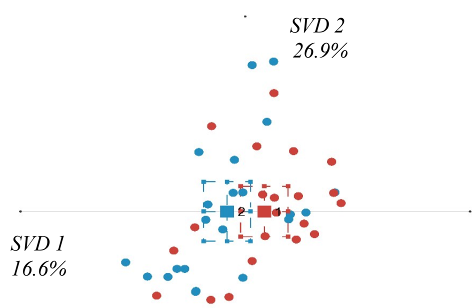

Figure 4.19. Centroids of epistemic network of each cluster in Self-Efficacy for Learning and Performance (SELP) construct in projection space.

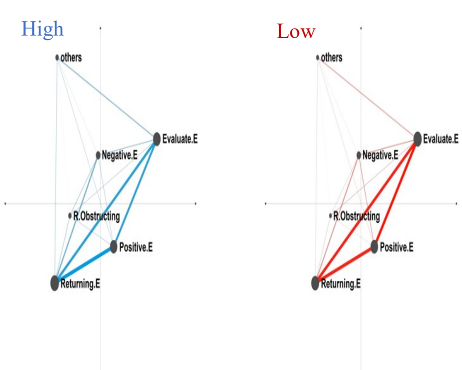

Figure 20. Epistemic network graph of high-SELP cluster (blue, on left) and low-SELP cluster (red, on right).

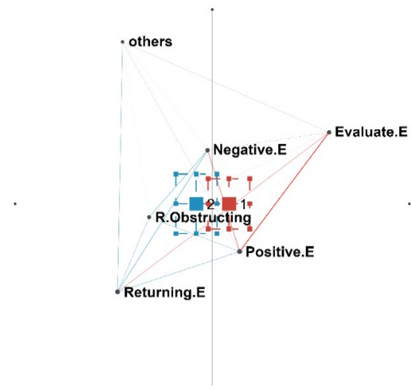

Figure 21. Difference network graph between the high-SELP and low-SELP clusters

4.6 Students' Test Anxiety (TA) and Their Course Reflection

The projection graph of students with high- and low-test anxiety (TA) is displayed in Figure 22, with maximum variance accounting for 24% in dimension-X and 16% in dimension-Y. Figure 23 presents the reflection network made by high-TA group in the left blue graph and low-TA group in the right red graph. Significant differences between high and low TA groups are revealed by the difference network graph in Figure 24. On the right we note the frequent reflections by the high-TA group, using "Returning to Experience" and "Utilizing Positive Feelings" more than the low-TA group. The low-TA group used "Utilizing Positive Feelings", "Recollecting Negative Feelings" and "Re-Evaluation Experience" more in their reflections. This means that high TA students tended to revisit their experience by recollecting positive feelings about their learning and the experience, while low TA students tended to re-examine their knowledge obtained from their learning by recollecting both negative and positive feelings about the experience.

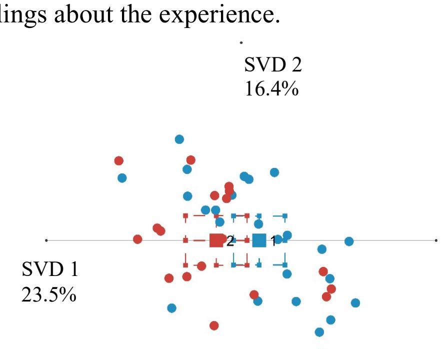

Figure 22. Centroids of epistemic network of each group in Test Anxiety (TA) construct in projection space.

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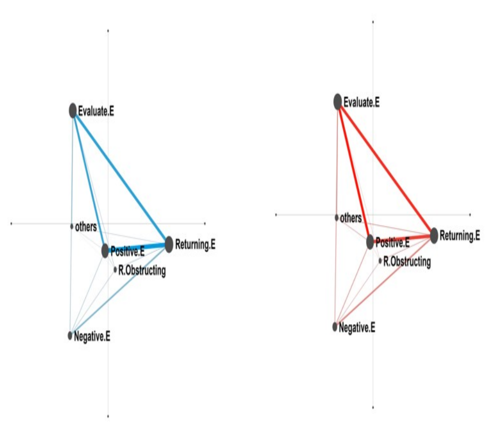

Figure 23. Epistemic network graph of high-TA group (blue, on left) and low-TA group (red, on right).

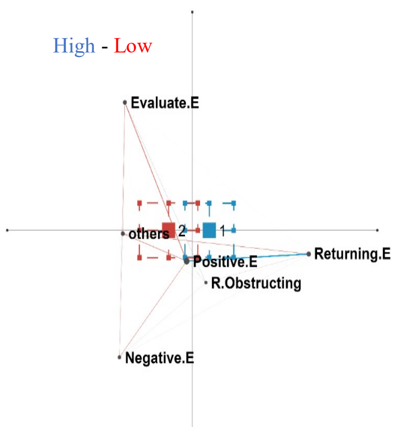

Figure 24. Difference network graph between high-TA and low-TA clusters

4.7 Metacognitive Awareness Inventory (MAI)

The high and low groups in terms of Metacognitive Awareness Inventory (MAI) were projected into two-dimensional projection space, as shown in Figure 25, with maximum variance accounting for 12% in dimension-X and 30% in dimension-Y. The reflection network for each group is shown in Figure 26, with the high-MAI group on the left in blue and the low-MAI group on the right in red. To understand how the students reflected differently, we generated the difference network graph shown in Figure 27. Clearly, the low-MAI students have a strong connection between “Returning to Experience” and “Recollecting Negative Feelings”, as shown in the red link on the left. This means that when they re-examined the knowledge obtained from their experience, they recollected negative feelings about the experience. The high-MAI students reflected differently. They revisited their experience and re-examined the knowledge obtained to try to remove obstructing feelings, as in the blue links on the right of the graph.

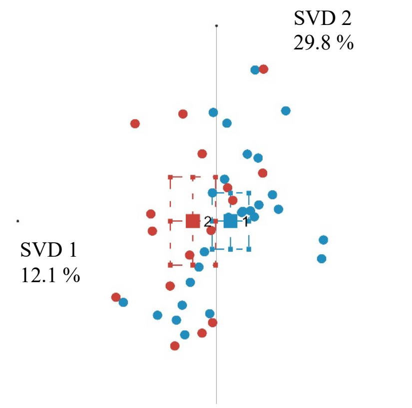

Figure 25. Centroids of epistemic network of each group in Metacognitive Awareness Inventory (MAI) construct in projection space.

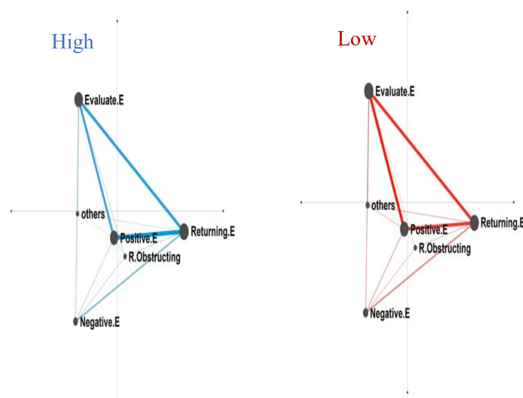

Figure 26. Epistemic network graph of high-MAI group (blue, on left) and low-MAI group (red, on right).

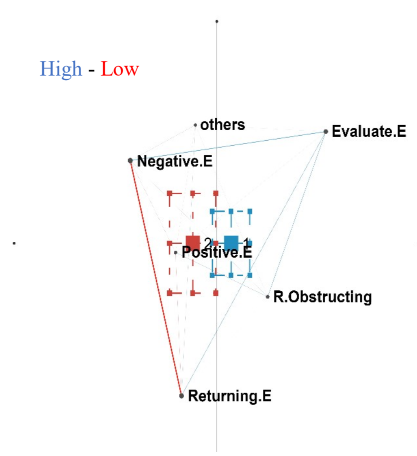

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Figure 27. Difference network graph between high-MAI and low-MAI groups

4.8 Language Learners' Metacognitive Writing Strategies (MWS)

Three clusters of students were projected in two-dimensional space, as shown in Figure 28, with maximum variance accounting for 15% in dimension-Y and 33% in dimension-X. The graph represents the centroid of each cluster as follows: medium-MWS in red; high-MWS in blue; and low-MWS in green. The confidence intervals (squares) for three groups overlap, meaning that there is a similarity between the groups in terms of their course reflections. Furthermore, we created a difference network graph between three clusters, as shown in Figure 30 and 31. The graph present the difference network between high-MWS and medium-MWS clusters (left), between high-MWS and low-MWS groups of students (middle); and between medium-MWS and low-MWS groups of students (right). The weakness of the links seen in the graph indicates that there are little differences between the students' reflections in the three clusters. As shown in Figure 30, the medium MWS students have more connection between Returning.E, Evaluate.E and Positive.E than the low MWS students, as on the right. While those students with medium MWS have stronger connections between Returning.E, Evaluate.E, and Negative.E than those with high MWS, as in the left. Furthermore, if we compare the high with low MWS groups of students, the student with high level in MWS have more connections between the Evaluate.E and Positive.E, as seen in Figure 31.

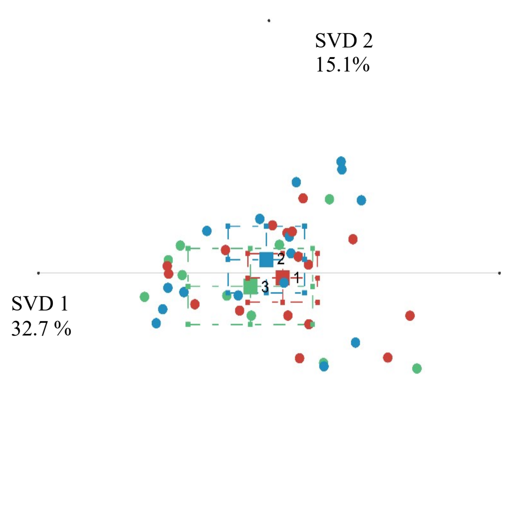

Figure 28. Centroids of epistemic network of each cluster Metacognitive Writing Strategies (MWS) construct in projection space.

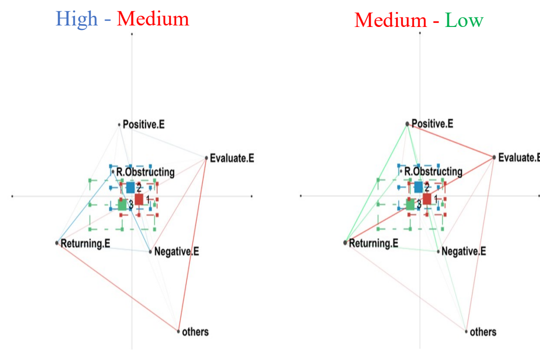

Figure 30. Difference network graphs between high-MWS and medium-MWS clusters (left) and between medium-MWS and low-MWS clusters (right).

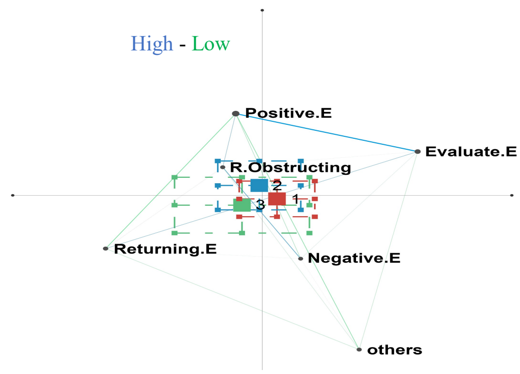

Figure 31. Difference network graphs between high-MWS and low-MWS clusters

5. DISCUSSION

ENA revealed a large and significant difference in reflective behavior between students with a high Intrinsic Goal Orientation (IGO) and those with a low IGO. The high-IGO students had stronger connections between "Returning to Experience", Re-Evaluation Experience, and "Removing Obstructing Feelings". By contrast, students with low IGO were more likely to have a strong connection between "Returning to Experience", "Utilizing Positive Feelings", and "Re-Evaluation Experience". This indicates that students with lower IGO tend to revisit and re-examine their learning experience to recollect their positive feelings about the course experience, while those with a higher level usually do so while trying to remove their obstructing feelings.

ENA was an effective tool for revealing the connections of the groups of students (high, low, and medium Extrinsic Goal Orientation (EGO). It showed that the reflection network of students in the medium-EGO group differed clearly from the other two groups. Students with a high motivation to learn through EGO tended to revisit their learning experience in tandem with "Utilizing Positive Feelings", while those with lower motivation had stronger connections between revisiting their learning experience and "Recollecting Negative Feelings". However, students with medium-EGO tended to revisit and re-examine their learning experience in tandem with "Others learning experience". Our network analysis also showed that the students with high Expectancy Beliefs (EB), who had a high expectation of success in the tasks, tended to reflect while "Removing Obstructing Feelings", frequently alongside "Returning to Experience" and "Re-Evaluation Experience". By contrast, the low-EB group re-examined their learning experience alongside "Others learning experience". ENA also found a difference in reflection by the high Self-Efficacy (SE) and low-SE groups. The low-SE group had more connections between "Re-Evaluation Experience" and "Utilizing Positive Feelings", while the high SE group tried to overcome the obstructing feelings that had hindered them in their interaction with the course tasks.

Regarding the relationship between students' Test Anxiety (TA) and their learning reflection on the new methodology of learning that was adopted on their course, based as it was on continuous assessment rather than tests, ENA revealed valuable results. The students with high TA tended to revisit their experience with positive feelings about their learning and the experience. However, low TA students tended to re-examine the knowledge obtained from their learning experience while recollecting negative feelings about the experience. The Task Value (TV) that the students attributed to the coursework was also examined in relation to their course reflections. ENA showed that the students with high TV had more connections between "Returning to Experience" and "Utilizing Positive Feelings", while students with low TV had more connection between "Recollecting Negative Feelings" and "Re-Evaluating Experience".

For the six motivational learning constructs of intrinsic and extrinsic goal orientation (IGO/EGO), task value (TV), expectancy beliefs (EB), self-efficacy (SELP), and test anxiety (TA), we observed that the two prevailing reflections among students with strong motivation for learning are "Utilizing Positive Feelings" and "Removing Obstructing Feelings". This means that students who had a positive feeling about their good experience and who tried to overcome the obstructing feelings that hindered their learning process have a high level of self-regulation of their learning. By contrast, "Recollecting Negative Feelings" and "Re-Evaluating Experience" were more frequent among students with low self-regulation over their learning process, as they examined the knowledge obtained from the course by recollecting negative feelings about their learning experience. Moreover, ENA revealed that reflective behaviors in "Intrinsic Goal Orientation", "Expectancy Beliefs", and "Self-Efficacy in Learning and Performance" contained no negative feelings about the learning experience of students with either high or low motivation to learn, in the IGO and SE constructs.

Furthermore, our study uncovers the association between students' reflections and their Metacognitive Awareness Inventory (MAI) and their Metacognitive Writing Strategies (MWS). ENA has been shown to be an effective method to reveal differences in the reflections of high- and low-MAI students. The two groups differ significantly in that the low-MAI students had strong connections between "Returning to Experience" and "Recollecting Negative Feelings", while among the students with high-MAI "Returning to Experience" was more frequently connected to "Removing Obstructing Feelings". Students with a high level of metacognitive awareness of strategies to know and regulate their cognition revisited their experience by recollecting the salient events with an emphasis on removing their obstructing feelings, while those with low level of metacognitive awareness revisited their learning by recollecting their negative feelings to the experience. In the literature, ENA has been applied in conjunction with self-reported reflection to investigate metacognitive diversity among learners in cooperative learning [44]. Our finding adds to this literature that finds that ENA to be an effective method to analyze how reflection patterns vary between groups.

Examining the skills, strategies, and performance of students through their reflective writing has been a focus for many researchers [25,26,27,45], proving the effectiveness of reflective writing in improving general writing skills and performance. Our study also explored the association between students' metacognition about writing strategies and their learning reflections, as the course involved several writing tasks. The difference network of low, medium, and high MWS showed that the co-occurrence of "Returning to Experience", "Utilizing Positive Feelings", and "Re-Evaluating Experience" was more frequent across all groups of students in the MWS construct. This means that their reflective behaviors were

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prominent when they revisited the learning experience: recalling salient events, recounting the features of the experience to others, and recollecting positive feelings about learning and the experience. They all tended to relate new knowledge to that which they already possessed. The difference networks also showed that students with high metacognitive writing strategies had more connections between "Utilizing Positive Feelings", and "Re-Evaluating Experience", while the lower group had more connections between "Returning to Experience", "Recollecting Negative Feelings", and "Removing Obstructing Feelings".

6. CONCLUSION

ENA and cluster analysis techniques have proven effective in revealing and analyzing differences in the reflective behaviors of groups of students in several self-regulated learning constructs. The two most prominent reflections observed among students with high self-regulated learning skills, regarding their intrinsic/extrinsic goal orientation, task value, expectancy beliefs, self-efficacy, test anxiety, metacognitive awareness, and metacognitive writing strategies, were "Utilizing Positive Feelings" and "Removing Obstructing Feelings". By contrast, students with low SRL skills in these learning constructs frequently used "Recollecting Negative Feeling" and "Re-Evaluating Experience", apart from the Intrinsic Goal Orientation, Expectancy Beliefs, and Self-Efficacy learning constructs, which showed no negative feelings about the learning experience. Our approach adds to the literature that modeling students' reflections as a network graph provides valuable insights into their learning experience. The difference network graph in ENA was instrumental in investigating how reflections patterns vary between groups of students. Furthermore, the results of our research provide instructors with knowledge of students' impressions of a specific teaching or learning method, satisfaction with the learning experience, and whether they were able to overcome obstacles during the learning process. Linking these results to the level of student performance and self-regulation of learning enables the instructor to provide appropriate interventions and support students' self-regulated learning processes.

Although our proposed approach shows promise in addressing important issues in research on associating students' written reflections on a particular learning experience with their self-regulated learning, the current study has several limitations that must be acknowledged. First, this study relied on data from just one semester of a particular course in a single educational institution, and this may negatively affect the generalizability of the results and the broader application of its analytical approach. Second, due to the peculiarities of the design of the course in this study, the results obtained are somewhat limited. To address these issues, we recommend applying our 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 classify (code) the reflection report transcripts automatically. This would ease the adoption of the proposed analytic approach since there would be no need to code the transcripts manually, as had to be done in the current study.

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