The Mediating Role of Learning Analytics to Improve Student Academic Performance

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***Abstract*—Recent indicators of the success of every college graduate still refer to the cumulative academic achievement index. The era of disruption of the digitalization of education has posed different challenges and problems to universities to improve student academic performance. The objective of this study was to determine the extent of influences and relationships of antecedent factors, including soft skills and learning analytics, the intervening variables in improving this performance. This study engaged 203 active students taking courses in the fifth and sixth semesters of universities in Pontianak, West Kalimantan, Indonesia. The research was in the form of surveys. Questionnaires were distributed online through Google Form. SEM-PLS Method was conducted for the analysis. Results show strong influences and relationships between academic, emotional learning and soft skills through learning analytics in improving student academic performance. Furthermore, the negative influences of soft skills have insignificance on this performance. Lastly, a socio-economic factor is irrelevantly linked to learning analytics and student academic performance. All of these findings indicate that academic, personal, socio-economic antecedents are no longer relevant to previous research.**

Keywords—Learning Analytics, Soft Skills, Academic Emotional Learning, Student Academic Performance

I. INTRODUCTION

The era of technological disruption has increasingly influenced various fields of life, especially education and teaching at universities. It requires the readiness and capabilities of lecturers and students to always synchronize all learning materials [1]. Teaching is no longer principally on deliveries of lessons and assignments to students. In order to ensure fine teaching and learning system, it should initially involve lecturers giving intensive guidance. For this reason, they should conduct monitoring until the students complete the whole learning process [2]. The expansion of universities with an increasingly diverse number of students presents major challenges in the teaching and learning process. A dynamic university environment with rapid changes requires the readiness of lecturers to actualize the skills and expectations of students. The university success is associated with graduate success in applying their knowledge and competencies [3,4]. The learning process management system and its relation to a number of antecedent factors influencing student academic performance are necessary.

During this time, most of the studies exploring student academic performance tend to concentrate on cumulative semester grades, gender, lecturer capabilities and education, teaching methods, class atmosphere, class attendance, the use of the internet, semester examination results, and socio-economic family conditions [5,6,7]. Additionally, there is an assessment only referring to indicators of student achievement index, semester examinations [8,9], and certain subject grades without being related to other factors [10]. All of them tend to differ from one another. Nevertheless, there is a belief that the results are justifiable. They are undoubtedly valuable and helpful for universities in formulating policies to improve student academic performance. They also serve as inputs for student parents to conduct evaluation [11].

In reality, however, there is no guarantee for graduates with high grades to be easily employed based on their competencies [12]. Previous researchers state that lecturing failure is influenced by social behavior [13], learning attitude, understanding of materials, learning difficulties, and learning activity improvement [14]. Besides, emotional stress, learning activities, and situations of taking academic examinations are important variables for student academic performance [15]. Traditional academic success is often derived from structured data, including demographic, academic variables, not unstructured ones [16]. A number of indicators often used to measure student academic performance begins to show disharmony between the teaching and learning system and graduate capabilities to work or manage their businesses independently [17].

Obstructions encountered are inseparable from this era with new teaching and learning system. In terms of data, the education digitalization model leads to more complex size, rapid movement, diverse format, reliable, sustainable processing, as well as accuracy and values [18]. Academic activities and presentation of course materials are accessible online. Students can have learning materials anytime and anywhere. The lecturing system has also developed into the model of distance education named e-learning. It focuses on student independence of learning and accessing each material [19] and provides opportunities for the academic process and learning activities through various media platforms, including learning management systems, open-source, and social networking systems [20,21]. Nonetheless, this circumstance always poses obstacles to conducting supervision on learning behavior and habits when improving student academic performance. Difficulties of identifying and reducing the risks of failure and late intervention are also the causes of the mismatch of teaching and learning [22]. It

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is particularly noted that trends and patterns of the effectiveness of the learning process and mechanisms exist. Here, the learning analytics approach is useful for improved student academic performance.

Several previous studies have shown that learning analytics can boost education quality and learning awareness can help lecturers and students make decisions more effectively and constructively [23]. Others pertain to the investigation and prediction of academic performance, identification of risks of failure, and increasing student retention rates [24,25,26]. Learning analytics assures a better education system and greater results for all stakeholders [27], and facilitates the evaluation of the effectiveness of teaching and learning patterns to detect learning behavior and student understanding [28].

Learning analytics can, in fact, more specifically contribute to student academic performance. In general, previous research exploring this matter is still rarely found. This study emphasizes the extent of influences and relationships of antecedent factors in academic, personal, socio-economic [29], academic, emotional learning [15], and soft skill [30] forms in order to improve student academic performance mediated by learning analytics to anticipate graduate needs in the era of disruption of digitalized education today and in the future. The research problem is on the assumption that this performance is a result of the influences of antecedent factors through learning analytics. Meanwhile, the research novelty is on this analytics, becoming an intervening variable and complement of previous antecedent factors, academic, emotional learning, and soft skills.

II. Literature Review

Learning analytics becomes a tool used to measure, collect, analyze, and report data regarding students as well as to predict learning patterns [31]. The goal is to understand, optimize, produce, and boost the learning process flexibly and effectively [32]. Learning analytics enables universities to respond to opportunities and challenges of digitalized learning at the moment and in the future [33] quickly. It analyzes learning outcomes and provides a holistic, dynamic perspective of the learning process as well as relevant information for decision making [34]. Such analytics provides benefits of improving quality, increasing retention rates, anticipating and reducing risks of failure, as well as conducting better assessment through the reference of personal learning outcomes to actualize a more flexible learning process [35].

Learning analytics has essential roles in understanding human learning, teaching, and education through identification and validation of the size of relevant processes, results, and activities. Primary components, including lecturers, students, material content, and higher education institutions [36,37] guarantee learning success. Learning analytics can help all lecturers deliver all lecturing materials, which are understandable for students [38]. Aforesaid components are required to match the challenges of digitalized education with the capability to organize a learning system and feedback on learning content [38,39]. Learning analytics emphasizes the interaction of students, their partners, course materials, lecturers, and academic environment as the process of continuous learning analysis to predict student academic achievement. The indicators cover the learning process, curriculum design, course recommendation [40], and student behavior [41].

Through learning analytics, higher education institutions can immediately take preventive actions to eliminate the risks of failure of studies. Furthermore, results of analysis and prediction support decision making to boost student academic performance measured by Grade Point Average (GPA) [5]. This average is as vital as the capabilities to quickly take special precautions for low achievers [42] and to improve the image of higher education institutions in societies and industries. Indicators measuring student academic performance are motivation, discipline, and learning methods [43].

Antecedent factors, however, refer to several previous studies. They are (a) an academic factor including material presentation, lecturer ability, attendance, and semester examination; (b) a personal factor including learning method, family background, academic qualification, and study time management; (c) a socio-economic factor including parental work, family relationship, friend relationship, and social activity [29]; (d) an academic, emotional learning factor including affection, behavior, cognition, somatic, and motivation [15]; and (e) soft skills including integrity, communication, responsibility, social skill, positive attitude, and teamwork [30].

III. Research Method

This research consisted of the areas of the background, literature review, problems, research design, hypotheses, collection, and analysis of data, results, and conclusion [44]. Respondents, i.e., all fifth and sixth-semester students actively learning at universities in Pontianak, completed the questionnaires. Since they already had experiences and recognized previous study results, it was expected that they could provide answers more accurately. Primary data was obtained by means of online surveys through Google Form. 203 out of 249 respondents successfully completed and returned the questionnaires (response rate = 81.53%). Data were processed using Likert Scales with intervals ranging from strongly agree (score 6) to strongly disagree (score 1) [45]. Additionally, secondary data was obtained from reports on the student GPA in academic years 2017/2018 and 2018/2019 as well as odd semester 2019/2020. After the two types of data had been collected, analysis and interpretation of data using the Structural Equation Modeling (SEM) Method and Partial Least Square (PLS) Approach was conducted. The examination of SEM-PLS comprises the design of a conceptual model, computation with the algorithm analysis method, and the bootstrapping process. The data distribution can, therefore, meet the normality assumption, produce a path diagram model, and bridge model evaluation through SmartPLS ver 3.2.7 [46].

Examined hypotheses encompassed H1: An academic factor had positive influences on learning analytics; H2: A personal factor had positive influences on learning analytics; H3: A socio-economic factor had positive influences on learning analytics; H4: Academic emotional learning had positive influences on learning analytics; H5: Soft skills had positive influences on learning analytics; H6: Learning analytics had positive influences on student academic performance; H7: An academic factor had positive influences on student academic performance; H8: A personal factor had positive influences on student academic performance; H9: A personal factor had positive influences on student academic performance; H10: A socio-economic factor had positive influences on student academic performance; H11: Academic emotional learning had positive influences on student academic performance; H12: Soft skills had positive influences on student academic performance; H13: An academic factor had positive influences on student academic performance through learning analytics; H14: A personal factor had positive influences on student academic performance through learning analytics; H15: A personal factor had positive influences on student academic performance through learning analytics; H16: A socio-economic factor had positive influences on student academic performance through learning analytics; H17: Academic emotional learning factor had positive influences on student academic performance through learning analytics; H18: Soft skills had positive influences on student academic performance through learning analytics.

IV. Results and Discussion

This study elaborated on the path analysis of the model and estimation using PLS Algorithm. The bootstrapping process was further conducted to obtain an optimal value of data distribution in meeting normality assumptions. An algorithm creating the number of the subsample (resample) with a method called sampling with replacement (resampling with replacement) was in use. Each resample contains rows that are selected at random and, if needed, reselected from the original set of data [46]. Referring to SEM-PLS Model, this study included these constructs: academic, personal, socio-economic factors, academic, emotional learning, soft skills, learning analytics, and student academic performance. Each of them had indicators determined based on previous literature.

To give description of each construct, the academic factor had indicators of presentation material (AC1), lecturer ability (AC2), attendance (AC3), and semester examination (AC4); the personal factor had indicators of learning method (PS1), family background (PS2), academic qualification (PS3), and study time management (PS4); the socio-economic factor had indicators of parental work (SE1), family relationship (SE2), friend relationship (SE3), and social activity (SE4); the academic emotional learning had indicators of affection (AEL1), behavior (AEL2), cognition (AEL3), somatic (AEL4), and motivation (AEL5); soft skills had indicators of integrity (SS1), communication (SS2), responsibility (SS3), social skill (SS4), positive attitude (SS5), and teamwork (SS6); learning analytics had indicators of learning process (LA1), curriculum design (LA2), course recommendation (LA3), and student behavior (LA4); and student academic performance had indicators of motivation (SAP1), discipline (SAP2), and learning method (SAP3).

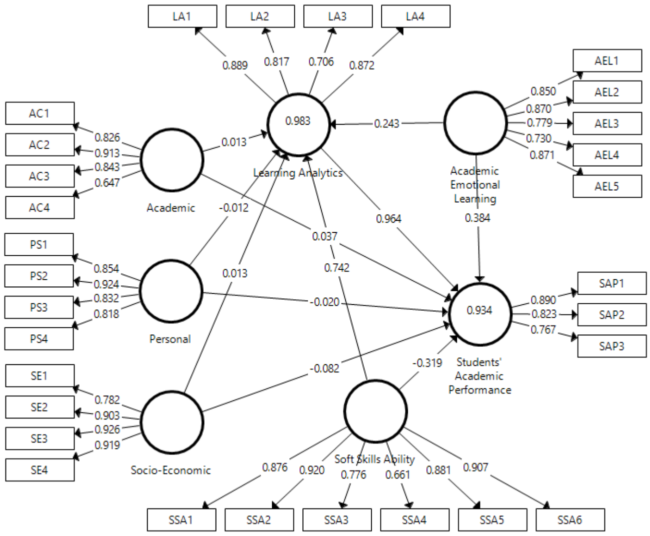

Fig. 1. Path Diagram of Research Model

Following this, the validity test was performed to determine the convergent and discriminant validity by referring to the Average Variance Extracted (AVE). Here, the latent variable could be more than half of the variance of the average indicators. The outer model represented through the research path diagram model showed influences of constructs (see Figure 1). However, the measurement results showed an invalid path diagram because there were two indicators with factor loadings, which were smaller than 0.70 [46]. The two indicators were the semester examination (AC4) and social skill (SS4) with respective factor loadings = 0.647 and 0.661. For this reason, they were excluded from the research model (see Figure 2).

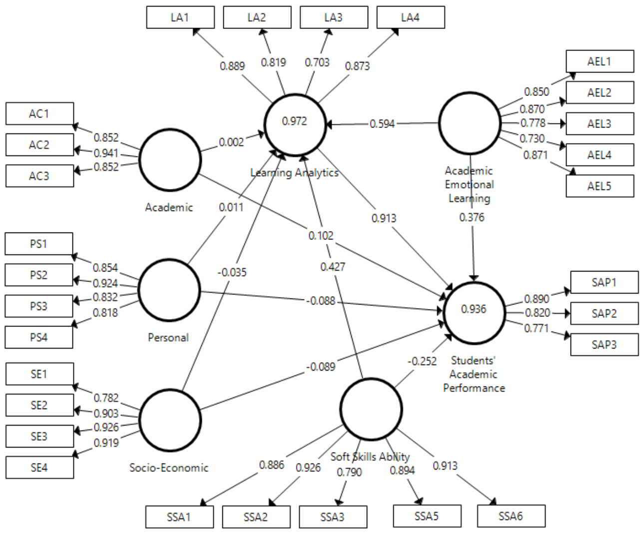

Fig. 2. Valid Path Diagram of Research Model

Another stage was to test the discriminant validity of each construct using the Fornell-Larcker Criteria. Table I indicated testing outcomes of the discriminant validity of constructs. Meanwhile, Table II indicated those of reliability and validity based on the value of Composite Reliability (CR), Cronbach's Alpha (CA), and AVE. A criterion is that CR should be greater than 0.80. Others are that CA and AVE should be respectively greater than 0.70 and 0.50 [46].

TABLE I. DISCRIMINANT VALIDITY

Fornell-Larcker Criterion	AC	AEL	LA	PS	SE	SS	SAP
Academic (AC)	0.883						
Academic Emotional Learning (AEL)	0.683	0.822					
Learning Analytics (LA)	0.662	0.975	0.824				
Personal (PS)	0.947	0.719	0.698	0.858			
Socio-Economic (SE)	0.681	0.913	0.861	0.719	0.884		
Soft Skills (SS)	0.627	0.946	0.969	0.664	0.807	0.883	
Student Academic Performance (SAP)	0.660	0.951	0.963	0.683	0.842	0.921	0.829

TABLE II. CONSTRUCT RELIABILITY AND VALIDITY

Fornell-Larcker Criterion	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted
Academic (AC)	0.858	0.882	0.913	0.779
Academic Emotional Learning (AEL)	0.878	0.882	0.912	0.675
Learning Analytics (LA)	0.839	0.851	0.894	0.679
Personal (PS)	0.880	0.889	0.918	0.736
Socio-Economic (SE)	0.906	0.919	0.935	0.782
Soft Skills (SS)	0.928	0.930	0.946	0.780
Student Academic Performance (SAP)	0.770	0.780	0.867	0.686

Next, the inner model was analyzed through bootstrapping on the SmartPLS application program. This process aims to test the significance of indicators of each construct and to obtain a t-value that can be used to test whether there are relationships among constructs. An indicator is declared significant if the t-statistic is greater than 1.96 [46]. Based on the path coefficient, not all original sample values were positive. Influences of personal (0.088), socio-economic (0.089) factors and soft skills (0.252) on student academic performance and of the socio-economic factor on learning analytics (0.035) were found. A negative value indicated that there was a weak, insignificant relationship. In addition, there were constructs with positive influences and yet weak, insignificant relationships. Understandably, better influences of personal, socio-economic factors represented soft skills bringing a reduction of student academic performance and learning analytics. Positive influences and strong relationships, nonetheless, were interpreted as the principle, the better the exogenous constructs were, the better the endogenous constructs would be. Not all t-statistics were greater than the t-table, so that insignificance existed. Table III only presented construct values with positive, significant influences.

TABLE III. PATH SIGNIFICANCE TEST

Fornell-Larcker Criterion	Original Sample (O)	T Statistics (|O/S TDEV|)	P Values
Academic Emotional Learning → Learning Analytics	0.594	7.548	0.000
Academic Emotional Learning → Student Academic Performance	0.376	2.077	0.038
Learning Analytics → Student Academic Performance	0.913	5.323	0.000
Soft Skills → Learning Analytics	0.427	7.752	0.000

Seeing the adjusted R-squared reference, the value of student academic performance was 0.934 (93.4%), meaning that it was strongly influenced by academic, personal, socio-economic factors, academic, emotional learning, soft skills, and learning analytics directly and indirectly. The remaining percentage (6.6%) represented influences brought by external constructs. The interrelationship among constructs of the path diagram model in this research is a novel finding with important contributions as it represents a very high value for universities to improve student academic performance. Then, the adjusted R-squared value of learning analytics was 0.971 (97.1%), reflecting the influences and relationships in predicting student academic performance. These analytics was powerfully associated with the need to boost the performance. Another finding was that the R-squared predictive relevance was 0.998 (99.8%), nearly 100%. This research model is, thus, fundamental and beneficial for universities inside and outside Pontianak.

Regarding the path coefficient of each construct, the highest value was found in learning analytics with positive, direct, significant influences on student academic performance (0.913). It was followed by those of academic, emotional learning on learning analytics (0.594), soft skills on learning analytics (0.427), and academic, emotional learning on student academic performance (0.376). Comprehensibly, with their crucial role [23], learning analytics activities should always be properly and precisely conducted to improve such performance [24], relying on academic, emotional learning. This affirmation serves as the evidence of H4, H5, H6, and H11 and confirms previous research [25,26,27] with a novel feature. It is clear that strong influences and relationships between academic, emotional learning and soft skills assure the success of implementing learning analytics to improve student academic performance.

Indirect relationships among constructs were indicated by academic, emotional learning bringing positive, significant influences on student academic performance through learning analytics (0.542). The path coefficient was still higher than the direct influences on student academic performance. This statement was reinforced by the influences of soft skills on student academic performance through learning analytics (0.390). Despite the fact that this value was lower than the direct influences of soft skills on learning analytics, it was still above the average of other constructs and fulfilled H17 and H18. Therefore, such analytics became a vital factor compared to antecedents.

On the other hand, the academic construct had positive, direct, yet insignificant influences on student academic performance. Next, the personal construct had no direct influences since it had negative, insignificant values on student academic performance (0,000) despite its direct, positive influences on learning analytics. However, these two factors were unlike the socio-economic one with its indirect influences. Here, the success of improving student academic performance infrequently depended on it. This finding rejects a number of previous research results [5,6,7,13], stating that it plays an important role in improving this performance. The academic factor required enhancement. It could be seen that factor loadings of material presentation (AC1), lecturer ability (AC2), and attendance (AC3) were high, yet insignificant.

V. CONCLUSION AND FUTURE RESEARCH

Learning analytics fundamentally boosts student academic performance. In spite of a very high coefficient of determination, it should be integrated with academic, emotional learning and soft skills. Socio-economic factors are, however, totally irrelevant to learning analytics and student academic performance. This research can be in continuation to specifically find out the improvement priority (academic performance or GPA) in order to ensure every graduate career success.

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