Original Article

Establishing the Correlation between Identifying Slow and Advanced learners Scale on Regular Academics among Undergraduate Students

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Abstract

Purpose: Education is changing drastically with innovation impacting it the most. Bringing changes in the constantly changing world is important. This can only occur when we identify and categorizeour students into various types of learners, which can help us correctly deliver the knowledge. This was achieved by using the traditional method of categorizing the scores of students from the previous exams they have taken for example their 12th marks or previous years result. This method does not contain other domainsthat can focus on areasthat can improve the overall score of the student as a learner. The study aimed to find the reliability and correlation to effectively identify slow and advanced learners.

Methods: The study was conducted at a health university. First-year BPT undergraduate students were selected to identify slow and advanced learners. Data collection was carried out by a subject teacher appointed to assess students during class sessions. Students were evaluated per lecture, using the tool over the whole academic year.

Results: The overall scale demonstrates strong internal consistency with a Cronbach's alpha of 0.9307. While most items contribute positively to the scale's reliability. The correlations between total scores and other scores show that higher academic performance in these areas is positively associated with total scores.

Conclusions: The tool demonstrates strong reliability and validity in identifying slow and advanced learners, making it a valuable resource for educators aiming to enhance student learning outcomes.

Keywords: slow and advanced learner, identifying slow and advanced learner scale, reliability, correlation

Introduction

In today's educational landscape, the diversity of learning abilities among students has become increasingly evident. As educators strive to provide quality education to all, one of the fundamental challenges they face is the identification and support of slow and advanced learners.[1] Traditional educational systems often employ a one-size-fits-all approach, which inadequately addresses the unique needs of each learner.[2] This discrepancy can lead to slow learners falling behind and advanced learners not being sufficiently challenged, thereby hindering their educational progress.[3]Recognizing

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these limitations, the development of tools to better identify and support these distinct groups of learners has become a critical objective.[4]

Existing methods for identifying learners who deviate from the norm in terms of learning pace are often subjective and based on limited criteria, such as standardized test scores and teacher observations.[1] While these methods can offer some guidance, they frequently lack the depth needed to fully capture the complexities of individual learning processes. For slow learners, this can result in delayed identification and intervention, exacerbating learning gaps over time. Conversely, advanced learners may not receive the stimulation and resources they require to continue progressing, potentially leading to disengagement and underachievement.[5]

The development of a tool has significant implications for educational practices. With more precise data on learner capabilities, educators can design targeted interventions that address specific learning challenges or accelerate advanced learners.[6] For slow learners, this could mean the implementation of tailored support programs, differentiated instruction, and regular progress monitoring. For advanced learners, this tool could facilitate access to enriched curriculum, advanced placement opportunities, and mentorship programs.[7] Ultimately, this targeted approach can enhance educational outcomes, foster a more inclusive learning environment, and contribute to the overall goal of equitable education.[8,9]

The purpose of this study is to present a comprehensive framework and assess the reliabilityof a tool (identifying slow and advance learner scale) and its correlationto identify slow and advanced learners effectively. This tool employs a data-driven methodology that considers various educational metrics, behavioural patterns, and cognitive abilities to create a nuanced understanding of each learner's capabilities. By doing so, it provides educators with actionable insights to tailor their teaching strategies, ensuring that each student receives the appropriate level of support and challenge.

The introduction of a novel tool for the identification of slow and advanced learners seeks to bridge these gaps by integrating multiple data sources and advanced analytical techniques. By utilizing a more holistic approach, this tool can provide a more accurate and timely identification of learners' needs. This comprehensive analysis allows for a more personalized educational experience that aligns with each student's unique learning profile.

Procedure

The study was conducted at a health university, where a specialized[Identifying Slow and Advance Learner Scale (ISAL)] tool was developed and patented. First-year BPT undergraduate students were selected to identify slow and advanced learners. Data collection was carried out by a subject teacher appointed to assess students during class sessions. A maximum of five students were evaluated per lecture, using the tool developed for this purpose. This assessment process continued throughout the academic year. After scoring all the students, their 12th-grade marks and internal assessments were recorded, and an overall score was calculated. The collected data was then recorded and analysed.

The tool comprises five components: Lesson Awareness, Lecture Deliberation, Practice, Recall, and Performance. Lesson Awareness and Lecture Deliberation each include four subsets, Practice includes three subsets, and Recall and Performance each have two subsets. Each subset was scored on a scale from 0 to 4, with 0 representing poor, 1 as fair, 2 as average, 3 as good, and 4 as excellent. The lowest possible score for a subset was 0, and the highest was 4.

Students were categorized based on their overall score as follows: a score of 0 to 15 indicated a poor learner, 16 to 30 indicated a below-average learner, 31 to 40 indicated an average learner, 41 to 50 indicated a good learner, and 51 to 60 indicated an advanced learner. Additionally, classification was based on 12th-grade marks and class test performance: students scoring less than 40% were classified as poor learners, less than 50% as below-average learners, 50% to 60% as average learners, 60% to 85% as good learners, and more than 85% as advanced learners. The identification of slow and advanced learners was further refined using theReceiver-operating characteristic curve (ROC), with details provided in the Results section.

Statistical Analysis

The data was analysed using SPSS software, version 29.0. To assess the reliability of the tool, Cronbach's alpha test was employed, which measures the internal consistency of a scale. This test evaluates whether different items within the scale are related to each other, indicating their reliability. The correlation between 12th-grade marks, overall scores, and internal assessment marks was determined using Pearson's correlation coefficient. A t-test was conducted to compare the marks between male and female students. Additionally, to identify slow and advanced learners, the ROC curve was utilized. This analysis illustrates the sensitivity (true positive rate) versus (1 - specificity) (false positive rate) across the entire range of test thresholds.

Table 1. Overall Cronbach alpha: 0.9307 Standardized alpha: 0.9313

Items	Mean if deleted	SD if deleted	Item total correlation	Alpha if deleted
1.1	36.1212	7.9191	0.7076	0.9249
1.2	36.2020	7.8031	0.7605	0.9231
1.3	36.4950	7.8346	0.7389	0.9238
1.4	36.5859	7.9137	0.6639	0.9261
2.1	35.7273	8.0489	0.6441	0.9269
2.2	35.8283	8.1004	0.5298	0.9295
2.3	36.7475	7.8320	0.6394	0.9274
2.4	37.1313	7.9119	0.5699	0.9296
3.1	36.3232	7.9313	0.6473	0.9266
3.2	36.1212	8.0344	0.6586	0.9265
3.3	36.0808	7.8890	0.7522	0.9236
4.1	36.1616	7.8363	0.7926	0.9224
4.2	36.3434	7.7683	0.8195	0.9213
5.1	36.0808	7.9515	0.7757	0.9236
5.2	36.6364	8.2724	0.2756	0.9354

Table 2. Spilt half reliability of the scale

Summery	Value
Cronbach alpha, full scale	0.9308
Standardized alpha	0.9310
Cronbach alpha, first half	0.8660
Cronbach alpha, second half	0.8598
Split-half reliability	0.9591
Guttman split-half	0.9550
Intrinsic validity	0.9793

Table 3. Correlation between Total scores with 12th marks and internals marks by Karl Pearson's correlation coefficient

Variables	Mean	Std.Dv.	r-value	t-value	p-value
Total scores	71.2632	9.1235			
12th marks	38.8947	8.2171	0.2890	2.9113	0.0045*
Total scores	9.1684	2.2344			
1st internal	38.8947	8.2171	0.2681	2.6836	0.0086*
Total scores	10.6526	2.6847			
2nd internal	38.8947	8.2171	0.2269	2.2467	0.0270*
Total scores	10.1263	2.5401			
3rd internal	38.8947	8.2171	0.3865	4.0411	0.0001*

*p<0.05

Table 4. Comparison of male and female students with total scores, 12th marks and internals marks by t test

Variables	Male		Female		t-value	p-value
	Mean	Std.Dev.	Mean	Std.Dev.		
Total scores	37.48	5.83	39.28	9.11	–0.8603	0.3917
12th marks	69.62	9.30	71.54	8.98	–0.8628	0.3904
1st internal	8.45	2.80	9.27	2.09	–1.4522	0.1497
2nd internal	9.43	3.26	10.81	2.56	–2.0544	0.0427*
3rd internal	9.14	2.78	10.39	2.41	–2.0398	0.0441*

*p<0.05

Table 5. Sensitivity and specificity summery

Cut off Value		95% CI			95% CI		LR+	PPV	NPV	Accuracy	
		Lower	Upper		Lower	Upper					
>=26	0.9583	0.8575	0.9949	0.0784	0.0218	0.1888	1.0399	0.4946	0.6667	0.5051	0.0368
>=27	0.9583	0.8575	0.9949	0.0980	0.0326	0.2141	1.0625	0.5000	0.7143	0.5152	0.0564
>=28	0.9167	0.8002	0.9768	0.0980	0.0326	0.2141	1.0163	0.4889	0.5556	0.4949	0.0147
>=29	0.8958	0.7734	0.9653	0.1176	0.0444	0.2387	1.0153	0.4886	0.5455	0.4949	0.0135
>=30	0.8958	0.7734	0.9653	0.1373	0.0570	0.2626	1.0384	0.4943	0.5833	0.5051	0.0331
>=31	0.8542	0.7224	0.9393	0.1569	0.0702	0.2859	1.0131	0.4881	0.5333	0.4949	0.0110
>=32	0.8542	0.7224	0.9393	0.2157	0.1129	0.3532	1.0891	0.5062	0.6111	0.5253	0.0699
>=33	0.8542	0.7224	0.9393	0.2549	0.1433	0.3963	1.1464	0.5190	0.6500	0.5455	0.1091
>=34	0.8125	0.6737	0.9105	0.3137	0.1911	0.4589	1.1839	0.5270	0.6400	0.5556	0.1262
>=35	0.7500	0.6040	0.8636	0.3725	0.2413	0.5192	1.1953	0.5294	0.6129	0.5556	0.1225
>=36	0.6875	0.5375	0.8134	0.3725	0.2413	0.5192	1.0957	0.5077	0.5588	0.5253	0.0600
>=37	0.6667	0.5159	0.7960	0.4902	0.3475	0.6340	1.3077	0.5517	0.6098	0.5758	0.1569
>=38	0.6458	0.4946	0.7784	0.5686	0.4225	0.7065	1.4972	0.5849	0.6304	0.6061	0.2145
>=39	0.5625	0.4118	0.7052	0.6078	0.4611	0.7416	1.4344	0.5745	0.5962	0.5859	0.1703

Continue....

>=40	0.5000	0.3523	0.6477	0.6863	0.5411	0.8089	1.5938	0.6000	0.5932	0.5960	0.1863
>=41	0.4792	0.3329	0.6281	0.7059	0.5617	0.8251	1.6292	0.6053	0.5902	0.5960	0.1850
>=42	0.4792	0.3329	0.6281	0.7255	0.5826	0.8411	1.7455	0.6216	0.5968	0.6061	0.2047
>=43	0.3750	0.2395	0.5265	0.7451	0.6037	0.8567	1.4712	0.5806	0.5588	0.5657	0.1201
>=44	0.2917	0.1695	0.4406	0.8039	0.6688	0.9018	1.4875	0.5833	0.5467	0.5556	0.0956
>=45	0.2708	0.1528	0.4185	0.8039	0.6688	0.9018	1.3813	0.5652	0.5395	0.5455	0.0748
>=47	0.2708	0.1528	0.4185	0.8627	0.7374	0.9430	1.9732	0.6500	0.5570	0.5758	0.1336
>=48	0.2292	0.1203	0.3731	0.8627	0.7374	0.9430	1.6696	0.6111	0.5432	0.5556	0.0919
>=49	0.2083	0.1047	0.3499	0.8627	0.7374	0.9430	1.5179	0.5882	0.5366	0.5455	0.0711
>=50	0.1875	0.0895	0.3263	0.8824	0.7613	0.9556	1.5938	0.6000	0.5357	0.5455	0.0699
>=51	0.1875	0.0895	0.3263	0.9020	0.7859	0.9674	1.9125	0.6429	0.5412	0.5556	0.0895
>=52	0.1458	0.0607	0.2776	0.9412	0.8376	0.9877	2.4792	0.7000	0.5393	0.5556	0.0870
>=53	0.1042	0.0347	0.2266	0.9412	0.8376	0.9877	1.7708	0.6250	0.5275	0.5354	0.0453

The Cut-off point of total score is >=38

Table 6. Area under curve (AUC) of accuracy pf predication of high learners

Criterion	Count	AUC	SE	Z-value	P-Value	95% Confidence Limits	
						Lower	Upper
Total scores	99	0.6031	0.0574	1.7970	0.0723	0.4787	0.7038

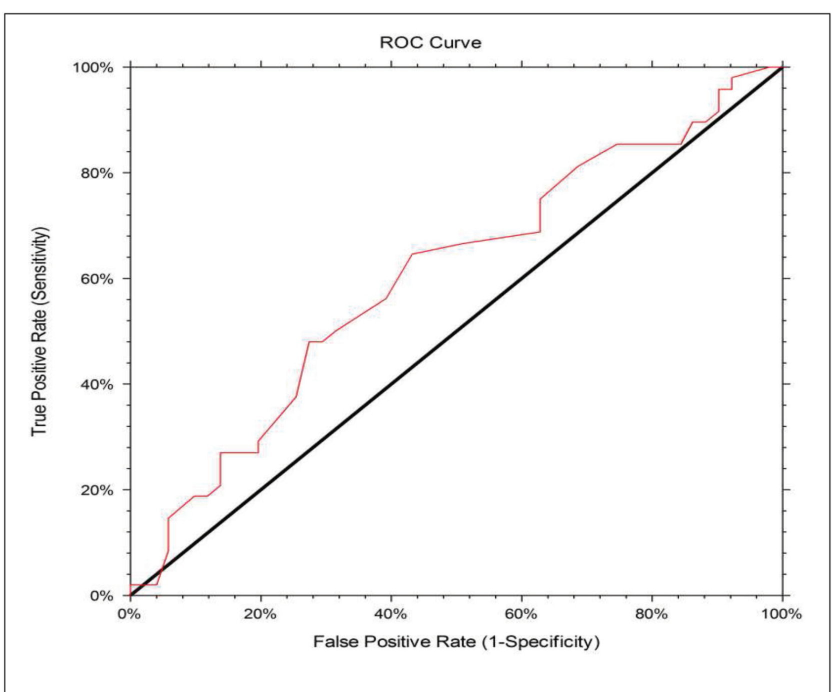

Figure 1: ROC curve

Results

The overall Cronbach's alpha for the scale is 0.9307, and the standardized alpha is 0.9313. These high values indicate excellent internal consistency, suggesting that the scale reliably measures the intended learning attributes across different student groups.

Item Analysis

Each item's contribution to the scale's reliability was analysed to determine its impact on the overall Cronbach's alpha if the item were deleted. Items 1.1 to 4.2 have strong item-total correlations (0.6441 to 0.8195), indicating good alignment with the total scale score. Their removal leads to only a minor decrease in Cronbach's alpha, suggesting they positively contribute to the scale's internal consistency. Items 1.2 (0.7605), 1.3 (0.7389), and 1.4 (0.6639) have high item-total correlations and slightly lower alpha values if deleted (0.9231 to 0.9261), indicating they contribute to the scale's overall consistency but can be removed with minimal impact. In contrast, items 2.2 (0.5298) and 2.4 (0.5699) have lower correlations. Their removal increases Cronbach's alpha to 0.9295 and 0.9296, indicating these items may not align well with the scale's construct and their deletion could enhance reliability.Item 5.2 has a low item-total correlation of 0.2756 and a significantly lower alpha if deleted (0.9354), suggesting it is the least consistent with the scale. Removing it could enhance the overall reliability, indicating it may not effectively measure the intended construct. (Table 1).

The full-scale Cronbach's alpha of 0.9308 indicates high internal consistency. The first half's alpha is 0.8660, and the second half's is 0.8598, both reflecting good reliability but lower than the full scale. The slight difference suggests that both halves are consistent but could be improved to match the overall reliability (Table 1).

Split-Half Reliability (0.9591) and Guttman Split-Half Reliability (0.9550) indicate very high reliability between the two halves of the scale, demonstrating consistent measurement of the construct. A high split-half reliability reflects the scale's internal consistency and stability. Intrinsic Validity (0.9793) shows the scale's effectiveness in accurately measuring the intended construct, highlighting how well the items fit together and comprehensively cover the construct (Table 2).

Correlation

There are moderate positive correlations between total scores and 12th marks ($r = 0.2890$, $p = 0.0045$) and between total scores and 1st internal marks ($r = 0.2681$, $p = 0.0086$), indicating that higher marks in these areas are associated with higher total scores. A weak positive correlation exists between total scores and 2nd internal marks ($r = 0.2269$, $p = 0.0270$), suggesting a weak association. In contrast, there is a strong positive correlation with 3rd internal marks ($r = 0.3865$, $p = 0.0001$), indicating a significant relationship where higher marks correlate strongly with higher total scores (Table 3).

Analysis between the Genders

Comparison of male and female students' academic performance using t-tests reveals no significant differences in total scores, 12th marks, and 1st internal marks ($p > 0.05$). The t-value is close to zero for these metrics, indicating similarity between genders. However, significant differences were found in 2nd and 3rd internal marks ($p < 0.05$), with female students scoring higher in 2nd internal marks, suggesting that gender impacts these scores (Table 4).

Sensitivity and Specificity

Sensitivity: The proportion of true positives correctly identified by the test. It ranges from 0.1042 to 0.9583, with higher values indicating better ability of the test to detect positives when they are present. Specificity: The proportion of true negatives correctly identified. It ranges from 0.0784 to 0.9412, with higher values indicating better ability of the test to identify negatives when they are absent (Table 5).

At a cut-off of 26, sensitivity is high (0.9583), but specificity is low (0.0784), leading to many false positives. While it effectively identifies most positives, accuracy is low (0.5051) and the Youden Index is also low (0.0368), indicating poor overall performance. Lower cut-offs provide high sensitivity but lack precision, resulting in many incorrectly labelled negatives. (Table 5).

At a cut-off of 38, sensitivity is 0.6458 and specificity is 0.5686, indicating a more balanced performance compared to lower cut-offs. With a Youden Index of 0.2145, this cut-off offers a better overall balance between correctly identifying positives and negatives. Intermediate cut-offs like this one improve overall test performance by effectively balancing sensitivity and specificity (Table 5).

At a cut-off of 52, sensitivity is low (0.1458) while specificity is high (0.9412), indicating the test is effective at identifying negatives but poor at detecting positives. The Youden Index of 0.0870 is lower than at other cut-offs, reflecting less effective overall performance. Higher cut-offs provide high specificity but miss many positives (Table 5).

The cut-off of 38 is optimal, balancing sensitivity (0.6458) and specificity (0.5686) with reasonable accuracy and a higher Youden Index than lower cut-offs. It effectively distinguishes between slow (n = 50) and advanced learners (n = 49), categorizing students based on scores. (Table 6 and figure 1).

Discussion

The findings from the current study underscore the robustness of the scale used to assess the academic performance of undergraduate students, as evidenced by the high Cronbach's alpha values of 0.9307 and 0.9313. These figures indicate excellent internal consistency, confirming that the scale effectively measures the intended learning attributes across diverse student populations.

The item analysis reveals that items 1.1 to 4.2 contribute positively to the scale's reliability, with item-total correlations ranging from 0.6441 to 0.8195. These strong correlations suggest that these items align well with the overall construct being measured. Importantly, the minimal decline in Cronbach's alpha upon their removal implies that these items are integral to the scale's reliability. In contrast, items 2.2, 2.4, and especially item 5.2 demonstrate weaker correlations, with the latter exhibiting an item-total correlation of just 0.2756. The significant improvement in Cronbach's alpha if these items were excluded points to their inadequate alignment with the overall construct, suggesting a need for review or potential removal to enhance scale reliability.[10]

The split-half reliability analysis further affirms the scale's consistency, with high reliability coefficients indicating that both halves of the scale measure the intended constructs effectively. The intrinsic validity score of 0.9793 highlights the scale's capacity to accurately assess the relevant attributes, reinforcing the overall efficacy of the measurement tool.[11]

The correlations between total scores and various academic performance metrics reveal insightful trends. Notably, a moderate positive correlation exists between total scores and 12th-grade marks (r = 0.2890) as well as 1st internal marks (r = 0.2681), indicating that higher performance in these areas is associated with better total scores. The strongest correlation is observed with 3rd internal marks (r = 0.3865), suggesting a substantial relationship and highlighting the importance of ongoing academic assessment in predicting overall performance.[12]

Interestingly, the weak positive correlation between total scores and 2nd internal marks suggests that while there is some association, it is less pronounced than with other measures. These findings emphasize the need for targeted support for students, particularly in internal assessments, to optimize overall academic performance.

The analysis reveals no significant differences in total scores, 12th marks, or 1st internal marks between male and female students. However, significant gender differences are noted in 2nd and 3rd internal marks, with female students performing better in these areas. This highlights the complex dynamics of academic performance across genders and suggests that while overall metrics may be similar, specific assessments may reveal gender-related trends that warrant further exploration.[13]

The evaluation of the diagnostic tool reveals varying sensitivity and specificity at different cut-off points. While the lower cut-off (>=26) demonstrates high sensitivity, it suffers from low specificity, resulting in many false positives. The optimal cut-off of >=38 strikes a balance, providing a reasonable accuracy and better performance in distinguishing between slow and advanced learners. This finding is critical for educators in tailoring interventions based on student performance, ensuring that both high and low performers receive appropriate support.[14]

Conclusion

The tool demonstrates strong reliability and validity in identifying slow and advanced learners, making it a valuable resource for educators aiming to enhance student learning outcomes. Its effectiveness in correlating with academic performance and distinguishing between different learner types highlights its potential for broader application in various educational contexts. ISAL helps the teacher to identify the differential learner and cater them according to the need of the learner. This immediately classify the student into slow and advance learner, a slow learner can be addressed with extra focus and special care to accommodate their need and advance learner can be challenged with lateral information to upgrade their knowledge and can be encouraged be a part of research at an early stage. Further research could explore the tool's applicability across different age groups, disciplines, and cultural settings, as well as investigate the underlying factors contributing to the observed gender differences in academic performance.

Ethical Clearance/*:* Since the study is an observational study data was collected through the interview method no ethical clearance was taken. Oral consent from the participants was taken.

Conflict of interest: Nil

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