Leveraging Expert Insight to Define Multifaceted Student Engagement Levels in Higher Education Online Learning Using a Belief Rule-Based Framework

Chong Ke Ting [1*], Noraini binti Ibrahim [2], Sharin Hazlin binti Huspi [3] and Wan Mohd Nasir bin Wan Kadir [4]
[1, 2, 3, 4] Faculty of Computing, Universiti Teknologi Malaysia, Skudai, Malaysia.
*keting-1997@graduate.my

Received: 9 September 2024
Received in revised form: 2 December 2024
Accepted: 15 December 2024
Published: 24 December 2024

ABSTRACT

Educational Data Mining (EDM) is an interdisciplinary field that aims to address education issues by using vast amounts of educational data. Meanwhile, the Ministry of Education Malaysia desires to promote online education to raise teaching and learning standards and increase efficiency. Therefore, it is crucial to increase student engagement for improving the teaching and learning process, institutional effectiveness, as well as EDM research. Although student engagement is getting more important with the growth of online learning, there is no clear consensus to identify and differentiate student engagement into distinct levels. Moreover, student engagement is a multidimensional construct that is made up of behavioural, cognitive, emotional, and social engagement. The purpose of this paper is to collect and analyse the professional view and opinion of three educational experts on student engagement so that they can be utilised to develop the rules that will distinguish between levels by implementing a belief rule-based system. According to the experts' findings, it is critical for the lecturer to identify students who are having problems engaging with online learning early on so that they can be helped to engage more fully and, as a result, do better academically. Besides, prediction of student engagement level depends on multiple dimensions, while statistical methods like mean, median, and quartile can be utilised to translate numerical data into verbal terms. Lastly, the best time to extract data for the student engagement level prediction is the week before mid-semester break.

Keywords
Educational Data Mining, student engagement, online learning, Learning Management System, rule construction.

Introduction

Educational Data Mining (EDM) is an interdisciplinary field made up of pedagogy, psychology, computer science, machine learning, and statistics. The goal of EDM is to discover the hidden patterns in massive educational datasets due to the development of online learning (Luo & Wang, 2020). It tackles educational-related concerns, which include decision-making, course and online educational resource improvement, and provides helpful insight into student engagement and academic success (Hasan et al., 2020; Luo & Wang, 2020). More importantly, the critical elements that affect student engagement need to be identified at an earlier stage so that the instructors can make informed decisions on time to improve student achievement and prevent them from dropping out (Hooshyar & Yang, 2021).

The accurate identification and prediction of student engagement failure is important for enhancing the teaching and learning process, research, and institutional efficiency in EDM (Altaf et al., 2019; Fredricks et al., 2004). The Ministry of Education Malaysia considers online learning (OL) as a key component of higher education, focussing on outcome-based education (Ministry of Education Malaysia, 2015). Therefore, almost all the universities and higher education in Malaysia are implementing blended learning due to its potential in improving the teaching and learning process (Ibrahim & Ismail, 2021). Furthermore, according to Garrison et al. (2010), the Community of Inquiry framework is an important guideline for the design of OL courses, where cognitive, social, and teaching presence are essential for OL implementation. The successful OL implementation highly relies on active student engagement, encompassing behavioural, cognitive, emotional, and social engagement (Fredricks et al., 2004). On the other hand, it offers all the students with an enriched learning experience that is flexible, accessible, interactive, student-centred, self-paced, and multifaceted (Ibrahim & Ismail, 2021).

The Ministry of Education Malaysia aims to encourage online learning for improving teaching and learning quality while boosting the cost effectiveness for education implementation (Ministry of Education Malaysia, 2015). Moreover, the global education system has changed towards online learning during the COVID-19 pandemic due to the restrictions on physical interaction (Marcus et al., 2024). However, attrition and student dropouts are still critical issues that need to be addressed during the implementation of online learning to ensure the successful course completion (Marcus et al., 2024; Tan et al., 2021). Moodle platform is the famous learning management system that implemented for the student to get notification, access course content and extra resources, do homework and assignments, take quizzes and test or have online discussions in a forum (Ibrahim & Ismail, 2021). Even though student engagement in online environments is crucial for ensuring student achievement, it is challenging to evaluate and predict the student engagement levels (Ayouni et al., 2021). The study on student engagement can give instructors insightful data on how students are learning, which allows them to pinpoint the students' learning gaps and enhance students' learning opportunities (Orji & Vassileva, 2020). Unfortunately, the instructors are struggling to obtain the timely feedback on student engagement due to the inadequate information on students' LMS usage (Nguyen et al., 2018). Furthermore, classification machine learning approaches that are useful for classifying and predicting data are rarely implemented to predict student engagement level. This mainly due to lack of clear consensus to differentiate and label student engagement into distinct levels that can be used to build the training data for the classification algorithm.

Before the implementation of classification techniques, a labelling strategy must be developed to label the data into different levels because there is no gold standard to measure student engagement levels. Manual labelling and cluster labelling are the two famous approaches implemented in EDM to label data. However, the implementation of cluster labelling simply relies on the general observation of the collected and does not consider the educational psychometrically (Khan & Colella, 2022; Mandinach & Beth, 2021). Even though human knowledge is playing important roles in facilitating the current and future of educational advancement, the process of student engagement level manual labelling by human educational experts to ensure the excellent quality of the labels is time-consuming, expensive, and requires a large amount of labour (Khan & Colella, 2022).

Therefore, a belief-rule-based (BRB) framework is proposed to categorise and label student engagement into distinct levels. The conventional rule-based system tackles the real-world problems that require human intelligence by using human expert knowledge. Rule-based systems can identify and maintain the human experience even better than human experts, and they provide faster results (Abraham, 2005). Furthermore, rule-based approaches are expressive and transparent models that can be read and maintained by teams from different backgrounds and immediately transfer the domain knowledge to rules (Waltl et al., 2018). As compared to conventional rule-based systems, BRB is designed to handle the uncertainty about the knowledge in the natural world (Yang et al., 2006). BRB can handle quantitative and qualitative comprehension and also fuzzy and probabilistic uncertainty (Fang et al., 2020).

In order to build a belief-rule-based system to differentiate and label the student engagement into distinct levels, the human expert knowledge needs to be collected and utilized. Therefore, this paper will cover the interview with three educational human experts to gather their knowledge for rule construction. Initially, the introductory part discusses a quick summary of the research. Subsequently, the literature review section presents the research backdrop, and the research methods section discusses the interview approach used in this study. The result and discussion portion analyse the outcome of the expert interview. Lastly, the conclusion talks about this work's overall scope as well as future directions.

Literature Review

In the digitalisation era, the rapidly evolving of OL implementation in higher education has made understanding and enhancing student engagement a paramount concern for educators and institutions alike. As the shift towards online learning modalities continues to accelerate, the ability to predict student engagement levels with precision and accuracy has emerged as a critical area of research and innovation (Altaf et al., 2019; Zainol et al., 2021). Sashank et al. (2023) mentioned that it is challenging to evaluate and identify students' engagement during OL. However, in online learning, ensuring student engagement and knowledge retention are crucial to successful course completion (Marcus et al., 2024). Since online learning are developing rapidly especially during COVID-19 pandemic, learning analytics became an important tool to access student's learning (Bunsu & Abd Halim, 2023). The poor technological infrastructure and heavy workload are the major challenges hindering the optimal utilization of blended learning (Ibrahim & Ismail, 2021). According to Saleh et al. (2021) some students are facing the issues during OL which include limitation of online learning tools, instrument, and excellent internet coverage. This is because some of the students are coming from poor family which is categorized as B40 family income. These issues become a challenge for the student to achieve a successful learning outcome (Saleh et al., 2021). Therefore, it is necessary to create a labelling method for student engagement level. The measure of student engagement is not properly and sufficiently defined by the researchers (Benabbes et al., 2023).

Users' interaction, which is form of digital footprints that can be processed and identified into the hidden pattern (Bunsu & Abd Halim, 2023). According to Al-Ashoor and Abdullah (2022) and Daniel (2019), it is important to overcome the challenges of querying and processing enormous educational datasets quickly and accurately. As compared to subjective methods which include surveys and questionnaire, study on digital footprints provide deeper insight into students' learning behaviour and assist learning institution based on data-informed decision making that related to students' learning issues (Bunsu & Abd Halim, 2023). However, there are limited numbers of scientists who are familiar with or interested in working with the dataset from the educational domain (Daniel, 2019). Due to the lack of professional personnel to provide technical enumeration for the dataset, the mishandling of the result or dataset led to the inadequate data processing that consequently caused the educational dataset to be unable to provide meaningful information and educational planning (Oladiji, 2018). Furthermore, human labelling might cause issues of observer bias based on the personal opinions of experts (Khan & Colella, 2022).

Student engagement is a multidimensional construct that is made up of behavioural, cognitive, emotional, and social dimensions (Ayouni et al., 2021; Binali et al., 2021; Fredricks et al., 2004; Gledson et al., 2021). It is necessary to measure the student engagement across all four dimensions since it can provide a more thorough picture of student engagement behaviour during online learning (Fredricks et al., 2004). This is because, according to Xu et al. (2021), student participation in OL encompasses more than just following instructions and finishing assignments. It also includes cognitive effort, emotional fulfilment from participating in learning behaviours, and peer interaction. However, there is no standardised attribute listed to measure student engagement, and there is limited research that studies the role of the different attributes in enhancing student engagement predictions, while published labelled datasets for student engagement are also limited. Different from behavioural engagement, cognitive engagement is the students' psychological investment during the learning process to comprehend the material, and achieve the highest level of understanding (Marcus et al., 2024).

Based on the research done by Sashank et al. (2023) and Ayouni et al. (2021), student engagement is divided into three different levels, which are actively engaged (AE), passively engaged (PE), and not engaged (NE), firstly based on the course grade that was obtained by the students. The dataset that used the research of Sashank et al. (2023) and Ayouni et al. (2021) is made up of 100 and 348 samples, respectively. Then, the labelled data is checked manually one-by-one by the lecturers for verification and approval. Then, the labelled data are utilised to train the classification model, which includes Decision Tree, Random Forest, Logistic Regression, and Long-Short Term Memory in the research of Sashank et al. (2023). Besides, Decision Tree, Support Vector Machine and Artificial Neural Network are implemented to predict the student engagement level in the research of Ayouni et al. (2021). Even though the manual verification process is a good practice to ensure the quality of the data labelling, it is time-consuming and requires large amounts of labour when the large dataset needs to be labelled (Khan & Colella, 2022).

Furthermore, Benabbes et al. (2023) utilised the K-means, Agglomerative, Birch and DBSCAN clustering approaches to cluster the general data distribution of data collected from the learning management system. Among the four different clustering approaches, the K-means clustering approach performs the best with $k = 3$. Therefore, the student engagement is labelled as AE, PE, and NE, respectively. The labelled data is then implemented to train and predict the student engagement by the J48, k-Nearest Neighbours, Bayes Net, Random Forest, Support Vector Machine, and Logit Boost models. However, cluster labelling only considers the aggregate observation of the collected data, ignoring the educational psychometric implications, which means the labelled data does not accurately reflect the psychometric measure used in education (Khan & Colella, 2022; Mandinach & Beth, 2021).

A conventional rule-based system that utilises the expertise of human experts to address real-life problems that require human intelligence. Rule-based systems have proven to be a highly successful and efficient method for accurately labelling the samples with high quality, subsequently solving the challenging issue of time-consuming sample labelling

(Waltl et al., 2018). However, conventional rule-based systems are unable to handle the uncertainty that occurs in real -world situations (Cihan, 2020). Therefore, the BRB is created to overcome the limitations of conventional rule-based systems for capturing the different uncertainties, which include the incompleteness, inconsistency, imprecision, and ambiguity in the real-world situation (Jamil et al., 2019).

As a conclusion, student engagement is getting more important and concerned by the lecturers in higher education, especially with the growth of online learning. However, the research that has been done for the student engagement level prediction remains limited. This is mainly due to the lack of clear consensus to label the student engagement into distinct levels. Moreover, the current existing labelling approach, which includes cluster and manual human labelling, is facing some limitations. Therefore, the BRB system, which can systematically and automatically label the data while considering human expert knowledge, can be used to label student engagement. Thus, educational experts' knowledge needs to be collected to build up the rules for the BRB system to classify the student engagement into distinct levels.

Research Methodology

The overall structure of the research is mostly made up of four phases, and this paper focuses on phase 2, which is the process of interviewing experts to gather knowledge. In this study, the rule-building step is crucial for differing student engagement levels. Figure 1 shows the research's general organisational structure.

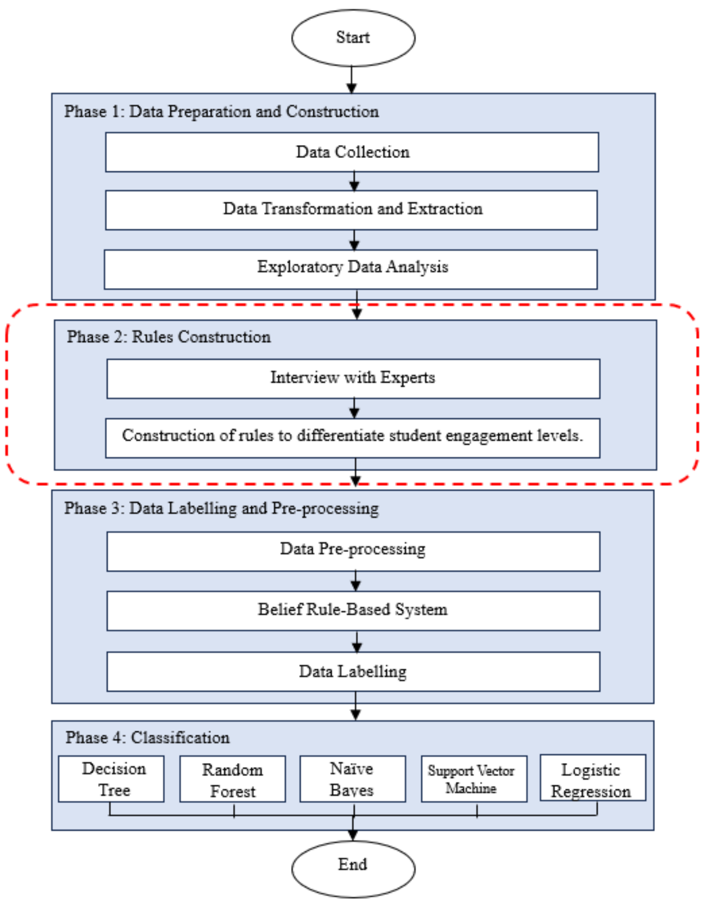

Figure 1. Overall Research Framework

Semi-structured interviews are implemented in this study to gather the knowledge from human experts to create the rules for distinguishing student engagement into different levels. The three experts are being questioned with a total of 11 questions to learn more about student engagement. Three experts are selected to collect the knowledge because, according to Khan and Colella (2022), most of the research that implemented expert annotation is inviting three experts to annotate the data. The interview questions are designed by referring to and modifying the questions from Usher and Hershkovitz (2022) based on their suitability for this research. Each expert's interview lasts about 45 minutes, and it is conducted separately for each expert. The educational expert group is made up of two associate professors and a senior lecturer from the School of Education in the Faculty of Social Science and Humanities at Universiti Teknologi Malaysia. Among the three experts, two of the interviews are conducted online using the Google Meet platform, while one interview is conducted in person at the expert's office as the expert's preferred medium. The questions that were asked in the interview are shown in Table 1.

Table 1 Interview Questions

No.	Question
Q1	How would you define student engagement?
Q2	In your opinion, do you believe that student engagement is a crucial aspect of implementing online learning?
Q3	In your view, do you think it is logical to categorize student engagement into behavioral, cognitive, emotional, and social dimensions?
Q4	What type of engagement is important to support student learning?
Q5	In your opinion, do you think that the interactions I have collected from learning management system log files are appropriate for measuring student engagement across various dimensions?
Q6	Which type of interaction is important to support the engagement?
Q7	I would like to know your opinion on how we can categorize student engagement into these distinct levels and determine the total number of levels involved.
Q8	During online learning, what are the typical obstacles or constraints you have faced when attempting to distinguish between different levels of student engagement?
Q9	So how can we divide each attribute value into different linguistic terms?
Q10	In your opinion, is the optimal time boundary that can be utilized for data extraction?
Q11	In your opinion, do you think that predicting student engagement levels would be beneficial for you and another lecturer as well?

The interview questions are made up of some general questions about the expert understanding of student engagement level, the importance of student engagement, and lastly, the knowledge on how to measure and differentiate student engagement level. The results obtained from the experts will be discussed in the following section.

Results and Discussion

In this section, the results that were collected from all three experts during the semi-structured interview will be analysed and discussed. The summarisation of the results obtained from each expert is demonstrated in Table 2.

Table 2 Result of Interview

No.	Expert 1	Expert 2	Expert 3
Q1	Behavioural, cognitive, and emotional engagement are the three components that reflect students are truly engaged in a specific learning environment.	Student interaction with the contents, instructors and the peers.	Student interaction with instructor, content, and peer for traditional engagements. However, an additional of student self-engagement and interface engagement for online learning.
Q2	Yes, it is very important for students to be engaged with online learning, but different students might engage differently. Although student's engagement is important, we also have to understand that students behave differently and they engage differently in online learning environment.	Student engagement is very important, especially if the course is fully online. So, if they don't engage well with the LMS, or online platform, they are not learning effectively, and we are actually hard to measure how well they are learning in fully online course.	Yes. Because when the student is lacking engagement, the objective of the lesson cannot be achieved.
Q3	It is acceptable to measure the student engagement based on the four dimensions, but it might be challenging on how to measure the emotional engagement.	It is best to categorise it into these four dimensions and we can improve it based on the dimensions.	It is acceptable to categorise the student engagement into all these four dimensions.
Q4	All four are important. But it is not necessarily has to be in balance. It depends on whether the aim of the online learning and learning outcome or on the online learning environment itself.	It is equally important because they are interrelated between each other. Besides, the measure for group assignment are concerned.	I think four of these is actually equally important and there are a completed cycle and dependent between each other
Q5	The overall interaction measurement is acceptable and it is rational to measure the emotional engagement based on lateness of submission.	The proposed interactions are acceptable. However, the chat and feedback might need to be included in the measure.	The collected data set is acceptable and there are representing quantitative data. Maybe can consider qualitative data such as chat the content in the forum.
Q6	All of these interactions are very important to measure to the extent of the engagement. But	All are equally important and are interrelated.	All the interactions are acceptable but maybe can consider achievement in the future.

	it depends on activity included in the course, more activity should be included.		
Q7	It is rational to divide student engagement into actively engage, passively engage and not engage.	It is rational to divide into active, passive and not engaged. However, the different between each level should be well defined, if not it will be very confusing.	No standard indicator to divide student engagement level. Can review other researcher approaches. Or use mean to divide into high and low or use quartile.
Q8	To identify students' engagement in a timely manner. An benchmark indicator to find out the student who are not engaged at earlier stage is needed instead of getting at the end of the semester.	Have to manually inform the student that the lecturer is actually viewing their interaction and notify them to access the material and etc.	To ensure the student are engaged week by week.
Q9	Use median to divide the values	Use quartile.	Use means and quartile
Q10	It is important to tell student which area that they are lacking and then which part that they should spend more time in online but might need to also include student performance. Tell the student how their engagement give impact on their academic performance	It is very important prediction of student engagement, and it can help the lecturer to utilize the prediction, So the prediction is important and then the awareness of lecturers on using the prediction data is also important as well.	Yes, it is very important especially now we are moving forward ODL program.
Q11	The week before mid-semester break will be the most suitable time period to extract the data.	Data before the mid-semester break will be good to predict the current semester. It might cause the loss of some interaction.	Before mid-sem break but maybe week by week to see

The result and feedback collected from all three experts are tabulated in Table 2. The results are discussing some general views on student engagement and how we can divide the student engagement into different levels. According to the findings, in the expert's opinion, student engagement is the interaction of the student with various mediums, which includes interaction with the content, instructors, and peers, as well as interaction with oneself and interface during online learning. Other than that, the expert mentioned that student interaction with the course content can be measured in various forms, which include behaviour, cognitive, emotional, and social engagement. This finding is similar with the research of Martin and Borup (2022), where student engagement can be categorized into the interactions with instructors, peers, and the learning interface. These three interactions are critical dimensions of the engagement that affect the behavioural, cognitive, and emotional aspects in online learning environment. The effective utilization of instructional technologies enhances these interactions, fostering a more engaging learning environment (Whiter, 2020). In addition, all three experts agree that student engagement is a critical component for online learning, especially for the fully online courses. This is because when a student is not engaged during online learning, they are unable to learn effectively to gain knowledge, and the lesson's aim is not met. However, since each student behaves differently during online learning, it is important for the lecturer to analyse and identify each student's behaviour when engaging in the learning environment. This finding emphasizes that tracking student engagement in different educational activities able to improve high-quality learning, and comprehensive analysis of student engagement can better prevent student from dropping out (Hussain et al., 2018).

In the meantime, the experts stated that it is reasonable to separate student engagement into four distinct dimensions: behavioural, cognitive, emotional, and social engagement. Many additional scholars, including Fredricks et al. (2004) and Binali et al. (2021), have identified and endorsed these elements of student engagement. Furthermore, experts agree that all four dimensions are vital and that the dimensions are interconnected and dependent on one another. However, it is not always distributed evenly and is determined by the learning outcome of the course design. Besides, the experts agree with the qualitative data collected in this research for the measurement of student engagement, and it is reasonable to measure emotional engagement by using lateness of submission, and all interactions collected from the learning management system play an equally important role in measuring the level of student engagement. Although the expert proposes that in the future, qualitative data such as chat and forum material be used as part of the measurement. However, due to the limited accessibility of the data and the utilisation of chat itself, chat is not included in the current research. The limited used on forum in LMS especially Moodle is often due to the non-intuitive and complex of the system, which include the forum features that discourage users from engaging fully with the features (Abdiansha & Utami, 2020). Most of the student are only utilizing a small fraction of LMS, primarily LMS is used to download materials rather than participating in discussion. In contrast, student prefer to utilized social media platforms like Facebook for discussions, since social media environments feel more informal and familiar (Gulieva, 2014).

According to experts, there is currently no conventional criteria for dividing student engagement level. As a result, the expert suggests that we evaluate alternative researcher methodologies or use a statistical method to divide the student engagement level in order to categorise it. The lack of gold standard for categorizing student engagement level is one of the critical issues that faced in the educational field especially online learning (Ayouni et al., 2021). Meanwhile, it is reasonable to categorise student engagement as actively, passively, or not engaged. The instructors propose using statistical approaches such as mean, median, and quartile to turn numerical attributes into verbal phrases such as high, medium, and low. Aside from that, most lecturers recommend gathering data the week before mid-semester break to predict student engagement levels, while taking the total semester data into account to predict the next semester output. Motz et al. (2019) mentioned that extracting logfiles before mid-semester break is suitable for predicting overall student engagement level since it captures early behavioural patterns, allowing instructors to identify at-risk students and implements timely intervention before academic outcomes occur, enhancing proactive support strategies.

Experts, on the other hand, are confronting certain difficulties in indicating student engagement during online learning. The issues are that the instructor must ensure that the students are engaged week after week, and they must manually check and communicate with the students. This is because student engagement is multifaceted construct that made up of behavioural, cognitive, and emotional dimensions, complicating its measure (Ma et al., 2022). Furthermore, lecturers are not provided with a standardised indicator to identify students who are having problems engaging in online learning at an earlier stage, but students who are not engaged can only be identified at the end of the semester, which is too late for intervention. All three experts agree that predicting student engagement levels is critical, especially as online distance learning (ODL) becomes increasingly popular. This finding emphasize the research of Wakjira and Bhattacharya (2022) where there is a need for real-time data visualization tools is critical, since many educators are overwhelmed by the volume of data generated, making it difficult to interpret the student engagement trend. The prediction output is significant since it serves as a guideline for the lecturer to notify the student where they are weak and need more time to develop, which can improve their academic achievement. However, as mentioned by Andrés et al. (2022), even though currently there are existing models on student engagement level prediction, while promising, still struggle with accuracy and require further refinement to be effective in diverse learning context.

Conclusion

In conclusion, experts believe that student engagement is a key component of successful online learning. Furthermore, it is critical to assess student engagement on all four dimensions, which include behavioural, cognitive, emotional, and social engagement. The study of student engagement from various perspectives can help the lecturer address the issues that are causing the students' lack of engagement and take appropriate action to guide the students with higher engagement and, as a result, improve the students' academic achievement. Moreover, it is appropriate to put students into three different levels: actively engaged, passively engaged, and not engaged. Statistical procedures such as median, mean, and quartile is appropriate for converting numerical data into verbal terms. Because one of the challenges in categorising student engagement levels is the lack of standard indicators, this research proposed a belief rule-based system that categorises and labels student engagement into different levels based on the expertise of the experts, which includes categorising data based on statistical techniques.

In the future, the data that was gathered from the learning management system should be labelled by utilising the belief rule-based system that was established based on the rules that were constructed using the knowledge gathered from the experts that were interviewed for this study. Aside from that, the data on the week before the midterm break should be retrieved so that a prediction can be made regarding the future result of the student participation at the end of the semester by implementing machine learning methods.

Acknowledgment

The authors thank the Universiti Teknologi Malaysia (UTM) for giving an opportunity and providing support to carry out this research. Besides, the author would like to extend sincere gratitude to the Pusat Pengurusan Data Universiti (PPDU) UTM and the FC Academic Office UTM for their invaluable support and prompt approval of student data for this research.

References

Abdiansha, & Utami, A. S. (2020). Analysis of Moodle Features to Build Moodle-Lite. Sriwijaya International Conference on Information Technology and Its Applications (SICONIAN 2019),

Abraham, A. (2005). Rule-Based expert systems. *Handbook of measuring system design*.

Al-Ashoor, A., & Abdullah, S. (2022). Examining Techniques to Solving Imbalanced Datasets in Educational Data Mining Systems. *Int. J. Comput*, *21*(2), 205-213.

Altaf, S., Soomro, W., & Rawi, M. I. M. (2019). *Student Performance Prediction using Multi-Layers Artificial Neural Networks: A Case Study on Educational Data Mining* Proceedings of the 2019 3rd International Conference on Information System and Data Mining, Houston, TX, USA. https://doi-org.ezproxy.utm.my/10.1145/3325917.3325919

Andrés, N., Gonzalez, O., & Freddy, T. (2022). Use of the Student Engagement as a Strategy to Optimize Online Education, Applying a Supervised Machine Learning Model Using Facial Recognition. International Conference on Applied Technologies,

Ayouni, S., Hajjej, F., Maddeh, M., & Al-Otaibi, S. (2021). A new ML-based approach to enhance student engagement in online environment. *PLOS ONE*, *16*(11), e0258788. https://doi.org/10.1371/journal.pone.0258788

Benabbes, K., Housni, K., Hmedna, B., Zellou, A., & El Mezouary, A. (2023). A new hybrid approach to detect and track learner's engagement in e-learning. *IEEE access*.

Binali, T., Tsai, C.-C., & Chang, H.-Y. (2021). University students' profiles of online learning and their relation to online metacognitive regulation and internet-specific epistemic justification. *Computers & Education*, *175*, 104315. https://doi.org/https://doi.org/10.1016/j.compedu.2021.104315

Bunsu, C., & Abd Halim, N. D. (2023). A review of trends and applications of learning analytics in higher education in the post-pandemic era. *Innovative Teaching and Learning Journal*, *7*(2), 19-24.

Cihan, P. (2020). Fuzzy rule-based system for predicting daily case in covid-19 outbreak. 2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT),

Daniel, B. K. (2019). Big Data and data science: A critical review of issues for educational research. *British Journal of Educational Technology*, *50*(1), 101-113.

Fang, W., Gong, X., Liu, G., Wu, Y., & Fu, Y. (2020). A balance adjusting approach of extended belief-rule-based system for imbalanced classification problem. *IEEE access*, *8*, 41201-41212.

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of educational research*, *74*(1), 59-109.

Garrison, D. R., Anderson, T., & Archer, W. (2010). The first decade of the community of inquiry framework: A retrospective. *The internet and higher education*, *13*(1-2), 5-9.

Gledson, A., Apaolaza, A., Barthold, S., Günther, F., Yu, H., & Vigo, M. (2021). Characterising Student Engagement Modes through Low-Level Activity Patterns. In *Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization* (pp. 88–97). Association for Computing Machinery. https://doi.org/10.1145/3450613.3456818

Gulieva, V. (2014). Moodle vs. Social Media Platforms: Competing for Space and Time. Conferinta" Bunele Practici de Instruire Online",

Hasan, R., Palaniappan, S., Mahmood, S., Abbas, A., Sarker, K. U., & Sattar, M. U. (2020). Predicting student performance in higher educational institutions using video learning analytics and data mining techniques [Article]. *Applied Sciences (Switzerland)*, *10*(11), Article 3894. https://doi.org/10.3390/app10113894

Hooshyar, D., & Yang, Y. (2021). Predicting Course Grade through Comprehensive Modelling of Students' Learning Behavioral Pattern [Article]. *Complexity*, *2021*, Article 7463631. https://doi.org/10.1155/2021/7463631

Hussain, M., Zhu, W., Zhang, W., & Abidi, S. M. R. (2018). Student engagement predictions in an e-learning system and their impact on student course assessment scores. *Computational Intelligence & Neuroscience*.

Ibrahim, S., & Ismail, F. (2021). Factors and Challenges in Implementing Blended Learning in English Language Teaching at Tertiary Level. *Innovative Teaching and Learning Journal*, *4*(2). https://itlj.utm.my/index.php/itlj/article/view/50

Jamil, M. N., Hossain, M. S., ul Islam, R., & Andersson, K. (2019). A belief rule based expert system for evaluating technological innovation capability of high-tech firms under uncertainty. 2019 Joint 8th International Conference on Informatics, Electronics & Vision (ICIEV) and 2019 3rd International Conference on Imaging, Vision & Pattern Recognition (icIVPR),

Khan, S. S., & Colella, T. J. (2022). Inconsistencies in Measuring User Engagement in Virtual Learning–A Critical Review.

Luo, J., & Wang, T. (2020). *Analyzing Students' Behavior in Blended Learning Environment for Programming Education* Proceedings of the 2020 The 2nd World Symposium on Software Engineering, Chengdu, China. https://doi-org.ezproxy.utm.my/10.1145/3425329.3425346

Ma, Y., Wei, Y., Shi, Y., Li, X., Tian, Y., & Zhao, Z. (2022). Online learning engagement recognition using bidirectional Long-Term recurrent convolutional networks. *Sustainability*, *15*(1), 198.

Mandinach, E. B., & Beth, J. (2021). Data ethics in education: a theoretical, practical, and policy issue. *Studia paedagogica*, *26*(4), [9]-26.

Marcus, V. B., Atan, N. A., Yusof, S. M., & Tahir, L. (2024). Exploring Cognitive Engagement in Extreme e-Service Learning for Multimedia Creative Course During the COVID-19 Pandemic. *Innovative Teaching and Learning Journal*, *8*(1), 24-40.

Martin, F., & Borup, J. (2022). Online learner engagement: Conceptual definitions, research themes, and supportive practices. *Educational Psychologist*, *57*(3), 162-177.

Ministry of Education Malaysia. (2015). *Malaysia Education Blueprint 2015-2025 (Higher Education)*.

Motz, B., Quick, J., Schroeder, N., Zook, J., & Gunkel, M. (2019). The validity and utility of activity logs as a measure of student engagement. Proceedings of the 9th international conference on learning analytics & knowledge,

Nguyen, V. A., Nguyen, Q. B., & Nguyen, V. T. (2018). *A Model to Forecast Learning Outcomes for Students in Blended Learning Courses Based On Learning Analytics* Proceedings of the 2nd International Conference on E-Society, E-Education and E-Technology, Taipei, Taiwan. https://doi-org.ezproxy.utm.my/10.1145/3268808.3268827

Oladiji, A. A. (2018). Challenges of Data in Educational Planning. *KIU Journal of Humanities*, *3*(2), 221-228.

Orji, F., & Vassileva, J. (2020, 7-11 Sept. 2020). Using Machine Learning to Explore the Relation Between Student Engagement and Student Performance. 2020 24th International Conference Information Visualisation (IV),

Saleh, N. S., Rosli, M. S., Abu Bakar, T. S., Md. Ali, A., & Isa, K. (2021). Exploring Students Satisfaction towards Online Learning in the Midst of COVID-19. *Innovative Teaching and Learning Journal*, *4*(2). https://itlj.utm.my/index.php/itlj/article/view/54

Sashank, Y. T., Kakulapati, V., & Bhutada, S. (2023). Student Engagement Prediction in Online Session. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*(2), 43-47.

Tan, K. H., Chan, P. P., & Mohd Said, N.-E. (2021). Higher education students' online instruction perceptions: A quality virtual learning environment. *Sustainability*, *13*(19), 10840.

Usher, M., & Hershkovitz, A. (2022). Interest in educational data and barriers to data use among massive open online course instructors. *Journal of Science Education and Technology*, *31*(5), 649-659.

Wakjira, A., & Bhattacharya, S. (2022). Student Engagement Awareness in an Asynchronous E-Learning Environment: Supporting a Teacher for Gaining Engagement Insight at a Glance. *International Journal of Technology-Enabled Student Support Services (IJTESSS)*, *12*(1), 1-19.

Waltl, B., Bonczek, G., & Matthes, F. (2018). Rule-based information extraction: Advantages, limitations, and perspectives. *Jusletter IT (02 2018)*.

Whiter, K. A. (2020). Strategies for engaging students in the online environment. In *Handbook of research on fostering student engagement with instructional technology in higher education* (pp. 305-326). IGI Global.

Xu, H. M., Qu, J. H., Ma, X., & Ling, Y. T. (2021). Prediction and visualization of academic procrastination in online learning.

Yang, J.-B., Liu, J., Wang, J., Sii, H.-S., & Wang, H.-W. (2006). Belief rule-base inference methodology using the evidential reasoning approach-RIMER. *IEEE Transactions on systems, Man, and Cybernetics-part A: Systems and Humans*, *36*(2), 266-285.

Zainol, S. S., Hussin, S. M., Othman, M. S., & Zahari, N. H. M. (2021). Challenges of online learning faced by the B40 income parents in Malaysia. *International Journal of Education and Pedagogy*, *3*(2), 45-52.