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Design of self-regulated learning framework for professional development program through Learning Analytics

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Abstract

Integrating instructional design and educational technology into learning principles shifts the role of the learners and adds a new dimension to Learning Design (LD). The learning design is the logical framework that creates a path for self-regulated learning (SRL) in hybrid mode. Capturing the learners' details is a critical functionality for preparing the learners' logical learning path. Learning analytics (LA) would provide instructors with critical information that would support the learning design and improve training practice. Capturing learner data and performing learning analytics is a complex process in professional development programmes (PDP). In this paper, a dynamic logical framework is proposed to capture the learner data and provide a better SRL path for the trainees in the professional development programme. In this work, the MOODLE learning management system is used to collect learner data, which is then fed into learning analytics to better understand the various trainee's characteristics. The proposed framework will group the trainees using the hierarchical agglomerative clustering algorithm based on learning analytics. Each cluster is examined to provide a better training path and instructional materials through an appropriate learning design. During the professional development programme, the trainee's content learning and learning experiences are analyzed, and the output of assessment data is periodically provided into the framework, which dynamically moves the trainee from one cluster to another to provide a suitable training path. The impact of the proposed framework is assessed through an indirect assessment strategy, and the trainee is informed about their level of learning outcome from their professional development programme.

Keywords: Learning design, Learning analytics, Clustering, Learning management system (LMS), Machine Learning

1. Introduction

Technology-enabled learning refers to the use of technology to support and enhance the teaching and learning process. This can include a wide range of tools and platforms, from basic educational software and online resources to more advanced technologies such as virtual and augmented reality, adaptive learning systems, and artificial intelligence. Technology-enabled learning aims to improve the effectiveness and efficiency of education by providing new opportunities for engagement, personalization, and collaboration [1]. The use of advanced technologies in education has grown dramatically over the past few years, with Learning Management System (LMS), social media, interactive simulations, and game–based learning platforms. Integrating educational technologies in training programme provides the facility to record the learning process in the form of data. The potential aspect of data collection on different aspects of learning engagement and experiences have increased the usage of technology. To provide a better learning experience through technology, the domain of learning analytics can be used, and it is focused on data collection, processing, mining, analyzing, and reporting on learners and the context in which learning takes place [2]. To collect the data about the trainees, the LMS platform plays a critical role, and the data is used for analytics and helps in the design and delivery of online and blended learning experiences[3]. LMS would provide a centralized repository for storing and delivering learning content, such as videos, presentations, and documents in the form of learning design. This makes it easy for instructors to manage and distribute course materials and for learners to access and review them at any time [4]. In addition, LMS provides data and analytics tools that allow instructors to track learner progress and engagement and gain insights into the effectiveness of their training programmes. The data collection occurs when the learner interacts with the various activities and resources in the LMS platform. These data are known as log data, and they have been identified as a primary source of information that could be used by a variety of stakeholders, including trainees, students, teachers, and administrators, to help them to make better decisions [5]. Highly diverse learners enrolling in the self-learning platforms are typically asked to make judgments about their learning activities to succeed academically. Preparing the learning environment, which is adjusting to characteristics of learners' aspects such as gender, cognitive abilities, prior knowledge, learning style, etc., are being considered a crucial parameter for designing Self-Regulated Learning (SRL) [6]. To optimize the self-learning environment, it is necessary to employ the various learners' activities in learning analytics to get a better understanding of the learners [2], [7]. LA is the measurement, collection, analysis, and reporting of data about learners and their contexts for purposes of understanding and optimizing learning and the environments [8] in which it occurs, as shown in Figure 1.

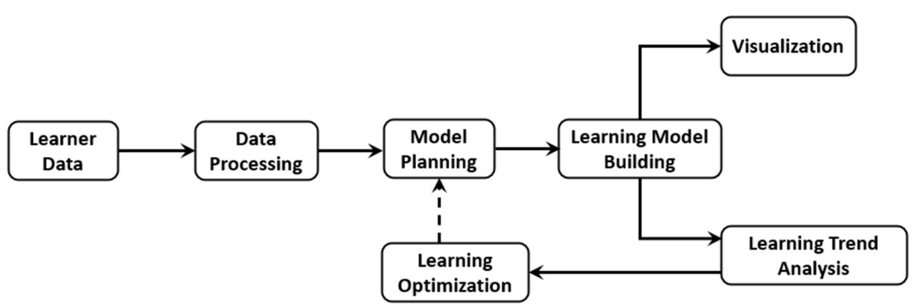

Figure 1. Phases of Learning Analytics

This can include data on learner performance, interactions with educational technology, and other factors that may affect learning. The data is often used to identify patterns and trends, which can inform decisions about instructional design, curriculum revision, and other aspects of the learning experience [9]. It also helps to identify at-risk learners, personalize instruction, and evaluate the effectiveness of educational interventions.

The design of instructional materials is the process of creating educational experiences to improve learner outcomes. It involves selecting instructional methods, content, technology, and assessment strategies that align with learning goals and support learner engagement and achievement.

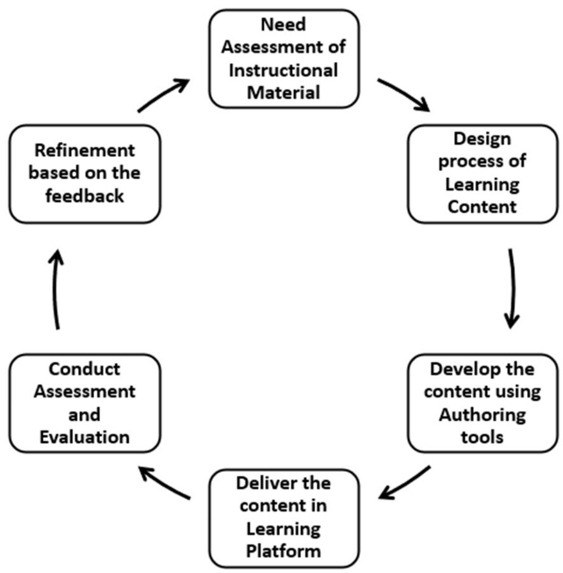

Figure 2. Learning Design Phases

LD process consists of several key steps, which are shown in Figure 2. To start the learning design, it is necessary to determine the needs of the learners and the objectives of the training programme. This information is used to inform the development of the instructional materials. Designing the learning experience is the subsequent process that considers the ability level of learning outcomes. It is required to provide the solution in creating instructional materials, activities, and assessments that support learning [10].

The development of instructional materials, activities, and assessments is the core process of the learning design. Learners are allowed to learn in a range of ways, including online, blended, and in-person training [11]. So, deciding the form of delivery methods is one of the essential components of learning design. In continuation with the delivery of learning materials, regular assessments and evaluations are conducted to measure learning engagement and empowerment to identify areas for improvement [12].

Many researchers have discussed the benefits of LA in education and training programmes, including its ability to improve learner engagement and achievement, provide personalized learning experiences, and enhance the effectiveness of educational programs. A few researchers have also discussed the challenges and ethical considerations associated with the use of Learning Analytics, such as privacy and data security, and the need to balance the benefits of these tools with the potential risks.

2. Literature Review

Recently researchers and developers from the educational community started exploring the potential adoption of LA and LD techniques for gaining insight into online learners' activities and progress. Sclater et al. & Wong et al. [13],[14] explained that learning analytics in self-regulated learning aims to the current state of the applications of learning analytics to measure and support learners' self-regulated learning in online learning environments. LA would identify the trainees likely to struggle academically early on and offer individualized, just-in-time support. Khalil et al. [15] have proposed a learning analytics life cycle that consists of data generation, which is often from learning platforms like massive open online courses, learning management systems, and virtual learning environments, tracking of information about the learners on the learning platforms, analysis which is to identify patterns and extract information from the data and finally action which may include prediction, intervention, and personalization.

According to Winne et al. [16], LA for SRL has two elements such as calculation, which is based on traces of actions carried out during learning activities, and recommendation, which provides the details on what should be changed about how learning is carried out, and instructions about how to go about changing it. Thus, the use of LA can afford learners opportunities to exercise SRL and ultimately develop their relevant SRL learning strategies, skills, and knowledge needed for their academic- and future work successes.

Choi et al.[17] provide an overview of the typical intervention methods, including emails, phone calls, instant messages, postings and news on LMS, group consultations, in-person consultations, video recordings, peer review, and online courses. The most significant problem, according to Rienties et al.[18] is the ambiguous effect that various sorts of interventions will have on learners' attitudes, behaviours, and cognitive processes. The intervention has been found to present difficulties for both learners and trainers. According to Werners et al. [19], at-risk learners may struggle to understand the learning analytics data and take appropriate action, which calls for strong metacognitive abilities and self-regulation.

Avella et al.[4] examined analytic methods, primary benefits, and challenging issues in higher education settings by analyzing more than 100 journal articles on learning analytics from 2000 to 2015. The authors found visual data analysis and social network analysis were the most commonly used analytic methods. Other analytical techniques, such as prediction, clustering, and relationship mining, were also widely applied in LA. The authors concluded that the main benefits of LA were to improve curriculum design, enhance learners' and instructors' performance, and provide personalized learning services. The most identified challenges of LA include how to track, gather, and analyze data, how to connect LA with learning science, how to optimize learning environments with analytics results, and how to address ethical and privacy concerns. Schwendimann et al. [20] examined educational dashboards to categorize learning contexts, data sources, visualizations, and analysis types in both LA and educational data mining by reviewing more than 50 research articles between 2010–2015. The authors found that most of the learning dashboards were designed for learners' self-monitoring and for instructors to monitor students in formal higher education settings. The data sources of dashboards have heavily relied on behaviour logs from a single LMS platform. The visualization types, which were like that of traditional dashboards, utilized bar charts, line graphs, tables, pie charts, and network graphs. In terms of analysis type, the authors revealed that most of the studies in their review were exploratory or proof-of-concept without authentic evaluations. Therefore, it wasn't easy to evaluate the actual impacts of the learning dashboard on learning effects.

In conclusion, the literature review on self-regulated learning highlights the importance of learning analytics in self-regulated learning by considering multiple factors in designing effective learning experiences. The study suggests that the use of multimedia, gamification, and adaptive learning can lead to more effective learning outcomes. Integrating learning experiences in self-regulated learning has a lot of challenges, such as engaging and motivating learners, creating effective assessments, balancing simplicity and complexity, incorporating technology effectively, ensuring accessibility and inclusiveness, staying up-to-date with current trends, and measuring success.

Integrating LD-LA helps prepare a self-regulated learning environment that actively controls one's cognition. The major challenge in designing the SRL framework is self-motivation which motivates the learning in which the materials should be suitable for their learning style, difficulty in monitoring the learning progress, which creates the gap between the learner and guide, difficulty in setting the learning outcome level and limited self-awareness which is very much needed for understand their learning style. Hence in this work, a framework is designed to implement self-regulated learning with the help of learning design with analytics.

3. Design of Self-Regulated Learning Framework

Integrating learning analytics into learning design involves using data to inform and guide the design of instructional materials, assessment strategies, and learning environments to optimize and achieve learning outcomes. The essentials of integrating learning design with learning analytics are data collection, analysis, visualization, and management. In this proposed system, pertinent data such as assessment data of pre-requisite and learner interaction data were collected from the learners of a training programme on “Web Application Development” offered through (www.nitttrc.ac.in/lms). The collected data are analyzed using various descriptive analytics functions for feature extraction, machine learning algorithms for grouping the learners, and data analysis methods to extract insights and information that can inform the design and development of learning activities. The data is also fed into visualization methods to generate reports, presentations, and dashboards.

In this PDP, the learners are provided training on web application development using web development tools. In this training programme, before the start of the training and during the training, the learner data on their learning progress is periodically collected. So that the learners can be clustered into categories based on their learning features to provide proper instructional assistance in the self-learning environment. In this proposed system, clustering has been carried out through a Hierarchical Agglomerative algorithm. The design framework for SRL is shown in figure 3. The SRL framework is suitable for different kinds of learners with their abilities, skills, pace and style of learning. The learner data are collected from the MOODLE LMS (www.nitttrc.ac.in/lms), which provides a range of information such as visual or spatial, Auditory, kinesthetic, read/write, interpersonal, intrapersonal, and logical or mathematical referring to the different approaches. Following a specific learning approach for developing various types of abilities is challenging.

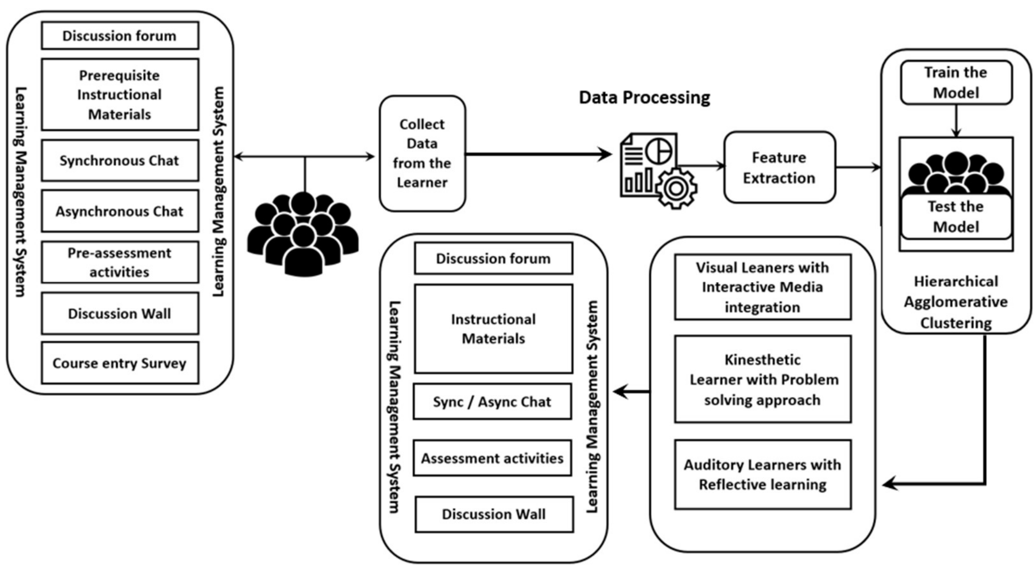

Figure 3. SRL Framework for PDP through Learning Analytics

In this PDP, the abilities, skills and learning styles must go together for SRL to achieve the learning outcome. So, most of the trainees in the PDP have a combination of learning approaches, and the way in which the individuals learn can change depending on their abilities to develop. Further, the approaches to learning are not fixed and can change over time, based on learning experiences and personal preferences.

3.1 Data Collection from MOODLE LMS for SRL

The PDP is offered to the faculty members in the domain of Information Technology / Computer Science and Engineering of technical institutions of the country who wish to develop their skills in web application development. A total of 289 participants have registered for the PDP and the duration of the programme is 45 days. To design the learning path and learning design, a framework is designed to facilitate the participants of the programme. In this proposed work, the system collects demographic information such as age, gender, location, and educational background, learning behaviour data that express how learners engage with the LMS, including the time spent on the platform, the number of resources accessed, and the learning activities, Social presence in the digital wall, peer group interaction in synchronous and asynchronous chat activity, pre-assessment activity, learning preferences data which includes information on the type of content that learners prefer, such as videos, simulations, or interactive activities, as well as their preferred learning pace and style and feedback data which includes on learner feedback on different activities. The fundamental data such as pre-assessment activity, age, gender, location, and educational background are considered for the prerequisite activity of the programme. Assessing the prerequisite activity is the key to understanding the learner to design the learning path.

3.2 Data pre-processing

One of the most challenging issues in the grouping of learners through a clustering algorithm is the removal of noise instances. Usually, the removed instances have excessively deviated instances with too many null feature values. These excessively deviating features are also referred to as outliers. In real-world data, the representation of data often uses too many features, but only a few of them may be related to the target concept. In this proposed method, all the data instances are collected, but only the required features are processed for the clustering algorithm. Redundancy in the vertical and horizontal records has been identified, which are filtered. Incomplete data is an unavoidable problem in dealing with real-time data collection. In this system, one of the most important values as ‘unknownness', is created in the dataset by the trainee while performing the pre-training activities in the LMS.

3.3 Feature selection for the design SRL framework

The LMS would provide all kinds of data about the learner and their activities. In this system, nine activities are placed in pretraining activities along with the different kinds of learning materials. The pretraining activities were conducted for five days in the total number of days of the training programme. All 289 trainees are generating high-dimensional data in the LMS. Extracting the necessary features provided a model which is highly suitable for the group of learners and provides a suitable learning path for training. Learners’ features are collected from the LMS and constructed as a learner dataset. In the dataset, few features are categorical data, and few features are continuous data. The categorical features are verified through the Chi-square method (X2) for testing the relationship between categorical variables.

$$X^2 = \sum \frac{(Observed\ Value - Expected\ Value)^2}{Expected\ Value}$$

It is a statistical hypothesis test that assumes that the observed frequencies for a categorical variable match the expected frequencies for the categorical variable. The p-value of the chi-square test indicates that the difference between the observed and expected frequencies is statistically significant and rejects the null hypothesis. For a selection of the numerical features performed using the correlation method.

To design the SRL framework, the following features such as practice on web application fundamentals 1 & 2, a discussion forum to ask clarification or questions, a pre-test as self-assessment but the scores are captured in the LMS, a digital wall to collaborate with other trainees of this programme, chat activity which is carried out as synchronous and asynchronous mode, learning material through the spoken tutorial and video material with interactive assessment were collected from the participants of the programme. From the collected data, a heat map is generated, which is shown in figure 4.

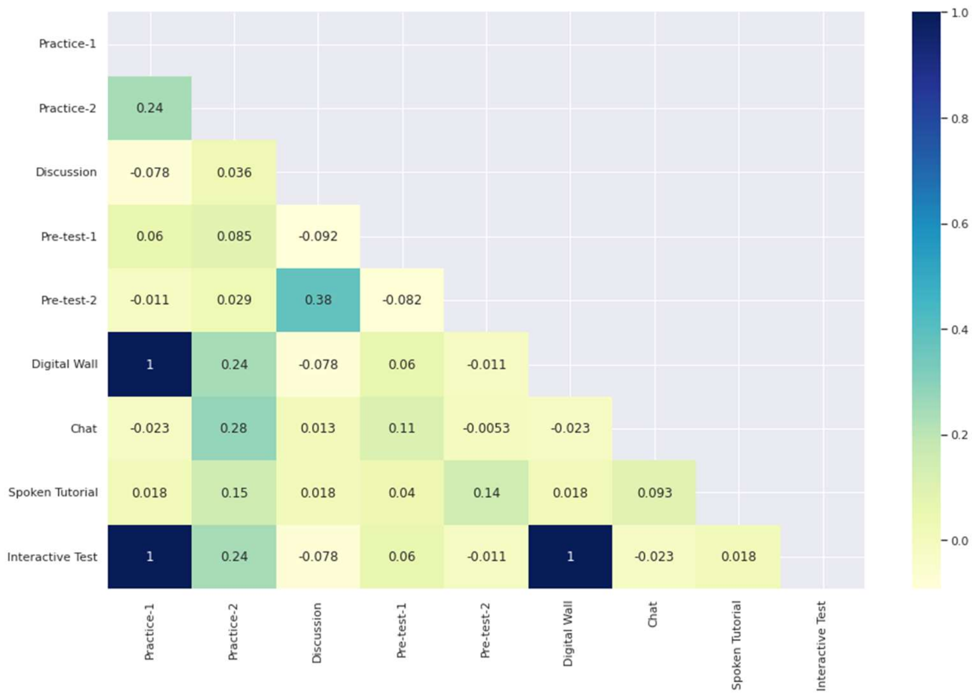

Figure 4. Heat map with correlation coefficient with learner features

The correlation-based feature selection method selects the features of learners that have a high correlation with the target variable and a low correlation with each other.

3.4 Clustering the learners based on the Learner Features

The proposed SRL framework is addressed the different groups of learners in the self-learning environment. The clustering algorithm is used to group learners based on their performance or characteristics, which can help in identifying patterns, segmenting learners, and personalizing their learning experiences. To group the learners into clusters, the Hierarchical Agglomerative clustering algorithm (HCA) is used, which follows the bottom-up approach method of clustering. This algorithm considers each learner as a single cluster at the beginning and then starts combining the closest pair of clusters together. It does this until all the clusters are merged into a single cluster that contains all the learners.

3.5 Agglomerative Clustering algorithm

Agglomerative clustering is based on hierarchical clustering which is used to form a hierarchy of clusters. This technique is used in unsupervised machine learning tasks where a learner dataset is not labelled, and the task is to group similar features learners.

1. ***Begin with n clusters of learners, each containing one learner and number the cluster of the learners*** 1 ***through*** n.
2. ***Define*** r, s ***are two clusters, not necessarily single point clusters.***
3. ***Compute the between-cluster distance*** $D(r,\ s)$ ***as the between-object distance of the two-learner group in r and s respectively,*** $r,\ s\ = 1, 2,\ \ldots,\ n$. ***Let the square matrix*** $D = (D(r,\ s))$. ***If the learners are represented by quantitative vectors, then use Euclidean distance.***
4. ***Find the most similar pair of clusters*** r ***and*** s, ***such that the distance,*** $D(r,\ s)$, ***is minimum among all the pairwise distances.***
5. ***Merge*** r ***and*** s ***to a new cluster*** t ***and compute the between-cluster of learner distance*** $D(t,\ k)$ ***for any existing cluster*** $k \neq r,\ s$. ***Once the distances are obtained, delete the rows and columns corresponding to the old cluster*** r ***and*** s ***in the*** D ***matrix, because*** r ***and*** s ***do not exist anymore. Then add a new row and column in*** D ***corresponding to cluster*** t.
6. ***Repeat Step 3 a total of*** $n - 1$ ***times until there is only one cluster left.***

In the agglomerative clustering algorithm, the process is to group similar instances starts by creating multiple groups where each group contains one learner at the initial stage, and then it finds the two most similar groups, merges them, and repeats the process until it obtains a single group of learners of the most similar instances. The learners' features are collected from the LMS and are shown in table 1.

Table 1: Learner Features collected from LMS for Clustering Algorithm.

Sl.no	Feature	Description
1	Gender of the Learner	Male/ Female
2	Disability	Yes / No
3	Practice – 1	Learners are provided with fundamental activities on Web development & Design considerations - Scores are collected
4	Practice – 2	
5	Discussion forum	Learner participation in the discussion forum with peer or guide – Durations are collected and converted as score

Sl.no	Feature	Description
6	Pre-Test 1	Learner basic knowledge in the web application environment is collected with game-based activity – Scores are collected
7	Pre-Test 2	
8	Digital wall	Learner can participate in the digital wall for social presence. Each participation is computed as a score
9	Chat Activity	Guide enabled a synchronous chat activity where the learner can chat with guide and peer group. Scores computed and collected.
10	Instructional material – Spoken tutorial	To meet the prerequisite of web application development, few instructional materials were provided. The material integrated with inline assessment. Usage duration and assessment scores are computed.
11	Instructional material – Interactive video content	To meet the prerequisite of the PDP, video instructional materials were provided. The Videos are interactive video with assessment. Usage duration and scores are computed.

The features are fed into the agglomerative clustering algorithm with training and testing data. In the dataset, the gender of the user, demography of the user, and disability are categorical data. This clustering algorithm accepts the categorical and numerical data for the clustering of the learners. The training and testing data are 70% and 30%, respectively, placed in the algorithm. The clustering process will be represented by a binary tree known as a dendrogram. The initial groups are on the leaves, and each time two groups are merged, which will join in the tree. The dissimilarity between the groups being joined determines the height of the divisions.

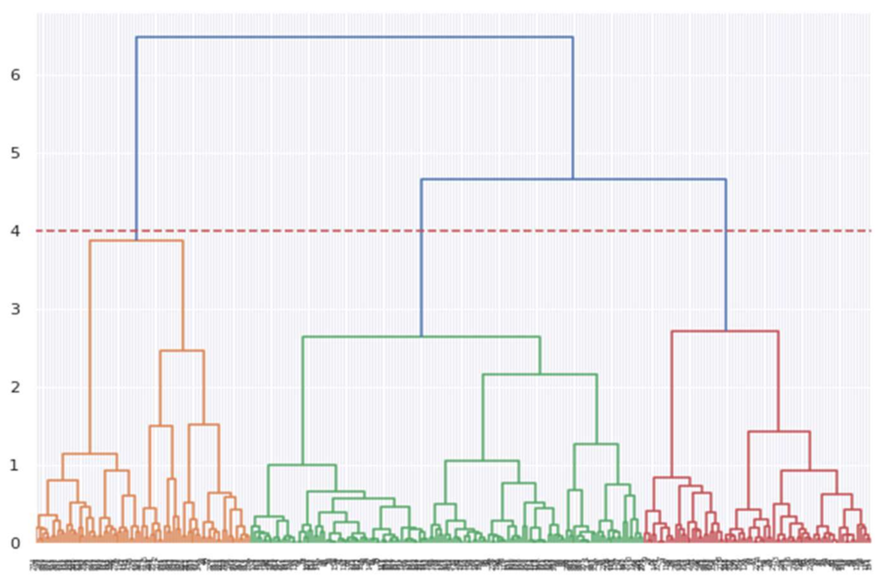

Figure 5. Dendrogram of agglomerative clustering

The tree root is a category that contains all of the learner data. If the tree is cut at any given height, it will produce a number of clusters. If two vectors are at the level, then the hierarchy comes together in a single cluster, and they will remain in that cluster for all subsequent clusters. Each agglomerative scheme phase corresponds to a type of dendrogram stage to identify the clusters. In this approach, the elbow method [21] is used to find the optimal number of clusters from the dendrogram. The point on the dendrogram where the slope of the dendrogram changes most drastically is identified for choosing the number of clusters that corresponds to that point. Cutting the dendrogram at the resulting point of the elbow method created in a specific level of clustering to group the learners.

Table 2: Cluster of the Learner using HCA.

Sl.no	Cluster	Number of Learners
1	Learning Design -1 (L1)	75
2	Learning Design -2 (L2)	79
3	Learning Design -3 (L3)	135

The agglomerative algorithm produced the dendrogram where the x-axis contains the learner features, and the y-axis represents the distance between these features. The fetched data from the LMS has provided three clusters as this line cuts the dendrogram at two points. The cluster details of the learners are shown in table -2. The three clusters represent the type of learners with respect to learning and the ability to be demonstrated at the end of the learning. The proposed system has been implemented only for the online training programmes with MOODLE LMS. The proposed SRL does not support for offline or hybrid training programmes.

4. Results and Discussion

The resultant cluster data is compared with the trainees' features which are collected from the learning management system. The comparison details show that 46.7% of the trainees are learning with a simulated method of content design to achieve learning ability at the application level. Learning design-2 consists of 36.9% of trainees, and they are learning with interactive video-based lectures to achieve the ability to the application level. The remaining 25.9% of learners are learning through the lecture method and self-reading method and achieving the ability of application level. The details are shown in Fig 6.

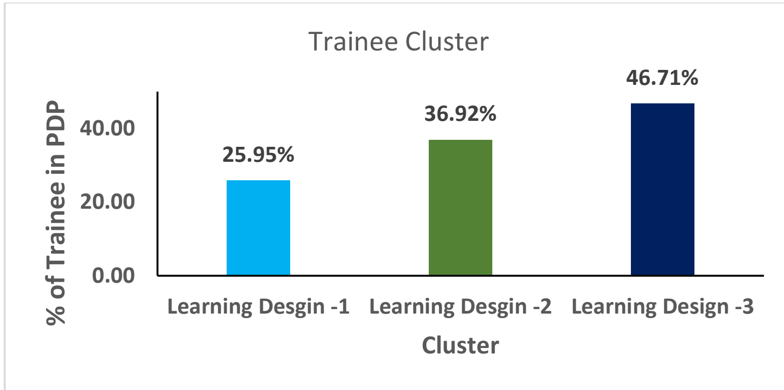

Figure 6. Learner Group clustering

Hence, the trainees are taking different learning paths with suitable learning designs to reach the same level of ability. To achieve the learning outcome, the learning path is defined, and each learning path has its own learning design with different activities to drive the learner in self-regulated learning. The learning path is not fixed for the entire training programme for an individual learner.

The learner can change the path while moving from one learning outcome to another learning outcome. The learner also give details such as the progress of learning in the learning management system, strength and weaknesses, and experimenting with various learning strategies and feedback. The proposed SRL framework is designed in such a way as to conduct the periodical review of the need assessment of the learner to help in changing the learning path.

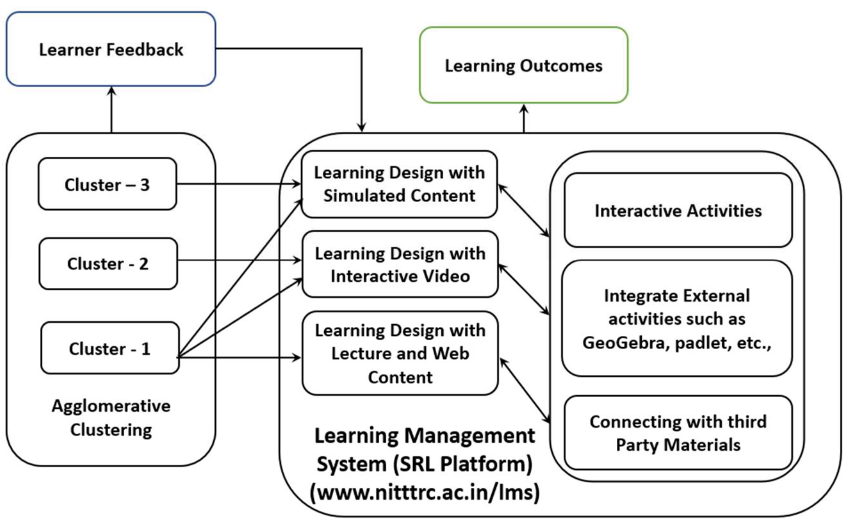

Figure – 7. Learning Path with Learning Design

The periodical assessment in the SRL framework would provide the learning gap in knowledge or skills that need to be addressed. So, the proposed SRL framework system will guide the learner to change the learning path to achieve the outcomes of the training programme. The proposed system would provide flexible learning options that can help them adjust the learning path to their needs. For instance, offering asynchronous learning activities or self-paced learning can help learners who need more time to master the material. Additionally, offering a range of interactive and external learning activities, such as simulations, quizzes, or discussions, can cater to different learning styles and preferences. If a particular learner in the training programme is struggling with a concept, the learner can move lower-order ability-based learning design to get the concrete concept. Continuous feedback and recommendations of the proposed system help the learner to adjust the learning path. The learner survey activities on the effectiveness of the learning activities and whether they felt that the learning path met their needs provide essential information for future learners. Use this feedback to adjust the learning path for future learners and improve the training program's overall effectiveness.

5. Conclusion and Future Work

The proposed SRL framework helps the learner to optimize their learning and achieve learning outcomes. This proposed system has been tested with 289 PDP participants of the web application development program, which is for a duration of 45 days. The SRL system addresses the learner in the training programme to adjust the learning path and help the trainer to design the learning content to meet the learner's flexibility. The entire system was developed for an online training programme with the help of www.nitttrc.ac.in/lms. The SRL framework shows that learning analytics interventions have enabled the learner to enhance their learning. So, the SRL framework can be extended with respect to learning analytics in order to examine the relationship between the various activities in the training programme to determine how to create successful intervention approaches for the self-regulated learning environment, and also it can be extended further for the hybrid mode of training (physical mode and online mode) programme.

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