Measuring the Effects of Student Satisfaction and the Engagement Level of Personalized Adaptive Learning Using an AI-Enabled Learning Pathway Tool

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Abstract
Critical voices on the traditional "one-size-fits-all" education system, which assumes a uniform approach for all students, abound for not meeting individual student learning needs. Expecting teachers to cater to the diverse learning needs of each student is seen impractical and unrealistic. There is a growing demand for personalized student-centered education, aiming to accommodate the unique learning needs, abilities, and interests. Modern educational systems are incorporating innovations like Artificial Intelligence (AI), which not only personalize students' educational experiences but also make them adaptive. The concept of Personalized Adaptive Learning (PAL), which systematically tailor instruction to individual learners has gained prominence as a key educational reform effort in contemporary systems. As more teachers embrace PAL, it presents an opportunity to explore the relationship between student satisfaction and their level of engagement. In this study conducted in Singapore, PAL was implemented to 1061 students across three subjects – theory-based marketing, calculation-based statistics, and procedural airway bill calculation. The analysis is done by using factor analysis, Kruskal-Wallis test, Friedman test and Kendall tau correlation coefficient. The results revealed significant differences in the ratings of the three subjects between different constructs (lesson content, personalization and mobile devices) except for the system user interface construct. Moreover, there was a significant difference between all constructs among the students. Interestingly, the level of engagement is significant for three constructs: system user interface, lesson content and personalization. These findings provide insights into the factors that are likely significant antecedents for planning, designing and implementing PAL to enhance student satisfaction.

Keywords: Learning Pathway, Personalization, AI

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Introduction

In recent years, there has been a remarkable increase in the adoption of education technology. Educators and policymakers have endeavored to personalize education to solve achievement gaps, lack of student motivation, and more effective and efficient instruction (Tetzlaff et al., 2020). In the Singapore context, to enhance teaching and learning, educational institutes are encouraged to embrace new teaching methods and technologies to cater to learners of diverse backgrounds to relieve teachers' workload and enable them to focus on areas such as learners' social-emotional development (Chan, 2022). According to Ng (2022), the integration of artificial intelligence into education systems could spark the greatest positive transformation in educational systems (Khan, 2023). Artificial intelligence could contribute to creating a personalized education system for each student that caters to his strengths and interests and adapts to the way they learn.

Personalized adaptive learning (PAL) seeks to tailor the learning experience to each student's individual learning style to address the individual needs and interests through "what, when, how and where students learn" (Costa, Rebeca & Tan et al., 2021). Along with AI bringing remarkable advancements to learning systems by enhancing their technology through the optimizing of key components - domain knowledge, the learner's current knowledge level, instructional measures like assessments, and the user interface. By integrating technologies such as AI as part of the digital learning environment, PAL platforms could build customized learning paths to meet the diverse needs of every learner based on the just-in-time profile of learners' motivation or learning gaps painted by AI-enabled data. Eventually, PAL suggests optimal choices of learning activities or pathways, departing from the traditional approach of delivering content through mass lectures. In the affordance of adaptive learning technologies, educators can rely on the analytics and learning algorithms generated based on the students' digital learning footprints to identify gaps in learning, analyze real-time updates of their performance and progress to improve their learning (Educause Learning Initiative, 2017).

The worldwide pandemic has accelerated the transformation of the traditional education system, resulting in a significant demand for asynchronous e-learning. This shift presented unique challenges to educators, in terms of mindset change and a change in skillset applied in classroom practice. While face-to-face contact in classrooms has been limited, both educators and learners must adapt to new technologies and teaching and learning methods. PAL empowers learners to take ownership of their learning experience (Yazon et.al., 2002) as they have greater control over the content they study and the pace at which they learn anytime anywhere and expedite their future continuous learning (Walkington, 2013). Despite its potential benefits, there are difficulties associated with designing, implementing and measuring PAL which is a complex undertaking fraught with challenges. These include user-perceived adequacy of the system user interface, user satisfaction with personalized learning packages, organizing content, and use of mobile devices to support learning.

A learning environment is made up of various dimensions elements that influence students' learning experiences and outcomes. According to Fraser et al. (2012), while the physical and social aspects are essential, instructional strategies and learning resources are also necessary to facilitate conceptual understanding and cultivate knowledge acquisition. Studies indicate that learner satisfaction and self-efficacy have an impact on learning and learning outcomes (Yakubu & Dasuki, 2018; Zogheib et al., 2015). Learner satisfaction is widely recognized as an indicator of the effectiveness of a learning system (Forster et al., 2020; Oho, 2017). Thus, learner satisfaction and acceptance should be considered when assessing a learner's perception of any learning system. Learner satisfaction refers to how learners perceive a particular learning system's usefulness and effectiveness in enhancing student learning outcomes, reflecting their personal feelings and experiences during learning activities, and how they perceive the learning systems' quality and engagement. Typically, if learners are more satisfied with a particular learning system, they are more likely to continue engaging with it (Salam, 2022). Cidral, et al. (2018), hence the importance of measuring learner satisfaction in assessing the long-term success of the learning system.

According to Klem and Connell (2004), there is strong empirical evidence supporting the connection between engagement and academic achievement, with engagement explicitly tied to academic tasks and activities. The instructional design and how the PAL system provides each learner individualized learning paths in real-time by allowing them to progress along their unique learning path through the course based on their knowledge, skills and learning needs are interlinked with the student engagement level. Engagement is considered multidimensional encompassing students' emotions, behaviour such as participation, and academic learning time (Fredricks, Blumenfeld, & Paris, 2004) which is critical in connecting important contexts and consequently affecting desirable outcomes. Both learner satisfaction and engagement are essential in helping stakeholders comprehend system functionalities, pedagogical support, and instructional design for a productive learning experience for all users. Therefore, there is a need to evaluate the effects of student satisfaction on the engagement level of PAL. The authors of a forthcoming paper will discuss the direct and significant relationship between engagement level and learning outcomes.

Background and Aims of Study

The institution at which our research was conducted, Temasek Polytechnic, piloted the PAL using the LMS Brightspace Learning Pathway (Brightspace LeaP). LeaP is a PAL tool that builds personalized learning paths for learners without leaving the LMS (D2L, 2023). How does LeaP work? LeaP determines and recommends instant personalized learning paths based on course-specific learning objectives, activities and assessments that adjusts to each learner's learning state and needs as they interact with the tool by the semantic mapping of objectives, learning resource, assessment questions and mastery information of each learner. This can be useful for a range of personalized activities such as reviewing content, preparing for tests, providing remedial support for struggling learners, or even functioning as a primary or secondary source of learning. With this feature, teachers can save time and reduce their workload and thus enhancing work productivity.

In this study, we have implemented LeaP to 1,061 students across 3 subjects for a full semester, each offered by different school, at an educational institute of higher learning in Singapore with a total population of about 13,000 students. LeaP served as additional revision materials for Subject A and Subject C, aiding students in their preparation for the Mid-Term test. Additionally, it was utilized as a revision package to prepare students for the skill-based assessment in Subject B's Practical test. The LeaP packages are embedded in the LMS and was made accessible to students taking these 3 subjects at least 2 weeks prior to the respective assessments till the end of the semester for students to use the tool for final exam revision if needed. The breakdown of students is shown in Table 1. A brief orientation was provided at the beginning of the semester with the purpose of using LeaP and providing guidance on the use of LeaP packages during designated lesson weeks. At the end of the semester, we felt that it would be an opportune time to evaluate the effects of student satisfaction on the level of engagement in PAL. To achieve this, we employed a questionnaire as our primary research instrument. Our objective was to ascertain whether there were any noticeable disparities in the constructs used for the questionnaire and to determine the relationship between satisfaction and engagement of PAL. Additionally, separate ethical consent for data collection is not obtained for several reasons. Firstly, LeaP is integrated as a learning tool within the existing learning system and is accessible to all students enrolled in the three subjects. As part of the course enrollment process, students have already provided consent for the use of the learning system and covers the use of LeaP as well. Furthermore, the data is collected in an aggregated form where the anonymity of the students are ensured.

The research questions for this study are as follows:

- Are there significant differences between perceived satisfaction among the students?
- Are there significant differences between perceived satisfaction within the subjects?
- Are there significant relationships between perceived satisfaction and engagement among students?

Our research is driven by a straightforward motivation - we firmly believe that higher levels of student satisfaction can boost student engagement in a course, leading to improved student learning outcomes (Gray and Diloreto, 2016). We aspire our study to contribute to the refinement of the instructional design of the PAL, with the goal of better catering to the needs of individual learners.

	Subject A (Offered by School A)	Subject B (Offered by School B)	Subject C (Offered by School C)
No. of Classes	24	20	2
Year of Study	1	1	3
No. of Teaching Staff	11	6	2
No. of Students taking the subject	539	484	38
No. of Students tried LeaP and took the survey	315	135	36

Table 1: Profile of participants

Methodology

As this study assumes a quantitative methodology, a questionnaire is employed as our primary research instrument, focusing on the learners' satisfaction with the system user interface, personalized learning packages generated, the content organized, and the effectiveness of accessing LeaP using mobile devices. Quantitative surveys are useful for obtaining a large amount of information from a large sample size in a relatively short period of time. The use of questionnaires can provide standardized and consistent data collection, which is helpful when measuring subjective opinions and attitudes (Kabir, 2016). Quantitative research is also useful for identifying patterns and relationships among variables, which can be helpful in identifying potential factors that may influence learners' satisfaction with the PAL system.

To have a more reliable comparison with the student engagement, LMS LeaP content reports for all 3 subjects were extracted. Diagnostic test results, which are also known as pre-tests, and activities the learner has done are used the rank the content's effectiveness in helping the learner understand the learning objective. Semantic algorithms are deployed to derive the relationship for each of the learning objectives, content items and questions within the course content repository. Based on these three elements, LeaP makes intelligent individualized recommendation paths to offer reading content to the learners. Learners will then try the practice questions and take the post-test to evaluate their understanding of the defined learning objectives. Both the pre-test, practice questions and post-test attempts are recorded in the LMS LeaP content reports and are used for defining the 5 levels of engagement.

LeaP engagement level	Defined by
0	Attempted none of the tests
1	Attempted pre-test only
2	Attempted pre-test and practice questions
3	Attempted pre-test and post-test
4	Attempted pre-test, post-test and practice questions

Table 2: Level of engagement

In this study on learner satisfaction, a Likert Scale survey with 23 Likert Scale type questions that evaluated student satisfaction on 4 constructs (System User Interface (S), Lesson Content (L), Personalization (P) and Mobile Devices (M)). Additionally, 1 multiple-choice question was included to gain insight into why students did not use LeaP and 1 open-ended question was included to complement the quantitative data and enhance support for learning. Most of the survey questions were designed and adapted from prior research that focused on evaluating learner satisfaction and personalized learning by Lim, et al. (2022) and Zhang, et al. (2022). These learner satisfaction questions were validated in their research publications to support personalized learning experiences of students in high schools and tertiary institutes. However, an additional construct "M" is established to measure the mobile functionality provided by our learning. The validity of these constructs will be discussed in the findings later.

Data was collected using MS Forms, then analyzed using SPSS software and visualized using Power BI. Factor analysis was used to test the validity of the 4-constructs used, followed by reliability, Kruskal-Wallis and Friedman tests to determine if there is significant difference between the perceived satisfaction among students and within subjects. Lastly, Kendall's tau non-parametric correlation coefficient is used to measure the relationship between satisfaction and engagement.

Findings

Explanatory factor analysis is used to examine the factor structure of the 23-item instrument for a sample size of 486. This sample is large enough for factor analysis and the correlation matrix FOR all coefficients are greater than 0.3, suggesting that factor analysis is appropriate (Tabachnick and Fidell, 2007). The Kaiser-Meyer Olkin (KMO) measure of sampling adequacy is 0.968 and Bartlett's test of Sphericity have a significance level of 0.000 suggests that there is a high degree of correlation making factor analysis worthwhile.

Principal components factor analysis is applied as extraction technique with varimax as the orthogonal rotation method to extract underlying factors. The first 3 factors recorded eigenvalues of above 1 with a total of 73.916 per cent of the variance (Cumulative %). All the items in Figure 1 have absolute loading above 0.3.

Item Code and Description	Factor 1	Factor 2	Factor 3
P4_Enables me to choose what I want to learn	0.966		
P6 Records my learning progress and performance	0.894		
P3_Recommends the most suited pathway for my learning	0.856		
P5_Enables me to track my learning progress	0.845		
P9 LeaP was effective in personalizing my study for the Mid-Semester Test.	0.829		
P10_LeaP was effective in personalizing my learning on Marketing Fundamental topics	0.822		
P2 Provides me the flexibility to complete my learning	0.770		
P7_Has a positive impact on my learning	0.769		
P8_I enjoy learning using LeaP content packages	0.768		
P1 Provides me with multiple opportunities to bridge my learning gaps	0.764		
L3_Provides sufficient content	0.716		
L5 Enables me to learn the content I need	0.678		-0.309
L6_Supports my learning	0.667		-0.302
L4_Provides useful content	0.629		-0.333
L2 Provides content exactly fits my need	0.612		-0.336
L1_Provides up-to-date content	0.476		-0.429
M2 Little or no functional differences between the mobile and desktop devices		0.826	
M1_Easy access using mobile devices		0.777	
S2_User-friendly			-0.851
S1 Easy to use			-0.787
S4_Instructions are clear			-0.787
S3 Easy access to content and learning packages			-0.681
S5_Lesson goals are clear	0.380		-0.543

Figure 1: Pattern matrix

Factor 1 includes variables related to the effectiveness and flexibility of the LeaP learning platform. The high loadings on Factor 1 (P1-P10, L3) suggest that learners perceive LeaP as an effective and flexible platform for their learning. Factor 2 (M1-M2) includes variables related to the ease of access to LeaP using mobile devices. Factor 3 (L1-L2, L4-L6, S1-S5) includes variables related to the usability and clarity of instructions. Based on the theory behind the constructs and the content of the item, the L-items are more conceptually related to Factor 3 which may be more meaningful to be grouped with the S-construct, along with S5. S3, having a higher absolute loading for Factor 3, is decided to be grouped in the S-construct. Two reliability tests are run with one excluding L5 and L6 and the other including L5 and L6 to decide if L5 and L5 are invalid items that do not contribute much to the interpretation of factors. The Cronbach Alpha values are above 0.9 for all constructs for all the 2 runs should suggest very good internal consistency reliability for the sale in this sample. But based on Pallant (2000), the constructs have a small number of items (e.g. less than 10), the Cronbach alpha value may not be reliable. The mean inter-item correlation value is suggested.

There is a slight regrouping of the items into 3 factors. (S) and (L) are combined to become Usability and Clarity (U). Personalization (P) included L3 and Mobile Devices (M) remain unchanged. Reliability Run 1 test was conducted for the 21 items excluding L5 and L6 and Reliability Run 2 test was conducted including L5 and L6. The mean inter-item correlation values from Run 2 improved for (U) only. This may be an indicator not to exclude L5 and L6. L5 and L6 are included for all further analysis.

Run 1: 3-factors (21 items – excluding L5 and L6)

Construct	No. of items	Inter-item Correlations	Cronbach Alpha
(U) Usability and Clarity [S+L]	8	0.667	0.941
(P) Personalization [+L3]	11	0.683	0.959
(M) Mobile Devices	2	0.747	0.855

Run 2: 3-factors (23 items – including L5 and L6)

Construct	No. of items	Inter-item Correlations	Cronbach Alpha
(U) Usability and Clarity [S+L]	10	0.679	0.955
(P) Personalization [+L3]	11	0.683	0.959
(M) Mobile Devices	2	0.747	0.855

Run 3: Preliminary 4-factors (23 items – including L5 and L6)

Construct	No. of items	Inter-item Correlations	Cronbach Alpha
(S) System User Interface	5	0.725	0.909
(L) Lesson Content	6	0.718	0.941
(P) Personalization	10	0.695	0.953
(M) Mobile Devices	2	0.748	0.855

Figure 2: Reliability tests

Run 3 was done on the preliminary 4 constructs using all 23-items in their initial grouping to confirm our hunch that that the preliminary grouping would be more advantageous. The improvement in the mean inter-item correlation values for all factors suggested that the items within these factors are measuring the intended construct in a consistent and reliable manner. Hence the researchers made the decision to fit a 4-factor model for all further analysis, with S5 grouped under L-construct using the results of the pattern matrix for the preliminary 4 constructs as they felt that S5 would land itself better to the L-construct based on its' item description. This grouping will be used for further analysis. Establishing content validity is essential to ensure construct validity. Notably, after conducting factor analysis tests, the 4-factor model appears to be more suitable, aligning with the constructs confirmed in the studies conducted by Lim, et al. (2022) and Zhang, et al. (2022) as shown in Table 3. The constructs and items underwent review by a panel consisting of LeaP administrators and piloted subject teams, ensuring the refinements before the survey was released. Kruskal-Wallis, Friedman test and Kendall's tau correlation coefficient are used to examine the differences between satisfaction and the relationship between satisfaction and engagement level based on the normalized sum of each of the 4 constructs (O'Rourke et al., 2019).

Item Code and Description	Adapted from
S1 S2 L1 L2 L3 L4 L5 L6 P3 P4 P6	Lim, et al. (2022)
S5 P1 P2	Zhang, et al. (2022)

Table 3: Question design

Initially, a mixed between-within subjects ANOVA is used to analyze both between subject grouping (Subject A, Subject B and Subject C) and within subjects' satisfaction ((S) containing S1-S4, (L) containing L1-L6+S5, (P) containing P1-P10 and (M) containing M1-M2) can be done using one analysis. Although the assumption of homogeneity of variances is not violated (by Levene's Test), but the Box's Test of Equality of Covariance Matrices assumption is violated due to unequal sample sizes across different subjects. Non-parametric Kruskal-Wallis and Friedman tests are deemed more appropriate instead.

Normalized Construct	Subject	Mean	Median	Std. Dev	Construct Mean	Construct Median	Construct Std. Dev	Mean Rank	Asym. Sig
(S) Construct	Subject A	3.7677	3.73	0.78226	3.744	3.78	0.80302	246.75	0.121
	Subject B	3.6323	3.73	0.86675				226.88	
	Subject C	3.9561	4.00	0.68563				277.42	
(L) Construct	Subject A	3.8625	3.97	0.76679	3.7969	3.905	0.78879	254.80	0.013
	Subject B	3.6167	3.68	0.83413				213.26	
	Subject C	3.8983	4.00	0.71320				257.99	
(P) Construct	Subject A	3.8130	3.89	0.76672	3.7435	3.82	0.77485	254.08	0.017
	Subject B	3.5561	3.51	0.78756				214.30	
	Subject C	3.8389	4.00	0.69481				260.44	
(M) Construct	Subject A	3.3992	3.00	0.96110	3.3748	3.00	.	246.90	0.001
	Subject B	3.1956	3.00	0.94084			0.95496	217.25	
	Subject C	3.8333	4.00	0.78457				312.19	

Figure 3: Descriptive Statistics & Kruskal-Wallis results

Using the Kruskal-Wallis test as shown in Figure3, there are significant differences in the ratings of the three subjects between the constructs (L), (P) and (M) with alpha less than 0.05. There is no significant difference in the ratings for construct (S) across the three subjects. Different subject learners do not rate (S) construct differently. As LeaP is an integrated tool in the LMS, students had similar levels of familiarity and experience with the LMS user interface, which affects their perception of the system user interface in LeaP. The design and usability of the LeaP are consistent across subjects, leading to similar perceived satisfaction across the board.

Subject B gave the lowest ratings for all constructs. Their cohort size is relatively huge and only one LeaP package was implemented as supplementary material for revision in preparation for the Term Test. The poor ratings may be attributed to a lack of LeaP exposure and poor communication at the beginning of the semester. Additionally, the independent sample test showed that learners from Subject A and Subject B rated the (L) construct differently. This is arguable as Subject A has launched 6 LeaP supplementary packages throughout the semester and learners have a higher degree of familiarity with the tool.

Subject C has the highest mean rank and highest median across all 4 constructs. Subject A and Subject B are introduced to LeaP at the start of the semester. As Subject A and Subject B are using LeaP as supplementary material for the first time, they may face some unfamiliarity and are the first to encounter any obstacles from using the PAL. Moreover, Subject C commenced using LeaP about two weeks after other subjects, and had the smallest cohort, making communication and control more manageable. Furthermore, as a result, they could have benefited from the prior issues experienced by Subject A and Subject B. By then, most technical difficulties had been resolved, and the introductory briefing was more streamlined, allowing learners to establish their own expectations for the tool. So, it's understandable that Subject C has the best perceived satisfaction level across all 4 constructs.

Construct (M) has the lowest median scale across all subjects. Subject B has the lowest median scale for constructs (L) and (P). These could be the area of foci for better user experience. Recommendations on these will be discussed in the next section.

Normalised Weighted	Mean Rank	Chi-Square	df	Asymp. Sig.
(S) Construct	2.53			
(L) Construct	2.68	136.871	3	0.000
(P) Construct	2.80			
(M) Construct	1.99			

Table 4: Friedman Test

From the Friedman Test shown in Table 4, there is a significant difference between all constructs. The students' ratings of the four different constructs are significantly different from each other. It is possible that the students have different preferences for learning styles and approaches, which may affect their perceptions of the usefulness and effectiveness of PAL. Additionally, the students may have different levels of prior knowledge and experience in the subject area, which could affect their engagement with and perceived satisfaction level of PAL. Other factors such as technological proficiency, motivation, and cognitive ability could also contribute to the differences in the students' ratings.

Using the Kendall's tau non-parametric correlation coefficient (Table 5), all four correlations ranged from 0.044 to 0.102 showing positive correlation with the overall engagement level. All have a statistically significant p-value less than 0.05 except for (M), which indicates that the likelihood of these correlations being a result of chance is low. The 3 factors (S), (L) and (P) have a significance level of less than 0.05, indicating that their correlation with overall engagement level is statistically significant, except for the (M) factor. These results can provide useful insights to guide future efforts aimed at enhancing engagement levels. The findings suggest that improving the (S), (L) and (P) factors could be key foci to have a positive impact on learner engagement level, while the use (M) factor may not have a significant influence on engagement.

		Normalised Weighted Sum of			
		System User Interface (S)	Lesson Content (L)	Personalization (P)	Mobile Devices (M)
Overall Engagement Level	Correlation coefficient	0.102	0.065	0.093	0.044
	Sig. (2 tailed)	0.002	0.044	0.004	0.193

Table 5: Kendall’s tau correlation coefficient

Conclusion and Recommendations

Based on the qualitative feedback, learners have varying levels of understanding about the benefits and functionality of PAL, which resulted in some learners being hesitant to try out the new AI-enabled self-study tool and prefer to revise the subject on their own. This presents an opportunity for school administrators and educators to come together and develop a shared playbook or detailed introduction to PAL for the learners to be familiar with the system user interface, lesson content and self-tracking reports to monitor learners’ performance. Educators can reflect on their pedagogical strategies and adapt them to learners’ needs by promoting the use of PAL. By considering the unique nature of the subjects and students with different levels of prior knowledge and experience in the subject area, we can create a scaffolding approach that will increase awareness, enhance motivation, and provide greater clarity on the use of this innovative tool. Effective communication is often considered the first and most critical step towards successful implementation which could be in the form of an engaging introductory video or a live demonstration shown at the beginning of each course. Clear and easy-to-follow step-by-step guide should be available for troubleshooting any common technical issues that may arise. Working collaboratively to develop a shared vision and detailed understanding of PAL and its benefits can ensure a positive and successful experience for all learners.

Although LeaP is an off-the-shelf product integrated into the LMS, we can still work towards improving the usability of the tool to improve the overall user experience. A well-designed user interface and personalized learning content can increase learners' interest and engagement, leading to higher participation in the learning process (Thanyaluck et al., 2022). Our findings can be shared with the vendor as valuable customer feedback and we can collaborate with them to propose enhancements to the system user interface and the organization of LeaP content, making LeaP more user-friendly and beneficial for both learners and teaching staff.

The educational benefits and technological impact of personalized adaptive learning are highlighted in studies by Costa et al. (2021), Taylor et.al. (2021) and Murray et al. (2015). We believe that teaching staff can take advantage of personalized adaptive learning to plan the course delivery more efficiently and re-organise the learning resources into smaller portions to allow LeaP to recommend study paths more effectively. This will help to optimise the use of teaching resources, saving time and reducing the workload of teaching staff, while reducing the need for repetitive remedial and consultation sessions. LeaP can also be a valuable tool for assessment revisions. As successful learners share their experiences through word of mouth, this can create a positive ripple effect and inspire others to adopt this innovative approach to learning. By harnessing the capabilities of AI and embracing personalized adaptive learning, we can revolutionize the field of education and ultimately achieve greater success in education.

Limitations of Research

While our study highlights the importance of improving the usability and clarity of learning materials to increase learner engagement, we recognize that the findings may not be generalizable to other subject areas. However, we believe that our research provides a valuable foundation for future investigations. Despite our sample size being large enough for qualitative research, the findings are analyzed based on self-reported data using a questionnaire. Though efforts are made to validate and ensure the reliability of the data collection instrument, we acknowledge that the data may have an inherent bias due to the representation of a specific group of learners with its own characteristics which may not be representative of the population. We encourage further research on larger and more diverse groups of LeaP learners to gain additional insights and improve the generalizability of our findings. By building upon our study, we hope to enhance the quality of education and create a more positive and engaging learning experience for all students.

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