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The Use of Learning Analytics to Track and Improve Linguistic Competency

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Abstract: The purpose of this study is to investigate how children from low-income backgrounds might benefit from playing serious games in order to improve their language skills. With the use of learning analytics, we were able to covertly measure students' progress and provide them with individualized feedback after they played serious games in class. A total of 85 kids, including 41 males and 44 girls, ranging in age from 9 to 12 (m=10.6; SD=0.7), were surveyed for the study. All of the participants were deemed at risk owing to their socioeconomic status. To determine how well two games aimed at enhancing language abilities worked, researchers used a pre-experimental design that included both pre- and post-tests. Learning analytics can effectively evaluate the competencies that students have acquired and identify their specific needs when they are facing academic challenges. Additionally, this analytics approach can predict academic performance using scores collected during game-based learning. The results show that (a) incorporating serious games into the curriculum can greatly improve linguistic competence in disadvantaged students. (b) With targeted systematic interventions, these students can achieve performance levels comparable to their peers. These findings help fill in some of the blanks in our understanding of how to best use educational technology and instructional practices to support at-risk students.

Keywords: *educational technology, verbal learning, linguistic competency, learning analytics*

Introduction

The rise of data-driven methods and digital technology have caused a sea change in the educational sector in the last several years. Learning analytics, which provides a fresh viewpoint on how educational data can be used to improve learning outcomes, has been an important subject of focus among these. The goal of learning analytics is to enhance educational decision-making and the learning process by collecting, measuring, analysing, and reporting data on learners and their surroundings. Statistical analysis, data mining, and machine learning are just a few of the many approaches that are a part of it. The goal is to get insights into the learning patterns, strengths, and problems of students. Learning analytics play an increasingly important role in meeting the growing need for tailored learning experiences. This is especially true in domains such as language learning, where complicated linguistic competency necessitates nuanced evaluation and assistance.

Learning Analytics in Education

In the ever-changing world of education, learning analytics has become an indispensable tool for guiding decision-making and individualized learning through data-driven tactics. Learning analytics, which is defined as the study of how students learn and how that data is used in the classroom, allows teachers to improve their methods of instruction and the results their students achieve. Learning analytics makes use of tools like machine learning, artificial intelligence (AI), and big data analysis to reveal trends that may otherwise go unnoticed, thereby benefiting educators and students alike. Instead of depending just on generic teaching approaches, this approach enables educators to customize education to meet the unique requirements of every student. Learning analytics have become more important due to the proliferation of digital education technologies and online learning platforms, which allow for the real-time tracking of student progress and the subsequent adaptation of the learning experience. Educators can better assist students when they can examine specific interactions, such the amount of time spent on activities, the correctness of exercises, and the frequency of involvement. In niche fields like language learning, where evaluating and improving linguistic competency necessitates a sophisticated comprehension of the student's advancement, learning analytics becomes particularly useful in response to the rising need for customized learning experiences.

Linguistic Competence and Communication

A person's proficiency in both comprehending and producing language is at the heart of their linguistic competence. Phonology refers to a language's phonetic system, morphology to its grammatical structure, syntax to its arrangement of words and phrases, semantics to its meaning, and pragmatics to its application in context. The ability to generate and understand new phrases is known as linguistic competence, a concept popularized by Noam Chomsky. The ability to communicate effectively in a variety of settings is foundational to academic success, social integration, and career advancement. But, especially in contexts involving more than one language or among students learning a new language, the path to linguistic competence is convoluted and differs greatly from one student to the next. Because language learning is continuous and ever-changing, traditional ways of evaluating linguistic ability (e.g., standardized exams, written essays, and oral examinations) frequently fail to do so. Without the in-depth tracking of continuous growth or the capacity to emphasize modest gains over time, these systems simply give a snapshot of a learner's abilities. Here is where learning analytics really shine, providing a game-changing examination of language development that is both thorough and ongoing.

The Intersection of Learning Analytics and Language Education

One major advancement in the evaluation, development, and improvement of linguistic competence has been the use of learning analytics into language curricula. Teachers can improve their awareness of their students' language ability and tailor their teaching techniques to their specific needs by incorporating analytics into language learning platforms and classroom situations. Duolingo, Babbel, and Rosetta Stone are just a few examples of digital language learning programs that employ analytics to monitor user engagement, mistake patterns, and topic mastering. Such systems can track a user's vocabulary repetition or grammatical rule problems, for instance. The platforms can then use this information to provide individualized lessons or activities. Analytics aren't only useful for digital platforms; they can also help classroom teachers track student progress and fine-tune lessons based on data collected via online quizzes, assignments, and interactive exercises. With the use of real-time data, learners may receive feedback just when they need it, enhancing their learning experience. Also, using learning analytics, teachers may see where a class is struggling and work together to provide students with more focused instruction or supplemental resources. Learning analytics enables a transition to a more adaptable, learner-centered approach in language teaching by offering detailed and all-encompassing data.

Review Of Literature

Ramya Rajendran (2023) The goal of learning analytics, a relatively new area of study, is to improve the efficacy of education by collecting and analyzing data. Including the present research landscape, important ideas, models, benefits, and problems, this article gives a thorough introduction to the field. It takes a look at how several learning analytics models—such as cluster, social, descriptive, predictive, and prescriptive models—are applied in the classroom. Underscoring its ability to revolutionize education through data-driven insights, the report also draws attention to obstacles to learning analytics' wider implementation and proposes directions for further research.

Riina Kleimola (2022) Using learning analytics, universities can better equip their students with the skills they'll need for the future. Results from this study that drew on interviews with 19 educators highlight the importance of traits including self-awareness, learning literacy, flexibility, and teamwork. These can be aided by learning analytics, which promote introspection, goal-setting, and efficient utilization of digital resources. Nevertheless, there has been little research into how to really put these statistics into practice. The research provides helpful information for teachers who want to improve their students' competency development by making strategic use of learning analytics.

Ruben Morales-Menendez (2022) Enhancing learning and improving educational results are the goals of Learning Analytics, which analyzes student data. Most schools utilize it to increase student retention, but some also use it to improve their teaching techniques. In order to detect vulnerable pupils and act before it's too late, many schools create their own tools. This preventative measure helps with the transition to new pedagogical approaches, which was particularly evident during the COVID-19 epidemic. Researchers and educators may gain valuable insights into the study's practical usage, problems, and possibilities of Learning Analytics.

Hayo Reinders (2018) Language instructors may use learning analytics to keep tabs on their students' participation and understanding, finding out who is paying attention, having trouble, and potentially dropping out. When teaching a language, this method shines because some pupils may have difficulty articulating their demands. Learning analytics facilitates prompt actions by seeing any problems at an early stage. Learning analytics as it pertains to language instruction is defined and discussed in this article, along with its potential uses, pros, and cons.

Alex Rayon (2014) Assessing student abilities is a tough task, but universities are putting a lot of emphasis on them for student growth. This is where SCALA comes in; it's a system that uses data from students' social interactions and interactions with resources to help with competence evaluation. SCALA compiles results from six different types of assessments and provides instructors with a dashboard that includes enhanced rubrics to evaluate the collaboration skills of a sample of twenty-eight students. Using clustering and association rule mining, SCALA delivers a visual tool to enhance competency evaluation through data-driven insights.

Objective Of The Study

1. To evaluate the effectiveness of serious games, Leobien and Walinwa, in enhancing linguistic competence among socio-educationally disadvantaged students.
2. To analyze the relationship between serious game indicators and academic performance in core subjects.

Hypothesis

H1: There is no significant improvement in linguistic competence among socio-educationally disadvantaged students through the use of serious games like Leobien and Walinwa.

H2: There is no significant correlation between serious game indicators and students' academic performance in core subjects.

Research Methodology

A one-group pretest-posttest pilot study preceded the experiment (Shadish et al., 2002). Pre-experimental evaluation can assess an intervention's feasibility and results without a control group (Campbell & Stanley, 1963). These methods can show intervention results without causation.

Sample size

The study involved 85 students (48% girls, 52% boys, M = 12.5) from three suburban middle schools, with grades 6 (20%), 7 (35%), and 8 (45%).

Participants

The study included 75 socio-educationally challenged children from four public schools in disadvantaged Asturias neighborhoods. The sample is 48% female (36) and 52% male (39). 6.7% were in 4th (9-10 years), 52% in 5th (10-11 years), and 41.3% in 6th. The students' academic disparity showed socio-educational disadvantage.

Instruments

Serious games Walinwa and Leobien were used to test language skills utilizing game Learning Analytics. Both systems awarded students final and starting marks for language skills and global success measures. Before and after these programs, academic performance was recorded.

Procedure

The intervention was carried out during the second term of the 2020–2021 academic year, with serious games incorporated into Spanish Language and Literature classes. The games were alternated weekly over 50 sessions, each lasting 15 minutes, to maintain engagement and prevent boredom.

Data Analysis

Data was processed with SPSS 24.0. Non-parametric tests were utilized because some variables have a non-normal Kolmogorov–Smirnov distribution. Student-t tests for normally distributed data and Wilcoxon rank-sum for non-normal data were used for pre-test–post-test comparisons. Effect sizes were calculated using Cohen's d or r. Pearson's correlation coefficient and Spearman's Rho were used to evaluate the relationship between language gains and academic achievement, with R^2 indicating GLA's predictive potential.

H1: There is no significant improvement in linguistic competence among socio-educationally disadvantaged students through the use of serious games like Leobien and Walinwa.

H2: There is no significant correlation between serious game indicators and students' academic performance in core subjects.

Table 1: Gender Distribution of Respondents

Gender	Frequency	%
Female	41	48%
Male	44	52%
Total	85	100%

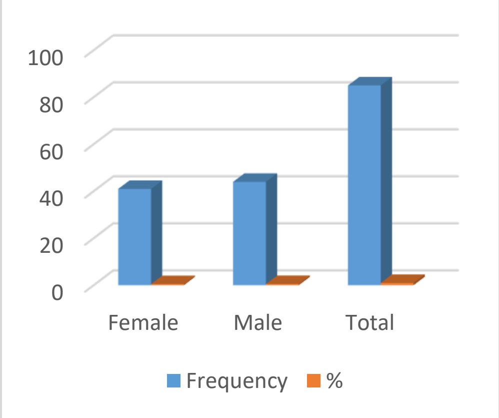

Figure: 1 Showing percentages of Gender

There were 85 participants in the research, with 44 men (52% of the total) and 41 females (48%), suggesting a somewhat male preponderance but still a very balanced gender distribution. The results may be more broadly applied because of the increased variety in the sample that results from include both sexes. To gain a more well-rounded grasp of the study issue and draw more inclusive conclusions about the intervention's effect on academic achievement, it is important to include a varied set of participants.

Table: 2 School Year Distribution of Respondents

School Year	Frequency	%
4th grade (age 9 to 10 years)	6	7.1%
5th grade (age 10 to 11 years)	44	51.8%
6th grade (age 11 to 12 years)	35	41.2%
Total	85	100%

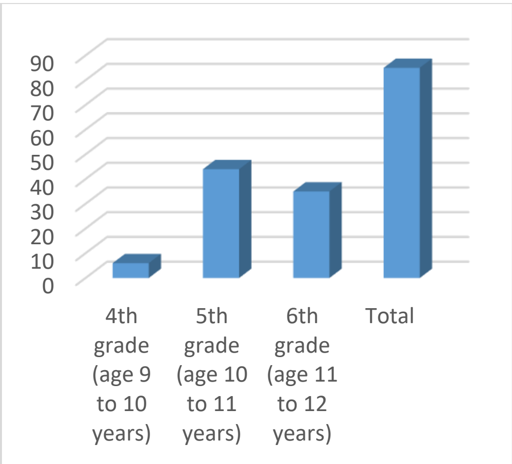

Figure: 2 Showing percentages of school years

A total of 85 pupils from three different grade levels made up the sample. The following grades were represented: 6th grade (years 9–10), 5th grade (ages 10–11), and 6th grade (ages 11–12): 44 students (51.8%), 35 kids (41.2%), and 1 student (7.1%), respectively. The findings show that more than half of the sample is in fifth grade, which is a rather high concentration. This preponderance might indicate that the intervention or study is aimed squarely at this age bracket, which could provide insight on unique developmental requirements or guide future educational practices. By include students from both the fourth and sixth grades, the research is able to cover more ground when looking at academic achievement and associated effects during these critical years.

Table 3: Results of the Pre-test–Post-test Comparison and Effect Size of the Sub-Materials

There is no significant improvement in linguistic competence among socio-educationally disadvantaged students through the use of serious games like Leobien and Walinwa.

Sub-Materials	t	Z	p	d	R
Comprehension	–5.523		.000	0.638	
Attention	–6.042		.000	0.698	
Letter and Phrase	–5.787		.000	0.668	
Memory	–6.170		.000	0.712	
Word	–5.789		.000	0.668	
Sequencing	–6.066		.000	0.700	
Syllable and Text	–5.918		.000	0.683	
Reading Speed		–4.851	.000	–0.693	

All measures show statistically significant differences, with p-values of.000 across the sub-materials. Comprehension has the greatest deficit ($z = –5.523$) and Reading Speed the least ($z = –4.851$). Cohen's d effect sizes vary from 0.638 for Comprehension to 0.712 for Memory, suggesting medium to substantial differences. These results indicate that pupils' performance in these areas is significantly lower than expected, indicating possible difficulties with these essential abilities. The consistent trends across sub-materials suggest focused treatments to strengthen these skills, particularly in areas with the biggest impact sizes, including Memory and Attention, to improve academic achievement.

Table 4: A correlation between Sub-Material/Global Indicator Scores and Academic Results

There is no significant correlation between serious game indicators and students' academic performance in core subjects.

Indicator	Natural Sciences	Social Sciences	Spanish Language	Mathematics	English
Effectiveness	r = .290*	r = .301*	r = .324	r = .319	r = .330
R^2	.084	.091	.104	.102	.109
Sig. (bilateral)	.016	.013	.007	.008	.006
Performance	r = .098	r = .176	r = .167	r = .267*	r = .409
R^2			.071	.167	
Sig. (bilateral)	.425	.150	.172	.028	.001
Main Topic	r = .354*	r = .395*	r = .498	r = .399	r = .383*
R^2	.125	.156	.248	.159	.147

Indicator	Natural Sciences	Social Sciences	Spanish Language	Mathematics	English
Sig. (bilateral)	.023	.011	.001	.010	.013
Grammar Topic	r = .114	r = .252	r = .265	r = .346*	r = .143
R^2				.120	
Sig. (bilateral)	.482	.117	.099	.029	.380
Other Content of Walinwa Method	r = .164	r = .194	r = .244*	r = .165	r = .118
R^2					
Sig. (bilateral)	.204	.123	.031	.195	.428

Analysis of academic performance measures across topics shows significant correlations. Effectiveness revealed substantial positive relationships in all subjects, notably in English (r =.330, p =.006), demonstrating that increasing effectiveness improves performance, explaining 10.9% of English performance variation. The only factors with significant relationships with performance were Mathematics (r =.267, p =.028) and English (r =.409, p =.001). The Main Topic also showed substantial positive correlations across all disciplines, notably in Spanish Language (r =.498, p =.001), explaining 24.8% of the variance, underlining its importance to student progress. The Grammar Topic had a significant association only in Mathematics (r =.346, p =.029), whereas Other Content of the Walinwa Method had a positive correlation only in Spanish Language (r =.244, p =.031). These studies emphasize the importance of effectiveness and comprehending important subjects in improving academic achievement, notably in English and Math.

Table 5: Distribution of Initial Academic Results by Kolmogorov–Smirnov Test, Skewness, and Kurtosis

Material	K-S	gl	p	Skewness	z-skewness	Kurtosis	z-kurtosis
Natural Sciences	.177	85	.000	.284	1.003	–.265	–.474
Social Sciences	.237	85	.000	.353	1.247	.539	.964
Spanish Language	.209	85	.000	–.064	–.226	–.566	–1.013
Mathematics	.200	85	.000	.841	2.972	.960	1.717
English	.196	85	.000	.631	2.229	–.414	–.741

Since all p-values are below.001, the Kolmogorov-Smirnov (K-S) test for academic topics shows that none of the score distributions are normal. Natural Sciences (.177), Social Sciences (.237), Spanish Language (.209), Mathematics (.200), and English (.196) have considerable K-S variances. Natural Sciences, Mathematics, and English have positive skewness, suggesting poorer scores. Social Sciences likewise has a positive skew. Spanish Language has a little negative skew, indicating a more symmetrical distribution around the mean. English has a mesokurtic distribution, indicating significant peakness, whereas Natural Sciences, Social Sciences, and Mathematics have platykurtic distributions: flatter forms with fewer extreme scores. Given the non-normal distribution of scores among respondents, these findings suggest non-parametric statistical approaches for additional research.

Table 6: Leobien and Walinwa Sub-Materials Data Distribution Based on Kolmogorov–Smirnov Test, Skewness, and Kurtosis

Sub-Material	K-S	gl	p	Skewness	z-skewness	Kurtosis	z-kurtosis
Comprehension	.204	85	.000	–.704	–2.228	.201	.323
Attention	.231	85	.000	–.461	–1.542	–.748	1.268
Letter and Phrase	.176	85	.000	–.512	–1.712	–.180	–3.278
Memory	.147	85	.001	–.246	–0.833	–.110	–5.291
Word	.216	85	.000	–.639	–2.035	.064	.104
Sequencing	.167	85	.000	–.449	–1.487	–.267	–0.449
Syllable and Text	.123	85	.034	–.109	–0.342	–.742	–1.182
Reading Speed	.116	85	.200*	.012	.305	–.665	–.866
Effectiveness	.073	85	.200*	.003	.010	–.384	–.674
Performance	.095	85	.200*	.165	.571	.130	.228
Main Topic	.083	85	.200*	.162	.581	.128	.272
Secondary Topic	.120	85	.200*	–.245	–.547	.502	.576
Accent Marking	.089	85	.200*	.168	.427	–.679	–.884
Grammar Topic	.121	85	.200*	.164	.306	–.247	–.238
Other Content	.093	85	.200*	–.231	–.666	–.394	–.579
Memory	.217	85	.025	–.576	–1.075	–.216	–0.208
Attention	.333	85	.000	–.698	–2.289	.203	.336
Vocabulary	.175	85	.000	1.982	2.618	.472	.591
Mean Global Score	.151	85	.200*	.968	1.806	.132	0.127

Most distributions considerably depart from normality, as demonstrated by p-values below.001, according to the findings of the Kolmogorov-Smirnov (K-S) test for various sub-materials. According to the K-S statistics, there is a noticeable skewness in both Attention (.231) and Vocabulary (.175). Whereas Vocabulary shows a positive skewness (1.982), more students scored lower, Attention shows a larger degree of negative skewness (-.461), suggesting a concentration of higher scores. Comprehension (.204) and Word (.216), two more sub-materials, show a similar pattern of considerable negative skewness. Kurtosis values denote different distribution forms; for example, Vocabulary has a mesokurtic distribution, which indicates a moderate peak, in contrast to the platykurtic distributions shown by Attention, Memory, and Comprehension, which are defined by flatter peaks and fewer extreme scores. Reading Speed, Effectiveness, Performance, and subjects like Main Topic and Secondary Topic all have p-values over.200, which indicates that they could follow a normal distribution. However, the K-S test does not completely establish normality for these measures. Results from most sub-materials do not follow a normal distribution, hence it is recommended that future investigations use non-parametric statistical approaches.

Table 7: Academic Outcomes Pre- and Post-Test Results and Their Effect Size

Material	Z	P	R
Natural Sciences	–4.275	.000	0.494
Social Sciences	–3.244	.000	0.374
Spanish Language	–4.541	.000	0.524
Mathematics	–4.854	.000	0.560
English	–5.695	.000	0.657

With p-values of.000 for all materials, the study of academic performance across topics shows substantial variations from the predicted mean. Every topic has a significant z-score, but the English one exhibits the biggest discrepancy ($z = -5.695$), which means that pupils are having the greatest trouble with it. The Social Sciences, on the other hand, show the mildest dispersion ($z = -3.244$). Again, English has the strongest correlation ($R = 0.657$), next Mathematics ($R = 0.560$), and finally, Natural Sciences ($R = 0.494$) in terms of the correlation coefficients (R), which indicate moderate to strong correlations between students' performance and their projected results. These results suggest that pupils are having a hard time in every class, but especially in English. Improving students' understanding and performance in these crucial subjects may need individualized approaches to teaching and learning as well as supplementary resources.

Table 8: Conclusions Regarding the Participants' Average Academic Performance

Material	Average	%	Deviation	Max	Min	Range
Natural Sciences	6.54	58.59%	1.168	8	4	4
Social Sciences	7.43	68.41%	1.089	8	4	4
Spanish Language	6.41	58.59%	1.287	8	4	4
Mathematics	6.98	63.88%	1.163	8	5	3
English	6.63	61.67%	1.124	8	4	4

Examining students' grades in various classes shows that they have varied degrees of success. With an average score of 6.54 in Natural Sciences and 6.41 in Spanish Language, students are performing slightly over average, amounting to 58.59%. The average score in the social sciences was 7.43 (68.41%), which indicates a higher understanding of the subject matter as compared to other areas. The average scores in mathematics and English were 6.98 and 6.63, respectively, showing a modest degree of skill. Students' scores are grouped tightly around the average, as seen by the very low variability across all topics (standard deviations ranging from 1.089 to 1.287). Consistent ranges of 4 for most topics, with maximum scores ranging from 4 to 5, indicate the need for specific interventions to improve student performance, particularly in Spanish Language and Natural Sciences.

Conclusion

Incorporating serious games into school curricula is a fantastic approach to assist students from low-income homes in improving their language abilities. Teachers may make these games work even better for their students by tailoring them to meet specific learning goals and individual student profiles. The importance of systematic educational methodologies is highlighted by the study, as is the application of learning analytics to provide rapid insights into students' progress, enabling tailored support for individuals with challenges. Furthermore, the predictive potential of serious games makes them useful as intervention tools, particularly with students who are not performing up to par. Taken together, the findings stress the need of cautious use of serious games and learning analytics to improve educational outcomes and promote inclusive classrooms.

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