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USING DECISION TREE TECHNIQUE TO ANALYZE STUDENTS' REFLECTIVE THINKING, FEEDBACK, AND PERFORMANCE

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ABSTRACT

This study aims to apply a decision tree technique to understand how learning performance patterns in an educational blogging environment can be formulated and forecasted based on reflective thinking skills, feedback types, and performance test increment levels. A case study research design was adopted, involving qualitative data from students' reflections on blogs and quantitative data on students' performance. Data collection spanned 14 weeks and involved 18 postgraduate students enrolled in the Authoring System course. The data was prepared in *.arff* format and mined using the WEKA 3.6.6 machine learning toolkit to generate learning performance patterns. A random tree algorithm was applied to classify the data and evaluated using a three-fold cross-validation parameter. As a result, eight learning performance patterns were generated for three increment categories: P3, P4, and P5. From the generated patterns, it is evident that the higher the increment category of learning performance, the higher the levels of reflective thinking skills and feedback types utilised by students in their reflections. Moreover, Descriptive Reflection (DR) was noted as the most influential attribute differentiating the variables predicting all three learning increment classes. In addition to learning performance patterns, the overall performance of this predictive model was moderate (recall = 50%, precision = 50%) and acceptable (ROC = 61%). The findings are beneficial in identifying at-risk students, such as those struggling with reflection and displaying lower reflective thinking skills and feedback. This can alert instructors to take early action for intervention purposes.

Keywords: *Reflective Thinking, Feedback, Learning Performance, Decision Tree Data Mining, Blogging*

1. INTRODUCTION

Developing reflective thinking skills is essential due to its global significance and applications beyond the educational domain. Reflective thinking involves revisiting past experiences or subjects, learning from them, and making adjustments for future actions [1]. This process enables students to continually examine and reflect on their beliefs, values, attitudes, and assumptions, ultimately fostering active, aware, and critical thinkers. The development of these skills is crucial not only for academic success but also for personal and professional growth, making it a vital area of research.

Numerous studies have proposed various strategies, methods, and tools to promote effective reflective thinking in learning. Digital mediums, such as online discussion forums [2], e-portfolios [3], blogs [4], and Twitter [5], are popular for facilitating reflective thinking. These platforms offer easy access to and sharing of information and experiences among peers and instructors [6]. Participants benefit from increased opportunities and trust to discuss each other's experiences openly, gaining diverse perspectives that prevent overgeneralisation of individual experiences [7]. This reflective approach also enhances learning about the decision-making process [8].

Despite the recognised benefits of reflective thinking, assessing its impact on student learning often relies on self-reported data from questionnaires [13, 14], summative assessments like quizzes, or analysis of students' blog posts [15, 16]. While statistical analyses are common in such research, relying solely on self-reported data and summative assessments provides limited insights into students' reflective thinking skills. This gap in understanding necessitates the exploration of more sophisticated analysis techniques that can offer a deeper evaluation of reflective thinking and addressing poor academic performance among students for timely support and intervention [9].

Written reflections, whether digital or paper-based, are typically evaluated manually through content analysis using reflection models/frameworks developed by scholars such as [17, 18, 19]. These models aim to describe the mastery or application of reflection [20]. However, other researchers, including [21, 22, 23, 24, 25], have employed data mining techniques to analyse reflective thinking performance in meaningful ways. Data mining links students' performance with other learning processes/outcomes, such as interaction posts, behaviour, or demographic data, to gain a deeper understanding of students' competencies. This approach is particularly useful in education, especially for analysing behaviour in online learning environments, as it uncovers hidden information that would be difficult and time-consuming to analyse manually [9, 26].

Using a data mining approach, particularly decision tree techniques, can reveal detailed patterns of learning performance based on reflective thinking skills and types of feedback in an educational blogging environment. Decision trees are especially valuable because they provide clear, interpretable rules that can be easily understood by educators who may not be experts in data mining. This makes decision trees a practical tool for translating complex data insights into actionable strategies for teaching and learning. These patterns provide valuable insights for instructors' pedagogical practices and intervention designs, helping to reduce student dropout rates [10, 27]. Educational researchers favour classification methods like decision trees because their rules are straightforward and comprehensible to non-experts in data mining [26].

Therefore, this study aims to employ an educational data mining approach, specifically decision tree techniques, to uncover and predict learning performance patterns based on reflective thinking skills and feedback types in an educational blogging environment. This research is significant because it addresses the current gaps in assessing reflective thinking and provides a data-driven approach to improve educational outcomes. Traditional methods of evaluating reflective thinking, such as self-reported surveys and summative assessments, often fall short in capturing the depth and nuances of students' reflective processes. By employing data mining techniques, particularly decision tree algorithms, this study offers a more comprehensive and accurate analysis of reflective thinking skills. This approach not only uncovers hidden patterns and relationships in students' learning behaviors but also generates clear, actionable insights for educators. As a result, educators can design more effective pedagogical strategies and targeted interventions, ultimately enhancing the overall learning experience and equipping students with critical 21st-century skills. This research bridges the gap between traditional assessment methods and the need for more robust, data-driven evaluations, thereby significantly contributing to the field of education.

2. RESEARCH METHODOLOGY

A case study research design incorporating both quantitative and qualitative data was used to formulate and forecast the learning performance patterns based on reflective thinking skills, feedback levels, and performance tests, in an educational blogging environment. The quantitative data consisted of performance test scores, whereas the qualitative data were collected from the students' reflections on blogs (i.e. reflective thinking skills, feedback levels). Scholars such as [11] and [12] stated that implementing a combination of data sources provides a better research design. Furthermore, the combination of quantitative and qualitative data is crucial in allowing in-depth understanding about the issues examined in this research and presents greater assurance in terms of making mindful decisions on the research results.

A cohort of 18 postgraduate students enrolled in the Authoring System course was selected through purposive sampling to participate in this study, which spanned 14 weeks. Purposive sampling was selected because this was the only cohort enrolled in the aforementioned course. Additionally, purposive sampling is appropriate for research involving content analysis, as it allows the researchers to focus on informants with the most expertise on the research topic [28]. The instruments used in this case study are case discussion activities, reflection activities and learning performance tests (see Table 1). Details explanation about learning instruments can be found in [29].

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Table 1: Learning instruments

Instruments	Details
Case Discussion Activities (course blog)	Case 1: Flash test Drive
	Case 2: To Animate or Not to Animate Camp: Frequently Asked Questions
	Case 3: My Idea of Flash
	Case 4: It's A House…It's A Condominium…It's A Website
	Case 5: Trouble is a Business, For Some
	Case 6: Where Does Security Lie?
Reflection Activities (student's blog)	Reflections based on themes i.e. personal information, what and how-to tutorials, expression of feelings, seeking help, sharing outside resources/notes, and recollection of own experiences.
Learning Performance Test	Pre-test
	Post-test

For the analysis, the researchers analysed the data gathered according to its types and purposes. The levels of reflective thinking skills and types of feedback used by students when involved in case discussion and reflections in blogging environments were identified by looking through all the posts, comments and replies made by them. Reflective thinking skills and the feedback were content analysed through a deductive approach following [17] and [30] coding schemes, respectively. Those data were later converted quantitatively (descriptive statistics: frequencies). The performance tests, meanwhile, were scored based on the answer schemes, and later transformed into level of increment. Details on level of increment can be found in [31]. Finally, data of reflective thinking skills, types of feedback, and performance test increment levels were analysed through a data mining technique, namely decision tree mining technique, in order to formulate the pattens.

To generate learning performance patterns, the data was prepared in *.arff* format. This format is necessary for mining the data using the open source software, WEKA 3.6.6 machine learning toolkit. An *.arff* file contains a list of instances (students) and their corresponding attribute values, such as reflective thinking, feedback, and performance test increment level. The types of feedback and levels of reflective thinking skills attributes are in numeric form, while the performance test increment level attribute is in ordinal form, as shown in Figure 1.

```
@relation
@attribute reflective thinking DW numeric
@attribute reflective thinking DR numeric
…
@attribute feedback DL numeric
…
@attribute increment level ordinal {P1, P2, P3, P4, P5}

@data
4, 5, …, 2, 5, …, P6
…
```

Figure 1: Dataset representation for decision tree

3. RESEARCH FINDINGS

3.1 Learning Performance Patterns based on Reflective Thinking Skills and Types of Feedback in Educational Blogging Environment through Decision Tree Technique

To formulate and forecast such patterns, a data mining technique, specifically the decision tree, was employed. By using this analysis technique, hidden behaviour patterns which reside in the data can be uncovered, extracted and turned into meaningful rules to improve understanding of the data. In this case, question such as "How likely is Student X to use feedback and reflective thinking skills to achieve P5 increment level in learning performance?" can be answered.

In general, through deductive content analysis of transcript data from both the course and individual blogs, a total of 3745 segments from 604 posts were extracted and coded under the reflective thinking (i.e. Descriptive Writing (DW), Descriptive Reflection (DR), Dialogic Reflection (DLR), Critical Reflection (CR)) and feedback (i.e. Direct Link (DL), Course Link (CL), Brainstorm (B), Limited Focal (LF), Open Focal (OF), Application (A)) levels, as tabulated in Table 2.

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Table 2: Distribution of reflective thinking, feedback and learning performance across students

Person	f Post	Reflective Thinking (RT)					Feedback (F)							Learning Performance
		DW	DR	DLR	CR	Total RT	DL	CL	B	LF	OF	A	Total F	
S1	24	35	21	2	1	59	0	0	3	0	0	3	6	P3
S2	31	55	49	2	2	108	0	0	18	0	3	12	33	P5
S3	22	43	49	7	2	101	0	0	10	2	1	3	16	P4
S4	46	113	81	11	0	205	0	1	68	0	3	40	112	P5
S5	34	101	125	19	11	256	0	0	32	4	4	45	85	P5
S6	33	65	46	3	0	114	0	0	3	0	0	1	4	P4
S7	15	28	42	11	5	86	2	0	4	0	0	0	6	P5
S8	36	77	24	1	2	104	0	0	7	1	0	16	24	P3
S9	32	60	24	5	3	92	0	0	4	0	1	0	5	P4
S10	38	116	44	5	1	166	0	0	25	1	1	22	49	P4
S11	22	36	27	2	0	65	0	0	10	0	0	3	13	P3
S12	53	291	185	13	4	493	1	0	75	4	3	89	172	P4
S13	16	13	16	10	1	40	0	0	2	0	0	0	2	P3
S14	14	27	14	2	0	43	0	0	0	0	0	0	0	P4
S15	61	196	129	6	3	334	0	0	35	2	3	23	63	P5
S16	42	148	86	6	5	245	0	1	21	2	0	13	37	P5
S17	41	105	138	4	1	248	1	1	18	0	1	12	33	P3
S18	44	105	114	8	3	230	1	0	47	7	3	38	96	P5
Total	604	3745												

The research question was furthered answered by using a data mining technique known as a decision tree. A decision tree is a type of supervised learning classification that aims to predict outcomes for a new dataset (referred to as the testing dataset) based on a known dataset (referred to as the training dataset). The known dataset includes various input attributes and one target attribute for the class. Using these attributes, a learning algorithm constructs a model that can make predictions for a new dataset and determine its accuracy. In this study, the eleven input attributes in numeric form consist of four levels of reflective thinking skills (i.e. DW, DR, DLR, CR) and six levels of feedback types (i.e. DL, CL, B, LF, OF, A). The one class target attribute, meanwhile, was in ordinal form from the three types of learning performance increment (i.e. P3, P4, P5).

In order to construct the learning performance patterns, a random tree algorithm was utilised to classify the 18 instances, which represent data from 18 students. The evaluation of this classification was carried out using a three-fold cross-validation parameter, which enhances the model's ability to generalise to an independent dataset. Three-fold cross-validation involves dividing the data into three segments and performing three iterations of training and validation. During each iteration, one segment of the data is used for validation (testing), while the remaining two segments are used for training [32]. Before proceeding with mining the dataset, it is important to determine if there is an imbalanced class condition, as this can affect the creation of unbiased models. Fortunately, in this study, imbalanced class was not a concern, as the numbers of students falling into the three increment categories were fairly balanced (P3 = 5 students, P4 = 6 students, P5 = 7 students).

The tree structure, which is displayed in Figure 2, is generated directly from the complete training dataset. The decision tree model consists of fifteen nodes. The oval shapes represent the input attributes, such as reflective thinking and feedback. On the other hand, the rectangular shapes indicate the class target attribute, which in this case is the increment. The number of students who achieved a specific performance increment is shown within the brackets of the rectangular nodes, also referred to as leaf nodes. As depicted in Table 3 which deduced from

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Figure 2, eight learning performance patterns have been identified in relation to the respective increment categories. Specifically, three learning performance patterns were seen to lead to the P3 and P4 increment categories, whilst only two learning performance patterns were acknowledged for the P5 increment category.

Table 3: Learning performance patterns according to increment levels

Category	Rules
P3	DR ⇒ A
	DR ⇒ A ⇒ DW
	DR ⇒ DR ⇒ DR
P4	DR ⇒ A ⇒ DW
	DR ⇒ DR ⇒ CR ⇒ OF
	DR ⇒ DR ⇒ DR
P5	DR ⇒ CR
	DR ⇒ CR ⇒ OF

As shown in Figure 2, Descriptive Reflection (DR) was noted as the most influential attribute that differentiated the variables predicting all three learning increment classes. In the first situation (left side of the tree, where the DR value was less than 34.5 times), students who provided an Application (A) type of feedback (1.5 times or more) showcased a P3 increment in performance (with three students belonging to this category).

On the other hand, for low value of Application (A) feedback (fewer than 1.5 times), Descriptive Writing (DW) was further identified as a predictor of a good increment grade. Students who posted more non-reflective description / non-justification statements (20 or more), in response to the Application type of questions, were able to achieve a P4 increment category (two students fall into this category). This whole first situation indicates a rather direct result where students who displayed lower level sequences of thinking and feedback in reflection activity, such as asking simple questions based on the existing information from the experience/event and/or merely describing a surface experience/event under discussion, would end up reaching a passing grade with a lower performance increment. This is probably due to constraint in dealing with limited knowledge/information to draw

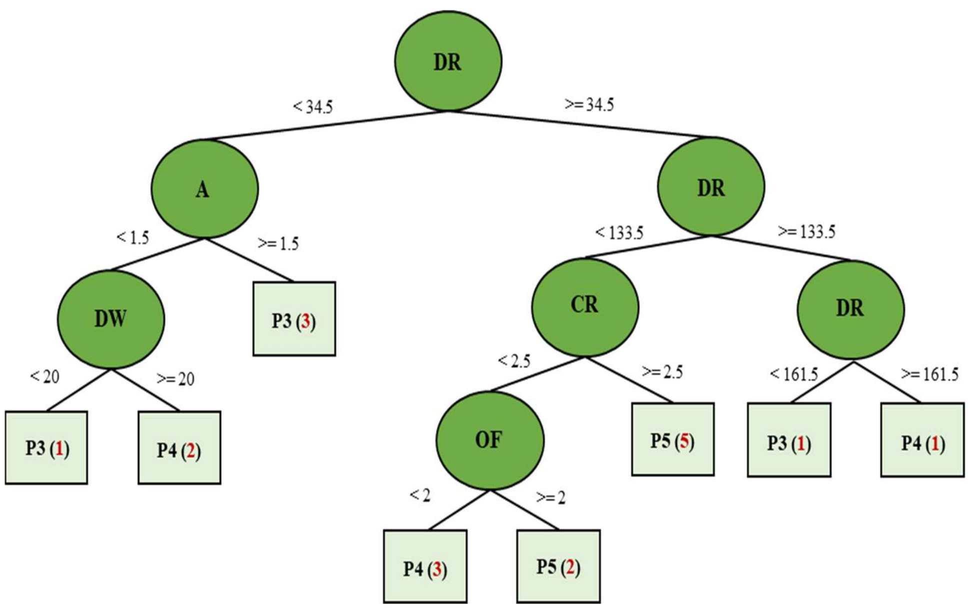

Figure 2: Decision tree structure from training set

further inference/evaluation and hence attain good performance. For this condition, extra effort/contribution in descriptive writing practice is definitely needed to enable students to further increase their performance category. This also points to several actions that should be taken by the instructor, especially in helping students to understand how to use information/experiences/ feedback to reflect effectively.

For the second situation (the right side of the tree, where the DR value was 34.5 times or more), highly engaged high performance orientation could be inferred. A contribution of Critical Reflection

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(CR) statements (2.5 times or more) towards certain topics for discussion and reflection becomes the next predictor that promoted a P5 increment in performance for five students. Subsequently, engagement with ideas/exchange of opinions with students happened when feedback was made to marshal information/experience through the Open Focal (OF) feedback type, which is opinion-oriented in nature, and again that led to passing grades with higher performance increment. More frequent provision of the OF feedback type (on two occasions or more) discriminated the performance increment between the P4 and P5 categories.

Overall, although not all types of reflective thinking and feedback emerged in the learning performance patterns, it is evident that those patterns suggest distinct key findings, that is, the higher the increment class, the better the levels of reflective thinking and feedback practised by students in doing reflection through blogging, and vice versa for the lower increment class (see Table 3). This can also be beneficial in finding students who are struggling to carry out reflection and displaying lower reflective thinking skills and feedback, and alerting the instructor to take early action.

Since the learning performance patterns tell us little about the performance of this data mining model, other metrics, such as classification accuracy, recall, precision and ROC area, need to be assessed in order to have a clear understanding about the model's performance. Therefore, from the three-fold cross-validation mining process, the overall accuracy of the model, which is defined as the ratio of correct predictions to total predictions, was found to be 50%, where nine out of 18 instances were correctly classified and the remaining nine instances were incorrectly classified. As accuracy tends to hide some details of the model performance, a confusion matrix was then used to reveal other significant findings. A confusion matrix is able to show how the model is confused when it makes predictions by showing the number of correct and incorrect predictions by the classifier, and also the types of errors, which are broken down by each class and organised in the form of a matrix (Witten et al., 2011) (see Tables 4 and 5). The matrix may also reveal some insights into why the accuracy of the model is at an average level.

Table 4: General 2x2 confusion matrix

	Predicted Class A	Predicted Class B
Actual Class A	True Positive	False Negative
Actual Class B	False Positive	True Negative

Table 5: Learning performance of 3x3 confusion matrix

	Predicted P3	Predicted P5	Predicted P4
Actual P3	2	2	1
Actual P5	1	5	1
Actual P4	1	3	2

As depicted in Tables 4 and 5, the rows in the matrix correspond to actual classes, whereas the columns correspond to predicted classes. In the confusion matrix table structure, there are four main standard categorisations for each cell, namely True Positive, True Negative, False Positive, and False Negative. The following explains these categorisations in detail:

1. True Positive (TP) is defined as actual positives in the data which have been correctly classified as positive by the model. In our learning performance case, the three situations for TP include (a) the number of P3 students correctly retained as P3 class, (b) the number of P4 students correctly retained as P4 class, and (c) the number of P5 students correctly retained as P5 class. Based on the data in Table 5, TP for P3, P4 and P5 are 2, 2, and 5, respectively.

2. True Negative (TN) is described as actual negatives in the data which have been correctly classified as negative by the model. In the context of our learning performance case, the three situations for TN are (a) the number of non-P3 students correctly retained as non-P3 class, (b) the number of non-P4 students correctly retained as non-P4 class, and (c) the number of non-P5 students correctly retained as non-P5 class. Based on the data in Table 5, TN for P3 is (5+1+3+2 = 11), P4 is (2+2+1+5 = 10), and P5 is (2+1+1+2 = 6).

3. False Positive (FP) refers to actual negatives in the data which have been mistakenly classified as positive by the model. In this study context, the

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three situations for FP are (a) non-P3 students mistakenly classified as P3, (b) non-P4 students mistakenly classified as P4, and (c) non-P5 students mistakenly classified as P5. Based on the data in Table 5, FP for P3 is (1+1 = 2), P4 is (1+1 = 2), and P5 is (2+3 = 5).

4. False Negative (FN) refers to actual positives in the data which have been mistakenly classified as negative by the model. In this study context, the three situations for FN are (a) P3 students mistakenly classified as non-P3, (b) P4 students mistakenly classified as non-P4, and (c) P5 students mistakenly classified as non-P5. Based on the data in Table 5, FN for P3 is (2+1 = 3), P4 is (1+3 = 4), and P5 is (1+1 = 2).

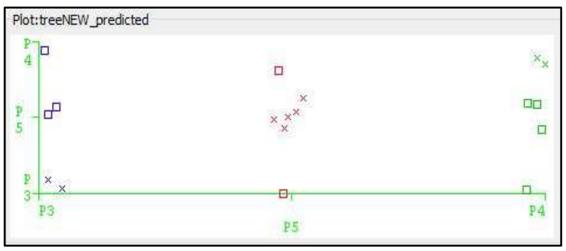

Figure 3: Tree classifier error

As illustrated in Figure 3, the P3 students who were correctly predicted as P3 increment class were students S1 and S11. Meanwhile, student S8, who was supposed to belong to the P3 class, was incorrectly predicted to be in the P4 increment class. Similarly, S13 and S17 were both incorrectly classified as belonging to the P5 increment class instead of the P3 class. Moreover, P4 students who were correctly predicted as being in the P4 increment class were students S3 and S6. S12, who was supposed belong to the P4 class, was incorrectly predicted as belonging to the P3 increment class. Similarly, S9, S10 and S14 were all incorrectly classified as belonging to the P5 increment class instead of the P4 class. Finally, P5 students who were correctly predicted as belonging to the P5 increment class were students S4, S5, S15, S16 and S18. Likewise, S7 and S2, who were supposed to belong to the P5 class, were incorrectly predicted as belonging to the P3 and P4 increment class, respectively.

Apart from the above findings, the confusion matrix is more meaningful if it is translated into other metrics, such as the recall, precision and ROC areas, to reveal hidden insights about the model's performance. Recall, also known as sensitivity or True Positive Rate, refers to how many data have been truly classified as positive by the model out of all the positive data points. Recall is calculated using the formula of TP/(TP + FN).

Table 6: Decision tree accuracy output by class

	Recall/ Sensitivity/ TP Rate	Precision	ROC Area	Class
	0.4	0.5	0.623	P3
	0.714	0.5	0.63	P5
	0.333	0.5	0.583	P4
Average	0.5	0.5	0.612	-

Based on the results revealed in Table 6, Recall for P3, P4 and P5 are 0.4, 0.3 and 0.71, respectively. This means that the success rate for the correct prediction of learning performance class for P3, P4, and P5 are 40%, 30% and 71%. The low success rates for P3 and P4 were due to the effect of the higher FN value; meanwhile, the higher success rate for P5 was because of the effect of the lower FN value.

Similarly, when it is necessary to be absolutely sure that a certain learning performance class is considered as true rather than as false, the value of FP must be at the lowest level [32]. This is what we refer to as Precision, which gives values for how many predictions are actually true out of all the points that have been identified as positive. Precision is calculated using the formula TP/(TP + FP). In our case, the Precision rate for all types of performance class is only at an average level, i.e. 50% (see Table 6), which is a better result compared to P3 and P4 Recall but not P5 Recall. Nevertheless, between Recall and Precision, more attention should be given towards Recall because students under the P3 and P4 classes are in danger of not receiving correct reflective thinking and feedback intervention and there is also a higher chance that they will be ignored by the instructor, since they are predicted to have a better learning performance class than is actually the case. For P5 Recall, students will receive more intervention, since they are predicted as having lower performance, and this can be considered as wasted, because in reality they do not need such intervention to excel, although it might be helpful for extra reflective thinking and feedback training.

Lastly, an analysis of the ROC area was conducted as a way of summarising the classification information. ROC area reflects how much the model

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is able to distinguish between classes, in which the sensitivity of a predictor (True Positive Rate) is contrasted against the specificity (False Positive Rate). The higher the ROC area, the better the model is at separating students with P3, P4 and P5 class categories. The rule of thumb in interpreting ROC area value, as outlined by [33] is: ROC area = 0.5 (No separation); 0.6 ≥ ROC area > 0.5 (Poor separation); 0.7 ≥ ROC area > 0.6 (Acceptable separation); 0.8 ≥ ROC area > 0.7 (Excellent separation); ROC area > 0.9 (Outstanding separation). Based on the ROC area values in Table 6, there are 62%, 58% and 63% chances that the model is able to discriminate the P3, P4 and P5 increment classes, respectively. For P3 and P5, the separation is acceptable, however poor separation is identified for P4. It should be noted that for social sciences research, especially on thinking skills behaviour, it is not easy to achieve clear class separation, as in medical or engineering problem contexts. What is important is that these classification accuracies are able to tell how the predictive model might be used in decision making and aiding better intervention.

4. DISCUSSION

This study sought to predict students' learning performance (measured as increment levels) based on data patterns of reflection through blogging, which included feedback types and reflective thinking levels. The prediction via a decision tree data mining approach gives a number of alternative learning performance patterns, through which different learning approaches taken by students with different performance increments were identified. Those patterns might also inform the instructor with useful insights for intervention purposes. Besides, under the constructivist point of view, helping students to learn how to attempt problems and find solutions (in this case, through the patterns) is important for encouraging reflexivity [34].

As understood from Figure 2, eight learning performance patterns were identified in relation to the respective increment categories. Specifically, three learning patterns were associated with the P3 increment category (DR ⇒ A; DR ⇒ A ⇒ DW; DR ⇒ DR ⇒ DR) and P4 (DR ⇒ A ⇒ DW; DR ⇒ DR ⇒ CR ⇒ OF; DR ⇒ DR ⇒ DR), whereas only two learning patterns were linked to the P5 increment category (DR ⇒ CR; DR ⇒ CR ⇒ OF). Among all variables, DR was noted as the most influential attribute that differentiated all three learning increment categories. Although not all types of reflective thinking and feedback emerged in the learning performance patterns, it was evident that those patterns suggest a clear nexus between an increase in learning performance and students' reflective thinking and feedback ability. In other words, as the increment category improved, so did their reflective thinking and feedback levels, and vice versa for lower increment category (see Table 3).

Accordingly, for the P3 increment, the presence of DW, DR and A predictors, and the combination among them (DR ⇒ A ⇒ DW (< 36 times); DR ⇒ A (≥ 36 times)) were attributed to lower performance increments. It is perceived that the lower performing students may tend to respond to the reasoned explanation of what had been discussed (DR) by merely (1) generating surface questions (A), and (2) stating the idea/solution/basic knowledge to the problem descriptively from the presented factual information without further elaboration (DW). This finding is in line with [35] study, which found that students whose reflective thinking levels were low had poor performance with regard to learning compared to those with high reflective thinking levels. Among the possible explanations for this is that this group of students, which can be labelled as "superficial thinkers", may be inclined to adopt a surface level of reflective thinking and feedback based on what is plainly visible to them at the time. As this study is about a technical course where the majority of the contents deal with step-by-step processes, it was expected that this type of surface description and question would be frequently used by all students (see Table 2) and hence would become the significant predictor for the P3 performance group. Additionally, based on the observation of the discussion threads, conversations that are supposed to be reflective can easily end after the students respond using the DW and A types of thinking and feedback. Though [17] acknowledged that descriptive writing is a starting point for students to shift to other levels of reflective thinking, students may struggle to achieve this if they are not being trained to lessen the spectrum of effortlessly agreeing with other people's opinions/criticisms. This can be done through questioning one's stance, as that might open the blind-spots in one's knowledge and reflective thinking.

The presence of an individualistic orientation was noted for one student in the P3 category, where the DR type of reflective thinking was repetitive and independent, meaning that it was not associated with other types of reflective thinking skills and feedback

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(DR ⇒ DR ⇒ DR). It also reached a certain degree of continuity and happened quite frequently (DR ≥ 329.5 times). Although the DR type of reflective thinking was commonly used and easily mastered without requiring any trigger from specific questions/support due to its low level reflective thinking condition [17], this pattern might not reflect normal learning progress; moreover, not many students practiced these learning patterns (P3 = 1 student; P4 = 1 student). The difference between students in P3 and P4 is just how frequent they were in repetitively projecting the DR level in reflection (P3 = DR < 329.5 times; P4 = DR ≥ 329.5 times). For future intervention purposes, it is the role of the instructor to break this kind of repetitive chain by asking more questions to model its usage, and to judge whether that can raise students' reflective thinking skills and feedback to a higher level.

Furthermore, the instructor should also encourage students to try to balance the usage of other reflective thinking and feedback types instead of excessively engaging in the same level of reflection and feedback most of the time. In fact, this is what differentiates students who belong to the P3 category from those in P4 and P5. It was noted that students in the P4 and P5 categories were engaged in a range of different reflective thinking and feedback levels, and these groups of students can be labelled as "highly engaged high-performance individuals" as they have benefitted from the five predictors: that is A, DW, DR, OF, and CR. Although the hinge is still on the use of DR, the CR and OF were also established as strong predictors of the success of students' learning performance. Besides, this specific pattern (DR ⇒ DR ⇒ CR ⇒ OF), which corresponds to three P4 students and two P5 students, only differs in terms of the frequency of usage of these variables during the reflection process. The more the students were engaged in CR (≥ 2.5 times) and OF (≥ 2 times), the higher the learning performance that was achieved, and vice versa. This also implies that excellent performance was associated with increased usage of high-level feedback and reflective thinking. Besides, [36, 37] also suggest that students who were more critical committed fewer errors compared to non-reflectors.

Additionally, the two students in the P5 category who seemed to struggle to achieve high performance directly from engaging in the CR level (use of diverse perspectives/contexts), as compared to other P5 students, appeared to try to evaluate their comprehension by questioning the situations experienced by them using the OF type of feedback (which is a broad opinion-oriented question) to rationalise the critical information/knowledge that they had just experienced or had presented to them. This is a plausible action, since such questioning seems to allow them to engage in exploration and thus liberate their thinking to a new level and lead to greater learning performance.

In addition to learning performance patterns, further assessment of the predictive model's performance was critical to the development of a quality model for intervention. From the confusion matrix results (which were generated from the three-fold cross validation), the overall performance of this predictive model was moderate (recall = 50%, precision = 50%) and acceptable (ROC = 61%). This result is not comparable with the literature, since no other studies have used the exact same predictors as this study, which is solely based on discussion analysis messages (in this case, reflective thinking skills and feedback types), hence this is a new contribution to the body of knowledge. The strength of the specific classes of learning performance, especially for P3 (40%) and P4 (33%), could cause harm for future intervention. This is because the small recall success rates for the P3 and P4 categories indicate that many students who should belong to these two groups actually belong to the other performance group, namely P5 (see Figure 3). The drawback of this situation is that these misclassified students are at risk of not receiving the correct reflective thinking and feedback intervention and there are also higher chances that they will be ignored by the instructor, since they are wrongly predicted to have better learning performance. Meanwhile, P5 students who are incorrectly classified as P3 and P4 will receive more intervention, since they are predicted to have lower performance. This can be considered as wasted effort, because in reality they do not need such intervention to excel because they are excellent enough, although it might be helpful for extra reflective thinking and feedback training.

Based on the data available in Table 2 and Figure 3, it would be easy to track down these misclassified students (i.e. S2, S7, S8, S9, S10, S12, S13, S14, & S17) in order to flag them for future intervention. Nevertheless, careful examination of these data did not help much in revealing clear explanations as to what causes the confusion, because the frequency data is too dispersed to define the boundaries across the reflective thinking and feedback level dataset. Moreover, the predictive model only relies on the messages expressed in the

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blogging environment to inform about the potentially struggling students' thinking and feedback behavioural patterns. Furthermore, this prediction model is limited in the sense that it was generated based on a semester aggregated dataset rather than on weekly data, hence, it is hard to uncover the possible causes if we do not have the specific week's predictive model. This also explains why many researchers are now looking to establish predictive models that are based on week-by-week data for efficient intervention purposes (see [38, 39]).

While there are many explanations that could clarify this misclassification problem, we postulate, that it could be due to the implication of a misfit between the format/scope of the test itself and the reflection activities in the blogging environment, where the former focuses more on knowledge acquisition and the latter on knowledge processing. This is because, during the blogging activities, there is a possibility that some of the misclassified students will copy and paste information from the internet or peers (regardless of whether they really understand it or not) and simply use it as their stand/opinion to discuss the cases/problems in the instructor's/peers' blogs. Therefore, they were easily labelled as individuals who used high levels of reflective thinking and feedback types if the copied information happened to be at high level. Note that during the codifying process, especially for the reflective thinking aspect, the instructor did not take into account whether the responses/statements/answers given by the students were correct or not. Rather, the focus was more on whether they displayed certain types of thinking and feedback. When this happened, it might have contradicted their actual performance levels during the post-test and hence reflected on the misclassification of output. Although the instructor told students to acknowledge their sources of information, only a few students adhered to this requirement, and did so infrequently.

For learning performance patterns to be practical, they can be programmed and embedded in the blogging environment in widget/plugin form. EnquiryBlogger is an example of a learning analytics plugin to track and support learners' awareness and reflection using blogs [40]. Additionally, the Other Sensors recommendation system provides students with recommendation based on their post behaviour [41]. Authors [41] also found that by interacting with the recommender system, the percentage of interaction increased up to 83.3%. This kind of intelligent recommender has been implemented in many previous works related to learning analytics for personalised learning, as reviewed by [42]. The eight empirical learning performance patterns which generated in the present study work based on the frequency benchmark value associated with each pattern. If the students are off-track from the benchmark value, they will be red-flagged and notified by the recommender system to adjust their approach and strategies taken in reflecting and giving feedback until they are back on track: i.e. until they show better learning performance. Besides that, instructors may also intervene to follow-up with the affected students on the problems that they face, and hence can make informed decisions/interventions. The instructor can undertake extra validation in the form of surveys or even careful analysis of the individual's reflection/discussion on learning tasks' content to double-check whether the student is really at risk or not, and thus can further advance the intervention design.

5. CONCLUSION

The conclusions of this research were reached by employing a systematic methodology that integrated content analysis, quantitative conversion, and data mining techniques. Reflective thinking skills and types of feedback were content-analysed using established coding schemes ([17] and [30]), and the data were converted into quantitative forms through descriptive statistics. Performance tests were scored and transformed into levels of increment as detailed in source [31]. Eight learning performance patterns were identified in relation to the respective increment categories, highlighting the notion that there is no one-size-fits-all concept for reflection in the learning process. Among all variables, DR was acknowledged as the most influential attribute that differentiated all three learning increment categories. Although not all types of reflective thinking and feedback emerged in the learning performance patterns, it was evident that those patterns suggest a clear nexus between an increase in learning performance and students' reflective thinking and feedback ability.

By enhancing the comprehension of reflective thinking skills and the feedback approach, this study underscores that educational blogging can be utilised to improve the practice of reflection and promote the development of reflective thinking skills. Reflective thinking and feedback are crucial factors in enhancing students' learning performance, as evidenced by the overall increase in learning performance levels, where all students scored slightly above average (P3, P4, P5), and none fell into the low achievers' category (P1, P2). These learning performance patterns further highlight the potential advantage of a recommender system for future adoption, which can assist in developing a more systematic reflective thinking process through a personalised approach by identifying the possible at-risk students based on the frequency value gained. With the available ten predictor variables and one dependent class, this predictive model stood at the 61% ROC efficiency for its forecasting goal, indicating that while the model is acceptable for dealing with thinking and interaction behaviour data, further work is needed to improve its efficiency.

The purpose of this study was to address the significant gaps in assessing reflective thinking skills by leveraging advanced data mining techniques, particularly decision tree algorithms, to analyse and predict learning performance patterns. Reflective thinking is crucial not only for academic success but also for personal and professional growth, making it a vital area of research. Traditional methods of evaluating reflective thinking, such as self-reported surveys and summative assessments, often fall short in capturing the depth and nuances of students' reflective processes. This study aimed to fill that gap by offering a more comprehensive and accurate analysis through data mining, providing valuable insights into how different types of reflective thinking and feedback impact learning outcomes.

Using decision tree techniques, this research was able to reveal detailed patterns of learning performance based on reflective thinking skills and types of feedback in an educational blogging environment. Decision trees are particularly valuable because they generate clear, interpretable rules that can be easily understood by educators, even those who are not experts in data mining. This makes decision trees a practical tool for translating complex data insights into actionable strategies for teaching and learning. The findings of this study offer a data-driven approach to improving educational outcomes by enabling educators to design more effective pedagogical strategies and targeted interventions. This research bridges the gap between traditional assessment methods and the need for more robust, data-driven evaluations, significantly contributing to the field of education by enhancing the overall learning experience and equipping students with critical 21st-century skills.

6. IMPLICATIONS OF THE FINDINGS

The analysis of learning performance patterns from textual data in the blog environment and performance test data provides insights into the types of feedback that promote the development of reflective thinking skills. It also reveals the connection between these skills and students' learning performance. This knowledge can greatly enhance instructors' ability to make informed decisions and implement effective interventions in course design, delivery, and review. By understanding which data truly influence reflection activity in 21st century learning, instructors can make meaningful changes and improvements. This study also addressing the importance of how educational cultural change towards data-driven decision-making affects learning and teaching aspect. The generated learning performance patterns through decision tree mining technique have in turn extended the prior conceptual of reflective thinking skills by [17] and feedback framework by [30] by discovered how feedback sequenced, or manipulated to provoke or inhibit reflective thinking skills since these two concepts have previously been seen as separate entities.

7. LIMITATIONS OF THE STUDIES AND RECOMMENDATION FOR FUTURE RESEARCH

In this study, we examined a group of 18 postgraduate students who were enrolled in the Authoring System course as part of their Master's in educational technology program. However, it is important to note that our findings are limited to this specific group and course. In order to make more widespread conclusions about the impact of reflective thinking and feedback, future research should include a broader range of courses from various disciplines. Next. this study is also heavily reliant on the students' blogging interaction data, specifically on reflective thinking and feedback variables as the main predictors for classifying and detecting students who are at academic risk. Although decent performance of prediction outcomes was achieved from this data, being restricted to only one source of data might cause the findings to be interpreted and reasoned from only one perspective. In future, demographic data can be collected to complement the findings on reflection data and predictive learning performance patterns. The medium results for confusion matrix performance also suggest the need to further employ other learners and learning characteristics that may

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exist in different data sources in future validation works. Finally, the interpretation of the data collected is limited due to time constraints. In this study, the prediction of learning performance was based on a semester aggregated dataset instead of weekly data. As a result, it is difficult to identify the specific causes of certain behavioural performance. This limitation hinders the ability to intervene effectively. If it had been possible to address all the limitations listed in this study, it could have provided a deeper understanding of the reasons behind students' thinking and performance patterns. Despite these shortcomings, this study does offer some guidance on integrating working feedback to enhance reflective thinking skills through educational blogging environments.

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REFERENCES

[1] L. Mortari, "Reflectivity in research practice: An overview of different perspectives", International Journal of Qualitative Methods, vol. 14, no. 5, pp. 1-9, 2015. https://doi.org/10.1177/1609406915618045

[2] L. Postma, A. S. Blignaut, K. Swan, and E. A. Sutinen, "Reflections on the use of grounded theory to uncover patterns of exclusion in an online discussion forum at an institution of higher education"; International Journal of Qualitative Methods, vol. 12, no. 1, pp. 529-550, 2013. https://doi.org/10.1177/160940691301200128

[3] P. Slepcevic-Zach, and M. Stock, "ePortfolio as a tool for reflection and self-reflection", Reflective Practice, vol. 19, no. 3, pp. 291-307, 2018. https://doi.org/10.1080/14623943.2018.1437399

[4] V. Savicki, and M. V. Price, "Components of reflection: A longitudinal analysis of study abroad student blog posts", Frontiers: The Interdisciplinary Journal of Study Abroad, vol. 29, no. 2, pp. 51-62, 2017. https://doi.org/10.36366/frontiers.v29i2.392

[5] S. Benko, M. Guise, C. Earl, and W. Gill, "More than social media: using Twitter with preservice teachers as a means of reflection and engagement in communities of practice", Contemporary Issues in Technology and Teacher Education, vol. 16, no. 1, pp. 1-21, 2016. https://www.learntechlib.org/primary/p/151579/

[6] S. Hamid, J. Waycott, S. Kurnia, S. and S. Chang, "Understanding students' perceptions of the benefits of online social networking use for teaching and learning", The Internet and Higher Education, vol. 26, pp. 1-9, 2015. https://doi.org/10.1016/j.iheduc.2015.02.004

[7] C. Epp, G. Akcayir, and K. Phirangee, "Think twice: exploring the effect of reflective practices with peer review on reflective writing and writing quality in computer-science education", Reflective Practice, vol. 20, no. 4, pp. 533-547, 2019. https://doi.org/10.1080/14623943.2019.1642189

[8] H. Gresch, M. Hasselhorn, and S. Bögeholz, "Enhancing decision-making in STSE education by inducing reflection and self-regulated learning", Research in Science Education, vol. 47, pp. 95-118, 2017. https://doi.org/10.1007/s11165-015-9491-9

[9] S. Maniyan, R. Ghousi, and A. Haeri, "Data mining-based decision support system for educational decision makers: Extracting rules to enhance academic efficiency", Computers and Education: Artificial Intelligence, vol. 6, no. 100242, pp. 1-13, 2024. https://doi.org/10.1016/j.caeai.2024.100242

[10] J. Niyogisubizo, L. Liao, E. Nziyumva, E. Murwanashyaka, and P.C. Nshimyumukiza, "Predicting student's dropout in university classes using two-layer ensemble machine learning approach: A novel stacked generalization", Computers and Education: Artificial Intelligence, vol. 3, no. 100066, pp. 1-12, 2022. https://doi.org/10.1016/j.caeai.2022.100066

[11] D. Kember, "To control or not to control: the question of whether experimental designs are appropriate for evaluating teaching innovations in higher education", Assessment & Evaluation in Higher Education, vol. 28, no. 1, pp. 89-101, 2003. https://doi.org/10.1080/02602930301684

[12] M. Y. Feilzer, "Doing mixed methods research pragmatically: Implications for the rediscovery of pragmatism as a research paradigm", Journal of Mixed Methods Research, vol. 4, no. 1, pp. 6-16, 2010. https://doi.org/10.1177/1558689809349691

[13] O. Cimen, and M. Cakmak, "The effect of feedback on preservice teachers' motivation and reflective thinking", Ilkogretim

Online, vol. 19, no. 2, pp. 932-943, 2020. doi:10.17051/ilkonline.2020.695828

[14] Y. C. Hong, and I. Choi, "Assessing reflective thinking in solving design problems: The development of a questionnaire", British Journal of Educational Technology, vol. 46, no. 4, pp. 848-863, 2015. https://doi.org/10.1111/bjet.12181

[15] G. Osman, and J. H. L. Koh, "Understanding management students' reflective practice through blogging", The Internet and Higher Education, vol. 16, pp. 23-31, 2013. https://doi.org/10.1016/j.iheduc.2012.07.001

[16] A. Salido, and D. Dasari, "The analysis of students' reflective thinking ability viewed by students' mathematical ability at senior high school", Journal of Physics: Conference Series, vol. 1157, no. 2, pp. 022121, 2019. DOI 10.1088/1742-6596/1157/2/022121

[17] N. Hatton, and D. Smith, "Reflection in teacher education: towards definition and implementation", Teaching and Teacher Education, vol. 11, no. 1, pp. 33-49, 1995. https://doi.org/10.1016/0742-051X(94)00012-U

[18] G. M. Sparks-Langer, and A. B. Colton, "Synthesis of research on teachers' reflective thinking", Educational Leadership, vol. 48, no. 6, pp. 37-44, 1991.

[19] H. S. Wald, J. M. Borkan, J. S. Taylor, D. Anthony, and S. P. Reis, "Fostering and evaluating reflective capacity in medical education: developing the REFLECT rubric for assessing reflective writing," Academic Medicine, vol. 87, no. 1, pp. 41-50, 2012. https://doi.org/10.1097/acm.0b013e31823b55fa

[20] S. C. Choy, J. S. C. Yim, and P. L. Tan, "Reflective thinking among preservice teachers: a Malaysian perspective", Issues in Educational Research, vol. 27, no. 2, pp. 234, 2017.

[21] Y. M. H. Al-dheleai, "A framework of social-based learning interaction through social networking tool", (Doctoral dissertation). Universiti Teknologi Malaysia, Johor, Malaysia, 2017.

[22] A. F. ElGamal, "An educational data mining model for predicting student performance in programming course", International Journal of Computer Applications, vol. 70, no. 17, pp. 22-28, 2013.

[23] S. K. Mohamad, Z. Tasir, J. Harun, and N. A. Shukor, "Pattern of reflection in learning authoring system through blogging", Computers & Education, vol. 69, pp. 356-368, 2013. https://doi.org/10.1016/j.compedu.2013.07.031

[24] N. M. Norwawi, S. F. Abdusalam, C. F. Hibadullah, and B. M. Shuaibu, "Classification of students' performance in computer programming course according to learning style", In 2009 2nd Conference on Data Mining and Optimization (pp. 37-41). Selangor, Malaysia, 2009. https://doi.org/10.1109/DMO.2009.5341912

[25] R. S. Shaw, "A study of the relationships among learning styles, participation types, and performance in programming language learning supported by online forums", Computers & Education, vol. 58, no.1, pp. 111-120, 2012. https://doi.org/10.1016/j.compedu.2011.08.013

[26] S.K. Mohamad, and Z. Tasir, "Educational data mining: A review", Procedia-Social and Behavioral Sciences, vol. 97, pp. 320-324, 2013. doi: 10.1016/j.sbspro.2013.10.240

[27] S. Joksimovic, D. Gasevic, T. M. Loughin, V. Kovanovic, and M. Hatala, "Learning at distance: effects of interaction traces on academic achievement", Computers & Education, vol. 87, pp. 204-217, 2015. https://doi.org/10.1016/j.compedu.2015.07.002

[28] H. Kyngas, S. Elo, T. Polkki, M. Kaariainen, and O. Kanste, "Content analysis in Finnish nursing research", Nursing Science, vol. 23, no. 2, pp. 138-148, 2011.

[29] S.K. Mohamad, and Z. Tasir, "Exploring how feedback through questioning may influence reflective thinking skills based on association rules mining technique", Thinking Skills and Creativity, vol. 47, pp. 101231, 2023. https://doi.org/10.1016/j.tsc.2023.101231

[30] M. E. Bradley, L. R. Thom, J. Hayes, and C. Hay, "Ask and you will receive: how question type influences quantity and quality of online discussions", British Journal of Educational Technology, vol. 39, no. 5, pp. 888-900, 2008. https://doi.org/10.1111/j.1467-8535.2007.00804.x

[31] S.K. Mohamad, Z. Tasir, and I. J. Yusof, "The Effect of Reflection Through Educational Blogging on Students' Learning Performance", Journal of Information Technology Education: Research, vol. 22, pp. 429-459, 2023. https://doi.org/10.28945/5209

[32] I. H. Witten, E. Frank, and M. A. Hall, "Data Mining. Practical Machine Learning Tools and Techniques", (3rd Ed). San Francisco: Morgan Kaufmann, 2011.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[33] S. Yang, and G. Berdine, "The receiver operating characteristic (ROC) curve", The Southwest Respiratory and Critical Care Chronicles, vol. 19, pp. 34-36, 2017.

[34] L. Xiao, S. Clark, M. B. Rosson, and J. M. Carroll, "Promoting reflective thinking in collaborative learning activities", In 2008 Eighth IEEE International Conference on Advanced Learning Technologies (pp. 709-711). Cantabria, Spain, 2008. https://doi.org/10.1109/ICALT.2008.280

[35] Y. Kim, "Cultivating reflective thinking: the effects of a reflective thinking tool on learners' learning performance and metacognitive awareness in the context of on-line learning", (Doctoral dissertation, The Pennsylvania State University, United States of America).

[36] I. Lindh, and S. Thorgren, "Critical event recognition: an extended view of reflective learning", Management Learning, vol. 47, no. 5, pp. 525-542, 2016. https://doi.org/10.1177/1350507615618600

[37] K. M. Roessger, "The effects of reflective activities on skill adaptation in a work-related instrumental learning setting", Adult Education Quarterly, vol. 64, no. 4, pp. 323-344, 2014. https://doi.org/10.1177/0741713614539992

[38] A. S. S. Albassam, "Detecting students at-risk using learning analytics", (Doctoral dissertation), University of Adelaide, Australia, 2019.

[39] S. Jiang, A. Williams, K. Schenke, M. Warschauer, and D. O'dowd, "Predicting MOOC performance with week 1 behavior", In Proceedings of the 7th International Conference on Educational Data Mining (273-275), London, UK, 2014.

[40] R. Ferguson, S. B. Shum, and R. D. Crick, "EnquiryBlogger: using widgets to support awareness and reflection in a PLE setting", In 1st Workshop on Awareness and Reflection in Personal Learning Environments. In conjunction with the PLE Conference (pp. 28-33). Southampton, UK, 2011.

[41] O. Holanda, R. Ferreira, E. Costa, I. I. Bittencourt, J. Melo, M. Peixoto, and W. Tiengo, "Educational resources recommendation system based on agents and semantic web for helping students in a virtual learning environment", International Journal of Web Based Communities, vol. 8, no. 3, pp. 333-353, 2012. https://doi.org/10.1504/IJWBC.2012.048056

[42] R, Bodily, R., and K. Verbert, "Review of research on student-facing learning analytics dashboards and educational recommender systems", IEEE Transactions on Learning Technologies, vol. 10, no. 4, pp. 405-418, 2017. https://doi.org/10.1109/TLT.2017.2740172