Tailoring Themes and Elements Based on Learning Styles and Player Types in Adaptive Gamification in Education

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***Abstract*—Gamification has become a powerful tool for enhancing student engagement in educational settings However, the effectiveness of a gamified system depends on its alignment with individual student characteristics. This has led to the rise of adaptive gamification, where game elements are tailored to meet the unique needs of each learner. This research aims to bridge the gap between adaptive gamification and student-centered learning by designing a personalized gamification platform based on the Felder-Silverman Learning Style Model (FSLSM) and Bartle's Four Player Types. However, traditional questionnaires can be overwhelming and potentially affect student engagement. This study aims to reduce lengthy versions of these questionnaires that retain diagnostic power while being more manageable for students, with the help of factor analysis and comparative analysis, FSLSM and Bartle's player type questionnaires were reduced. Then a questionnaire is developed with reduced version of FSLSM and Bartle's player type with some more questions to capture learners' preferences for gamification element, themes, and suggestions for improving the gamified platform for education. This developed questionnaire has been floated among college students. Out of 218 valid responses, fuzzy c-means clustering revealed four distinct clusters, with two major clusters showing strong preferences for specific gamification themes. These themes were integrated into the platform to create a more engaging and personalized experience. By reducing and validating the FSLSM and Bartle's questionnaires, this research offers a streamlined approach for educators to implement personalized gamification strategies in the classroom. The findings provide insights for developing effective, student-centered adaptive gamification systems in education.**

***Keywords*—Adaptive Gamification; Bartle's Player Type; Comparative analysis; Factor analysis; FSLSM; Fuzzy C means clustering.**

***ICTIEE* Track*:* Technology Enhanced Learning**
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I. INTRODUCTION

IN the rapidly evolving landscape of education, the integration of digital technologies has paved the way for innovative teaching and learning methodologies (Anitha, D., & Kavitha, D., 2018). One among them is gamification, which uses game design elements in non-game contexts and it has emerged as a powerful tool to enhance student engagement, motivation, and overall learning outcomes (Bai et al., 2020). However, the effectiveness of a gamified system depends on how well it aligns with individual characteristics of learners (Hamari et al., 2014). This gap has led to the rise of adaptive gamification in education, where game elements are tailored to meet the unique needs of each learner (Suresh Babu, S., & Dhakshina Moorthy, A., 2024).

Tailoring a gamified educational platform involves understanding the learning styles and player types of learners (López, M. S., & Tucker, C. S., 2019). Felder-Silverman Learning Style Model (FSLSM) is an effective framework that categorizes learners based on four dimensions: Active-Reflective, Sensing-Intuitive, Visual-Verbal, and Sequential-Global. By identifying these preferences, educators can adapt gamification strategies to complement how students learn best. For example, visual learners may benefit from more graphical elements, while reflective learners might prefer self-paced, contemplative activities. Bartle's Four Player Types categorizes learners based on personality: Achievers, Explorers, Socializers, and Killers which offer valuable insights into students' motivations and behaviors within a gamified environment. For example, while Achievers may be motivated by rewards and recognition, Explorers might be more engaged by the opportunity to discover new content or solve complex problems.

However, the traditional FSLSM and Bartle's Player Type questionnaires can be overwhelming for students, leading to fatigue and potentially affecting their accuracy because to know

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their learning style and player type, they have to answer 44 and 30 questions, totally 74 questions. This is particularly problematic when studying learning styles and player types, as students may lose interest in completing large-scale assessments, which may skew results and impact the adaptive mechanisms used in gamification (Bennis et al., 2022).

Therefore, this study aims to develop reduced versions of these questionnaires that retains effectiveness of as the traditional versions in identifying learners' learning styles and player types. Additionally, some more questions are introduced to capture learners' preferences for gamification elements, themes, and suggestions for improving the gamified platform.

This research is situated within the broader context of adaptive learning systems and personalized education. By combining insights from FSLSM, Bartle's Player Types, and learners' thematic preferences. This study aims to create a gamified educational platform that is not only effective but also deeply engaging and personalized to each student's unique profile. The main objective of this research is to answer the following research question: (i) How can the FSLSM and Bartle's Player Type questionnaires be reduced while maintaining their effectiveness in identifying student learning styles and player types? (ii) What are the most effective gamification themes for enhancing student engagement based on identified clusters of learning styles and player types?

II. Literature Review

Gamification in education has been extensively researched for its potential to enhance motivation and learning outcomes through the integration of game elements like points, badges, leaderboards, and challenges (Papadakis et al., 2019). However, traditional gamification is criticized for its one-size-fits-all approach, which may not account for individual learner differences. In response, adaptive gamification has emerged as an advanced method of integrating gamification into education (Srimathi. S., & Anitha, D., 2024). Unlike static gamification, adaptive gamification adjusts game elements in real-time based on learner behavior, preferences, and performance, providing a more personalized experience (Tondello et al., 2019). The studies have demonstrated that adaptive gamification leads to higher levels of student satisfaction and deeper engagement in learning. To create personalized experiences, adaptive gamification system effectively utilizes learning styles and player types of the learners that algin with individual preferences and motivations (López, M. S., & Tucker, C. S., 2019).

The Bartle's Player Type model (1996) has been extensively used in educational research to categorize students into different player types: Achievers, Explorers, Socializers, and Killers (Orji et al., 2017). Each type reflects a unique set of motivations and behaviors, such as a preference for achievement, exploration, social interaction, or competition. Recent studies have explored how these player types can be leveraged to design personalized gamified learning experiences. In adaptive gamification, player type questionnaires serve as a critical input to tailor the gaming environment, adjusting challenges, social features, and narrative elements to align with the player's motivations. For example, Achievers are motivated by goals and rewards, making elements like points and badges particularly effective for them. This dynamic mapping helps optimize engagement by ensuring that the game elements resonate with the player's core motivations, creating a more immersive and enjoyable experience (Fiş Erümit et al., 2021).

The Felder-Silverman Learning Style Model (FSLSM) is a well-established framework for understanding how individuals prefer to learn (Anitha, D., & Deisy, C., 2015). It identifies several dimensions of learning, including sensory preferences (visual/verbal), information processing (active/reflective), and understanding (sequential/global). In gamified educational environments, identifying learning styles allows for the customization of game elements to match the learner's cognitive processes (Barata et al., 2017). For example, visual learners might benefit from gamification elements that use rich visual aids, while active learners might thrive in hands-on challenges or simulations (Plass et al., 2015). The application of adaptive gamification in this context has been shown to enhance learning outcomes by aligning game design elements with individual cognitive preferences.

In adaptive gamification, the convergence of player types and learning styles presents a comprehensive approach to personalizing educational experiences. Long questionnaires can lead to participant fatigue, resulting in incomplete or unreliable data. Therefore, reducing the number of questions in the Felder-Silverman Learning Style Model (FSLSM) and Bartle's Player Type questionnaires becomes essential for maintaining the validity of data while also improving the user experience.

This research work aims to reduce the FSLSM and Bartle's Player Type, which allows researchers to identify the most representative questions while ensuring that the core constructs of the models remain intact and also the objective of this research is to create a gamified platform for education.

III. Research Question

These Research Questions (RQ) are suggested in order to address the particular goals of this study with the desired research purpose:

RQ1. How can the FSLSM and Bartle's Player Type questionnaires be reduced while maintaining their effectiveness in identifying student learning styles and player types?

RQ2. What are the most effective gamification themes for enhancing student engagement based on identified clusters of learning styles and player types?

IV. Experimental Methodology

To address the proposed research questions, the overall process of this research is presented in Fig. 1. The research initially involved designing reduced versions of both the Felder-Silverman Learning Style Model (FSLSM) and Bartle's Player Type questionnaires. These questionnaires were originally very extensive, consisting of a significant number of questions aimed at diagnosing the learning style and player type of students. In educational research, lengthy questionnaires can lead to participant fatigue, which often results in incomplete or unreliable data. This is particularly problematic when studying learning styles and player types, as students may lose interest in completing large-scale assessments, which may skew results and impact the adaptive mechanisms used in gamification. Therefore, reducing the number of questions in the Felder-Silverman Learning Style Model (FSLSM) and Bartle's Player Type questionnaires becomes essential for maintaining the validity of data while also improving the user experience.

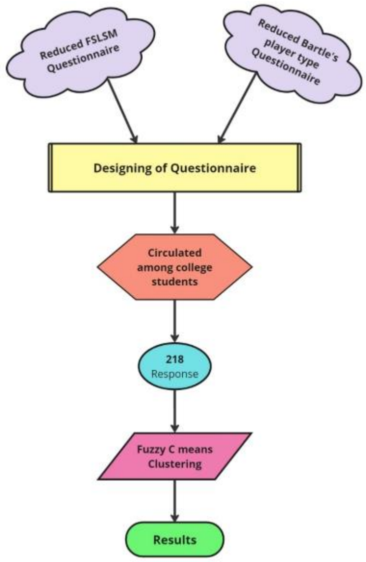


Fig. 1. Overview of the research process

However, to streamline the assessment process and reduce participant fatigue, a detailed analysis of the traditional FSLSM and Bartle's Player Type questionnaires was conducted to identify the most critical items that could still accurately reflect the underlying dimensions. The goal was to make the questionnaires shorter, more efficient, and user-friendly while maintaining their reliability and validity.

Fig. 2 illustrates the methodology employed to derive the reduced FSLSM questionnaire. Factor analysis was used as the primary technique to achieve this reduction. Factor analysis is a statistical method that identifies underlying relationships between variables (in this case, the individual questions on the FSLSM questionnaire). By analyzing the responses, this method groups the questions into factors based on their correlations, thereby reducing the complexity of the dataset while retaining the most important information. This process allows researchers to identify a smaller set of questions that represent the essential dimensions of learning styles, such as Active/Reflective, Sensing/Intuitive, Visual/Verbal, and Sequential/Global. In this study, factor analysis was applied to the responses gathered from students in government-aided college in Tamil Nadu. The students completed the traditional FSLSM questionnaire, and their responses were recorded for analysis. The results from factor analysis were obtained.

Similarly, Fig. 3 demonstrates the steps taken to develop the reduced version of Bartle's Player Type questionnaire. Bartle's Player Type model categorizes players into four types: Achievers, Explorers, Socializers, and Killers. The traditional questionnaire had numerous questions to distinguish between these player types, but it was also lengthy. Like FSLSM, it was reduced using a comparative analysis. Bartle's Player Type questionnaire and the reduced version of new questionnaire was developed by the author based on Bartle's player type (New Bartle's Player Type Questionnaire) was shared among students in government-aided colleges in Tamil Nadu. The students also completed the traditional as well as the new New Bartle's Player Type questionnaire developed by author. After gathering responses, a comparative analysis was then performed to assess whether the new questionnaire produced results consistent with the traditional. Comparative analysis involves comparing the outcomes of both the traditional and new questionnaires to ensure that they accurately measure the same underlying constructs (in this case, player types) and Bland-Altman Plot is employed to visualize the outcome. Bland-Altman Plot is a statistical plot which is used to visualize the agreement between two different measurement techniques, to illustrate the comparative analysis between the traditional and new versions of the Bartle's Player Type questionnaire. This plot helps identify any systematic differences and measure the consistency between the two questionnaires.

To further validate the accuracy of the reduced questionnaires, several statistical tests were performed. A Shapiro-Wilk normality test was conducted first. This test assesses whether the responses are normally distributed or not. The Shapiro-Wilk test results showed that the data from the reduced questionnaires not followed a normal distribution, allowing the researchers to proceed with further analysis. After confirming normality, Wilcoxon signed-rank test was conducted between the results of the traditional and reduced versions of both the FSLSM and Bartle's Player Type questionnaires. The Wilcoxon signed-rank test is a statistical method used to compare two sets of non-parametric data to determine if there is a significant difference available between them or not. In this case, the Wilcoxon signed-rank test was used to measure whether the reduction in questions significantly impacted the accuracy of the results. This test showed that there was no significant difference between the responses to the traditional and reduced questionnaires. The similarity between traditional questionnaire and reduced questionnaire is also measured using Spearman's Rank Correlation, it is a non-parametric statistical method that measures the strength and direction of a monotonic relationship between two variables. It assesses the similarity between two sets of data by comparing their ranks, rather than their actual values, and generates a correlation coefficient ranging from -1 to +1. A correlation coefficient of +1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and a value close to 0 suggests no correlation. The test result showing a high coefficient reflects a strong relationship or similarity between the two sets of data. All these validations indicates that the reduction process had not compromised the integrity of the questionnaires, and they still effectively captured the same information.

After validating the reduced FSLSM and Bartle's Player

Type questionnaires, the next phase of the research involved developing a more comprehensive questionnaire. In addition to the reduced questions, this questionnaire included items related to learners' preferences for gamification elements such as themes, stories, and design features. The goal was to identify the themes and elements that would best engage students based on their learning styles and player types. A sample screenshot of this designed questionnaire (DeQ) is shown in Fig. 4, and the questionnaire is available at https://forms.gle/wmTgREdwbfEg6KMp8. This expanded questionnaire was distributed to students and faculty members across various colleges in Tamil Nadu. A total of 218 valid responses were collected, providing a substantial dataset for analysis. To do analysis in the collected response at first Shapiro-Wilk test was performed to check the normality of the distribution and the results shows that the responses are not normally distributed which motivates us to do the further analysis.

To analyze the data collected from the comprehensive questionnaire, fuzzy c-means clustering was applied. Fuzzy c-means is a clustering algorithm that allows for the grouping of data points (in this case, student responses) into different clusters based on their similarities. Unlike hard clustering methods, fuzzy c-means allows data points to belong to more than one cluster with varying degrees of membership, which is useful when preferences overlap. In this study, the author set n=4 for the fuzzy c-means clustering process, anticipating the need to create four distinct themes for the gamification platform. The motivation behind this decision was that developing and managing a wide variety of themes would be challenging. Therefore, limiting the number of clusters to four made it feasible to design and implement distinct themes that aligned with the preferences of different student groups.

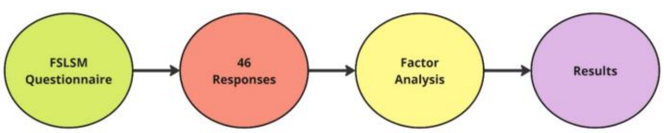


Fig. 2. Process flowchart for deriving the reduced FSLSM questionnaire through factor analysis.

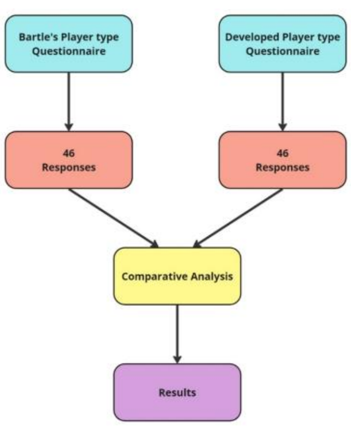


Fig. 3. Methodology for developing the reduced Bartle's Player Type questionnaire using comparative analysis.

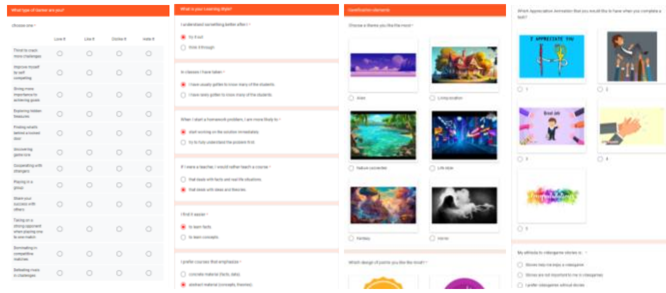


Fig. 4. Sample screenshot of designed questionnaire

V. Results

A. Shapiro-Wilk test

To measure the normal distribution of the data, Shapiro – Wilk test is conducted. The P-value shows that the FSLSM, reduced Bartle's Player Type and DeQ are not normally distributed which was tabulated in Table I.

TABLE I
RESULTS OBTAINED FROM SHAPIRO-WILK TEST

	P-value
Traditional FSLSM	9.68e-55
Reduced Bartle's Player Type	7.24e-24
DeQ	3.45e-54

B. Factor analysis

Exploratory Factor Analysis (EFA) is used to reduce the FSLSM Questionnaire. The results are obtained and it is tabulated in Table II.

TABLE II
RESULTS OBTAINED FROM FACTOR ANALYSIS

Q. No	Active/ Reflective	Q. No	Sensing/ Intuitive	Q. No	Visual/ Verbal	Q. No	Sequential/ Global
Q1	-0.189	Q2	-0.030	Q3	0.101	Q4	-0.017
Q5	-0.088	Q6	0.231	Q7	0.142	Q8	0.134
Q9	-0.011	Q10	0.257	Q11	0.102	Q12	0.144
Q13	0.129	Q14	-0.229	Q15	0.008	Q16	0.018
Q17	-0.439	Q18	0.049	Q19	0.140	Q20	0.083
Q21	-0.071	Q22	-0.041	Q23	0.199	Q24	0.154
Q25	-0.001	Q26	-0.104	Q27	0.064	Q28	-0.038
Q29	0.013	Q30	-0.056	Q31	0.103	Q32	0.260
Q33	0.079	Q34	-0.098	Q35	0.073	Q36	0.277
Q37	0.063	Q38	0.237	Q39	0.292	Q40	0.150
Q41	0.033	Q42	0.072	Q43	0.062	Q44	0.205

C. Comparative analysis

To compare the output of developed new Bartle's Player type questionnaire with the traditional Bartle's player type questionnaire, comparative analysis is used and it is visualized using Bland-Altan Plot as shown in Fig. 5.

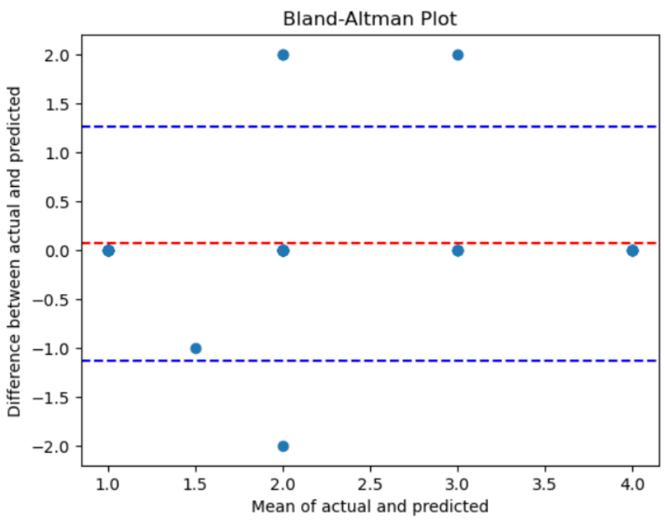


Fig. 5. Bland-Altman Plot of Traditional and new Bartle's player type questionnaire

D. Wilcoxon signed-rank test

To measure any significance difference present between traditional questionnaire and reduced questionnaire Wilcoxon Signed-rank test is performed as the data is not normally distributed which is tabulated in Table III.

E. Spearman's Rank Correlation

Additionally, to know the similarity between traditional and reduced questionnaire Spearman's Rank Correlation test is conducted to get the similarity level of the questionnaire which is tabulated in Table III.

TABLE III
RESULTS OBTAINED FROM WILCOXON SIGNED-RANK TEST AND SPEARMAN'S RANK CORRELATION

	Wilcoxon signed-rank test P-value	Spearman's Rank Correlation
Traditional Vs reduced FSLSM questionnaire	0.745	0.979
Traditional Vs new Bartle's Player type questionnaire	0.473	0.803

F. Fuzzy C means clustering

Fuzzy C means clustering is chosen to cluster the response of DeQ and the result is shown in Fig. 6. From the Fig. 6 it is clear that most of the learners are falls into 2 clusters cluster no 2 and 3.

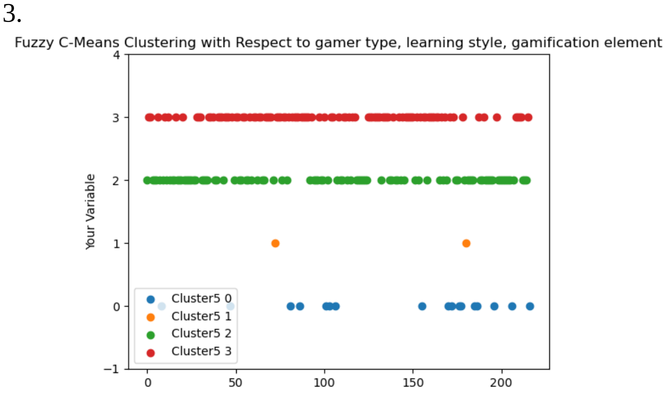


Fig. 6. Result of Fuzzy C- means Clustering.

VI. DISCUSSION

A. RQ1. How can the FSLSM and Bartle's Player Type questionnaires be reduced while maintaining their effectiveness in identifying student learning styles and player types?

To answer the above research question, the FSLSM and Bartle's Player Type questionnaires were reduced while maintaining their effectiveness in identifying student learning styles and player types through a methodical process involving rigorous statistical analyses. Given that the data were not normally distributed, non-parametric approaches has been adopted to ensure the robustness of the findings.

FSLSM has 44 questions for 4 dimensions of learning style, 11 question for each. For reducing the FSLSM questionnaire, an Exploratory Factor Analysis (EFA) was conducted. And the results are tabulated in Table II. Here positive value indicates that the question is more closely related to the first learning style in each dimension and negative value indicates that the question is more closely related to the second learning style in each dimension. For example, in Sensing/ Intuitive dimension, a loading of 0.25 (Q10) indicates a positive association with the Sensing style and a loading of -0.229 indicates a negative association, suggesting the Intuitive style. Therefore, the top three absolute loading/value for each dimension are derived and it is tabulated in Table IV.

TABLE IV
REDUCED QUESTIONNAIRE OF FSLSM FOR EACH DIMENSIONS

	Active/ Reflective	Sequential/ Global	Sensing/ Intuitive	Visual/ Verbal
Question Numbers	Q17 Q1 Q13	Q36 Q32 Q44	Q10 Q38 Q6	Q39 Q23 Q7

In contrast, the Bartle's Player Type questionnaire was reduced using a comparative analysis approach, visualized through a Bland-Altman plot. This method compared the traditional and new versions of the questionnaire to evaluate the agreement between them. From the Fig. 5 it is infer that the new Bartle's Player Type questionnaire shows a reasonable agreement with the traditional questionnaire, as most of the differences between the actual and predicted values lie within acceptable limits. This indicates that the reduced questionnaire can reliably approximate the results from the traditional questionnaire, though some minor deviations exist.

To further validate the reduced questionnaires, the Wilcoxon Signed-Rank Test and Spearman's Rank Correlation were applied for both FSLSM and Bartle's Player type. As the p-value > 0.05 in Wilcoxon Signed-Rank Test indicates and confirmed that there was no significant difference between the responses obtained from the traditional and the reduced versions of the questionnaires. Moreover, Spearman's Rank Correlation showed excellent similarity between the two versions, with correlation coefficients of 0.99 for FSLSM and 0.80 for Bartle's Player Type. These results demonstrated a strong correlation between the traditional and reduced questionnaires, indicating that the reduction process preserved the integrity and effectiveness of both models.

Through the application of factor analysis, comparative analysis, and non-parametric tests, the FSLSM and Bartle's

Player Type questionnaires were successfully reduced while maintaining their effectiveness in identifying student learning styles and player types. The high similarity scores and lack of significant differences between the traditional and reduced versions validate the reliability of the reduction process.

B. RQ2. What are the most effective gamification themes and design for enhancing student engagement based on identified clusters of learning styles and player types?

To address the above research question, this study wanted to determine the most effective gamification themes for enhancing student engagement by analyzing their learning styles and player types. Using fuzzy c-means clustering, the responses from students to DeQ questionnaires were grouped into distinct clusters based on their similarities in learning styles, player types and preferences. For each of these clusters, theme preferences and gamification element preferences were assessed based on the highest voting within the group. By examining Table V, the voting for each theme in each cluster was analyzed. For example, in Cluster no 2, the Fantasy theme received the highest number of votes, making it the most preferred theme for students in that group. Similarly, in Cluster no 3, the Nature theme was voted the highest, indicating its appeal to students within that cluster. These results demonstrate that different themes resonate more strongly with particular clusters, based on the students' identified learning styles, player types and their preferences.

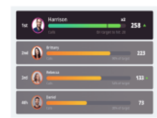
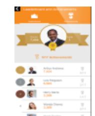
This clustering approach allowed us to identify themes that were highly recommended by the learners in each group. The study found that by tailoring the gamification themes to the preferences of the students in their respective clusters, student engagement could be significantly enhanced. For example, focusing on the Fantasy theme in Cluster 2 and the Nature theme in Cluster 3 provided a targeted approach to designing the gamified learning platform. Likewise, all other design elements, such as points, badges, and leaderboard, were also identified based on the preferences of students within each cluster which is tabulated in Table VI.

From Fig. 6 it is clear that students mostly fall into 2 cluster, therefore the designing of gamified learning platform mainly focus on the preferences of cluster no 2 and 3. The most effective gamification themes for enhancing student engagement were those that aligned closely with the preferences of the students within their respective clusters. By incorporating the highest-voted themes and gamification elements for each group, the study successfully created a more engaging and personalized learning experience.

TABLE V
VOTING FOR THEME IN EACH CLUSTER

Cluster No.	Count of Space theme	Count of Village theme	Count of Nature theme	Count of City theme	Count of Fantasy theme	Count of Horror theme
0	0	1	2	5	6	3
1	0	0	0	0	2	0
2	5	4	13	20	**40**	15
3	1	21	**46**	16	14	3
Total	6	26	61	41	62	21

TABLE VI
GAMIFICATION DESIGN PREFERENCES OF IDENTIFIED MAJOR CLUSTERS

	Cluster No - 2	**Cluster No - 3**
theme	 **Fantasy**	 **Nature Connected**
time-bound challenges	✓	✓
points		
Badges		
leaderboard		
levels		 (or) 
Appreciation Animation		

The gamified platform which is designed for the learners is shown in Fig. 7.

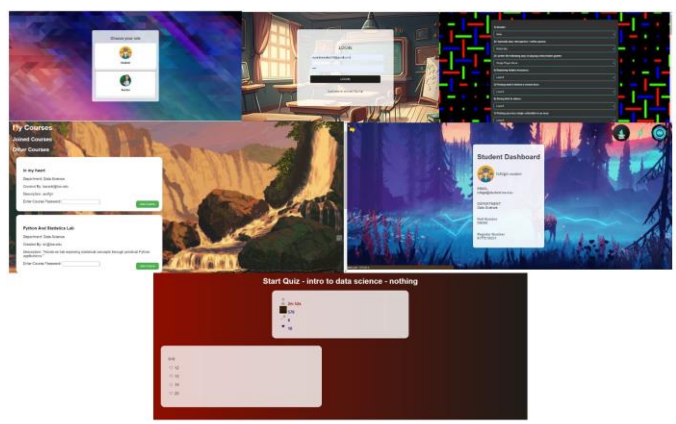


Fig. 7. Sample Screenshot of the developed gamified online platform for education.

CONCLUSION

This study aimed to reduce the FSLSM and Bartle's Player Type questionnaires to make them more user-friendly without compromising their effectiveness in identifying student learning styles and player types. Through the application of Exploratory Factor Analysis (EFA) for the FSLSM questionnaire and comparative analysis (Bland-Altman Plot) for the Bartle's Player Type questionnaire, we were able to create shortened versions of both instruments. The reduced versions were validated through robust statistical methods, including the Wilcoxon Signed-Rank Test and Spearman's Rank Correlation, which demonstrated high reliability and accuracy, with correlation coefficients of 0.99 for FSLSM and 0.80 for Bartle's Player Type. Fuzzy c-means clustering revealed distinct student groups based on their learning styles, player types, and gamification element preferences. These insights enabled the identification of gamification themes that resonate most with each cluster, highlighting the importance of personalized gamification in enhancing student engagement.

While the findings are promising, the study has its own limitations. The primary limitation is the relatively smaller sample size. A larger sample size could enable the identification of more precise and diverse clusters, leading to better alignment of gamification themes with individual preferences. Another challenge lies in the design of gamification platform; currently, the focus is primarily on two major cluster preferences. However, these themes may not fully address the diversity of preferences within a heterogeneous group of learners, potentially leading to deviations in engagement for few individuals.

Despite these, the findings underscore the potential of aligning gamification elements with individual preferences to create engaging, adaptive learning environments. Future research will explore the integration of cognitive abilities into adaptive mechanisms, aiming to design more dynamic platforms that tailor challenges and learning materials to individual needs. The exploration of integrating learning styles and player types into gamification design could provide deeper insights into creating adaptive learning systems that are not only engaging but also more inclusive and effective in addressing diverse learner needs.

Appendix

All the details of voting for the gamification design can be accessed at https://drive.google.com/file/d/1yE3FsS8JRQnIHcsshAg3NXK5NFmKUGTK/view?usp=sharing

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