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Improving the Effectiveness of Data-Driven Learning Management

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ABSTRACT: Big data represents a significant decision-making tool in educational processes, allowing for not only improvements in the quality of education, but also the formation of effective strategies, allowing users to effectively make decisions based on the results of predictive and prescriptive analytics. In addition, educational data are used to analyze and predict student behaviors and learning outcomes to ensure the high quality of educational programs.Nevertheless, even though educational data offer significant opportunities, there are a few challenges associated with their effective and timely application, such as compatibility, data processing and storage, security, confidentiality, and ethics.

This article reports on a study that aimed to determine whether the effectiveness of learning management could be enhanced through the development of a more rigorous academic environment and a stimulation intervention designed for a particular graduate program at a particular university. The study used data from several study groups. It collected qualitative and quantitative data to examine the impact of the environment and the stimulation of 173 students, as well as benchmark group data from 22 students. The results showed that exposure to a more rigorous academic environment with minimized gamification, as well as the application of a stimulation intervention, was successful in improving scores for several metrics. This article indicates the importance of updating and using educational data to enhance learning management, as well as the need to increase knowledge in this area.

KEYWORDS: learning management; educational data; stimulating intervention

INTRODUCTION

The prime objective of higher education is to help students develop the right outlook on life and values; in addition, of course, it aims to equip them with scientific knowledge and ideas, as well as to provide them with opportunities to express and develop their creative talents.

The rapid development of software and data analytics techniques, as well as the growing interest in applying business analytics principles to educational processes, has led to the emergence of educational data mining and the development of learning analytics for managing data-driven learning.

The core principle of learning analytics is to extract useful information from the large amount of data generated during the learning process. The information obtained is applied at various stages by participants in the educational process: students, teachers, heads of departments, and the administration of the higher education institution.

The reasons for using the data can vary depending on the situation: they might be used for predicting academic performance, implementing a red-flag system, reducing student attrition rates, etc.

In this context, the most urgent issues concern the timeliness and the accuracy of the data obtained. Learning analytics emerged more than 10 years ago; however, point metrics, which prove obvious or already established facts, have been used until now. The development of interactive technology in the educational sphere imposes new requirements for metrics, emphasizing the very essence of education.

The authors of this article contend that it is possible to use data in educational approaches, applying a tool that will provide an evidence base for decision making and its scaling: namely, data-driven learning management. Data-driven approaches can provide a clear overview of the growth points of participants in the educational process, whether they are students or teachers. These approaches also provide the tools necessary to support individual student development trajectories; additionally, they can help teachers to determine the best learning paths for each student.

LITERATURE REVIEW

In recent years, many researchers have focused on data-driven learning management. In this section, we discuss some of the existing works and research in this area and their impact on improving the effectiveness of learning management.

Improving the Effectiveness of Data-Driven Learning Management

A portfolio can be a useful tool for students and educational institutions, because it can reflect all of a student's achievements and interests during the educational process. This can include not only the results of academic work, but also their participation in extracurricular activities, such as projects, performances, conference presentations, and other activities that reflect the professional and personal growth of a student.

Thus, as part of the implementation of the "Development of a Unified Competency Model for an Advanced Technology Engineer" [17], the educational project of the Priority 2030 development program, the authors suggest assembling a versatile profile by evaluating students' soft skills and professional and digital competencies. Soft skills and digital competencies include communication, team building, entrepreneurial skills and project management, artificial intelligence and digital competencies, general digital skills, modeling and programming, advanced end-to-end technology, emotional intelligence, and effective thinking. Based on several indicators (i.e., the disciplinary grade point average and competency scores), a student is assigned a status – a level of competence proficiency. It is assumed that a student will be able to track his or her progress using this personal account. This approach to assessing a student's profile can help educational institutions to identify the hidden talents and potential of students, which, in turn, will help them to build a career and interact with future employers. In addition, this approach is expected to help students to more accurately identify their interests and professional goals.

The increase in the number of graduates can be considered to be one of the key indicators of learning management effectiveness. For example, Florida International University achieved a 10% increase in graduation rates by using a predictive learning modeling technique and effective preventive counseling [7]. Typically, a set of predictive performance modeling metrics includes the student's gender, ethnicity, place of residence, family income level, CGPA (cumulative grade point average), attendance rate, course, grades (completion of practical work, test scores, midterm grades), and total number of credit hours [1]. The predictive grade model proposed by the authors of the study helps students to avoid poor grades and helps instructors to predict the course completion rate, including a student's final grade, which is considered a direct indicator of his or her success.

Learning analytics is also used as the part of the implementation of early warning systems to predict student performance [4]. Western Governors University uses predictive modeling to improve the retention rate by identifying at-risk students and developing early intervention programs [9].

A number of studies claim that student emotional engagement data can be used to increase engagement in learning [15]. According to the authors of the study, epistemic emotions during online learning affect the learning process due to the lack of real-time feedback. In addition, it is noted that these emotions can limit or, alternatively, enhance the learning process. The study showed that positive emotions contribute to academic performance, while negative emotions can cause frustration or anxiety, leading to disruption in the learning process. It is also possible to identify a person's emotional state based on how they behave when studying using an online platform.

Recognition of a person's emotional state [5] has also been made possible by relatively new video-stream processing technology. By processing images from a video stream, an artificial neural network diagnoses a number of human states such as anger, surprise, disgust, and happiness. The pilot launch of this technology showed that the reliability of the obtained data is about 72% [16].

Neurointerfaces are gradually becoming a permanent element in learning [11]. Experts suggest using the technology to monitor the activity of the learners' brains and encourage them if they lose concentration. Additionally, neurointerfaces help to adjust the content to the individual characteristics of the students, to give them the right learning intensity.

Eye-tracking technology (the tracking of eyes movements) is used in education [18] on the basis that, through eye-tracking, it is possible to determine how well the student will pass the exam on the subject, even while they are still taking the course. It is possible to state with some accuracy the degree to which students are aware of what they are learning, and how well the knowledge is absorbed by the way they read materials or watch training videos.

Moreover, communication quality analytics can be used for a deep analysis of a teacher's public speaking skills [10]. The metrics used are speech content, coherence, comprehension, complexity, and emotionality.

With the widespread use of LMSs in higher education, attempts to analyze learning based on data from these systems have also increased in number. The data are not only used to analyze the learning outcomes of an individual student, but sets of indicators based on logarithmic data are also studied to facilitate group assessment in courses and to predict team assessment in group work [8]. The analysis of LMS data from one Australian university [6] found a positive correlation between student engagement and teachers' input, and, interestingly, a negative correlation between student engagement and course content. Some studies emphasize a particular format of instruction, such as a flipped classroom [2, 14]. They believe that tracking class preparation activities (interacting with content, taking tests, etc.) with learning analytics can predict at-risk students early on. Some research also focuses on increasing student engagement specifically for science, technology, engineering, and mathematics (STEM) students [12].

In addition, some studies argue that the level of student engagement in the learning process can be regulated by using smart badges as an element of the LMS [19]. Badges are solid tokens used to record achievements in academic or other fields. In addition to their utility as evidence of achievement, badges are of interest to higher education as a pure incentive to encourage students and learners in general to achieve well-defined goals and skills. In this respect, badges can be naturally integrated into digital learning platforms and as part of informal learning, providing incentives for participation, achievement and visibility for students. However, the level of student engagement in such learning activities depends to a large extent on how the badge and reward system is designed and applied if it is to be used effectively.

At the same time, some researchers emphasize the importance of appropriately applying elements of online course design to engage students in real-world activities [13]. For example, assignment prompts and self-assessment questions, tutor suggestions embedded in videos, or other design elements can encourage participants to apply the practice in their own contexts. This method can be loosely defined as a nudge intervention.

Specifically, the results of a study [3] conducted at a regional university in Australia showed that the use of stimulation intervention was a successful factor in increasing engagement in online courses, and it was also determined that prerequisites for such incentives were necessary to increase success rates.

The use of educational data may have different purposes that depend on the specific situation, such as predicting the performance of students, reducing the dropout rate, increasing student interest in the learning process, etc. The timeliness and accuracy of the data obtained are key factors. The field of learning analytics uses point metrics that confirm what is already known. However, the development of new interactive technologies in education requires the use of more effective metrics that reflect the essence of education.

The authors of this article propose that an evidence-based tool that helps make and scale data-driven decisions can be used in education. The basic idea is to use data for learning management, which should be personalized and adaptive; the emphasis is on building real-world, practical skills, not just ensuring adherence to academic standards. This approach allows us to consider the individual student's learning goals and the development of his or her personal potential.

Using data makes it possible to assess the growth points and development potential of everyone involved in the educational process, including both students and teachers. These approaches provide tools to support individual student development trajectories and can help instructors to determine the best learning paths for each student.

MATERIALS AND METHODS

This study was conducted using a mixed-methods approach that combined the collection of qualitative and quantitative metrics to examine the impact of various factors on student engagement across multiple study groups. Using a mixed methods approach allowed us to consider indicators of different metrics and obtain a more comprehensive picture. The study of the factors' influence was conducted across two study groups in the same online education program. The total number of students enrolled in two study groups was 173, with 103 starting in 2020 and 70 starting in 2021. The benchmark is the data from the same educational program that is implemented in a full-time format. There are 22 students in this traditional study group, and they began their studies in 2021. Since the authors of this article aimed to assess the impact of various factors on student engagement, the data were collected and analyzed using a set of specific metrics.

In Table 1, we list examples of various metrics that are related to the use of learning analytics.

Table 1. Examples of metrics, methods, and sources of data collection

Metric	Method / Source of Data Collection	Stakeholder
CSAT, Customer Satisfaction	Survey	Admins, students
CDSAT, Customer Dissatisfaction Score	Survey	Admins, students
CSI, Customer Satisfaction Index	Survey	Admins, students
NPS, Net Promoter Score	Survey	Admins, students
AR, Achievement rate	Statistical information	Admins
Movement of students	Statistical information	Admins
Employment rate of graduates	Statistical information	Admins
COR, Completion Rate	Statistical information	Admins
RR/PR, Retention rate / Progress rate	Statistical information	Admins, educators
Balance	Curriculum	Educators
Polls Rate Teachers	Survey	Educators, students

As these examples of metrics show, educational data can be used in a variety of areas (Figure 1), such as:

- Decision-making management;
- The choice of instructional design (education science);
- The analysis of the psychological factors that affect learning;
- Learning analytics.

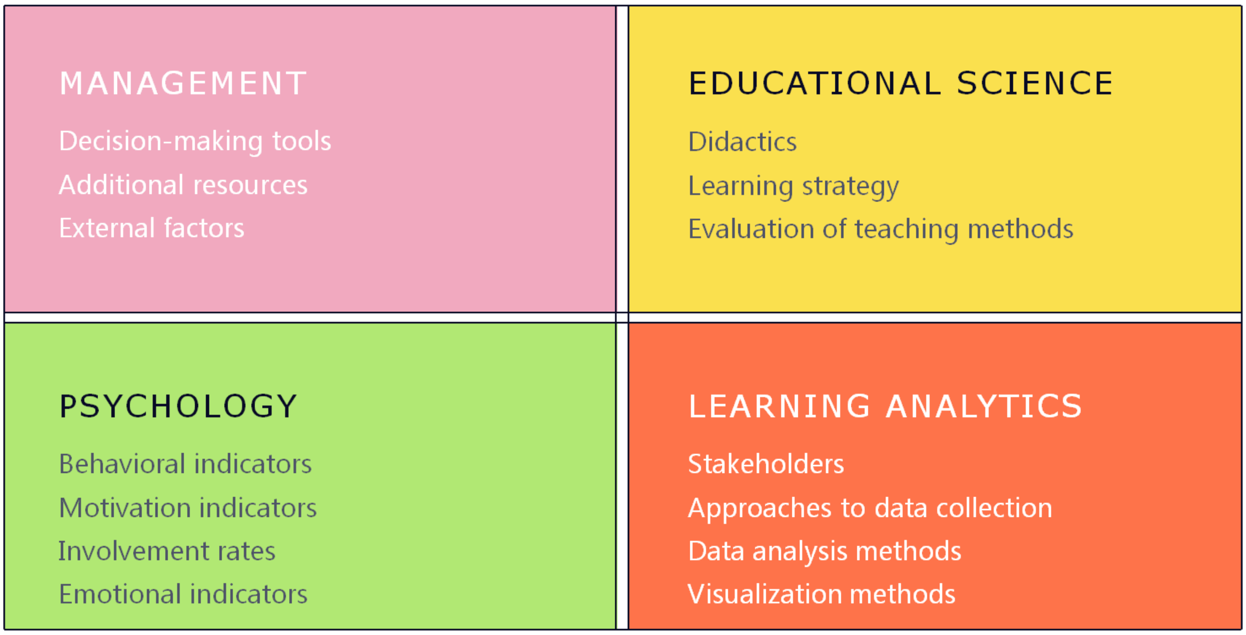

Figure 1. Parameters of data classification in different domains.

However, the real implementation of learning analytics begins only after identifying patterns that contribute to the development of deeper understanding in the areas of academic skills, cognitive competencies, and students' psychological behaviors. Therefore, it is important to sort the information collected according to the area under study and/or in need of improvement.

The authors identified five key metrics they considered critical to determining student engagement:

- Net Promoter Score, NPS—the index of loyalty, or the extent to which users are willing to recommend this program;
- Completion Rate, COR—the ratio of students enrolled to graduates;
- Retention Rate/Progress Rate, RR/PR—the progress of users within the program; the transition from level to level and/or the return of the student;
- Satisfaction Rate, SR—the level of students' satisfaction (the ratio of positive to negative feedback for the course);
- Achievement Rate, AR—% of positive grades (4 and 5, for example) in relation to the total number of those who took the final examination;
- Balance—the ratio of the main educational formats in the program.

The metrics were calculated using the following formulas:

$$\text{NPS} = \left(\frac{Number\ of\ students\ (8-9\ points)}{Number\ of\ interviewed\ students} - \frac{Number\ of\ students\ (0-6\ points)}{Number\ of\ interviewed\ students}\right) \times 100\%$$

$$\text{COR} = \frac{Number\ of\ graduates}{Number\ of\ students\ enrolled} \times 100\%$$

$$\text{RR} = \frac{Number\ of\ students\ in\ the\ end\ of\ the\ program - Number\ of\ students\ returned\ from\ academical\ leave}{Number\ of\ students\ in\ the\ beginning\ of\ the\ program} \times 100\%$$

$$\text{SR} = \frac{Number\ of\ positive\ feedback\ on\ the\ program}{Number\ of\ interviewed\ students} \times 100\%$$

$$\text{AR} = \frac{NUmber\ of\ scores\ higher\ than\ 4\ points\ (average\ performance\ for\ the\ program\ period)}{Number\ of\ graduates\ of\ the\ program} \times 100\%.$$

It is also important to note that the students of the two groups studied on different platforms: Platform 1 and Platform 2. Platform 1 involves many gamification elements of learning (progress, microbadging), the ability to evaluate the content and the teacher of a particular subject, etc. (Figure 2).

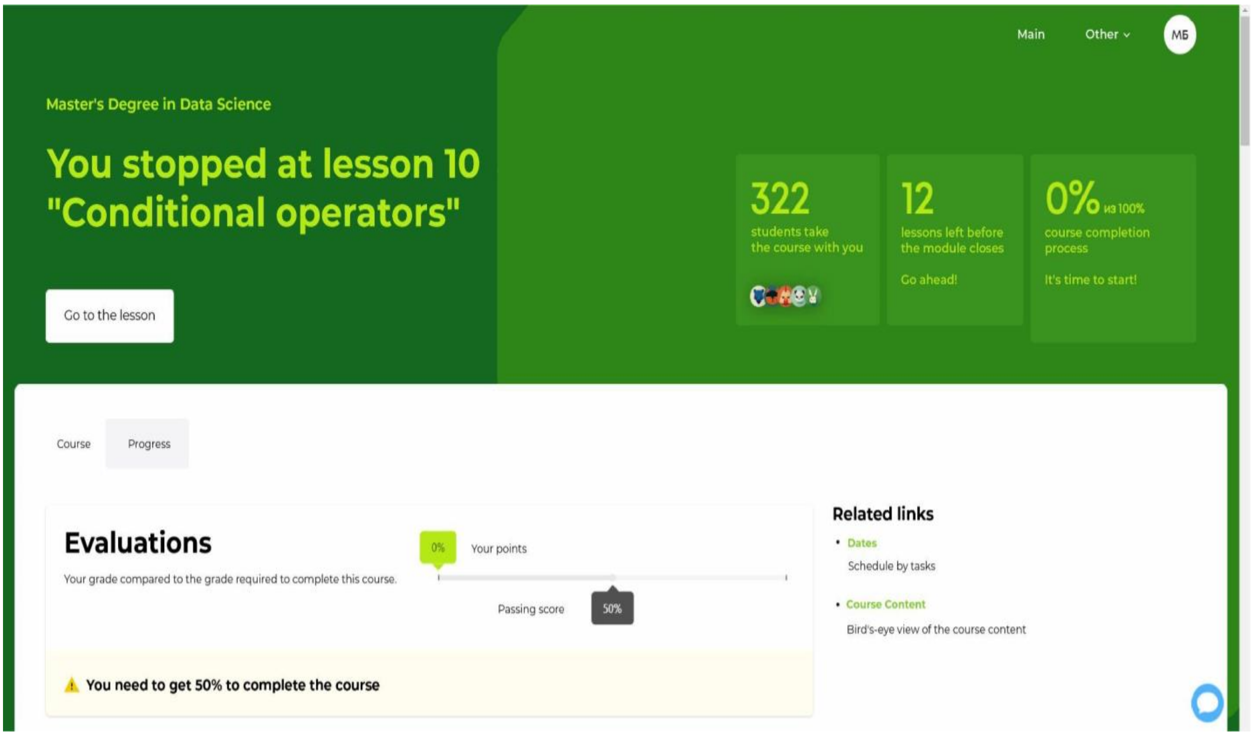

Figure 2. Screenshot of Platform 1.

Platform 2 looks more academic, and the use of gamification is minimized.

In addition, the progress of each student was controlled by a supervisor (one supervisor worked with fifty students). The functions of a supervisor included assisting students with all personal and administrative issues; the provision of interaction between the participants of the educational process, including synchronous and asynchronous communication; the control of each student's performance; and the results of mastering the graduate program. Platform 2 contains functions allowing users to create special reports on a student's participation and, at the same time, to issue warnings—for example, when a student has not appeared on the platform for more than one week (see Figure 3).

Figure 3. Screenshot of the student participation report on Platform 2.

Data were collected in several stages. First, each group took surveys at the end of the academic semester, and the survey results were used to calculate the metrics (Figure 4).

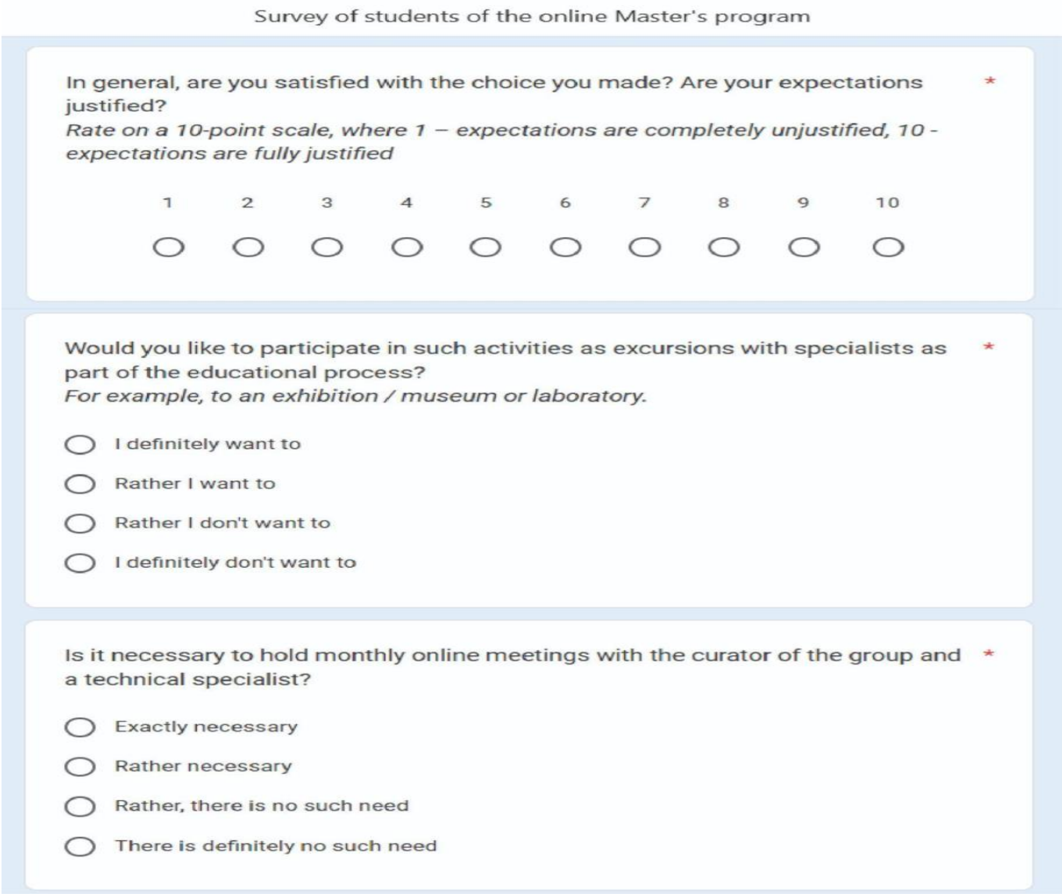

Figure 4. Example of questions in the student survey on the results of the academic semester.

Second, the study collected statistical data, such as the number of students enrolled and the number of graduates; the number of positive grades (4 and 5) in relation to the total number of those who reached the final examination; the average grade point, etc (Figure 5).

№	Name	Status	Average score				
			1 semester	2nd semester	3rd semester	4th semester	Graduate
1		academic leave	4,5	4,33	1,75	-	-
2		academic leave	4,75	5	3,75	-	-
3		academic leave	4,5	4	3,25	-	-
4		academic leave	4,75	4	3,5	-	-
5		Graduate	4,25	4,83	5	5	4,73
6		academic leave	4,8	4,5	-	-	-
7		Graduate	5	4,83	4,75	5	4,93
8		Graduate	4,75	5	5	5	4,93
9		academic leave	5	5	4,5	5	-
10		Graduate	4,75	5	4,5	5	4,80
11		Graduate	5	5	5	5	5,00
12		Graduate	4,5	4,83	5	5	4,80
13		Graduate	5	5	5	5	5,00
14		Graduate	5	4,83	5	5	4,93
15		academic leave	5	4	-	-	-
16	personal data	Graduate	4,75	5	5	5	4,93
17		academic leave	4,75	5	4,75	5	-
18		academic leave	4,75	5	4,75	5	-
19		Graduate	4,75	5	5	5	4,93
20		Graduate	5	5	5	5	5,00
21		Graduate	4,75	5	4,75	5	4,87
22		Graduate	5	5	5	5	5,00
23		Graduate	5	4,83	4,75	5	4,93
24		academic leave	4,8	4,1	-	-	-
25		Graduate	4,5	5	5	5	4,87
26		Graduate	4	4,67	4,25	4,5	4,33
27		academic leave	4	-	-	-	-
28		academic leave	5	3,5	1	-	-
29		academic leave	4,8	4,8	-	-	-
30		academic leave	4,75	5	3,5	-	-
31		Expelled	5	5	5	-	-
32		academic leave	4,6	4	-	-	-
33		academic leave	4,5	-	-	-	-

Figure 5. Example of statistical data on student performance.

Improving the Effectiveness of Data-Driven Learning Management

First, the data from the traditional student study group were analyzed to identify metrics to be adopted as a benchmark. Then, the data were collected and used to calculate metrics for two groups of online learners on the different platforms to examine the direct impact on student engagement.

RESULTS AND DISCUSSION

The effectiveness of a more rigorous academic environment can be determined by the increase in several metrics at once (Table 2). The data for the students in Group 2 showed that, after the gamification elements were minimized on the educational platform, the students' progress (retention rate/progress rate) increased by 31% compared to the data for Group 1. At the same time, the RR rate in the traditional group was 80%; the authors attribute this to the large number of educational paths between full-time programs, meaning that students can transfer if they wish. There is less choice or no choice at all in similar online programs at the same university.

Also in Group 2, a stimulation intervention into students' learning, whereby supportive supervisors responded to the platform notifying them of a student's long absence, increased the program's enrollment-to-completion rate (COR) by 40% compared to Group 1. The COR rate in the traditional group was 60%. The authors attribute this to the fact that learning analytics data are collected less frequently in traditional groups (usually at the end of the semester, which means once every few months) than in online learning, which uses a platform that issues red flags during the learning process. Consequently, there were more opportunities for Group 2 students to adjust their progress and grades.

Similarly, when the Group 2 students received notifications encouraging them to return to the learning materials and engage in the educational process, and also made a continuous effort, there was a 22% increase in the number of positive grades (4 and 5), relative to the number of positive grades in Group 1. Consequently, student satisfaction (the satisfaction rate) increased by 8%, as students felt that their efforts were paying off. This rate is identical to the results of the SR in the traditional group.

Table 2. Indicators of metrics based on the results of data collection and analysis in the three study groups.

Metric	Group 1 2020–2022	Group 2 2021–2023	Benchmark group 2021–2023
Format	Online Platform 1	Online Platform 2	Face-to-face
NPS	72%	60%	40%
RR	45%	76%	80%
COR	31%	71%	60%
SR	78%	86%	80%
AR	51%	73%	75%
Balance	Lectures—19% Practice—67%	Lectures—19% Practice—67%	Lectures—19% Practice—67%

The Net Promoter Score for Group 2 was 12% lower than that for Group 1. It is important to point out that the NPS was collected from groups during the first year, while the rest of the data were collected and analyzed at the end of studies. Additionally, since the other metrics show an increase in key metrics, the authors of the article believe that the NPS can be recognized as a secondary (non-key) metric of the study.

Limitations, Implications, and Future Research

Learning analytics has the potential to be used in a variety of contexts, including analysis and timely responses to student engagement levels. There are additional opportunities to improve and to use the combination of learning analytics and stimulation interventions as a tool to increase motivation or change student behaviors in online programs.

Although data-driven learning management is still in its early development stage, it has great potential in various applications. One important vector for development is the adoption of a strategic approach to the systematic and timely collection of educational data, which considers what data to collect, as well as the frequency and terms of collection.

This study can be considered as limited, as the data were collected from a single university. Although the experiences and decisions of the participants may not fully represent all student groups, the authors provided a detailed description of the research environment and methods. The data were collected from three different study groups, which may allow universities with similar contexts to use the recommendations of this study.

Future research might consider including more study groups at the same university and comparing data from other universities with a more rigorous academic environment. Additionally, future research may include in-depth interviews with students and teachers to explore their perceptions and gain a more meaningful understanding of both the positive and negative effects of this approach.

CONCLUSIONS

This article suggests that there are differences between the metrics of the two study groups when evaluating the impact of a more rigorous academic environment with minimized gamification, as well as a stimulation intervention. Evidence for increased learning effectiveness was gathered from both quantitative and qualitative data. Student learning on Platform 2 shows a significant increase in a number of metrics, whereas the gamified Platform 1 allows students to have more fun, being directly linked to their worsening performance and progress to final exams. The authors of this article also attribute this to a decrease in student subjectivity, which removes their responsibility for their progress in learning.

The benchmark of the study is the performance of the traditional study group, with students learning in a social environment and being guided by feedback and group performance in real time.

Obviously, a challenge faced by online programs is the organization of group work (i.e., team interactions) among students. Being in a face-to-face group directly affects and enhances students' learning outcomes.

The problem areas in the organization of team interactions are as follows:

- Technical problems: different devices, the availability of microphones and cameras, etc.;
- Different time zones, where a difference of more than three hours is critical;
- Team expectations, particularly the complexity of role assignment;
- The availability of space for training (i.e., a comfortable area with no one to distract participants from the process).

That said, tracking learning analytics for each student can help educators to not only tailor the course content for each student's unique needs, but also increase student adaptability and interest and provide more productive learning environments.

It is necessary to add special metrics, such as the engagement rate (the level of student engagement) and well-being (the level of well-being), to ensure the more effective use of learning analytics, because the key tasks of the university are not only the formation of competencies assessed according to educational standards, but also the education of the individual. These metrics refer to the ability of teachers and the university administration to listen to students and consider their needs and views. Assessing the level of student engagement in the learning process will help educators to adapt the learning approach and improve the quality of education. Moreover, assessing the level of student well-being can help us to address emerging issues and develop preventive measures that promote the health and well-being of university students. Therefore, the addition of these metrics can help to shape more person-centered learning in higher educational institutions.

Although universities are providing more and more opportunities for students to access online formats, they still fail to implement effective learning management, resulting in students' partial or complete failure to achieve the desired outcomes. Student retention in online programs remains at a lower level than that in full-time programs, which may be due to the difficulty in organizing teamwork. This study found that the strategy of creating a more academically rigorous environment and encouraging communicative interventions led to increased scores in key metrics.

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