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Blended Learning Based on Heutagogy as a Determinant of Student Engagement in Islamic Education

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Abstract: Blended Learning Based on Heutagogy as a Determinant of Student Engagement in Islamic Education. Objective: Blended learning by prioritizing a heutagogical approach in Islamic Education needs to be analyzed to determine the potential for successful student engagement. **Methods:** Therefore, this study classifies, regresses, and predicts the determinants of the interaction of 128 students in a literacy project using three indicator variables; discussions, presentations, and publications. **Findings:** This study found an *f* value of 85.79 +/- 5.83 (micro average: 86.27) with positive class completeness at an accuracy of 80.71% in classification analysis with a decision tree, *f* value 80.33% with an accuracy of 72.86%, and classification error of 27.14% in predictive analysis with Naïve Bayes, and the significance of t count 4.713 > t table 1.97912 in regression analysis with SPSS. **Conclusion:** This study concludes; that (1) discussion determines mastery in heutagogy learning, (2) discussion activities have a positive effect on understanding in heutagogy learning, and (3) discussion determines engagement in completing assignments.

Keywords: blended learning, heutagogical, Islamic education, student engagement.

Abstrak: Blended Learning Berbasis Heutagogi sebagai Determinan Keterlibatan Siswa dalam pembelajaran Pendidikan Agama Islam. Tujuan: *Blended learning dengan mengutamakan pendekatan heutagogis dalam Pendidikan Islam perlu dianalisis untuk mengetahui potensi keberhasilan keterlibatan siswa.* ***Metode:*** *Penelitian ini mengklasifikasikan, meregresi, dan memprediksi determinan interaksi 128 siswa dalam proyek literasi dengan menggunakan tiga variabel indikator; diskusi, presentasi, dan publikasi.* ***Temuan:*** *Penelitian ini menemukan nilai f 85,79 +/- 5,83 (mikro rata-rata: 86,27) dengan ketuntasan kelas positif pada akurasi 80,71% pada analisis klasifikasi dengan pohon keputusan, nilai f 80,33% dengan akurasi 72,86%, dan kesalahan klasifikasi 27,14% pada analisis prediksi dengan Naïve Bayes, dan signifikansi t hitung 4,713 > t tabel 1,97912 pada analisis regresi dengan SPSS.* ***Kesimpulan:*** *Hasil penelitian menyimpulkan; (1) diskusi menentukan ketuntasan pembelajaran heutagogi, (2) diskusi berpengaruh positif terhadap pemahaman dalam heutagogi, dan (3) diskusi menentukan keterlibatan siswa untuk menyelesaikan tugas.*

Kata kunci: *heutagogi, keterlibatan siswa, pembelajaran campuran, Pendidikan Agama Islam.*

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INTRODUCTION

Recently, innovative learning practices to accommodate the competence and competitiveness of graduates of the society 5.0 era have been initiated and designed by education stakeholders, both during the pandemic and after the Covid-19 pandemic (2020). One of the initiations of learning practices considered adequate is the blended learning model, which consists of two offline and online activities in one cycle. The main emphasis in the mixed learning process is to mainstream the achievement of habit creation, control independent learning cycles, and internalize the value of students' awareness to be directly involved in every learning activity. Hotimah et al. (2020) one of the initiations of learning practices considered adequate is the blended learning model, which consists of two offline and online activities in one cycle. The main emphasis in the mixed learning process is to mainstream the achievement of habit creation; control illustrates the practice of mixed learning in which students join and participate online, then participate in community-based face-to-face learning consisting of educators, practitioners, or fellow students. Community meetings across students and classes become a forum for students to share knowledge, ask questions, and respond to problems encountered when completing learning targets. Learning cycles and internalize the value of students' awareness to be directly involved in every learning activity.

The heutagogical approach is offered as an emerging and potentially highly congruent educational framework placed around practice-based learning (Bansal et al., 2020). Heutagogy proposes some concepts and techniques in response to changes in higher education. The heutagogical learning environment promotes the development of capable learners and places a premium on developing students' competencies, abilities, and capacities for learning. Heutagogy comes from Greek, which means self. Hase and Kenyon (2000) defined heutagogy as a learning concept whose activities are the result of decisions or decisions of each individual. The critical concepts of heutagogical learning are two-round learning and self-reflection. Two-round learning occurs when a learner questions and tests a person's values and assumptions. Heutagogy proposes a theoretical foundation for developing online educational tools. Distance education ideally facilitates a heutagogical approach to teaching and learning by establishing learning environments that are favourable to a heutagogical approach to teaching and learning (Blaschke, 2012). Numerous teaching practices in Indonesia have attempted to optimize and assess multiplatform media using the heutagogical approach (Widiaty, Ana, Riza, Abdullah, & Mubaroq, 2020). Another practice (2021) evaluates student work with a heutagogical approach.

However, no study has been conducted to establish a direct link between it and student engagement in Islamic Education instruction. The general problem faced is the reality of the consistency and awareness of students who are different in following the learning cycle as an indicator of engagement, especially during online and blended learning (2020) which have limited interface interaction space. Given the significant need for learning that can maximize student engagement, it is not surprising that empirical studies with this have produced mixed findings. Previous research was conducted by Kahu (2013), who introduced holistic dimensions of engagement, such as socio-cultural and psychological, so that engagement is not limited by conceptual understanding. In simpler terms, Kahu (2013) makes an analogy with the question of whether the anxiety experienced by students in the first year will impact both behavioral and cognitive dimensions at the same time?

The subsequent study was conducted by Gunuc & Kuzu (2015), which described the descriptive findings of the cognitive engagement scale in the campus environment but did not further analyze the activities that affect the scale level—complementing the study of Dyer et al. (2018) which examined the implementation of field trips which resulted in findings showing increased student responses to the development of ecological materials. Students should be involved in outdoor-based interaction activities, according to Dyer et al. (2018). However, not many institutions, particularly stakeholders, incorporate such activities into their curriculum at the higher education level, where the study context is mostly theoretical-normative. So the empirical study described in this article is carried out to further develop these findings in the context of a blended learning model in Islamic Education, which is widely used in various Indonesian universities and is commonly implemented in various types of Indonesian universities.

The findings of Ahmed & Mohammed Salih (Ahmed & Mohammed Salih, 2020), which describe the relevance of educator tactics in seeking learning engagement through a constant cycle of activities, are linear with the findings of this paper, at least theoretically. The findings of Bond et al. (2020) about the role of digital technology involvement in community-based learning interactions align with the findings of the study described in this article. From a conceptual standpoint, the research presented in this paper contributes to these findings by providing a curative identification of student discipline conduct that is driven by the duty to attend class. Students' natural curiosity (2018) was exploited in this research study to engage them in discussion activities that resulted in the completion of literacy projects based on article publications, which was also highlighted in the findings.

It is possible to fit the context of the demographic analysis of the suitability of learning needs in this study by choosing the case study site in Yogyakarta, in particular, the Islamic Education Study Program of Universitas Ahmad Dahlan. In examining interpretation, the discipline of Islamic Education is used as a material object. Using heutagogy projects, the primary goal of this study was to examine the impact of different forms of student involvement activities (2010) during blended learning on the completeness of Islamic Education learning in the context of Islamic Education. Engagement activities are found to be important determinants of learning mastery. The findings corroborate the relationship between involvement factors and predictions of possible activities in investigating these determinants. Following the Covid-19 pandemic, the findings can be used as a starting point for developing a model of Islamic Education based on bent learning, according to the findings (2020).

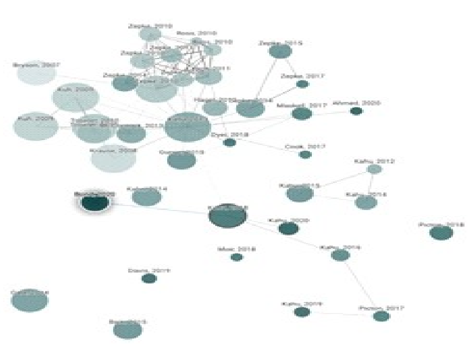

Figure 1. Visual mapping of learning engagement in higher education

METHODS

Students' Engagement: A Discussion

Research findings from journals and books on relevant topics, such as learning engagement, published between 2007 and 2020 were reviewed by researchers in order to identify research gaps (Figure 1). The paper identification page was used in the study conducted by researchers to identify research gaps (Mills, Lochrie, Dickinson, Metcalfe, & Egglestone, 2015).

Educational data mining (2021)

It is a series of routine operations that are used to investigate the added value of a data collection in the form of knowledge that has not been known until the results of manual analysis have been obtained. In the words of Bird et al. (2009), data mining is an automated analytical system that examines vast amounts of data or complex data in order to identify significant patterns or trends that are usually not seen by the people conducting the analysis. This article uses data mining to examine raw data in the field of education that was retrieved from the Google Drive database that contained components of student assessment scores during the Islamic Education lecture process, as described in the preceding section. Naïve Bayes analysis, regression, and decision tree (2014) were used to create the data mining model used in this study. Available software for analyzing the Naïve Bayes model and the decision tree is RapidMiner (2014), whereas SPSS (2019) is used for regression analysis. One hundred twenty-eight respondents provided statistical data (see Table 1), which was processed.

Procedure

Following the process architecture below (Figure 2), the research method employed consists of the following: (1) data collection; (2) initial data processing; (3) model application; testing; and (5) model interpretation.

Table 1. The distribution of respondents' data with RapidMiner

Discussion Engagement	Project Achievement	Presence Attribution
43.0	Not achieved	100.0
81.0	Achieved	100.0
66.0	Achieved	100.0
72.0	Achieved	90.0
69.0	Achieved	100.0

Variable	Type	Missing	Statistics
Discussion Engagement	Real	0	min = 19, max = 96, average = 61,316, deviation = 16,292
Project Achievement	Real	0	min = 16, max = 100, average = 83,987, deviation = 20,735
Presence Attribution	Nominal	0	min = 26, max = 50, average = 61.316, absolute count = 50/26, fraction = 0,658/0,342

Data analysis

Analysis of classification using a Naïve Bayes model

In probability classification, Naïve Bayes is a simple model that derives a set of probabilities by adding training data to generate the estimated parameters required for the classification process during analysis. According to Buntoro (2016), Naïve Bayes operates deeper than scenarios encountered in the real world, resulting in far more detailed results. The following formula was used to examine the Naïve Bayes model analysis scheme (Figure 2):

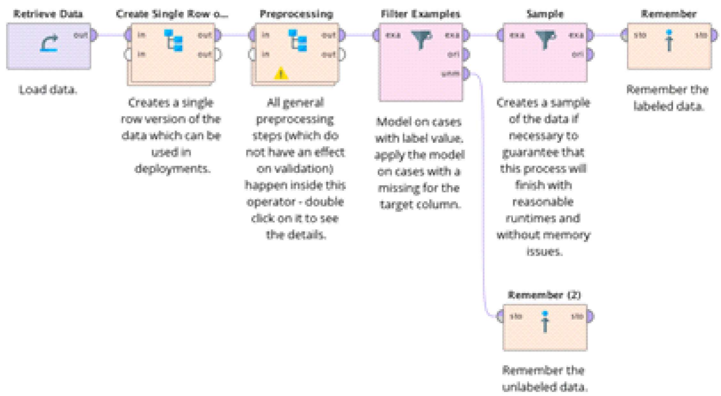

Figure 2. Data mining analysis procedures using the rapidminer algorithm

$$P(H|X) = \frac{P(X|H).P(H)}{P(H)}$$

X = data with an unknown class

H = hypothesized data using a specific class

P(H|X) = probability of hypothesis H based on X condition (posterior probability)

P(H) = hypothesis probability H (prior probability)

P(X|H) = probability X based on the conditions on the hypothesis H

P(X) = probability H

Regression analysis utilizing the Anova model

Multiple linear regression was used in this study to examine the relationship between the dependent variable (literacy) and more than one independent variable. Multiple linear regression is a statistical method for constructing a relationship model between the dependent variable (literacy) and more than one independent variable (independent). For this study, regression analysis was carried out through the use of a t-test with criteria, rejecting if the value > or sig value > was found and accepted if the value > or sig value > was found, as well as an f test using the following formula (2013):

$$F = \frac{R^2/k}{(1-R^2)/(n-k-1)} \qquad t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}}$$

R^2 = coefficient of determination

k = the number of independent variables

n = the number of data members or cases

t = significant values (t count) will be compared with the t table

r = correlation coefficient

n = number of samples

βn = the regression coefficient of each variable

$S\beta n$ = standard error of each variable's

Prediction analysis using a decision tree model

Building a decision tree with decision nodes connected by branches that go from the root node to the leaf node (Figure 1) is a classification strategy that involves categorizing data. According to Larose (2005), decision nodes based on each attribute will be analyzed, and each outcome will result in constructing a new branch in the process. Each branch will be directed either to another node or the end node to allow the user to make a selection (Figure 3). In terms of problem-solving, this decision will be helpful to you. A decision tree is used in this work to anticipate possible engagement activities. The decision tree is used in the following stages: generating training data, establishing the tree's root, and determining the Gain value. As a result of using the formula(Lewer, 2021), the attribute with the highest Gain value from among the current attributes will be chosen as the root, and the decision tree participation procedure will be stopped after all branches in node N have earned the same class.

$$\text{Entropy} = -\sum_{i}^{n} log_2(P_i)$$

n = number of features
i = feature
P = probability of i

■ RESULT AND DISCUSSIONS

Factors determine the completeness of learning

Initially, the dataset file in excel format from 128 students of the Islamic Education study program is read to serve as a source of material for grouping training data and testing data in the form of ExampleSet data during the modeling process (Figure 3). In the initial processing step, the dataset categories are changed from nominal to numerical, then from nominal to text, and finally from nominal to binominal in the initial processing step.

Seventy-six samples have one unique characteristic, and two common attributes are distributed to form two classification classes: the incomplete class (value = 0.345) with two distributions and the entire class (value = 0.655) with two distributions in the original ExampleSet categorization. Classification analysis of the dataset identifies two activities as having a significant impact on engagement, namely attendance and publication; the calculation of the classification class for the two variables indicates that discussion activities dominate the position of the variable with a tremendous influence value (Figure 3). This finding adds to the body of knowledge about heutagogy learning from previous research (Widiaty et al., 2020; Lynch et al. 2021).

Name	Type	Missing	Statistics		
Diskusi	Real	0	Min 60.602	Max 60.602	Average 60.602
Hadir	Real	0	Min 84.039	Max 84.039	Average 84.039
Publikasi	Nominal	0	Least TB (1)	Most TB (1)	Values TB (1)

Figure 3. The results of the preprocessing of the student engagement dataset

Total Time Number	Training Time 1000 Number	Scoring Time 1000 Number	Number of Feature Sets Number	Number of Generated Fe... Number	Number Models Number
6373	4343.750	15346.154	0	0	2

Figure 4. Modeling attributes for student engagement dataset

Additionally, this finding demonstrates that heutagogy-based learning does not always result in students failing to meet learning objectives due to their inherent freedom. Even quantitatively, heutagogy learning can serve as a vehicle for internalizing the delivery of spiritual values when combined with a community forum for idea exchange. Following that, missing value processing is applied to ExampleSet to generate two modeling attributes used to generate the discussion and attendance variables (Figure 4). This additional information can now bolster previously published research advocating for heutagogy in higher education (Blaschke, 2012). However, despite the application's in Indonesia, the features used as assessment variables are the same ones often used as approaches in blended learning programs worldwide.

Diskusi	Hadir	Publikasi ↓	confidence(Tidak Tuntas)	confidence(Tuntas)	cost	prediction(Publikasi)
80	100	Tuntas	0	1	1	Tuntas
69	60	Tuntas	0	1	1	Tuntas
68	100	Tuntas	0	1	1	Tuntas
50	90	Tuntas	0.667	0.333	0.334	Tidak Tuntas
71	100	Tuntas	0	1	1	Tuntas
Diskusi	Hadir	Publikasi ↑	confidence(Tidak Tuntas)	confidence(Tuntas)	cost	prediction(Publikasi)
40	100	Tidak Tuntas	0.833	0.167	0.667	Tidak Tuntas
65	100	Tidak Tuntas	0	1	1	Tuntas
38	100	Tidak Tuntas	0.833	0.167	0.667	Tidak Tuntas
53	100	Tidak Tuntas	0.667	0.333	0.333	Tidak Tuntas

Figure 5. The results of the completion of accurate publications with Naïve Bayes

In the following stage, the Naïve Bayes algorithm is used to analyze the classification of learning completeness, which results in the following real findings (Figure 6); the highest learning completeness (attendance = 100, discussion = 80), and the highest learning incompleteness (attendance = 100, discussion = 40). The classification produced a classification error count of 19.29 percent +/- 8.51 percent (micro average: 18.92 percent) for f measure: 85.79 percent +/- 5.83 percent (micro average: 86.27 percent) (positive class: completed) with an accuracy of 80.71 percent and a classification error count of 19.29 percent +/- 8.51 percent (micro average: 18.92 percent) for f measure: 85.79 percent +/- 5.83 percent with micro average: 86 (Figure 6).

How engagement affects how well you learn

Multiple regression tests revealed that discussion activity had a statistically significant effect on publication-based learning completeness

	true Tidak Tuntas	true Tuntas	class precision
pred. Tidak Tuntas	8	2	80.00%
pred. Tuntas	5	22	81.48%
class recall	61.54%	91.67%	

Figure 6. Accuracy of prescriptive analysis of learning engagement using Naive Bayes

with a p-value of 0.000 0.05, a count of 4.713 > t table of 1.97912, and a count of 4.713 > t table of 1.97912. As evidenced by the significance of 0.784 > 0.05 and t count of 0.274 t table 1.97912, the presence variable does not affect the completeness of the publication; however, the length of the publication is affected by the presence variable's presence.

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.644	.257		2.503	.014
	Diskusi (X1)	.018	.004	.425	4.713	.000
	Kehadiran (X2)	.001	.003	.025	.274	.784

a. Dependent Variable: Publikasi (Y)

Figure 7. The influence of variables x1 and x2 on y using the t-test from SPSS

The influence of each activity variable on learning completeness has a simultaneity of 0.000 0.05, an F count of 14,683 > F table 3.07, and an R Square of 0.19, with an F count of 14,683 > F table 3.07, and an R Square of 0.19 (Figure 7). This outcome bolsters the previous classification analysis's findings regarding the role of discussion variables in the heutagogy learning process. More precisely, this research establishes that the discussion variable influences the level of achievement of student articles.

Meanwhile, the attendance variable does not affect the length of time required to reach publication. In other words, students who have a high attendance rate and participation in class discussions will have the most significant impact on their level of learning completion. These findings contradict Ramli's assertion (2018) that external influences have no direct effect on internal components in self-directed learning. This research demonstrates that the discussion environment can operate as an internal element affecting the completeness of learning throughout the heutagogical cycle. Furthermore, this discovery contributes to the research of the importance of the availability of learning paths in learning activities, which is currently underway (Harrington & Thomas, 2018). Results in the form of increased time and degree of achievement in publications influenced by variables such as attendance and discussion provide compelling evidence that learning activities planned and designed continuously can impact mastery of knowledge and skills.

Variables that could potentially influence the learning process

When a decision tree was used to predict discussion scores, the results revealed that discussion scores greater than 52,500 were complete (incomplete = 9, complete = 40), and discussion ratings less than 52,500 were incomplete (incomplete = 14, complete = 5). According to the computation, the accuracy of the prediction calculation is 72.86 percent, with an f measure of 80.33 percent and a classification error of 27.14 percent (Figure 8).

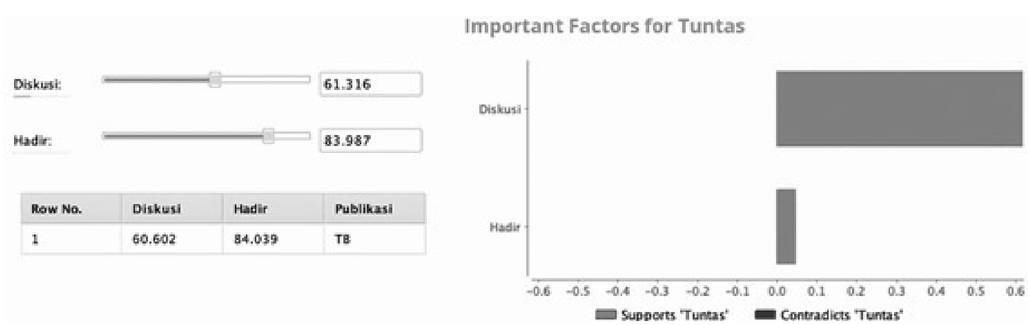

Figure 8. Prediction simulation of the learning completeness of Islamic Education

When comparing the availability of the discussion variable to the availability of the attendance variable, the prediction simulation reveals that the presence of the discussion variable has a more significant impact on the success of publications. Interestingly, this finding directly opposes the findings Anjar (2021) obtained in his study, which found that attendance has a positive correlation with learning outcomes. This study demonstrates that having a large number of attendances has little impact on the achievement of publications as an indicator of learning mastery.

CONCLUSIONS

This study's findings in the form of determinant factors of discussion variables for encouraging learning completeness are supported by the classification analysis of the Naïve Bayes model, which shows a value of 0.655 > 0.345 for the complete class cluster and a value of 0.345 for the incomplete class cluster. The Anova model's regression analysis revealed a statistically significant effect of discussion activity on learning completeness, as demonstrated by the significance of discussions and publications (0.784 > 0.05) and the value of 0.784 > 0.05 on the significance of discussions and publications. By predicting an 80:60 completeness in discussions compared to attendance for the achievement of scientific article publications in the category of unrecognized journals, decision tree analysis was successful in predicting discussion activity as the most potential variable to complete project-based learning.

Three types of support analysis were discovered using educational data mining analysis, which resulted in conclusions regarding the importance of student involvement through a variety of activities in the blended learning model in Islamic Education. Students' involvement in more than one aspect of activity will provide an impetus to attaining project-based autonomous learning aims, according to the findings of an investigation into three models of data mining algorithms (see resources). The importance of dialogic activities that result in direct engagement, such as those seen in discussion forums, is higher at the higher education level, and they are more effective in supporting comprehensive learning there. However, most students are more engaged in being involved administratively during learning, for as meeting attendance requirements, prevents them from achieving their full potential in independent learning.

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CONFLICT OF INTEREST

The authors reported no potential conflicts of interest.

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