INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN PROGRESSIVE EDUCATION & DEVELOPMENT
www.hrmars.com
ISSN: 2226-6348

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To Link this Article: http://dx.doi.org/10.6007/IJARPED/v12-i2/16961 DOI:10.6007/IJARPED/v12-i2/16961

Received: *05* March 2023*, **Revised:*** *07* April 2023*, **Accepted:*** *01* May 2023

Published Online: *21* May 2023

In-Text Citation: (Che Nawi et al., 2023)

To Cite this Article: Che Nawi, N. R., Omar, M. K., Sharef, N. M., Murad, M. A. A., Mansor, E. I., Nasharuddin, N. A., Samian, N., Arshad, N. I., Shahbodin, F., & Marhaban, M. H. (2023). Correlation between Students' Expectations and Demographic Characteristics Toward Features of Learning Analytics System in Malaysia. *International Journal of Academic Research in Progressive Education and Development*, *12*(2), 1073–1096.

Vol. 11(2) 2023, Pg. 1073 - 1096

http://hrmars.com/index.php/pages/detail/IJARPED	JOURNAL HOMEPAGE

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Correlation between Students' Expectations and Demographic Characteristics Toward Features of Learning Analytics System in Malaysia

[1]Nur Raihan Che Nawi , [1] Muhd Khaizer Omar, [2]Nurfadhlina Mohd Sharef, [2]Masrah Azrifah Azmi Murad, [2]Evi Indriasari Mansor, [2]Nurul Amelina Nasharuddin, [2]Normalia Samian, [3]Noreen Izza Arshad, [4]Faaizah Shahbodin & [5]Mohammad Hamiruce Marhaban

[1]Faculty of Educational Studies, Universiti Putra Malaysia, [2]Faculty of Computer Science and Information Technology, Universiti Putra Malaysia, [3]Positive Computing Research Center, Institute of Autonomous Systems, Universiti Teknologi PETRONAS, Malaysia, [4]Centre for Academic Excellence and Scholarship, Universiti Teknikal Malaysia Melaka, Malaysia, [5]Vice Chancellor Office, Universiti Sains Islam Malaysia

Corresponding Author's Email: nurraihan@upm.edu.my

Abstract

Learning analytics is the process of assessing, evaluating, and measuring student performance and the effectiveness of the teaching and learning process. This study investigates the relationship between three dimensions of learning analytics (summative, real-time, and predictive) and learning demographic characteristics (age, gender, categories of students, current semester, field of study, credit hours are taken in the current semester and CGPA). Questionnaires were distributed to 350 students enrolled in various programs at a public university in Malaysia. The study found that demographic profiles of the respondents which include age, gender, types of students, credit hours taken, concern for achievement, learning preferences, and learning motivation significantly contributed to learning analytic features. Additionally, the study revealed a strong and positive direction of learning analytic features: summative, real-time, and predictive based on the Pearson Correlation report. To comprehensively enhance the learning experience, the study recommends an extensive study related to learner profiling that considers intrinsic and extrinsic value such as assistive technology, learning performance, and motivation. The implications for other stakeholders such as teachers, learners, curriculum developers, and policymakers can be significant, as they can use learner profiling information to develop personalized learning plans, provide targeted support, design effective learning materials, and make informed education policy and funding decisions. A comprehensive understating of learner profiling and learning analytics can have far-reaching implications for various stakeholders in the education system,

potentially leading to more personalized, effective, and equitable learning experiences for all learners.
Keywords: Big Data, Learning Analytics, Machine Learning, Students' Expectations, Students' Profiling

Introduction

The education process has evolved in myriad ways—from the conventional and traditional teaching methods where educators play a central role to more advanced pedagogical methods for content delivery such as the Massive Open Online Courses (MOOCs), virtual reality, and blended learning, among others. Additionally, educators have been compelled to integrate technology into their teaching and learning processes (Beldarrain, 2006). Therefore, educators must put in a lot of effort in preparing and investing in technology, and designing a curriculum that meets technology requirements to ensure that learning "happens" (Lee & Yuan, 2018).

Meaningful learning experiences occurs when there is adequate interaction between teachers and students. Therefore, educators have to put in a lot of efforts to design a curriculum that embodies the values of interaction (Elias, 2011). The crux of the education process has always been centered on the use of technology that enhances interactions. This is important because, without the right tools and technologies, the learning process might be hindered and disconnected from the learning objective.

Therefore, understanding the extent of learning effectiveness is vital to flourishing the holistic learning ecosystem. In order to scrutinize learning effectiveness, learning analytics has been adopted to address the aforementioned issues in education. Learning analytics is a field that focuses on using data analysis and information technology tools to improve the learning process and outcomes. It involves the collection, analysis, and interpretation of data about learners and their contexts to optimize learning experiences and enhance educational effectiveness (Siemens, 2013; Ferguson, 2012; Jovanovic et al., 2017; Long & Siemens, 2011). According to Siemens (2013), learning analytics is a new discipline that focuses on the collection, analysis, and interpretation of data related to learning and learners. Learning analytics has the potential to transform education by providing insights into student performance and behaviour that can be used to optimize the learning process and improve educational outcomes. Meanwhile, Jovanovic et al (2017) discuss the challenges and limitations of learning analytics as a field. While learning analytics has great potential to improve education and enhance learning outcomes, there is a need to ensure that learning analytics tools are accessible and easy to use, and provide clear and meaningful insights to educators and learners.

This research was initially conducted as part of a broader learning analytic project, which involved the development of a chatbot, dashboard, and playbook to investigate learners' characteristics and profiling. The study of learning analytics is an important tool for improving the quality of education and ensuring that every student has the opportunity to succeed.

Firstly, this study aims to collect and analyse data on learners' behaviours and characteristics, which can help educators and administrators better understand how to improve the learning experience for students. By analysing data on how learners interact with educational materials and resources, for example, educators can identify patterns and trends that can inform changes to teaching methods or curriculum design. In addition, learning analytics can help to personalise the learning experience for individual students by collecting data on each student's learning preference, progress, and challenges. Educators can then tailor their instruction to meet the unique needs of each student, leading to improved learning outcomes and greater student engagement.

Finally, learning analytics projects can help to identify areas where additional support or resources may be needed. By analysing data on student performance and engagement, educators can identify students who may be struggling and provide targeted interventions to help them succeed. (Siemens, 2013; Gasevic, 2017; Baker, 2019). Inferential analysis was undertaken to determine the relationships that exist between the demographic profiling of the learners and learning analytic features. Conducting inferential analysis, allows researchers to identify correlations between different variables, such as age, gender, or educational background and the use of specific learning analytics tools or features. Understanding how different groups of learners engage with learning analytics can help educators and administrators to design more effective tools and resources that meet the specific needs and preferences of different learners.

The study of the relationship between demographic profiling and learning analytics features is important for improving the effectiveness and accessibility of learning analytics tools and resources, and ensuring that they are designed to meet the needs of all learners.

Learning Analytics in Technology – Enhanced Learning

The term "learning analytic" can vary depending on the context and field of study. Ochoa (2017) defines learning analytics as a measurement, collection, and data reporting tool used to understand the patterns of learning and to optimize learning performances during teaching procedures (Dawson et al., 2019; Ochoa, 2017). Understanding of what, when, why, and how the learning process occurs is crucial to enhancing a learner's holistic learning experience. Ferguson (2012) describes learning analytics as a significant area of technology-enhanced learning, with apparatus and assistive technology being the main parameters for learning analytics. Additionally, past research frequently indicates learning analytics in education as learning based on utilization of technology. The analysis of learning should begin with an examination of technology, education, and political factors that drive analytical development in the educational milieu (Silber-Varod et al., 2019). Learning analytics supports specific learning processes and visualization through specific interface technology to indicate course performances (Maseleno et al., 2018), which can then improve the Return of Investment (ROI), student feedback and teaching assessment tools.

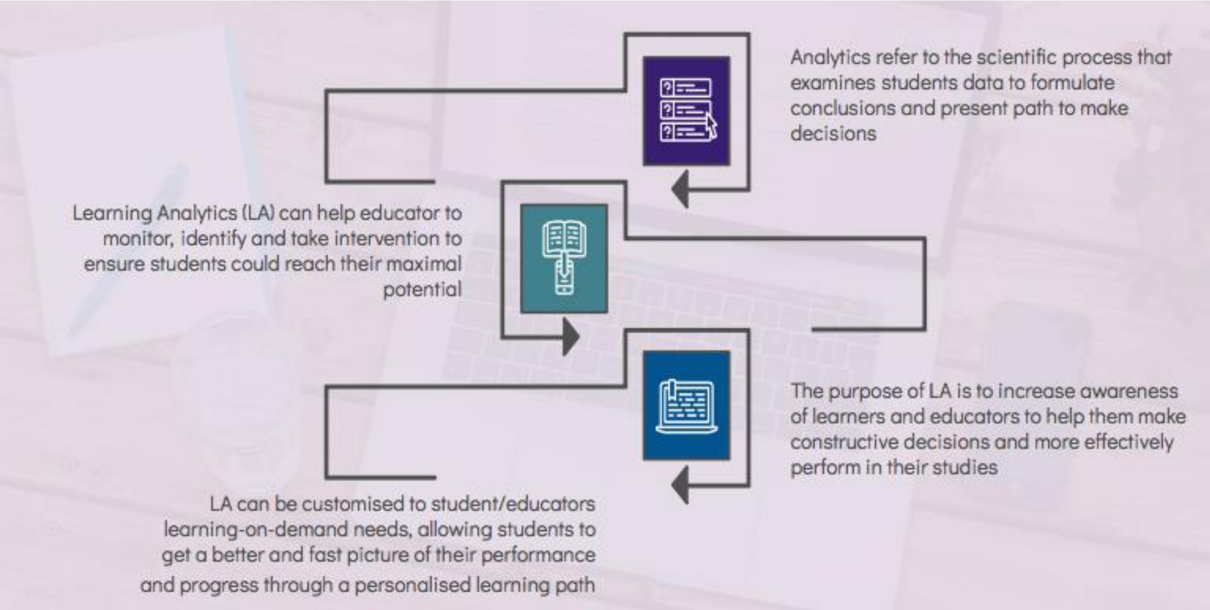

Fig. 1 Learning analytics cycle

Common research objectives that have been explored in learning analytics and educational data mining include modelling student behaviour, predicting performance, increasing reflection and awareness, predicting dropout, improving assessment and feedback, enhancing social interactions in learning environments, understanding the effects of students, and recommending resources (Papamitsiou & Economides, 2014; Verbert et al., 2012). These objectives are pursued using different techniques such as clustering, regression, text mining, social network analysis, statistics, and various visualization techniques (Vieira et al., 2018).

Besides using data from learning records, some studies use commodity wearable devices to capture a learner's physical actions and accordingly infer the learner's learning context, such as the student's activities and engagement status in class (Yu et al., 2017). The analysis of existing evidence for Learning Analytics indicates that there is a shift toward a deeper understanding of students' learning experiences compared to the impact of Learning Analytics in improving learning outcomes and supporting learning and teaching (Viberg et al., 2018). Other research on Learning Analytics include the study by Schumacher and Ifenthaler (2018) that addressed the features that students want from a Learning Analytic, and by Shibani et al. (2020) that investigated the issue from the perspectives of educators.

However, relying too much on technology for teaching methods may have negative drawbacks. Ferguson (2012) raised concern about the use of technology in learning, stating that students may feel isolated due to the lack of contact with teachers or peers. Additionally, they may become disoriented in the online space, experience technical problems, or lose motivation. Despite these circumstances, the scope of learning analytics extends beyond just technology. The broader scope of learning allows the medium to look at other aspects that contribute to the learning process as a whole. For instance, Shum and Ferguson (2012) denote the social aspect for learning as one of the spectrums in learning analytics. According to them, learning analytics comprises not only a recording process of student activities and viewing time but also personal information such as user profiles, academic results, and interaction data. The whole process is significant in the field of learning analytics.

Undoubtedly, educators are accountable to ensuring the success of the teaching process. Students have the rights and obligations to learn, which places a huge responsibility on the teachers (Rodzalan & Saat, 2015). One of the essential components of teaching deliverables is the dependence on the internet. Notably, internet technology has become a mandatory requirement in teaching and learning activities. An internet network is a group of computers that are connected, so that information can be shared (Nurdyasnyah & Andiek, 2015). This describes how shared knowledge and collaborative learning can be enabled through the internet. Indeed, the Internet has become the crux of learning analytics due to its role as a supporting tool for distance learning and MOOCs.

Learning analytics can focus on basic competencies that have not yet been tested for practicality and effectiveness, in order to provide a comprehensive presentation of all the necessary competencies in a package of learning modules (Nopriyanti & Sudira, 2015). Alternative supportive learning techniques and modern pedagogical approaches are viable options to enhance the interactive learning process and engage students through the use of learning analytics (Mahadiraja, & Syamsuarnis, 2020). The results of various applications of teaching and learning strategies have demonstrated that the learning analytics approach can optimize the learning ecosystem.

Educators bear a huge responsibility for providing significant feedback on the entire learning input and they would be able to do this with learning analytics. Pardo et al. (2019) claimed that technology plays an important role in advocating meaningful learning processes and in providing novel solutions to issues related to capturing learning effectiveness of students. The interaction of numerous learning technologies has led to the adoption of a new way to capture data based on students' learning performance. Data in a form of systematic data, also known as big data application, provide a meaningful tracing system of student learning performance (Lang et al., 2017; Pardo et al., 2019) in order to overcome and provide a quick-fix solution in supporting the students' learning experiences. By far, learning analytics is a practical solution whereby the planning and organization of learning processes provide self-assessments, deliver adaptive recommendations, and produce personalized analyses of their learning activities to enlighten issues related to holistic student matters (Schumacher & Ifenthaler, 2018).

The application of learning analytics can be utilized at different layers of the educational system. However, to ensure the success of learning analytics, understanding the practices in the educational system of the studied location is necessary. It will provide a preliminary understanding of students' current technological readiness and their attitudes towards learning. The following sub-sections describes the current practices in the teaching and learning process.

Learning analytics in Program Planning

Given the perspective of an educational administrator or a curriculum developer unit working at different phases, program planning is the most important phase. Program planning starts at the faculty level where different committees, made up of lecturers and expert panels appointed by the faculty, are formed to brainstorm the structure of the program and curriculum (Wiles & Bondi, 2019; Jocabsen 2017; Glatthorn et al., 2018; Orlich et al., 2017; Murray & Olcott, 2019)

Because assessments and evaluations are always in the form of norm standardization, where the cumulative grade of a student is being measured through a summative application, final examination, for example, has become mandatory in assuming the mastery level of the academic content being measured at that particular viewpoint. On top of that, formative evaluation is often overlooked although it has been laid out clearly in the study plan to report students' achievement in a holistic manner (Black & William, 1998; Scriven, 1972; Stiggins, 2004; Brookhart, 2003; Heritage, 2010).

Since conventional programs frequently overlook the coordination and implementation of authentic learning experience, learning analytics provides a solution by matching authentic learning activities with students' learning characteristics based on data analytic tools (Siemens, 2013; Gasevic et al., 2014, Jovanovic et al., 2017; Kovanovic et al., 2015). The coordination process of synchronization could show the present disruptions toward learning. On top of that, the incapability of students can trigger the intervention process in order to assist them to learn at their best. Nevertheless, imperfection might occur in this process as some programs limit their interdisciplinary agenda which will hinder meaningful learning experiences, especially in meeting students' expectations and learning needs. (Sengupta & Chudgar, 2016; Hargreaves & Shirley, 2018; Biesta, 2010; Kozleski & Engelbrecht, 2016)

Learning Analytics in Course Planning (Beginning of the Semester)

The program offers courses that support student learning (Allen & Seamen, 2014). Following the plan made for the semester, the faculty administrator can start the semester with several meetings to ensure the plan is well-executed throughout the semester. In a typical process, the course synopsis can be distributed to students since students are advised to make some learning preparations before attending their classes. Just as the class is about to start at the commencement of the semester, lecturers can prepare a teaching plan or proforma in the system. The system will display students' biographical information which allows lecturers to obtain information on the students' major, nationality, disability issues, and other relevant profiling. (Allen & Seamen, 2014, Kuo et al., 2013; Oblinger, 2003) Discuss the features and functions of learning management system (Blackboard & Moodle

In the system set for lecturers, the total number of students registered for a course can be determined, and the teaching medium can be in either one or more methods, for example, face-to-face, blended learning, and online platform (Dziuban et al., 2018; Siemens, 2008). To some extent, student performance on a specific course can determined through the University's Continuous Quality Improvement (CQI) system which reflects and monitors student performance in each course based on the students' results in the previous semester (Kuh & Kinzie, 2008; Reid & Ward, 2015)

The advantage of the whole system is that information can be accessed from the structured process of planning and execution of the curriculum. Even under the repetitive process i.e. the same course being conducted for different semesters, the system is able to assist university administrators to ensure successful implementation and delivery of the course in the program to students. Each program is usually structured to follow specific time frames and executed in accordance to the suggested approaches. However, this causes the system to compound with rigidity. Teaching could become less flexible, and the routines would cause lecturers and students to lose the ability to scrutinize the synergy (Johnson, 2014). The teaching and learning process would become stagnant. For example, lectures merely depend on students' demographic profiles without knowing specifically the background of the students. In some cases, information about students is rather descriptive and does not describe the students' holistic achievement at the university (Ferguson, 1998: Tomlinson, 2014). For example, the information merely describes the students' participation and contributions in co-curricular activities, specific organizations, and the community. It may also describe their industrial experience. Thus, data in the system can be classified as an entry-level data, presented at tool surface and is rather repetitive. Student performance is measured according to Outcome-Based Education (OBE) which provides a grade based more on a numerical context; therefore, less is known of the students' overall learning outcome or achievement (Ewell, 2011; Banta & Palomba, 2015; McMilan, 2018). As a certain grade is required as a prerequisite to enroll in another course in the program, it is important to have a system that can identify the real potential and readiness of the students. Therefore, it is necessary to emphasize the need to implement adaptive learning analytics in a course for the whole cohort. This approach can assist in determining the entire students' performance.

Learning analytics in Lesson Preparation

Educators bear a huge responsibility in ensuring that the learning process takes place effectively thus, preparing for each lesson is of utmost importance. Planning requires compiling of resources, preparing assessment activities, and ensuring teaching materials are in concordance with the teaching-learning outcome (LO). All the contents and planned activities will then need to be uploaded onto the learning management system (LMS) powered by Moodle or Blackboard to compound student academic performance. The lecturers are badgered by embedding at all possibilities of the learning process to tally up with the formative and summative assessments covering all course synopsis. In some cases, lecturers omit the dialogue process i.e. by having a consensus with the students on the assessment criteria (Nicol & Macfarlane-Dick, 2006). At times, the matter could be worse when students are unaware of the assessment criteria and only receive their final grade upon completing the final examination.

One of the challenges in preparing lesson plans is to deliver the contents using a different approach from the way they were presented in the previous semester. This is to ensure that the course is more dynamic and not repetitive. Nonetheless, lecturers are overloaded with administrative and other tasks which could affect their commitment in improvising the teaching and learning content (Darling-Hammond et al., 2017). In addition, the content of the curriculum might be duplicated from other courses without a comprehensive overhaul made to the curriculum at the developmental phase. Thus, in most events, the curriculum is not well-rounded so as to assess students' attainment of the different learning outcomes and only focuses to ensure that the learning process takes place (Larkin & deMarrais, 2010). Failure to make changes to the pedagogical content would result in a monotonous delivery of the instruction process and continued use of outdated resources.

Another barrier in lesson preparation is the competency level of the lecturers, especially the novice lecturers. Designing a competency development program or enrolling in a competency enhancement program is time consuming. Besides, the university usually assumes that lecturers or those with a postgraduate degree have the ability to teach and are familiar with the OBE system. However, some lecturers are not competent enough and are not well trained with the competency development procedure required by the system (Ngidi & Ndebele, 2019; Ahmed & Azam, 2015). For instance, the mapping of the course program outcome, particularly in justifying the elements in the constructive alignment, is a challenge to new lecturers compared to some senior lecturers. Although most lecturers can develop a teaching plan according to the course synopsis, many fail to have value added skills in the teaching and learning process (Brown et al., 2019; Ginkel et al., 2018). Adding added values in teaching is important as these values are supplementary elements that help students to master other components of soft skills and thus, increase their employability and readiness to face the challenging workforce environment.

Lesson Delivery

The lesson is a measure to check the effectiveness of the educators and students with regard to the content being delivered. Because the lesson is the premise of the deliverable process, educators bear a huge responsibility in ensuring that the process is successfully executed. As such, a myriad of instructional approaches and tools are introduced to educators. Due to the evolution of technology, the teaching process has now become more exciting and interactive. Upon entering an online teaching and learning environment, educators and students are likely to get accustomed to virtual learning platforms such as Zoom, WebEx, and Google Meet (Li & Lalani, 2020; Singh et al., 2020; Brown & Leidholm, 2002; Kim et al., 2005; Rovai, 2002; Strickland, 2020). When the instruction process is carried out using those platforms, the disposition of educators and students of the use of learning tools such as H5P, Socrative, TedEd, just to name a few, is vital (Salinas & Vilalon, 2020; Jankowski & Holas, 2019; Liaw et al., 2007). The importance of technological tools and their benefits to the current learning ecosystem is evident.

However, the trend, pattern, and heavy emphasis on technological tools have drawn negative feedback, especially from students who struggle to get an internet connection (Chia & Eng, 2021; Foucault-Welles et al., 2020). Indeed, many deliverable methods require the Internet as a medium of connectivity. Therefore, the existing teaching approach is not more of a one-size-fits-all since missing features, characteristics, and student data are prevalent. The current system does not emphasize the needs and data on learning style and competency requirements of individual learners, including available facilities and competency to utilize some features of the apps and tools on the Internet.

Although educators learn and utilize various teaching and learning strategies, they have to settle from truncated challenges of the competency elements especially when it comes to digitalization and additive systems to support learning. Instructors are compassionate for their students and do their best in their instructional approaches. The application of several technological tools may or may not enhance students' motivation toward learning due to the lack of confidence in utilizing the tools (Kay & Lauricella, 2011; Shroff et al., 2016). This, however, has become a challenge for educational dignitaries to ensure that teachers under their supervision can utilize existing apps and technology. Training has been provided through numerous webinar series and shared-sessions from educators across nations, to help teachers who struggle with their ideas of creative teaching and learning processes during COVID-19 (UNESCO, 2020).

It is interesting to note how graceful teachers can be despite the challenges in the teaching and learning milieu. In most cases, it is due to the absence of assistive tools to help instructors understand what and how the students feel toward their instructional approaches (Jaggers et al., 2014). Consequently, there are missing data on students' reflection and satisfaction, which are pivotal to trigger students' preliminary performance. Learning is often conducted in a classroom setting which requires space and interaction. One of the challenges is the struggle of the teacher to give attentive treatment to every student enrolled in the course (Fendri & Alshammari, 2018; Han et al., 2020; Kim & Lim, 2019). On top of that, students need authentic learning experiences to trigger deep affective components in learning. Although some instructors have taken the initiative to implement innovative teaching approaches in their classes, they neglect the point that each student is unique, and a one-size-fits-all teaching approach does not always work for some of them (Lee & Hannafin, 2016). Hence, capturing data on student learning styles can optimize the whole learning experience. The aforementioned issues in deliverable methods can be partially solved by adopting learning analytics.

Methodology

Data for this study were collected by utilizing a survey questionnaire. The implementation of the descriptive and correlational quantitative survey was done by selecting 500 students from a public university in Malaysia using the random sampling technique. 500 questionnaires were distributed, and 350 respondents (70%) completed the survey by providing valid information that was utilized for the research. The distribution and collection process of the questionnaires took almost a month to be completed. A descriptive and inferential analysis approach was used to interpret data obtained, which were mostly categorical. Apart from frequencies and percentages (to explain the general pattern of responses for the demographic part of the questionnaire), the mean and standard deviations of each variable were developed through the use of descriptive statistics. T-Test, ANOVA, and Pearson Correlation were employed to analyze the relationship among the studied variables. Before the actual study, the questionnaire was validated by a panel of experts. A reliability test was applied by analysing Cronbach's alpha to ensure that the items for each concept were homogeneous and measuring the concept of interest. Cronbach's alpha is a measure of reliability that varies from 0 to 1, with values from .60 to .70 being considered to be the lower limits of acceptability (Field 2016; Hair et al. 2014). It is noted that the reliability of the research concept lies between 0.603 and 0.778. Therefore, no item has been removed. The items were transferred to form meaningful concepts for further analyses. All items were answered on a 5-point Likert scale (1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree).

Results and Findings

Demographic Profile of Respondents

A total of 350 students (116 Males and 234 Females) from a public university in Malaysia completed the online survey using the Qualtrics software. More than half of the respondents (75.7%, n = 265) were between 22 and 24 years old. Majority of them were undergraduate students (94.9%, n = 332); 1.2% were Masters students (n = 4); and 14 were PhD students (3.9%). The respondents were students from nine faculties of the university. The highest number of participants were from education (60.6%, n = 212).This was followed by respondents from other faculties i.e. 8.9% (n = 31) from accounting, 7.1% (n = 25) from environmental studies, 6.6% (n = 23) from engineering, 4.6% (n = 16) from computer science, 4.0% (n = 14) from agriculture, 3.7% (n = 13) from medicine, 2.3% (n = 8) from biotechnology, and 2.3% (n = 8) from linguistics.

Majority of the respondents were Malaysian students (97.1%, n = 340). Only 2.9% of the respondents were international students (*n = 10*). More than half of the respondents (74%, *n = 259*) were Semester 5 and Semester 6 students. Majority of them (96.3%, *n = 337*) were taking more than 12 credit hours during the current semester. Over half of the respondents (70.0%, *n = 245*) claimed that their current Cumulative Grade Point Average (CGPA) to be in the range of 3.0 to 3.49 points, which is the 2nd Class Upper category. As far as grades are concerned, 98.6% of the students (*n = 345*) stated that they cared about their grades in the university.

Most of the respondents had no doubt about learning (99.4%, *n = 348*). When asked about their motivation to learn in the classroom, the results showed that most of the respondents (97.4%, *n = 341*) were motivated to learn in the classrooms. Only nine students (2.6%) claimed that they lacked the interest to learn in the classrooms. The reasons given were outdated learning facilities; lecturers' teaching style was not in line with the 21st-century learning system; and overcrowded classrooms. Some of the respondents suggested that the university provide online learning activities.

Majority of the respondents (335 students or 95.7%) believed that online learning would increase their interest in learning. In contrast, only 15 out of the 350 students (4.3%) were not interested in online learning. This was due to the poor internet connection at certain places, limited interaction between students and lecturers, and difficulties to ask questions related to learning.

Table 1
Demographic information of the samples

Demographic Variables	Frequency (*f*)	Percentage (%)
1. Age		
18-19	11	3.1
20-21	56	16
22-24	265	75.7
25-29	8	2.3
30-34	2	0.6
35 and over	8	2.3
2. Gender		
Male	116	33.1
Female	234	66.9
3. Categories of Students		
Malaysian	340	97.1
International	10	2.9
4. Current Semester		
1-2	17	4.9
3-4	41	11.7
5-6	259	74
7-8	31	8.9
9 and over	2	0.6
5. Field of Study		
Engineering	23	6.6
Education	212	60.6
Linguistics	8	2.3
Accounting	31	8.9
Medicine	13	3.7

Computer Science	16	4.6
Agriculture	14	4
Environmental Studies	25	7.1
Biotechnology	8	2.3
6. Credit hours are taken in the current semester		
Less than 12 credit hours	13	3.7
More than 12 credit hours	337	96.3
7. Current Cumulative Grade Point Average (CGPA)		
1.99 and below	2	0.6
2.00-2.99	16	4.6
3.0-3.49	245	70
3.5 and above	87	24.9
8. Do you care about your grades?		
No	5	1.4
Yes	345	98.6
9. Do you like to learn?		
No	2	0.6
Yes	348	99.4
10. Motivation to learn in a classroom		
No	9	2.6
Yes	341	97.4
11. Online Learning Interest		
No	15	4.3
Yes	335	95.7

Note: N = 350

Descriptive Analysis

This study focuses on students' expectations toward the features of the learning analytics system. The learning analytics system comprises three perspectives: (1) summative, (2) real-time, and (3) predictive (Ifenthaler & Widanapathirana, 2014). The summative perspective provides detailed insights after the completion of a learning phase (e.g. study period, semester, and final degree) which are often compared against the previously defined reference points or benchmarks. The real-time perspective uses ongoing information for improving processes through direct interventions while the predictive perspective is applied to forecast the probability of outcomes in order to plan for future strategies and immediate actions (Ifenthaler & Widanapathirana, 2014).

Table 2 describes the descriptive analysis of each perspective of students' expectations toward the features of the learning analytics system. A particular question asked was "Please indicate your level of agreement on the importance of the following features in your learning environment". In 350 questionnaires that were filled out and returned, the Real-time perspective has the highest overall mean, with (M= 4.22, SD = 0.527), followed by the Predictive perspective (M= 4.01, SD = 0.472), and the Summative perspective, which has the lowest mean (M = 3.70, SD = 0.543).

The Summative perspective indicates six features of the learning environment. The highest mean value (M = 4.05, SD = 0.464) is attributed to the "Revision of former learning content" of each student responding to the survey, while "Prefer self/independent learning rather than conventional classroom settings" has the lowest feature, with a mean value of (M = 3.05, SD = 0.638). Therefore, on average, "Revision of former learning content" is the students' most preferred feature in their learning environment as shown in the summative perspective.

Table 2 also displays the Real-time perspective with four features of the learning analytics system. The highest mean is "Reminder for deadlines" with (M = 4.73, SD = 0.619) while the rest of the features, "Collaborative learning with friends and colleagues", "Time needed to complete a task or read a text", and "Feedback for assignments" are reported with mean values of (M = 4.05, SD = 0.508), (M = 4.05, SD = 0.485), and (M = 4.05, SD = 0.496), respectively. This shows that on average, all the students prefer "Reminder for deadlines" as the best feature in their learning environment.

This research also evaluates Predictive as one of the learning analytics system perspectives. Five features are identified for this perspective. As shown in Table 2, "Term scheduler, recommending relevant courses" is the key feature of students' consideration when dealing with the learning environment (M = 4.07, SD =0.444), while the least important feature is "Considering the student's calendar for appropriate learning recommendations" with a mean value of (M = 3.94, SD = 0.545). Thus, generally, all the students consider "Term scheduler, recommending relevant courses" as the most crucial feature of the learning environment.

Table 2
Descriptive Analysis of the Features in the Learning Analytics System

Construct/ Variable	Features in Learning Analytics	Mean *(M)*	Overall Mean (M_O)	Std. Dev. *(SD)*	Overall Std. Dev. (SD_O)
Summative	Time spent online	3.99	3.70	0.505	0.543
	Prefer self/independent learning rather than conventional classroom settings	3.05		0.638	
	Timeline showing current status and goal	4.02		0.505	
	Comparison with fellow students	3.07		0.654	
	Newsfeed with relevant news matching the learning content	4.00		0.491	
	Revision of former learning content	4.05		0.464	
Real-time	Collaborative learning with friends and colleagues	4.05	4.22	0.508	0.527
	The time needed to complete a task or read a text	4.05		0.485	
	Feedback for assignments	4.05		0.496	
	Reminder for deadlines	4.73		0.619	
Predictive	Learning recommendations for successful course completion	4.00	4.01	0.470	0.472

	Prompts for self-assessments	3.99	0.421
	Further learning recommendations	4.03	0.481
	Considering the student's calendar for appropriate learning recommendations	3.94	0.545
	Term scheduler, recommending relevant courses	4.07	0.444

Note: N = 350

T-Test Analysis

An independent-samples t-test was conducted to compare the students' demographic profiles and features on learning analytics. A significant difference is recorded in the scores for gender (M=1.67, SD=0.471), types of student (M=1.03, SD=0.167), credit hours taken (M=1.96, SD=0.189), concern on grades (M=0.99, SD=0.119), learning concern (M= 0.97, SD=0.159), learning motivation (M=0.99, SD=.092), and learning analytics (M=3.97, SD=0.324); t (347)=228.389, p = 0.000. The results suggest that students' demographic profiles as mentioned previously do affect learning analytics features. Specifically, our results suggest that when students' demographic profiles that involve extrinsic values (i.e., gender, types of students, and credits hours taken) and intrinsic values (i.e., concern on grades, learning concern, and learning motivation) are considered, the features in learning analytics (i.e. summative, real-time, and predictive) possess a significant impact on the whole learning outcome.

Table 3
T-test results in comparing demographic profiles of the respondents on learning analytics.

Variable	*n*	M	SD	*df*	*t*	*p*
Gender	350	1.67	.471	349	66.220	0.000
Types of student	350	1.03	.167	349	115.339	0.000
Credit hours taken	350	1.96	.189	349	193.902	0.000
Concern on grades	350	.99	.119	349	155.181	0.000
Learning concern	350	.97	.159	349	114.992	0.000
Learning motivation	350	.99	.092	349	200.917	0.000
Learning analytics	347	3.97	.324	346	228.389	0.000

*significant at p<.000

ANOVA Findings

One-way Analysis of Variance between-subjects (ANOVA) was conducted to compare the effect of learning analytics features on students' age, current semester, field of study, and current cumulative grade point average (CGPA). A significant relationship was seen between age p<.05 and learning analytics with ($F_{4,341}$ = 3.428; p< .05). However, the ANOVA analysis involving the current semester, field of study, and CGPA did not significantly differ with learning analytics ($F_{4,342} = 0.673$; $p > .05$), ($F_{8,338} = 0.916$; $p > .05$), and ($F_{8,338} = 0.916$; $p > .05$), respectively. Taken together, these results suggest that age plays a significant effect on learning analytics features i.e. summative, real-time, and predictive measures.

Table 4
ANOVA analysis of demographic profiles on learning analytics

Predictor		Sum of Square	Degree of Freedom *(df)*	Mean squared	The value of F	*p*
Age	Between groups	1.740	5	.348	3.428	.005*
	Within groups	34.613	341	.102		
Current semester	Between groups	.284	4	.071	.673	.611
	Within groups	36.069	342	.105		
Field of study	Between groups	.771	8	.906	.916	.504
	Within groups	35.582	338	.105		
CGPA	Between groups	.771	8	.906	.916	.504
	Within groups	35.582	338	.105		

*significant at $p<0.05$

Correlation Analysis

Table 5 shows the results of the Pearson Correlation Analysis to determine the relationship of the learning analytics features: summative, real-time, and predictive. The correlations between summative and real-time were found to be strongly positively correlated at r (350) = .636, p = .000, followed by summative and predictive r (347) = .791, p = .00, respectively. The correlation between real-time and predictive was also found to be strongly and positively correlated at r (347) = .778, p = .000.

Table 5
Correlation analysis on learning analytics features

Predictors		Summative	Real-time	Predictive
Summative	Pearson Correlation	1	.636**	.791**
	Sig. (2-tailed)		.000	.000
	N	350	350	347
Real-time	Pearson Correlation	.636**	1	.778**
	Sig. (2-tailed)	.000		.000
	N	350	350	347
Predictive	Pearson Correlation	.791**	.778**	1
	Sig. (2-tailed)	.000	.000	
	N	347	347	347

** Correlation is significant at the 0/001 level (2-tailed)

Discussion

Learning analytics draws on the relationship between demographic profiling of learners and features that are being researched, as noted by (Lockyer et al., 2013; Long and Siemens, 2011). Learning analytics provides indicators of student failure, intervention measures, and contemplations toward the learning process of students. This study focuses on learners characteristics and profiling to understand the relationship between demographic profiling of learners and learning analytic features. The objective is to investigate the demographic characteristics that may or may not influence the learning process through learning analytics.

The study found a strong correlation among learning analytic features: summative, real-time, and predictive. Summative analytics analysis learning outcomes or performance data after a learning activity has taken place. Real-time analytics analysis data in real-time during a learning activity, and predictive analytics use data to make informed predictions about future learning outcomes. The study suggests that the different types of learning analytics features are interrelated and that the presence or absence of one may have impact the effectiveness of the others. This highlights the importance of integration different types of analytics features to improve the overall effectiveness of the system.

The study identified learner characteristics that contribute to the success of learning analytics, including age, gender, type, total credit hours, concern for achievement, learning preference, and learning. Learner characteristics, such as age and gender, can impact the learning process. Research suggests that older learners may have more developed metacognitive skills, which can lead to more effective learning strategies (Bjorklund & Pellegrino, 2002) and gender can influence learning outcomes (Hyde et al., 1990). The researchers also identified two types of motivation: extrinsic and intrinsic values. Extrinsic values refer to motivations driven by external factors, such as rewards, punishments, or social recognition, while intrinsic values refer to motivations driven by personal interests, curiosity, or a desire for personal growth or development. These motivations by factors such as grades, competition, or social approval. For example, a student who studies hard to earn a high grade in a course or to impress their peers is being motivated by extrinsic values (Ryan & Deci, 2000 and a student who studies a subject because they find it interesting or because they want to develop their skills is being motivated by intrinsic values (Ryan & Deci, 2000). The distinction between extrinsic and intrinsic values has been widely studied in the fields of psychology and education.

Research shown that intrinsic motivation is associated with higher levels of engagement, learning, and performance, while extrinsic motivation can be associated with lower levels of these outcomes (Ryan & Deci, 2000; Vallerand et al., 2008). Therefore, understanding and supporting intrinsic motivation is an important consideration in designing effective learning analytics systems.

The Signal posted in the findings, which depict the parameter of the learner's demographic characterization, such as age, gender, total credit hours, concern about their achievement, learning preference, and learning motivation, are essential in comprehending the learning analytics ecosystem. Analysing these demographic characteristics, can help educators and learning analytics designers understand the various factors that can influence a student's behaviour and performance in the learning environment. For instance, understanding a student's learning preference can enable educators to customize their instruction to better cater to the student's needs, Similarly, understanding a student's motivation can help designers develop interventions to enhance student engagement and performance. Additionally, demographic characteristics can help identify potential barriers to learning, such as social or cultural factors that may impede a student's ability to engage with the material. By comprehending these factors, educators and designers can develop strategies to address these barriers and support student success. Overall, demographic characteristics are a crucial aspect of the learning analytics ecosystem, as they provide insights into the diverse needs and motivations of learners. By considering these factors, educators and designers more effective strategies to supporting student learning and success.

The findings of the study have significant implications for teachers in terms of their ability to deliver effective learning content. The diverse range of student characteristics, such as academic background, personality traits, and learning preferences, can impact the effectiveness of teaching methods and materials. By collecting and analysing data on the on these characteristics, educators can gain insights into how to tailor their teaching methods to better meet the needs of individual students. This data can also help identify patterns and trends among different groups of students, enabling educators to personalize instruction and provide targeted support where needed.

That educators often focus on the grading system as a way to measure students' academic excellence, which can lead to a focus on extrinsic rewards rather than intrinsic motivation. The research by Deci, Koestner and Ryan (1999) found that students who are motivated by intrinsic factors, such as personal interest and enjoyment, are more likely to engage in behaviours that contributed to long-term success, while those motivated by extrinsic factors, such as grades as external rewards, may experience anxiety and disinterest in learning. This highlights the important of educators promoting intrinsic motivation in their students to help them develop a love for learning and a desire for personal growth.

The progress of students in learning is influenced by the way they are taught, and such as, educators need to use various teaching approaches to ensure effective learning takes place.

Victoroff and Hogan (2006) identified three characteristics that describe an effective learning experience: (a) characteristics of the instructors (personal qualities, "checking-in" with students, and interactive style), (b) characteristics of the learning process (focus on the "big picture," modelling and demonstrations, opportunities to apply new knowledge, high-quality feedback, focus, specificity and relevance, and peer interactions), and (c) learning environment (culture of the learning environment and technology). Whilst many educational-based types of research revolve around qualitative and behavioural observations, the expansion of learning technology combined with the advancement of storage and network evolution has encouraged the development of learning analytic studies (Siemens, 2013; Gasevic et al., 2015; Long & Siemens, 2011).

To ensure that effective learning experiences are provided, it is important for teachers to learn about these three characteristics and implement them in their teaching practices. Brown, Collins and Duguid (1989) suggest that teachers themselves should be responsible for learning about these characteristics and continuously reflect on and improve their teaching practices. However, teacher training programs of professional development workshops could also be provided to support teachers in developing these skills and knowledge. Ultimately, it is up to the individual teacher to continually improve their teaching practices to ensure effective learning experiences for their students.

The effective of learning analytics is one of the new young disciplines in the area of learning science (Sharef et al., 2020). This area brings together researchers and practitioners from various fields who intend to better understand and improve learning processes through data-driven insights. Learning analytics studies how to employ data mining, machine learning, natural language processing, visualization, and human-computer interaction approaches among others, to provide educators and learners with insights that might improve the learning process and teaching practices. The effectiveness of learning analytics applications in teaching and learning processes are indicated in the demographic profiles of the learners. Generally, understanding learners' characteristics will empower the learning analytics ecosystem and optimize the whole learning experience by creating a synchronization between students' capacity and capability for learning.

The landscape of learning analytics continues to expand as it is now possible to track the behaviour of the learners and teachers in the learning management systems, MOOCs, and other digital platforms that support educational processes (Leitner et al., 2017). Being able to collect larger volumes and varieties of educational data is only one of the necessary ingredients. It is essential to adopt, adapt, and develop new computational techniques for analysing and capitalizing on the data. Data mining techniques and other computational approaches with interactive dashboards are being used to get a better insight on the different learning processes.

One of the premises in learning analytics is to match the pedagogical approaches and students' learning preferences. In addition, adopting pedagogy-based approaches to learning analytics will propagate meaningful learning experiences. However, it is a mere challenge to collect and capture the subjectivity of the learning processes in a data form. Tsai and Gasevic (2017) agreed that the lack of guidance on data literacy culture among end-users of learning analytics has impacted the thoughts on assessments and evaluation processes. The lack of it hinders an effective delivery to students. The establishment of validated guidelines to oversee the soundness, effectiveness, and legitimacy of learning analytics shall be taken thoughtfully, considering the technological readiness and big data application awareness.

The rapid technological evolution including computer networking advancement has played a major influence in the future of the higher education landscape (Popenici & Kerr, 2017). Undeniably, machine learning will come in place soon, and it is to be adopted in the teaching and learning milieu. A collaborative learning environment will embed technological tools and computer assistive learning technology to promote holistic learning experiences.

The value-based education will be captured by the learning analytics tools and particularly, be imposed on curriculum development (Boholano, 2017).

Most experienced educators admonished ways of a so-called effective learning process. Teaching is an art to be delivered in the most crucial and careful way; therefore, it is not supposed to be incoherent or fraught with abundant information delivered in a rigid approach. As novice teachers may not always possess a natural ability to teach, learning analytics may provide solutions regarding this matter. The central challenges for teachers are in capturing students' attention, putting across the ideas, and ensuring retention of knowledge gained by students continues even after they have left school (Kalyani & Rajasekaran, 2018). Learning analytics determine students' performance in different phases: the pre and post-learning process including retention of learning input based on the data uploaded in the learning analytics tools. The system is frequently revisited by an educator to reflect on the effectiveness of the chosen pedagogical approaches, and this provides room for improvements through ongoing self-assessment.

Conclusion

Much attention and interest have been given in the field of learning analytics, and it has been proven that the new generation of students can benefit from it. Students provide valuable feedback on their learning needs and urge educators to understand their capacity and capability in the learning process. Learning analytics is imperative in the era of digitalization and online learning to maintain the balance between teaching and the effectiveness of the delivery in ensuring academic success. It is feasible to build a learning analytic system that is capable of capturing data and, more importantly, discerning the characterization of learners. Understanding learners' profiling has contributed to the important findings of the study; thus, neglecting these factors will have a detrimental effect on the overall learning analytics study. Researchers continue to measure the impact of learning analytics applications on teaching and learning and customize the data captured in learning analytic tools to combat the runoff and provide a relevant learning experience to students.

Suggestion for Future Research

As the impact of COVID-19 on education has become apparent, it is essential to address the challenges faced by students un the learning process. Neglecting the impact of learning deficiencies could potentially have negative consequences for their future career prospects. To overcome this challenge, it is necessary to invest in research related to learning analytics and develop tools that can diversify learning patterns. The objective of such research would be to support the relevance of universities as the forefront of knowledge creation by identifying innovative ways to promote effective learning and ensure that students' values are taken into account.

Acknowledgements

This study was funded by the Malaysian Research Grant University titled Enhancing Education for Human Capital Development through Establishing Future Learning Ecosystem (UPM/800-4/11/MRUN/2018/5539210. Appreciation also goes to Universiti Putra Malaysia (UPM), Research Management Centre (RMC), and the Innovative Learning Sciences Research Centre of Excellence (INNOVATE), UPM for the coordination and distribution of financial support for this study.

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