The Antecedent of Student Academic Achievement Prediction

Sandy Kosasi
Information System
STMIK Pontianak
Pontianak, West Kalimantan, Indonesia
sandykosasi@yahoo.co.id

Vedyanto
English Teaching Department
Santu Petrus Junior High School
Pontianak, West Kalimantan, Indonesia
vedy91@gmail.com

I Dewa Ayu Eka Yuliani
Information System
STMIK Pontianak
Pontianak, West Kalimantan, Indonesia
dewaayu.ekayuliani@gmail.com

Robertus Laipaka
Information System
STMIK Pontianak
Pontianak, West Kalimantan, Indonesia
rbt99laipaka@gmail.com

***Abstract*—The research goal was set to determine to what extent the influences of learning analytics and academic analytics, the antecedent factors in predicting student academic achievement through the use of big data were. There has been no discussion on progress, success, retention, or decline of this achievement. Therefore, this research has significance for the improvement of higher education institutions. The research was in the form of online surveys involving 203 respondents, i.e., leaders, structural staff, and academic advisors from each of these institutions in Pontianak. Tests of eight hypotheses were conducted through SEM-PLS Method, and two of them had no direct influences. The results show that the two antecedent factors, directly and indirectly, have different influences and significance values on student academic achievement prediction despite the critical roles of big data. In addition, results obtained through the application of learning analytics and academic analytics in relation to big data of higher education institutions, especially for the need to predict student academic achievement, are infrequently similar.**

Keywords—Learning Analytics, Academic Analytics, Big Data, Student Academic Achievement, Prediction.

I. INTRODUCTION

Data on students, lecturers, facilities, and curricula of higher education institutions is significantly increasing in number [1,2]. This circumstance is in line with the increasing empowerment of information technology in supporting the process of learning, teaching, and administration of operational documents with a growing number of academic community members [3]. Utilization of information technology is no longer limited to the process of registration form purchases, entrance tests, registration of study payment, study plan lists, academic advisory consultation, modification of study plan lists, class placement, learning presence, conformity of syllabi and learning programs, online or offline learning system activities, monitoring of assignment completion, extracurricular activities, and evaluation of the learning process, but it also includes all data processing activities of lecturers and academic staff pertaining to education and teaching, research, community services, and other supporting elements [4]. The tendency of a growing amount of academic data continues to happen rapidly over time [5]. Eventually, collections of digital data of higher education institutions are formed [4,5].

The ownership of an increasingly large amount of digital data is apt to reflect the needs of big data technology [6], providing the opportunities for higher education institutions to form a more modern education system and more dynamic mechanisms involving the academic communities in improving the education quality [6,7]. This fact refers to the use of such data for these institutions considering that they are useful, crucial for making data-based decisions effectively and efficiently. The utilization of big data refers further to a collection of datasets originating from teaching, scientific research, daily management, and other practical activities [8]. In essence, they are no longer used just to identify large, high, complex amount (volume), very fast movement (velocity), and diversity of formats for various structured and unstructured types (variety). However, they increasingly develop and include up to the dimensions of trust (veracity), the sustainability of data processing (volatility), accuracy (validity), and value [9,10,11].

The paradigm shift in the use of big data technology for higher education institutions is closely linked to the analytical ability to enhance decision making [11]. This fact is inseparable from the characteristics of big data allowing a new learning environment in which all students can frequently access course content anytime and anywhere while enjoying the learning activities through the learning management system. They have values in developing the learning ecosystem supporting the teaching and learning process, and enhancing the overall learning experience. Other data cover course management, capacity, and distribution of classes and students, as well as academic and lecturing activities. The existing composition of a huge amount of distributed data has important preferences in learning prediction, progress, decline, or failure of achieving academic achievement [11,12]. Obstacles, nonetheless, often appear during the implementation. For instance, the application system portfolios used are unable to process a huge amount of data changing quickly and are not in accordance with structures of the database architecture [12]. This limitation leads to invalid information and negative impacts in making decisions for predicting the student academic achievement, considering that the progress, retention, or decline of student academic achievement is inseparable from learning analytics and academic analytics [13].

These two antecedent factors have critical roles in realizing the capability of big data to predict student achievement in higher education institutions [13]. It is noted that those with analytical skills can support effective learning and academic analytics in predicting student abilities,

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weaknesses, and failure [14,15] based on previous academic scores [16]. Learning and academic analytics can simplify and facilitate predictive analysis and build a more comprehensive association of information on each student's performance [17]. Big data facilitates learning analytics by providing a lot of competitive advantage opportunities through descriptive, diagnostic, predictive, prescriptive analytics to achieve alignment of academic goals. Moreover, academic analytics can reduce the failure rate and operational costs during the learning process [18,19]. The contribution of big data through the two antecedents and learning processes can, hence, guarantee the reduction of failure intensity or enhance student retention, research innovation, and learning performance [20,21].

In general, previous research more conceptually and systematically discussing the need to predict student academic achievement for higher education institutions is absent. Also, recently, the empirical discussion on influences and relationships of antecedent factors of big data for the need of such the prediction has been rarely found. Thus, the novelty of this research is to determine the extent of the influences and relationships of learning analytics and academic analytics in predicting student academic achievement mediated through the use of big data.

The research problem formulated was on the assumption that the ability to predict student academic achievement was influenced by learning analytics and academic analytics through big data for higher education institutions. This was in line with the purpose of determining the extent of influences and relationships of factors as a single unit having the ability to predict student academic achievement for higher education institutions.

II. Literature Review

A. Learning Analytics

Learning analytics refers to the art and science of gathering, analyzing, and reporting data of students and the learning environment in order to better understand and improve the learning process [22]. Monitoring the progress of relevant processes supports independent learning and time management skills [23], evaluates reading skills and digital literacy understanding [24], and improves the lecturing ability to diagnose the problems related to student learning and offline and online academic activities [25].

Learning analytics emphasizes the interaction of students with course material, other students, lecturers, and the academic environment as a process of continuous learning analysis to predict student academic achievement. This analytics includes the learning process, curriculum design, course recommendations [26], and student behavior [27]. Higher education institutions can immediately take precautionary measures in eliminating risks of study failure. In addition, analysis and prediction results can be displayed. Accordingly, they can support decision making to improve student achievement.

B. Academic Analytics

Academic analytics crucially assists higher education institutions in improving student achievement and success, increasing student retention, and reduce the burden of responsibility and accountability [28]. This analytics is more focused on the analysis of academic performance achievement of educational and non-educational staff [29]. It is concerned with increasing resources, processes, and academic workflows in an effort to improve the competition, accreditation grades, assessment, and institutional regulation. Academic analytics has been adopted and used to maintain the teaching and learning process consisting of administration, finance, alumni, education, research, and employability sources [30,31].

C. Prediction of Student Academic Achievement

The academic success of students in a higher education institution is largely measured by Grade Point Average (GPA) with a maximum value of 4. A good GPA varies in any higher education institution. The majority agree that the interval of 3 to 4 represents good academic achievement [32]. The essence of GPA is the form of quick precautions for students frequently skipping the courses. Prediction results can reduce student failure intensity [33] and improve the image of higher education institutions [33,34]. Based on previous findings, essential factors influencing student achievement are motivation, discipline, and learning methods [35].

III. Research Method

The research was initially formulated by defining the background, literature review, problem, research design, and hypotheses. It further continued with the collection and analysis of data, research results, and conclusion [36]. Respondents consisted of leaders, three structural academic staff members, and five academic advisors from higher education institutions in Pontianak. Primary data was obtained through online surveys using google form addressed to 253 respondents. There were; however, only 203 respondents returning questionnaires with answers (response rate = 80.24%). This study modified the previous questionnaire version to pass the tests of validity and reliability. Data were mainly processed using Likert Scales with intervals ranging from strongly agree (score 6) to strongly disagree (score 1) [37]. Secondary data was derived from reports on all GPAs obtained by each student in academic years 2017/2018 and 2018/2019, and odd semester 2019/2020.

After all, data was collected, it was analyzed and interpreted with the Structural Equation Modeling (SEM) Method and Partial Least Square (PLS) Approach. SEM-PLS Model consists of two parts, such as the measurement part linking the observed variables to latent variables through confirmatory factor analysis and the structural part connecting latent constructs through the system of simultaneous equations [38]. Examination of SEM-PLS involves stages of designing a conceptual model, performing calculation with an algorithmic analysis method, and the bootstrapping process to obtain the distribution of data meeting the assumption of normality and to produce a path diagram model and model evaluation process using SmartPLS ver 3.2.7 [38,39], as well as drawing the conclusion and suggestions. This study focused on the needs of exploration and the extent of influences and relationships occurring in the construct of student academic achievement prediction of the antecedent factors in the forms of learning analytics and academic analytics mediated by big data.

Tested hypotheses comprised H1: learning analytics had positive influences on big data; H2: academic analytics had positive influences on big data; H3: learning analytics had positive influences on academic analytics; H4: learning analytics had positive influences on student academic achievement prediction; H5: academic analytics had positive influences on student academic achievement prediction; H6: big data had positive influences on student academic achievement prediction; H7: learning analytics had positive influences on student academic achievement prediction through big data; and H8: academic analytics had positive influences on student academic achievement prediction through big data.

IV. Results and Discussion

Creating and estimating a path analysis of the research model using the PLS Algorithm and the bootstrapping process to obtain optimal values of the data distribution in meeting the assumption of normality were discussed in advance. Bootstrapping applies an algorithm creating the number of subsamples (resample) with a method known as resampling with replacement. Comprehensibly, each resample contains a set of rows selected and reselected at random from an original set of data [38]. Referring to SEM-PLS Model, this study had constructs, i.e., learning analytics, academic analytics, big data, and student academic achievement prediction. Each of them had indicators determined through references to the previous literature review. Providing the description of indicators, learning analytics included learning process (LA1), curriculum design (LA2), course recommendation (LA3), and student behavior (LA4); academic analytics comprised administration (AA1), finance (AA2), alumni (AA3), education (AA4), research (AA5), and employability sources (AA6); big data encompassed volume (BG1), velocity (BG2), variety (BG3), veracity (BG4), volatility (BG5), validity (BG6), and value (BG7); and student academic achievement prediction consisted of motivation (SAAP1), discipline (SAAP2), and learning method (SAAP3).

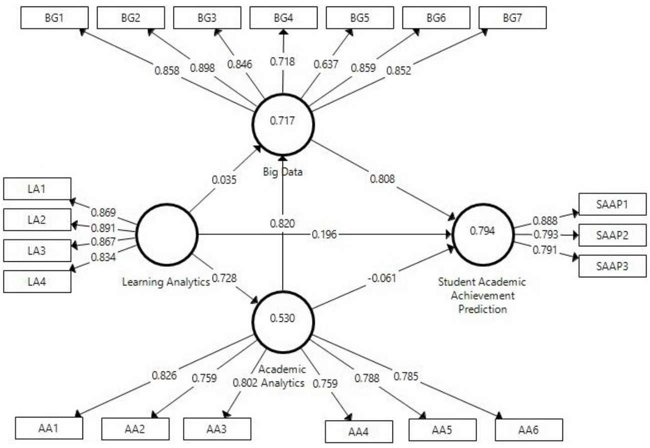

Fig. 1. Path Diagram of Research Model

Referring to the calculation results of Average Variance Extracted (AVE), the validity test was performed to determine coefficients of convergent validity and discriminant validity. It was noted that latent variables were more than half of the average indicator variance. A processed outer model indicated the influences of each construct represented through the path diagram (see Figure 1). Nevertheless, the loading factor value of volatility (BG5) was only 0.637. This indicator had to be excluded from the research model as it was less than the minimum limit (0.70) [38]. It showed the correlation between indicators and their constructs. Indicators with low loading factor values indicated that they were idle in the measurement model (see Figure 2).

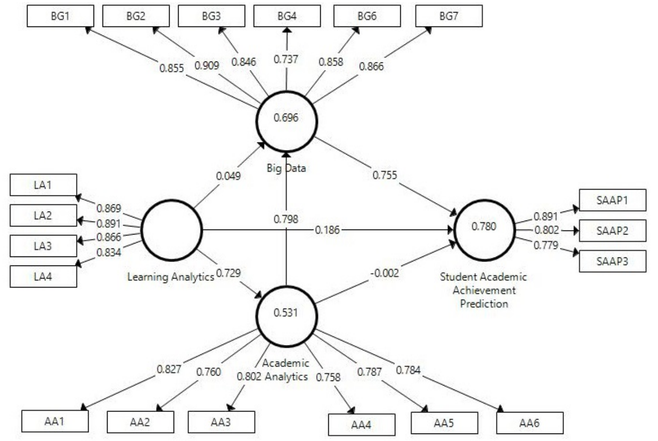

Fig. 2. Path Diagram of Valid Research Model

Following these, the discriminant validity coefficient of each construct required a test using Fornell-Larcker Criteria. The content in Table I presented the whole tested results of the discriminant validity of each construct. Contrarily, the content in Table II presented those of reliability and validity based on Composite Reliability (CR), Cronbach's alpha (CA), and AVE. A requirement to achieve good reliability and validity is that the CR coefficient should be greater than 0.80. Others are these: CA > 0.70 and AVE > 0.50 [38,39].

TABLE I. Discriminant Validity

Fornell-Larcker Criterion	AA	BD	LA	SAAP
Academic Analytics (AA)	0.787			
Big Data (BD)	0.834	0.847		
Learning Analytics (LA)	0.729	0.631	0.865	
Student Academic Achievement Prediction (SAAP)	0.764	0.871	0.661	0.825

TABLE II. Construct Reliability and Validity

Fornell-Larcker Criterion	CA	rho_A	CR	AVE
Academic Analytics	0.877	0.879	0.907	0.619
Big Data	0.920	0.924	0.938	0.717
Learning Analytics	0.888	0.893	0.923	0.749
Student Academic Achievement Prediction	0.765	0.778	0.865	0.681

Another step taken was to analyze the inner model through bootstrapping with the application program of SmartPLS. Such the process supports the testing of the significance of indicators of each construct to obtain a t-value that can be used to see whether relationships among constructs exist. An indicator is declared significant if the t-statistic is greater than 1.96 [39]. The outcome of the significance test of the path coefficient showed that only several original sample values were positive. A negative value was found in the influences of academic analytics on student academic achievement prediction (-0.002). Interpretatively, the better the academic analytics was, the lower the student academic achievement prediction was.

Other constructs, however, had positive values. This meant that the better an exogenous construct was, the better it would be to improve an endogenous construct, including each indicator. Furthermore, the t-statistic suggested the significance of influences of independent constructs on the dependent ones. Another outcome was that not all constructs had t-statistic that was greater than t-table. In other words, they did not wholly bring significant influences and had positive relationships (see Table III).

TABLE III. PATH SIGNIFICANCE TEST

Fornell-Larcker Criterion	Original Sample (O)	T-statistic (|O/S TDEV|)	P-Value
Academic Analytics → Big Data	0.798	14.473	0.000
Academic Analytics → Student Academic Achievement Prediction	-0.002	0.027	0.979
Big Data → Student Academic Achievement Prediction	0.755	13.829	0.000
Learning Analytics → Academic Analytics	0.729	22.796	0.000
Learning Analytics → Big Data	0.049	0.710	0.478
Learning Analytics → Student Academic Achievement Prediction	0.186	3.398	0.001

A computation reflected that there were two insignificant values as the probability value was greater than 0.05. To be precise, at first, academic analytics had no positive relationships and brought insignificant influences on student academic achievement prediction. Second, learning analytics had positive relationships but insignificant influences on big data. This affirmed that it was uncertain that academic analytics activities performed well could directly support the need to predict student academic achievement. These findings are irrelevant to a number of previous research claiming that academic analytics has important influences and relationships with the need to predict student academic achievement [40,41]. Learning analytics activities had a gap with big data capabilities. Here, full synchronization and conformity were unsuccessful in achieving.

Next, the adjusted R-squared value of student academic achievement prediction was 0.777 (77.7%). In other words, such the construct was strongly influenced by learning analytics, academic analytics, and big data directly and indirectly. Other influences were from other constructs excluded in this study (22.3%). The interrelationship among constructs of the researched path diagram model is a novelty, fundamentally contributing the GPA gained at higher education institutions, building retention, and reducing the risks of failure of each student. The other results were that adjusted R-squared values of both big data and academic analytics were respectively 0.693 (69.3%) and 0.529 (52.9%). Comprehensibly, these two constructs moderately influenced student academic achievement prediction. Despite this, their unity should be concerned. The moderate influence occurred since there were demographic, socio-cultural, infrastructural, psychological factors. Surveys were only conducted in Pontianak. Hence, the outcomes becoming inputs for all higher education institutions in this city could be different from the others found in other places. In essence, this research model could be a reference for the need to predict student academic achievement for higher education institutions in any city since the value of R-squared predictive relevance is 0.968 (very strong).

Concerning the path coefficient of each construct, the highest value was the influences of academic analytics on big data (0.798). It could be interpreted that such analytics directly and significantly influenced big data but indirectly influenced the ability to predict student academic achievement. Both of these constructs had a strong relationship. This finding certainly strengthens the previous research. With a path coefficient of 0.755, big data were required to predict student academic achievement. Meanwhile, learning analytics had a direct, significant influence on academic analytics (path coefficient equals 0.729) and on student academic achievement prediction (path coefficient equals 0.186).

All of these conditions have been answers to hypothesis tests of this study. Only H1 and H5 were not proven. The findings were critical in spite of the fact that their application to higher education institutions could vary, and there was no guarantee that all these constructs could be interconnected to influence each other. In terms of the hypothesis of formulated problems, the path coefficient of influences of learning analytics and academic analytics as antecedent factors on student academic achievement prediction through big data were respectively 0.602 and 0.037. With or without the construct of big data becoming an intervening variable, larger, smaller, or even insignificant results were obtained. The construct of academic analytics, however, brought positive, significant influences on student academic achievement prediction through big data (0.602). This value reflected better conditions. Contrarily, direct influences of learning analytics on student academic achievement prediction showed positive, significant results (0.186) compared to big data implemented as an intervening variable to produce positive, yet insignificant influences (0.037).

In a structural model of this research, accordingly, it could be seen that academic analytics and big data had fundamental representation compared to learning analytics in realizing the ability to predict student academic achievement of higher education institutions [42,43]. Learning analytics really influenced academic analytics, yet it was apparently insignificant for student academic achievement prediction (path coefficient = 0.729). This strengthens previous research [44,45]. On the other hand, academic analytics produced negative influences that were irrelevant to the needs of student academic achievement prediction, although numerous previous studies stated that the factor of this analytics had an important role in such the prediction [44,45,46].

In terms of the measurement model, it was noted that all constructs had indicators with loading factor values above 0.70, meaning that they were all valid and could be directly used in research. The student academic achievement prediction had indicators of motivation, discipline, and learning methods with consecutive loading factor values of 0.891, 0.802, and 0.779. Predicting student academic achievement represented in GPA, the third indicator should be improved. This was important to boost higher education institutions with fine preparation. Big data, however, had values of all indicators above 0.80, except veracity (loading factor value = 0.737). In this context, the dimension of data trust assurance remained to be an important concern since there were still delays and gaps. The highest loading factor value of big data was velocity (0.909), which occurred and changed very fast. Regarding learning analytics, loading factor values of the learning process, curriculum design, course recommendation, and student behavior were above 0.80 (exceeding the minimum limit of 0.70). Meaningfully, they were essential components of learning analytics. Another construct, academic analytics, possessed high loading factor values (0.827 and 0.802). This fact reflected that it was very helpful for the administration of institutions and for active students and alumni seeking jobs. To be precise, each higher education institution was required to produce graduates who were ready to work. The results indicated that the two antecedents had strong influences and relationships with student academic achievement prediction in higher education institutions.

V. Conclusion and Future Research

Generating student academic achievement prediction is inseparable from the influences of antecedent factors of learning and academic analytics. Learning analytics positively and directly influences academic analytics and student academic achievement prediction, not big data. Academic analytics, conversely, has negative influences. Thus, it is irrelevant to the needs of student academic achievement prediction, especially for higher education institutions in Pontianak. Future research can more specifically classify the dimensions of lecturers, students, and academics and involve all higher education institutions in West Kalimantan and other provinces due to the fact that only several institutions have been able to implement and empower the roles of the two aforesaid antecedent factors.

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