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TOPICAL REVIEW

AI-Based Personalized E-Learning Systems: Issues, Challenges, and Solutions

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ABSTRACT A personalized e-learning system is effective in imparting enhanced learning to its users. As compared to a conventional e-learning system, which provides similar contents to each learner, a personalized learning system provides specific learning contents and assessments to the learners. Personalization is based on Artificial Intelligence (AI) based techniques in which appropriate contents for each learner are determined using the level of comprehension of the learner and the preferred modes of learning. This paper presents requirements and challenges for a personalized e-learning system. The paper is focused in elaborating four research questions, which are related to identifying key factors of personalized education, elaborating on state of the art research in the domain, utilizing benefits of AI in personalized education, and determining future research directions. The paper utilizes an in-depth survey of current research papers in answering these questions. It provides a comprehensive review of existing solutions in offering personalized e-learning solutions. It also elaborates on different learning models and learning theories, which are significant in providing personalized education. It proposes an efficient framework, which can offer personalized e-learning to each learner. The proposed framework includes five modules i.e Data Module, Adaptive Learning Module, Adaptable Learning Module, Recommender Module, Content and Assessment Delivery Module. Our work also identifies significant directions for future research. The paper is beneficial for academicians and researchers in understanding the requirements of such a system, comprehending its methodologies, and identifying challenges which are needed to be addressed.

INDEX TERMS Adaptability, artificial intelligence, educational data mining, knowledge tracing, personalized e-learning, recommender systems.

I. INTRODUCTION

E-learning systems are gaining increased popularity due to their massive scalability and their immense potential of providing non-disrupted and affordable learning 24/7. Artificial Intelligence (AI) can significantly enhance e-learning systems through personalized content delivery to a learner [1]. In contrast to a conventional e-learning system, where all the learners that are studying at a specific grade are delivered identical contents, an AI based adaptive and personalized e-learning system delivers specific and targeted content to each learner [2]–[4]. A learner can experience improved learning through personalization, as the e-learning system can customize content delivery according to the strengths and weaknesses of the learner.

There has been a considerable research on the personalization of e-learning [5]–[7]. A review of this research area shows that most of the current AI-based personalized e-learning techniques are not integrated to create a more diverse, holistic personalized e-learning framework [7]. In this article, we propose such a framework that integrates knowledge tracing, learning mode adaptation, and recommender systems for the delivery of personalized e-learning content. In this way, we can integrate different AI-based techniques that have been researched and validated. Creation of personalized e-learning platforms in this manner results

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into a comprehensive system that mitigates the issues and shortcomings of individual models.

Personalization implies that each learner is assessed and taught individually. For this purpose, an AI-based system can be employed to assess a learner's level and determine appropriate contents. For instance, if a learner performs poorly on a specific topic, then the topic may be repeated - possibly through a different mode of content delivery [8]. Similarly, if a learner demonstrates higher level of comprehension, then learner may be taught the next level of content, which are related to the subject.

There are several methods of delivering personalized content, of which, adaptive learning and adaptable learning are the most widely employed [9], [10]. In the former approach, a recommendation strategy is built which delivers content according to the level of comprehension of the learner. Requirements exist in determining appropriate level of a learner and to determine and recommend suitable content [8]. In comparison, the adaptable learning technique is focused on delivering content through the preferred mode or medium of delivery. Since these preferences may be implicit, an adaptable learning system is needed to be artificially intelligent in determining the preferred modes.

Delivering personalized content to a learner could be extremely significant for an effective e-learning system. This is specifically useful where online education supplements physical classes, for example, in the recent pandemic (COVID-19) [11], [12]. In addition, personalized e-learning systems can also be implemented to educate masses, as it provides a cost-effective method to deliver education [13].

A personalized content delivery system has many computer-science related challenges [14]. It requires a smooth and capable mechanism exist through which learners can be continuously assessed and proper level of comprehension can be determined. Machine Learning (ML) and Deep Learning (DL) based models may be utilized to determine and match the appropriate level of content for the learner [15].

An extensive approach is needed which can cater subject-wise identification of comprehension levels. A capable recommendation system is required to be built which can extensively compare different techniques for ML and DL in order to built a recommendation system. Proper mechanisms for identification and selection of features that represent the interaction of a learner in various parameters are also needed such as assessment scores, screen on time, device type etc. This mechanism is needed to be incorporated in real-time so that the system is continuously trained and is able to capture updates on these features, iteratively [2].

Challenges exacerbates for adaptable learning components of the system. Such a system is based on the intrinsic principle of delivering content through a learner's desired mode of content delivery. For instance, a learner may get higher comprehension through videos, while another learner may prefer learning through games. Since this preference is assessed implicitly, an efficient mechanism is needed to be incorporated with the recommendation system [16], [17].

This paper is motivated by the immense potential possessed by a personalized e-learning system in addressing the challenges of delivering effective online education. It focuses on proposing an efficient architecture for a personalized e-learning system. It elaborates on various techniques and challenges for such a system and proposes solutions to encounter these challenges.

This work not only provides an in depth review of the current state of the art methodologies that are employed in the implementation of personalized e-learning systems, but it also discusses the challenges and requirements that are crucial for its implementation. In addition, it provides an efficient framework on which an effective e-learning system can be built. It also provides mechanisms, challenges, and future research directions, which can be considered by the community for future research prospects.

The remainder of this paper is organized as follows. The next section provides the selection criteria of the research papers analyzed in this article. Section III elaborates on requirements and challenges of a personalized learning system. Section IV describes significant work by other researchers. In Section V, we propose an effective model for a personalized learning system. In Section VI, we explain important issues for the community and conclude the paper in Section VII.

II. RESEARCH METHODS AND PROCESS

In this section, we provide details of our research methodology. Fig. 1 illustrates the research process. We have explored research papers using an extensive and explicit search approach. We selected research papers based on keywords, year of publication, their utilization of AI in providing personalized education, and their potential benefit. We reviewed our selected papers to identify a few important questions and their answers. This paper presents a meticulous description of our work in which we describe Research Questions (RQs), and provide a detailed description of their answers. Our contribution is novel in identifying research questions, determining requirements and challenges, describing a detailed review of literature, proposing a generic framework, and outlining future directions for research.

Following are the list of questions, we have investigated along with the specific section of the paper, which addresses each question:

1) What are the key factors in building a personalized e-leaning system? (Refer to section III)
2) What is the current state of the art on adaptive e-learning systems? (Refer to section IV)
3) How AI can be beneficial in implementing an effective personalized e-learning system? (Refer to section V)
4) What are the future research directions in the domain? (Refer to section VI)

Answers to the above mentioned questions are based on an extensive review of the existing literature, in which we collected and discussed information and knowledge related to personalized e-learning systems. In addition, we have

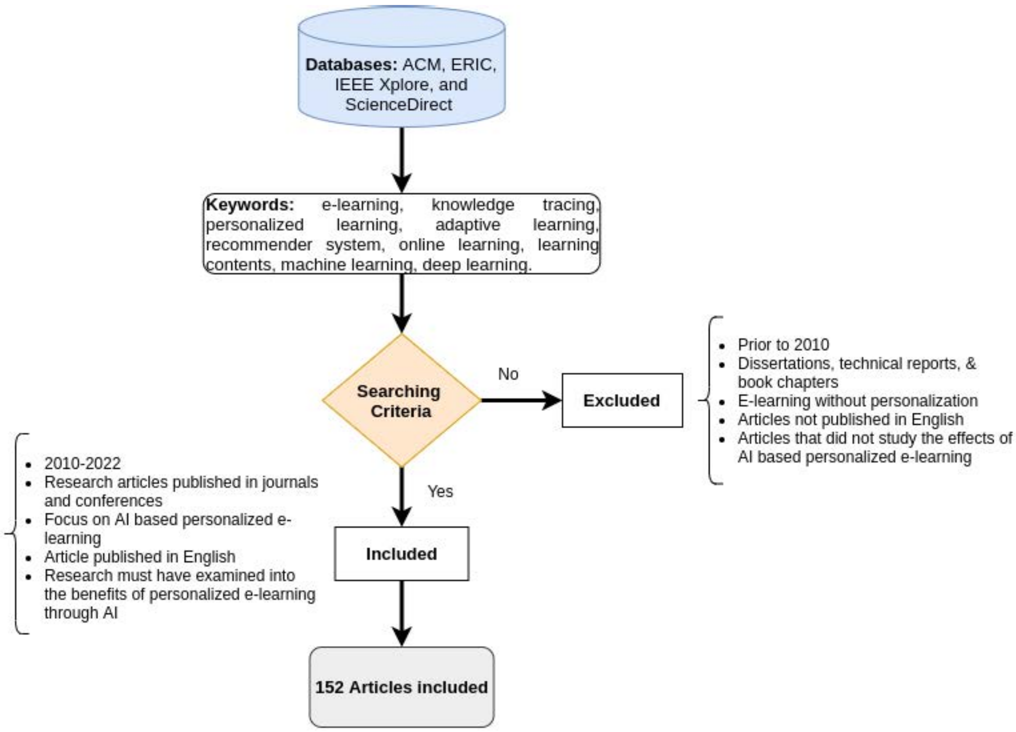

FIGURE 1. Flow diagram of research process.

also developed our framework based on requirements and challenges that are crucial for the implementation of such systems.

The above mentioned strategies contribute towards identifying requirements and challenges for a personalized e-learning model, proposing an extensive model that can meet these requirements, and describing directions for future research.

III. PERSONALIZED E-LEARNING MODEL: REQUIREMENTS AND CHALLENGES

In this section, basic requirements for personalization are discussed. These are focused towards building an adaptive and adaptable environment for individual learners. Assessments and recommendations play a significant role in personalization [18]–[20]. The section also elaborates on various challenges, which exist in meeting these requirements.

A. REQUIREMENTS

A personalized learning system has following fundamental requirements:

1) **Adaptivity**: Adaptivity refers to the ability of imparting knowledge as per the level of each learner. A personalized learning system should be adaptive in order to deliver personalized content as per the level of each learner [2].
2) **Adaptability**: Adaptability implies delivering contents as per the learner's preferred modality. It requires that learning content are developed using different modes of learning. For instance, learners can be taught using games, videos, and read alouds. They may have different preferences and liking for each mode [21], [22]. The extent of modality can be further broken down to environments, backgrounds, colours, and objects used in the learning mode. For instance, gender-specific learning environment may be helpful in yielding enhanced learning. [23].
3) **Continuous Assessments**: Periodic assessments are integral part of a personalized learning system. This allows the system to assess attributes of adaptivity and adaptability. A personalized learning system should have a large corpus of assessments, which can meet the needs of adaptivity and adaptability [24].
4) **Robust and Continuous Data Collection and Retrieval**: The intrinsic features of adaptivity and adaptability require robust and continuous collection of data. In addition to assessments' results from learners, other attributes such as usage patterns and learning trends may also be important for determining similarities among learners [25].
5) **Recommendation using Adaptivity and Adaptability**: Recommending effective contents is intrinsic for personalized learning. This is achieved using an AI-based engine, which computes personalized recommendations based upon a learner's assessment and usage data. These recommendations should be continuously updated in order to improve a learner's experience [15].

6) **Evaluation of Recommendation using Knowledge Tracing**: A personalized learning system recommends personalized content to each learner. However, this recommendation should also be tested and assessed in order to evaluate the performance of the system and identify measures for improvement [26].

B. CHALLENGES

The above mentioned requirements have identified various challenges these are related to development of an adaptive and adaptable personalized e-learning framework:

1) **Feature Identification and Collection**: A personalized learning system recommends content on the basis of features. However, identification of correct set of features is challenging. For instance, questions such as which objects, themes, or colors in a game are useful to impart a specific concept to learners of a specific age group and gender [27]. This question requires identification of correct set of features as well as an extensive process to collect the right attributes in order to identify the appropriate relationship [28].
2) **Adaptable Contents**: The e-learning system should contain learning content of a particular topic in multiple modalities. Provision of content in multiple modalities will serve the needs of learners [29]. A personalized learning system requires that adaptable content are delivered to each learner. Generation and delivery of adaptable content is a challenge [30]. It requires that personalized content are generated on the basis of suitable set of features such that learning can be enhanced. An efficient mechanism is needed in this regard, which can incorporate the right set of features to generate contents using multiple modalities.
3) **Knowledge Tracing** A personalized education system requires that comprehension level of the learner should be traced such that the concepts, which are not understood by the learner, should be identified clearly. Challenges exist in identifying and tracing the level of the learner. This is accomplished through assessments [31]. However, designing assessments and mapping them to concepts is an extensive tasks. In that, an incorrect response of an assessment may map to lack of knowledge in multiple concepts. Similarly, a correct response of an assessment item may not necessarily imply that all knowledge concepts have been comprehended completely.
4) **Continuous Assessments and Data Collection** A personalized education system relies on assessment results, user logs, and modality dataset to meet the requirements of adaptive and adaptable learning [3]. However, as these results are continuously changing, identifying and utilizing correct interval for computation of result is not trivial. This may vary for different learners as well.
5) **Elicitation of Learners Preferences** The elicitation of a learner's preference for a certain mode of learning content is a challenging task. We recommend elicitation of learner's preferences using explicit and implicit data gathering techniques. Preferably, a diagnostic test should be presented to a learner [32]. This test can consist of content of different modalities and an assessment for each modality. For example, we can devise the test to first present a text of Pythagoras theorem and take an assessment afterwards. We do this same practice with video and other available content modalities. The assessment will provide an explicit measure of learner's performance on a modality. We then analyze the learner's behavior while they interact with the learning content of a specific modality. This analysis can include the engagement time, learners activity and other related measures. These measures are implicit data features for identifying the learner's preferences.
6) **Updating of Learner's Preferences** With the acquisition of knowledge, the learner's preferences might also change. At the start, a learner might prefer video and animated lessons for basic introductory concepts and then wants more detailed text-based explanations for advanced concepts [2]. To address this problem, the learner model needs to be updated with a new set of training data extracted using explicit and implicit data gathering techniques.
7) **Feature Engineering of Learner-Content Interactions** The data of learner-content interactions in its basic form does not reveal patterns. We need to perform feature engineering on the raw interactions data to come up with meaningful patterns [32]. To model the preferred modality detection as a machine learning problem, there is a need to extract learner's behavioural signals from the data. These signals will work as a proxy for the psychological parameters that are requisite to model a learner's preferred modality. For instance, a learner skimming through a lesson is not properly focusing on the learning material. By extracting features such as scroll and cursor movements, we identify the learner's attention in the learning activity. Designing such features greatly helps in modelling the learners behavior and preferences [33].
8) **Evaluation of Detected Preferred Modality** The evaluation of the detected preferred modality is an important component of the overall adaptable learning model. The accuracy of this model will define the learner's experience and performance. Incorrectly detected modality and subsequent content recommendation will hinder the learner's performance and the learner may face difficulty in understanding the lessons [33].

It is pertinent to identify state of the current work from existing research in meeting the above mentioned requirements and challenges. In the next section, we describe significant work in the domain.

IV. RELATED WORK

We present significant related work on five important components of personalized e-learning. These include learning theories and models, adaptivity, adaptation of learning modality, assessments and user behaviour, and personalized recommendation systems. Various techniques have been studied to improve these components in the field of online learning. Basic requirements for personalization are discussed in brief in this section regarding significant methods that can be implemented for the adaptivity of personalizde online learning. Below, we provide a detailed overview of existing work by other researchers that utilized machine learning, deep learning, and rule based models for these components. The models are based on supervised and unsupervised learning that can be used for learner's performance prediction.

To build personalized e-learning systems, the student's past behavior data are analyzed for the determination of student's comprehension level and for the recommendation of learning content. This kind of analysis is mainly performed using machine learning techniques. For instance, student's past performance data can be formulated as a sequence learning problem. For which, models such as Hidden Markov models and Recurrent Neural Networks can be utilized for modelling the student learning sequences and for the prediction of future responses.

For the recommendation of learning content, matrix factorization and deep learning based embedding techniques are employed for suggesting the right learning content to the student. Recently, there is a growing trend to couple Knowledge Tracing with e-learning based recommendation systems. We further discuss machine learning based techniques in this section covering the student modelling process and the learning content recommendation framework.

A detailed overview of the existing related research work is being provided below regarding the aforementioned five categories:

A. LEARNING THEORIES AND MODELS

Personalized e-learning aims to improve learning quality by enhancing knowledge and skills. According to research, the majority of e-learning solutions lack a pedagogical background and have serious flaws in terms of teaching strategies and content delivery, time and pace management, strict learning paths, and learners' focus preservation. There are five main educational learning theories that can be used to improve personalized e-learning:

1) **Behaviorism** - It is concerned with stimulus-response behaviors, as they can analyze human behavior in an observable manner. Task-based learning is best explained by this theory [34].
2) **Cognitivism** - External variables (such as information or data) and the interior mental process are both important for learning. It involves a variety of memories, motivation, and thinking. Users' learning improved through reasoning, and problem solving [35].
3) **Constructivism** Learner builds on his or her previous understanding and experience to construct a new knowledge. It emphasizes learning as a dynamic process that is personal and unique to each learner. Users can learn through experimentation, open-ended approaches, and discovery [36].
4) **Connectivism** It is informed by the digital era, differs from constructivism in that it identifies and addresses knowledge gaps. Complex learning, rapid changing core, diverse knowledge sources are best explained by this theory for learning [37].
5) **Humanism** Humanistic learning approaches are built on the concepts of humanism and take into account a learner's interests, goals, and passion in order to maximise their potential. Learners are encouraged to take responsibility for their own learning intrinsically rather than extrinsically motivated [38].

These learning theories were developed as a foundation for understanding how people learn as well as a way of explaining, describing, analyzing, and predicting how learning should occur. Learning theories help instructional designers understand how people retain and recall information and stay motivated and engaged in learning. The quality of instruction is designed by the systematic development of instructional specification using learning and instructional theory which make the acquisition of knowledge and skill more efficient, effective, and appealing. There are many instructional design models for e-learning: (1) the ADDIE model [39], Bloom's Taxonomy [40], Gagne's Nine Events of Instruction [41], Dick and Carey's model [39], ARCS Model [42], and Merrill's Principles of Instruction [43]. These models benefit both instructors and learners. It helps to lead learners to focus on a topic quickly and to remove distractions, increase the possibility of learning, and make the acquisition of knowledge and skill more efficient. It also helps instructors to organize contents, to sequence instruction effectively, to assist and support learners, and to promote engaging, meaningful, and active learning.

B. ADAPTIVITY

Adaptivity refers to delivering content as per the comprehension level of a learner. Learners have distinction in learning styles, interests, knowledge level, personality type and other factors [44]. Adaptivity aims to provide personalized learning paths in e-learning environments in order to enhance learning and performance of individuals. Pedagogically, it has been observed that the adaptive learning strategies that cater to the comprehension level and skills of each learner are more effective in comparison to the traditional approach of providing same educational material to all learners [9], [10], [45]. AI plays a pivotal role in identifying the level of a learner and identifying appropriate contents. Following subsections provide an overview of AI-based techniques to incorporate adaptivity in e-learning systems and summarize these techniques in Table 1. We classify the adaptive learning methods into five broad categories: Knowledge Tracing, Item Response Theory, Learning Factor Analysis, Classification of Learner's level, and Clustering of Learner's Level. As per our review and consideration, we found these five categories to be representative of the major themes found in the adaptive learning literature. But nevertheless there can be other methods and techniques employed for the purpose of adaptive learning.

1) KNOWLEDGE TRACING METHODS

Knowledge Tracing (KT) refers to the task of tracing learner knowledge and comprehension over time. The purpose of KT is to develop a model, which can predict a learner performance and knowledge concepts (KC) on future curriculum interactions. Knowledge tracing methods can be broadly classified into traditional and deep knowledge tracing methods [46].

In traditional KT, a learner performance can be traced using conventional machine learning approaches. Several techniques exist, which are used to built traditional knowledge tracing models. Such as in Bayesian Knowledge Tracing (BKT) [47] methods, a markov process is fitted for each skill to predict future performance based on learner's history of responses to assessments. BKT models are limited by the markov process assumption; that is, the current state depends only on the previous state. The main focus in KT is to extract textual features from a question and determine relationship with key concepts through knowledge tracing [48]. Such models rely on sequence modeling, in which interaction of previous questions and answers of a learner is utilized in order to predict the probability of correctly answering a question.

In Deep Knowledge Tracing (DKT), deep learning based sequential models are employed for the purpose of knowledge tracing where deep neural networks models such as recurrent neural network, Long Short Term Memory (LSTM) [49], and Gated Recurrent Units (GRU) [50] can model the sequential data up to a large number of previous states as compared to BKT. Bi-driectional LSTM models have also been used to extract comprehension of key concepts through DKT [51]. In addition, As per attention mechanism in Transformers have utilized attentive knowledge tracing (AKT) that can be used to learn weights and learn significance of different questions and key concepts in knowledge tracing [52].

Graphical representation is another approach in KT where multiple relational structures are utilized to find similarity between different knowledge concepts, dependency between various knowledge concepts, and their correspondence between questions and knowledge concepts [46]. For such trends, graphical representation is harnessed through Graph Neural Networks (GNNs). There are multiple models that have been proposed in the field of graphical representation such as Graph-based knowledge Tracing (GKT) [53], Graph-based Interaction knowledge tracing (GIKT) [54], Bi-Graph Contrastive Learning based knowledge tracing [55] and Structure-based knowledge tracing (SKT) [56].

The Forget-aware model is based on a learner's behavior of forgetting the concepts leading to low performance. This behavior exists mainly because of two reasons, delay between the previous interaction and the current interaction and number of attempts during the previous question. Both the complete forget of information and the partial forget of information have been considered in the literature [57].

DKT models have some limitations of tracing complex KCs. To overcome these limitations, several authors have extended work based on DKT models by incorporating augmented external memory structure, which is inspired by memory-augmented neural networks [58]. These models follow a Key-Value Memory Network (KVMN) that determines the knowledge state which has more rendering power then the hidden variables used in DKT. KVMN has two metrics such as key and value, where the key matrix stores KCs representations and the value matrix stores leaner mastery level [59].

2) ITEM RESPONSE THEORY

Item Response Theory (IRT) refers to the evaluation of all learners through the same scale while attempting dissimilar assessments by linking the learners' assessment scores. Deep Learning based IRT implementations have been widely employed to provide thorough insights about the learners abilities in adaptive E-learning systems [60], [61]. Many deep learning based frameworks have been developed in order to track and evaluate the knowledge progression of each learner [62]. Recently, an IRT model was utilized for knowledge interaction-enhanced knowledge tracing (KIKT), to estimate and trace the progression of learners' knowledge proficiency [63]. Another framework incorporated the Dynamic Key-Value Memory Network (DKVMN) based on a Memory-Augmented Neural Network for tracking the knowledge concept of the learner [59]. Forgetting functions have also been employed in conjunction with attention mechanisms to implement the deep IRTs [52].

3) LEARNING FACTOR ANALYSIS

Learning Factor Analysis (LFA) is a cognitive modelling technique of learner problem solving skills. LFA is complementary approach to KT and supports the efficient searching of cognitive models in an adaptive e-learning system. In this regard, different variants of Learning Factor Analysis have been developed that enhances the capability of the initial proposed model. Out of these variants, Performance Factor Analysis, which refines the knowledge component modelling, is most prominent [64]. Another variant include instructional interventions to the cognitive modelling process [65]. Based on the ideas of additive factors, skill-specific effects on problem solving were also integrated into LFA [66]. In similar fashion, Learning Factor Analysis models were enriched with the integration of learner reading interactions [67] and learner's recent performance history [68].

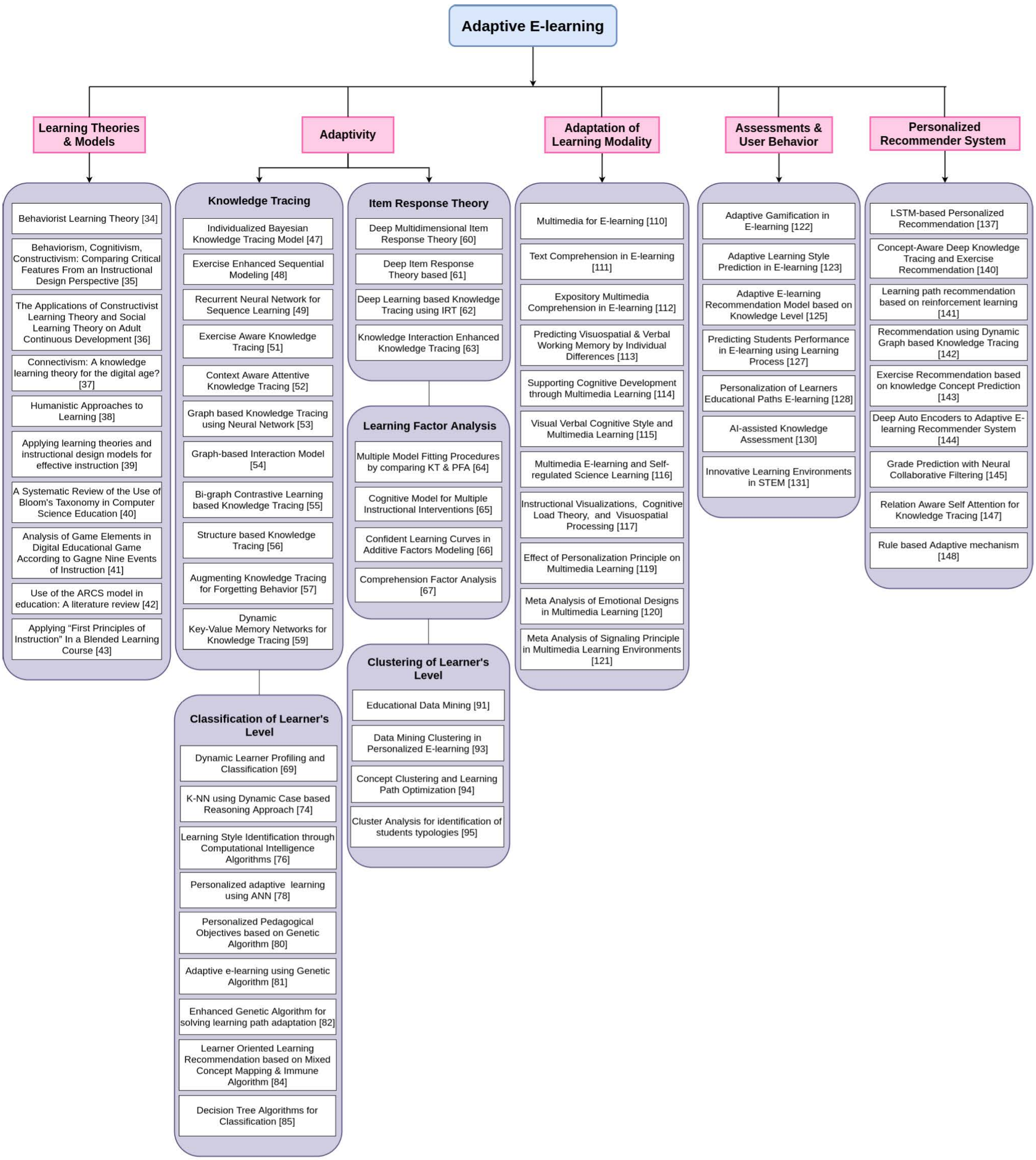

FIGURE 2. Related work on personalized e-learning.

4) CLASSIFICATION OF LEARNERS' LEVEL

Adaptivity can also be determined by computing the level of each learner through classification methods. Different approaches have been used to identify the level of a learner.

Bayesian Networks based models were used to predict learner performance based on probabilistic relationships among learner characteristics. It creates a learner classification model to build the learner profile and identify the

TABLE 1. **Comparative analysis of adaptive learning methods.**

Family of Models	Method	Dataset	Adaptive Learning Task
Knowledge Tracing	Exercise-Enhanced Recurrent Neural Network (EERNN) [48][51]	Statistics of Mathematics	Prediction of students' scores on future exercises
	GRU based Deep Knowledge Tracing with Constraint modeling [50]	ASSISTment 2009-2010	Modelling of students' knowledge states
	Attentive knowledge tracing (AKT) [52]	Statics2011, ASSISTments	Question-level knowledge tracing
	Graph neural network (GNN)[53]	ASSISTments, KDDCup	Modelling skill dependencies for knowledge tracing
	Graph-based Interaction model for Knowledge Tracing (GIKT) [54]	ASSISTments, EdNet	Learning the structure of knowledge concepts for knowledge tracing
	Bi-Graph Contrastive Learning based Knowledge Tracing (Bi-CLKT) [55]	ASSISTments, STATICS 2011	Modelling exercises relationships and knowledge tracing
	Dynamic Key-Value Memory Networks (DKVMN) [59]	Synthetic-5, ASSISTments, Statics2011	Modelling of latent knowledge states
	Knowledge Tracing Machine by modeling cognitive item Difficulty and Learning and Forgetting (KTM-DLF) [69]	ASSISTments2012	Individualized modelling of student knowledge state
	Deep Knowledge tracing + forget (DKT+forget) [57]	Junyi	Knowledge tracing using student learning attributes
	Deep Knowledge tracing (DKT) [70]	Algebra 2005-2006	Sequential modelling of students' learning behavior
	Bayesian Knowledge tracing(BKT) [47]	Algebra I	Modelling the mastery level of students from assessment responses
	Deep Knowledge tracing+ (DKT+) [56]	Junyi	Estimation of student's latent knowledge state
	Sequential Key-Value Memory Networks (SKVMN) [71]	STATICS	Modelling the dynamics of student knowledge states from interactions data
	Self-Attentive Knowledge Tracing (SAKT) [72]	ASSISTments2015	Knowledge tracing framework for sparse interactions data
	Self-AttentIve Neural Knowledge Tracing+ (SAINT+) [73]	EdNet	Latent knowledge estimation by modelling the exercise and response data separately
	Deep Graph Memory Networks (DGMN) [74]	ASSISTments2009	Modelling knowledge state dynamics across learning concepts
	Bayesian Knowledge tracing Model-Long Short Term Memory (BKT-LSTM) [75]	Algebra	Detection of students' knowledge states and prediction of future performance given their past outcomes
Item Response Theory	IRT for interaction-enhanced knowledge tracing [63]	Algebra, Statics2011, ASSISTments	Modeling different student abilities and problem difficulties
	Deep Item Response Theory (DIRT) [61]	mathematical data supplied by iFLYTEK Co., Ltd	Predict student performance utilizing the difficulty level of questions
	Deep Item Response Theory (Deep-IRT) [62]	ASSIST2009	Modelling of the student's learning trajectory and estimation of the student ability level and the item difficulty level over time
Learning Factor Analysis	Comprehension Factor Analysis model (CFM) [67]	Psychology MOOC GT - Spring 2013	Modelling student's reading behaviour
	Recent-Performance Factors Analysis (R-PFA) [68]	Assistments tutoring system	Predictive modelling of student's learning behaviour
Learner Modeling based on Supervised Learning	Decision Tree Algorithm (DTA) [76]	Manav rachna college dataset.	Rule based classification of learners' levels
	K-nearest neighbors and Naïve Bayes [77]	Educational dataset of secondary school in Gaza Strip (2015)	Similarity metrics based classification of learners' levels
	Support Vector Machine (SVM) [78]	-	Classification of learners' levels
	Ensemble Learning [79]	-	Classification of learners' levels using multiple models
	Genetic Algorithm [80]	-	Optimizing the learning path with respect to a learner's level
	v2.0 and AdaBoost [81]	10140 records with 10 attributes Collected from 3 different colleges in India	Classification of learner's level using weighting mechanism
Learner Modeling based on Unsupervised Learning	Density Based Spatial Clustering [82]	-	Clustering similar students based on the student properties
	K-Means [83]	Synthetic data of 57 students.	Clusering of students for the determination of distinctive learning behaviour

difficulty level of content to offer a specific rank [84]. It was mostly used to detect different learning styles among learners to identify the needs of individual learners to improve their learning performance [85]–[87].

The k-nearest neighbour (kNN) algorithm is one of the simplest methods to classify the proximity of learner with respect to different attributes. The algorithm is used to generate a similarity matrix to select 'k' most similar learners, which have similar behavior in order to provide a learning path according to their profile [88], [89].

Many researchers have used Artificial Neural Networks (ANNs) to classify learners characteristics, and mimic and monitor the cognitive progress of learners in the adaptive education system. A comprehensive research have used ANN to predict learner level by analysing learning styles from learners behaviour [90], [91]. Different features such as learning style, prior knowledge, and preference can be incorporated into ANN to classify difficulty level and learning path [92]. This is utilized to recommend most suitable learning materials for each learner and enhance the learner's performance. These methods require a large amount of training samples to improve classification [93], [94]. In adaptive e-learning systems, optimization algorithm such as genetic algorithm can also be used to generate an optimal learning path of learners. By incorporating learner profile and pedagogical objectives, these algorithms recommend relevant course contents for each learner [95]. The searching of optimal content for the learner's profile is based on the notion of information retrieval, which measures similarity between the learner profile and the learning objectives. It reduces the size of search space in order to find the relevant documents that fulfill the desired criteria [96]–[98]. These algorithms requires parameter setting in order to yield a optimal solution [99].

Decision Tree (DT) algorithms have been used to construct a hierarchical based tree classifier consisting of nodes and branches. The tree is divided into subtrees by a rule in each node [100]. It has been used to detect learners' behavior, learning styles, preferences, knowledge level, performances, content difficulty, and feedback of learners. Researchers have used decision trees in order to identify the complexity level of learning content and classify a learner as basic, intermediate, or advanced [84], [101], [102]. The most effective learning path for learners can be recommended by using various decision tree algorithms, such as the Iterative Dichotomiser 3 (ID3), the Chi-squared Automatic Interaction Detector (CHAID), Classification and Regression Trees (CART), and C4.5 [103]–[105].

5) CLUSTERING OF LEARNERS' LEVEL

Learners can also be clustered based on the their level of comprehension of content. Several clustering techniques have been described, which are based on learner profile and content filtering. These include Density Based Spatial Clustering [82], K-means, Fuzzy c-means, K-medoids, Hierarchical clustering [106], and Clustering by Fast Search and Finding of Density Peaks. These techniques are used to find similarity between data points and find outliers [107]. Clustering techniques are responsible in finding intelligence, association, and recommendation to provide powerful and personalized learning mechanism for learners. For instance, learners who have similar information such as skills, learning styles, preference, learning content, knowledge etc are grouped into same category which helps to identify homogeneous group of learners and find the optimal learning path for each learner [108], [109].

C. ADAPTATION OF LEARNING MODALITY

Presentation of learning content in the preferred mode of a learner significantly improves the overall knowledge acquisition process. This principle of modality has been extensively outlined and studied [110]. There are several other studies that emphasize the role of learning modality in multimedia based e-learning. Most of the work in this direction indicates that the preference of learning modality is hugely dependent on the differences in working memory of individual learner [111], [112]. In that, working memory implies the ability to store and analyze the incoming information before it decays [113].

In this context, several researchers have demonstrated presence of cognitive factors which can effect the working memory of a learner. These behavioural factors mainly relate the visual abilities and cognitive styles of individual learner towards the modality adaptation for personalized and beneficial learning [114]–[116]. Castro *et al.* [117] and Wong *et al.* [118] established the relationship between cognitive overload and learning modality. Similarly, the effectiveness of multimedia based e-learning is conditional to its presentation, as observed in [119]–[121]. All of these ideas suggest a need of the integration of adaptable modality determination and subsequent recommendation of learning resources for the realization of personalized e-learning.

D. ASSESSMENTS AND USER BEHAVIOR

Sustainable personalized learning can be accomplished through continuous analysis of data relating to assessments, user interaction, and learning behavior. Certain characteristics, such as learning style [17], [122], [123], knowledge level [124], [125], performance/score [126], learning goal [127], and learner profile [34], can provide insightful feedback for the learner's journey that derives the individualized learning paths [128]. Meta cognitive evaluation of an individual's learning can greatly encourage learner to further progress in any learning environment. This meta cognitive evaluation is also crucial in AI based adaptive systems through continuous assessments of every delivered learning module [129]. An adaptive system can utilize the stored assessment data of existing learners of an e-learning system. The system can then direct a new user through initial assessments for the identification of the comprehension level on a specific topic. It can also identify recommended learning content that addresses learner needs in order to devise a personalized learning path for each learner [130].

Various techniques related to tracking of leaner behaviour has been included in Table 2. For the adaptivity of learners behaviour we have used the crucial knowledge tracing methods. There are other techniques as well that can be used for performance analysis of learner but through the review we have analysed that widely used technique that has gain popularity among other models is of knowledge tracing.

E. PERSONALIZED RECOMMENDER SYSTEM

In an e-learning framework, a personalized recommender system is a reference system which recommends personalised learning content to each learner. This personalization is achieved by determining content that are likely be effective in learning [131]. This personalization can be computed for a learner through various factors such as level of learner, prior knowledge of learner and preferred mode of learning. There are main five approaches which is adopted by e-learning recommender systems to find preferred content for learner.

1) **Collaborative Filtering-based Recommendation:** It is a learner based filtering, employs the information related to prior learner behaviour and preferences. It recommends learning content based on similarities with other learners to the target learner. However, the main challenges to its performance are cold start and data sparsity [132]. In real-world applications, the rating matrix is frequently sparse, causing CF-based approaches perform poorly in recommendation system. There are two sub-categories of CF-based recommendation in e-learning: context-aware and deep CF-based recommendation methods take advantage of the growing amount of side information to address both the data sparsity and the cold start problems.
2) **Content-based Recommendation:** It finds the similarities among items by utilizing the contents. It analyzes a sufficient number of rated items that one user has already preferred and establish learner interest profile. Then, various profile-item matching techniques are applied to match new item features and learner profiles and determine whether or not a given item is relevant to the learner [133]. For content filtering, a major challenge is to identify learner preferences based on items. There are three sub-categories of content-based recommendation in e-learning: semantic-based, attribute-based, and query-based that can help to identify learner preferences based on items.
3) **Knowledge-based Recommendation:** These systems make recommendations to learners based on domain knowledge about how different items satisfy learner needs. Knowledge-based recommender systems need to use three categories of knowledge: information about the learners, information about the items, and information about the item's match with the learners needs. Knowledge-based strategies aggregate knowledge about learners and learning resources for use in the recommendation process in the context of e-learning. Ontology-based recommendation is a sub-category of knowledge-based recommendation [134].
4) **Tag-based Recommendation:** The tagging procedure allows the learner to use their own words or concepts that are important. Learners in e-learning environments can benefit from creating tags in various ways: first, tagging has proven to be an effective meta-cognitive method for engaging learners more effectively in the learning process. Learners can recall more by highlighting the most important parts of a text. Furthermore, tagging exercises may encourage learners to participate more deeply in the learning process and improve their knowledge of learning content. Gathering learner opinions on specific resources could result in better comprehensible resource recommendations for other learners [135].
5) **Hybrid Recommendation:** Hybrid model combine various algorithms and techniques to improve personalized recommendations for a given learner. In that, similarities with other learners are determined and it is integrated to identify user preferences for items. Hybrid systems take the benefits by combining basic approaches such as collaborative filtering, content-based filtering, knowledge-based and tag-based to can increase the performance of e-learning systems. [133].

In educational technologies, recommendation systems can be built on several requirements such as knowledge tracing, adaptivity, and adaptability. Using KT, learners are grouped together based on their comprehension of key concepts. This information is also used to recommend next contents as well [26].

In adaptive e-learning, recommendation is based on adaptivity or levels of learners. Similar learners are identified and contents are recommended based on their level. Reinforcement learning has also been used for adaptive learning based recommendation systems. Traditional recommendation systems have also been used to estimate knowledge state of individuals and recommend content accordingly [136]. Such as, Neural Network based classification system are used to analyse learning behavior and learning preferences to generate high-precision personalized recommendations using high-dimensional sparse matrix through vectorization [137]. This matrix uses 0 to 5 rating scale to compute similarity between users and items. Similarity among learners can also be determine by K-Nearest Neighbour which is most commonly used approach to recommend learning content [138].

In past, various algorithm was proposed which use the concept of collaborative filtering such as Partially Observable Markov Decision Process (POMDP) [139] recommends exercises. Similarly, Advantage Actor-Critic (A2C) - reinforcement learning method was build to recommend a personalized learning path according to the actual learning requirements of learner [140]. A graph-based recommendation system has also been proposed [141]. In that, knowledge vectors are selected as nodes and learners' mastery level is selected as edges. To achieve the final recommendation, such a graph is

TABLE 2. Comparative analysis of recommender systems in personalized e-learning.

Recommendation Method	Dataset	Issues Solved	Recommended Item	Knowledge Tracing
Partially Observable Markov Decision Process (POMDP) [139]	Math exercising dataset	Scalability	Mathematics Exercise	Yes
Neural Network [137]	Open Courses	Sparsity	Courses	No
Advantage Actor-Critic (A2C) Algorithm [140]	ASSISTments 2009-2010	Scalability	Knowledge Concept	Yes
K-Nearest Neighborhood [138]	Open Courses	Cold-Start	Learning Objects	No
Gated Recurrent Unit (GRU), Attention model [141]	ASSISTments 2012-2013	Information overload	Knowledge Concept	Yes
LSTM based Collaborative Filtering [142]	ASSISTments 2009–2010, Algebra 2005–2006, OLIES 2011	Cold-Start	Exercise	Yes
Deep Auto Encoders for Collaborative Filtering [143]	Open Courses	Cold-Start	Learning Objects	Yes
Neural Collaborative Filtering [144]	George Mason University	Cold-Start	Course	No
K-means [145]	MOODLE	Information overload	Learning Objects	No
Relation-aware self-attention model [146]	ASSIST-2012, Junyi	Sparsity	Exercises	Yes
Neural Network [137]	Open Courses	Sparsity	Courses	No
Rule based Adaptation Mechanism [147]	Learner portal	Scalability	Learning objects	No
LSTM + [136]	ASSISTments09-10, Intellilence18	Cold-Start	Exercise	Yes

clustered into node groups and a shared embedding is built for each group using Graph Neural Networks (GNNs).

Researchers observe that learners personalization can be improved by using deep learning based reccomendation methods. An LSTM based collaborative filtering model [142] has also been used to recommend exercises that takes knowledge concept prediction into account. Such a problem is mapped as a sequential learning problem, in which LSTM predicts questions based on sequential data.

An auto encoder based recommender system [143], [148] which takes user-based or item-based ratings in the rating matrix as input, generates an output through the encoding and decoding process, and optimises model parameters by minimising the reconstruction error. The learning element is based on interactions between learners and objects. A relation-aware self-attention model for Knowledge Tracing (RKT) [146] was proposed which adjusts the self-attention mechanism for the KT task. This strategy uses text information and learner performance on previously unexplored activities to learn the fundamental relationships between exercises. Each interaction in the series has an adaptive impact on later interactions. This approach can help instructors and system builders provide remedial material and exercises depending on learner needs in a proactive manner.

Grade prediction is another factor to take decision for next item. Neural Collaborative Filtering (NCF) has also been used. Using NCF, individual elements can have various dimensions and obtains better outcomes [144]. Usually, a personalized group-based recommendation approach is good in e-learning. A rich user profile can provide a more personalized recommendation by finding learner with comparable learning potential and attitude according to their learning behaviours and academic performance [145]. In few research, a rule based adaptation mechanism has been used to define the user interface components to improve learning path of the learner [147].

E-learning systems have observed enormous growth and research in developing personalised recommendation systems. We have summarized a detailed review of the existing work in Table 2.

The above mentioned description on related work asserts that there is a need of an extensive framework, which can cater the needs of personalization. Specifically, the requirements and challenges in Section III are needed to be addressed.

V. PROPOSED ARCHITECTURE

We now propose an intelligent framework for a personalized learning system that fulfils all the requirements and also aims to address the discussed challenges that are presented in Section III. The proposed framework is based on the five aforementioned learning theories including Humanism, Behaviourism, Cognitivism, Constructivism and Connectivism. This framework has been developed based on the ideas of the ADDIE model [39] in order to incorporate instructional design theories.

Fig. 3 shows the architecture of the proposed framework. It consists of five modules including; Data module, Adaptive learning module, Adaptability module, Content and assessment delivery module, and Recommender module. The data module is responsible for storing a learner's profile and assessment data. It also stores learning content and assessment questions. The results from assessments are utilized by the adaptive module to compute adaptivity level of a learner. Similarly, a learner's usage patterns and content interactions data are combined with the assessment results to determine the adaptability levels of a learner. The recommendation module takes input from adaptivity and adaptability modules and intelligently recommends content that are likely to increase learning of a learner. The task of the content and assessment delivery module is to deliver personalized content and assessments, which are recommended by the recommender module.

Following subsections explain the functionality of these modules in detail.

A. DATA MODULE

Learner interaction data is generated when a learner interacts with the e-learning platform. There are two possibilities for these learner interactions, such as, data for a new learner, and data for an existing user. In the former case, a learner's profile is created from scratch and is updated at each iteration of assessments, whereas in the latter scenario, existing profile is updated [149].

The data module stores the learning content and summative assessments. These are delivered to a learner by the content and assessment delivery module and as recommended by the recommender module. The data module also maintains a database that stores personal information of a user, assessment records, learning style, prior knowledge and the previous recommendations as recommended by the engine depicted in Fig. 4. These attributes are computed for every learner and are used iteratively to generate personalized learning path for each learner [150].

B. ADAPTIVE LEARNING MODULE

In our proposed framework for personalized e-learning, the Adaptive Learning Module is tasked with the determination of knowledge levels of every learner across all the knowledge-components present in a curriculum. Knowledge level of a learner can be discovered from the underlying learner and e-learning system interactions. A sequential machine learning algorithm can be trained on this learner-interaction data to first estimate the latent knowledge-states of a learner and then the corresponding knowledge-levels as shown in Fig. 5. This figure shows students' attempts on assessments are processed sequentially and weights for a recurrent model are learned accordingly, that best describes the available student-assessments data. An example of student interaction with an assessment can be the response which can be either correct or wrong. Similarly, the recurrent model can be a Hidden Markov Model or a Recurrent Neural Network which provides an explanation for the past attempted behaviour and provides predictions for the future responses of a student. The knowledge-states layer is composed of weights that the recurrent model learns and these weights signify the importance of a response relative to its position in the assessment sequence. Finally, the output layer is a function of knowledge-states and provides the mastery level for each of the knowledge component.

We present the functionality of adaptive learning module in Fig. 6. In this figure, a realization of knowledge tracing model for responses of a student for an arbitrary set of five knowledge components is shown. A correct response increases the mastery level probability on that particular knowledge component, while a wrong answer decreases the same probability. The values shown in this knowledge tracing heat map are arbitrary, as values in a real knowledge tracing model are smoother and follow a more realistic pattern. And the darker the color, the greater the mastery level for the respective knowledge component. The task of this model is to learn the weights that are to be used to predict future mastery level values based on the patterns of the dataset.

The dependency graph of knowledge components of a sample curriculum and an arbitrary prior knowledge vector of a learner is shown in Fig. 7. In the figure, a vector encoding the prior knowledge of a student is shown on a 0-1 scale, where 0 means no prior knowledge and 1 denotes complete expertise of the knowledge component. A dependency graph of this curriculum is shown as a representation of the student latent knowledge. Such a dependency graph provides a visualization of student's mastery level of underlying knowledge components. Also, an effect in the knowledge level of one knowledge component propagates to the other connected knowledge components.

The knowledge-levels output of this module is forwarded to the Recommender Module for the selection of learning resources necessary for the improvement of the student's current knowledge level.

C. ADAPTABLE LEARNING MODULE

The Adaptable Learning Module determines the preferred mode of learning for a learner. It can be perceived that an individual learner's learning preferences are implicit, subjective, and hard to be inferred from raw data. Therefore, in order to identify learning mode preferences, latent variables are to be devised and extracted from the raw learner interaction data available in the e-learning databases.

As an example of a latent variable, we suggest a three-dimensional data structure, termed as performance cube with a representation. It is a three-dimensional representation of the performance cube shown in Fig. 8. The three axes are knowledge component axis, content-modality axis, and

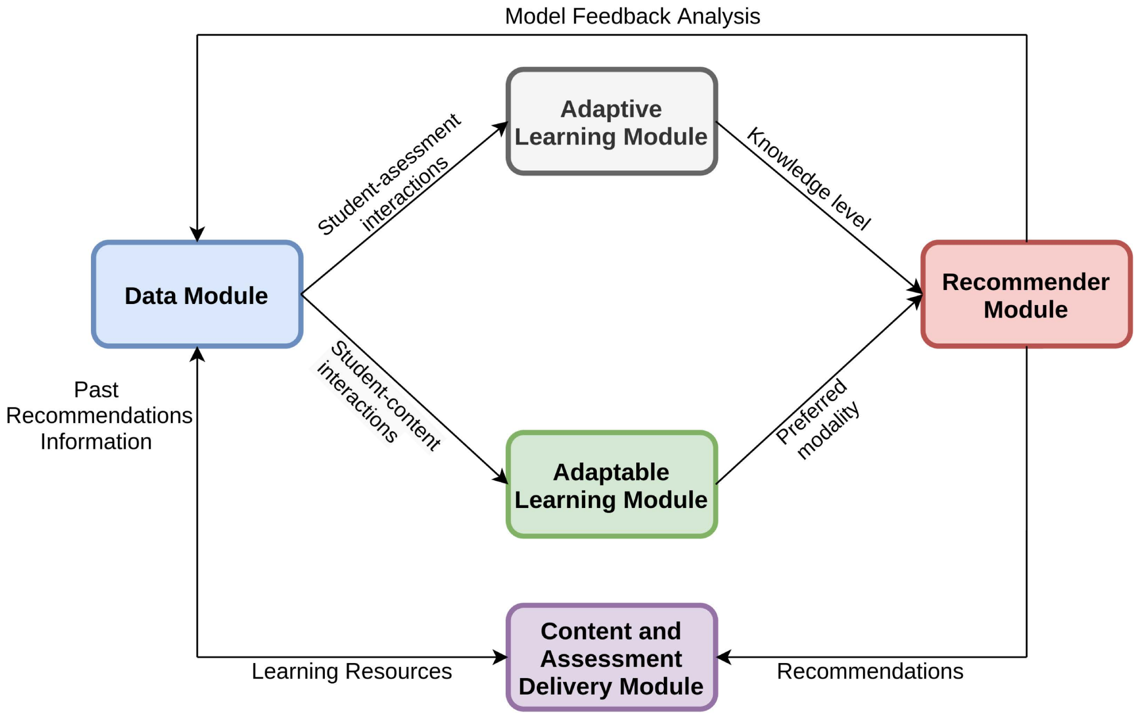

FIGURE 3. Proposed framework for personalized e-learning.

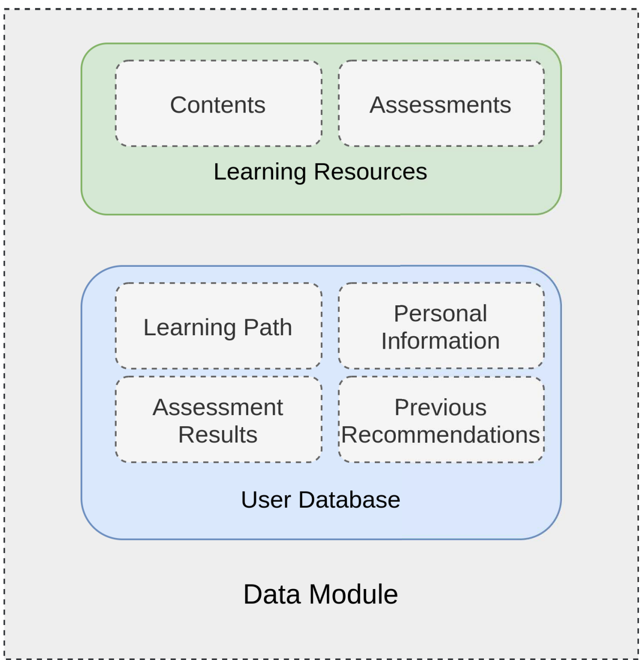

FIGURE 4. Data module.

the performance axis. A realization of a values tuple from this performance cube could be (Addition, Game, 1), which means the student performed correctly on an Ádditionássessment after interacting with a game modality. The performance cube can be termed as a feature representation that is to be input to a machine learning algorithm for the learning for underlying patterns. The performance cube assimilates performance of a learner on assessments pertaining to respective knowledge components and learning modes.

These performance cubes are defined for all the learners as means to find performance and learning modality relationship via an unsupervised machine learning algorithm as shown in Fig. 9. In this figure, a general adaptable learning framework is shown. It starts with feature engineering of the student-content interactions to construct performance cubes for every student. A student-content interaction is the learning content viewing and attempting of an assessment for the same content. This derived dataset of performance cubes is analyzed for effective content modalities in an unsupervised way. For instance, an association rule mining algorithm or a neural embedding based algorithm can be used to find the relationship between the learning modalities and performance, when applied to the interactions present in the performance cubes. The output of this unsupervised learning model; that is the learners' inferred modality preferences are conveyed to the Recommender Module for serving the content of learning modality pertinent to the learner's preferences.

D. RECOMMENDER MODULE

Recommender Module is incorporated with Adaptive Learning Module and Adaptable Learning Module to provide personalized learning content recommendations. In this module, Deep Learning based Recommendation Engine (DLRE) is designed to provide two major recommendations: rating prediction and top-N item ranking for the learning content as

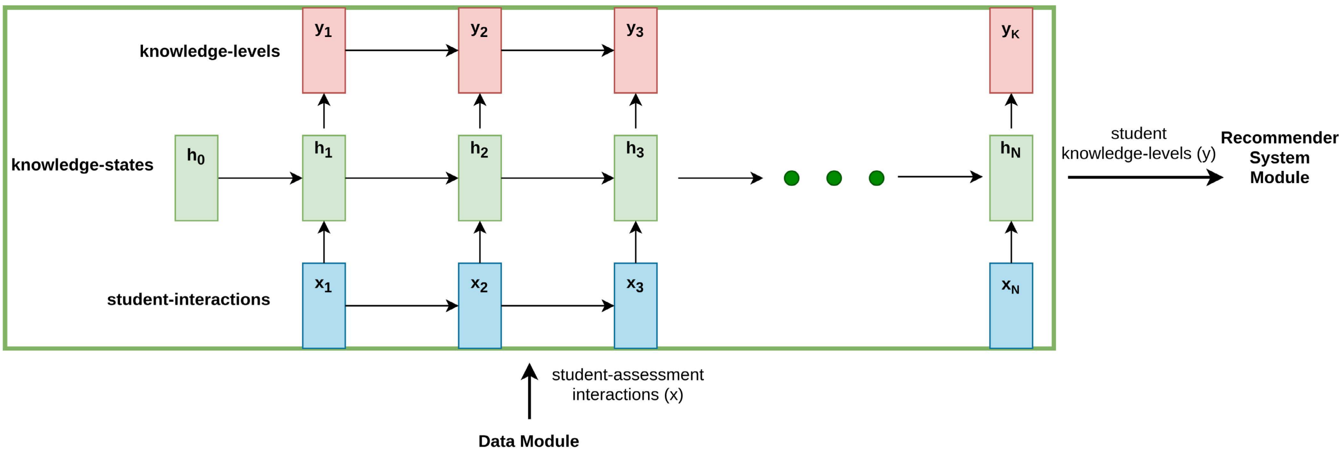

FIGURE 5. Adaptive learning module.

FIGURE 6. Knowledge tracing from student-interactions.

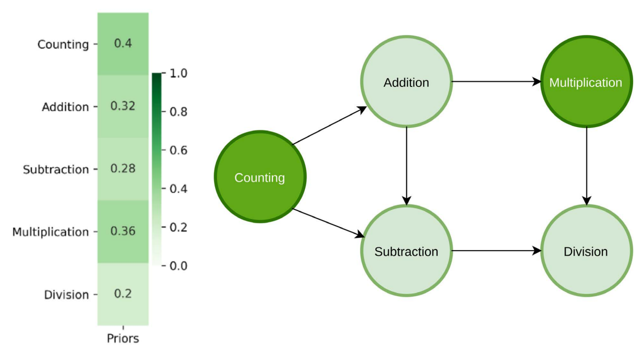

FIGURE 7. An example of student's prior knowledge vector and knowledge-components dependency graph.

shown in Fig. 10. DLRE takes input of user-item interaction matrix which contain learners (L) in a row, modality (M) in a column and probability of preferred mode (P), which is used for rating. DLRE is trained on this input data for rating prediction and item ranking. Rating prediction is a numerical value, Rij, indicating the predicted score of item j for user i whereas Item ranking is a list of the top N items that the learner will find most beneficial. The recommendation

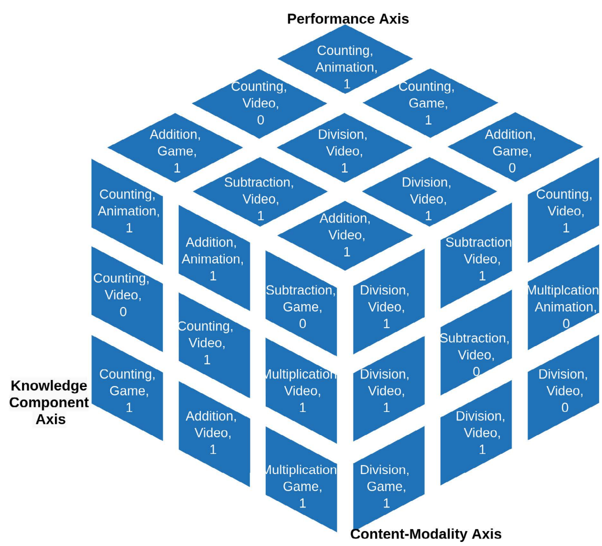

FIGURE 8. Performance cube.

framework maintains a high level of modularity and scalability, allowing new models to be easily integrated into the framework.

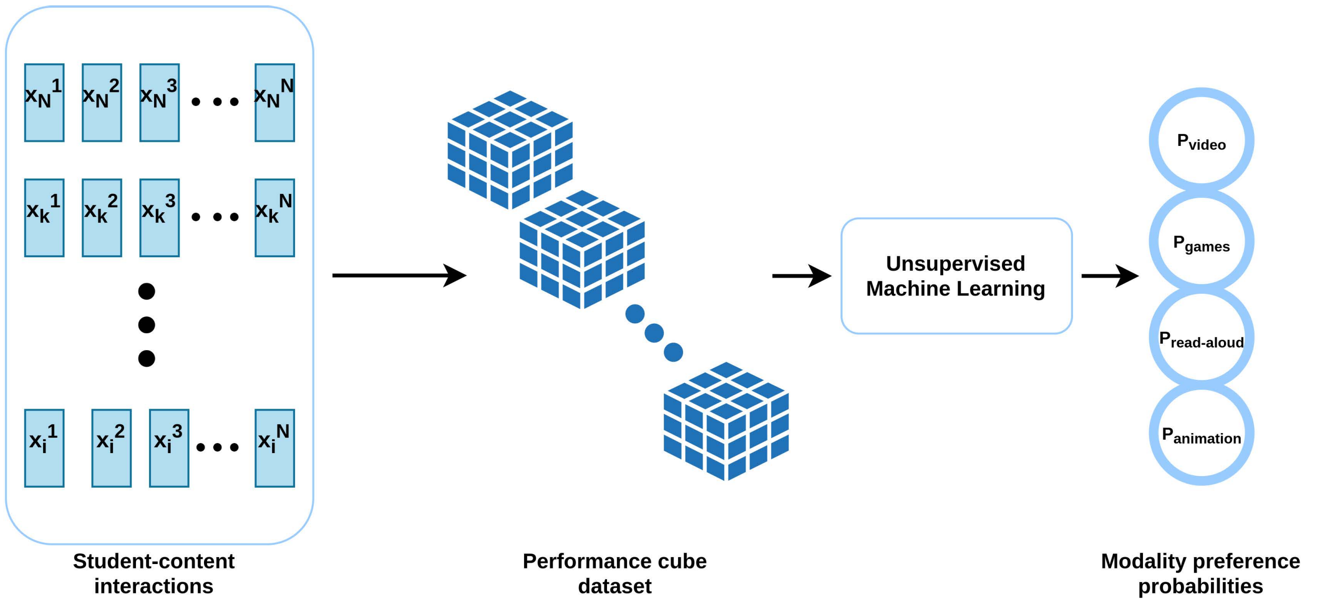

FIGURE 9. Adaptable learning module.

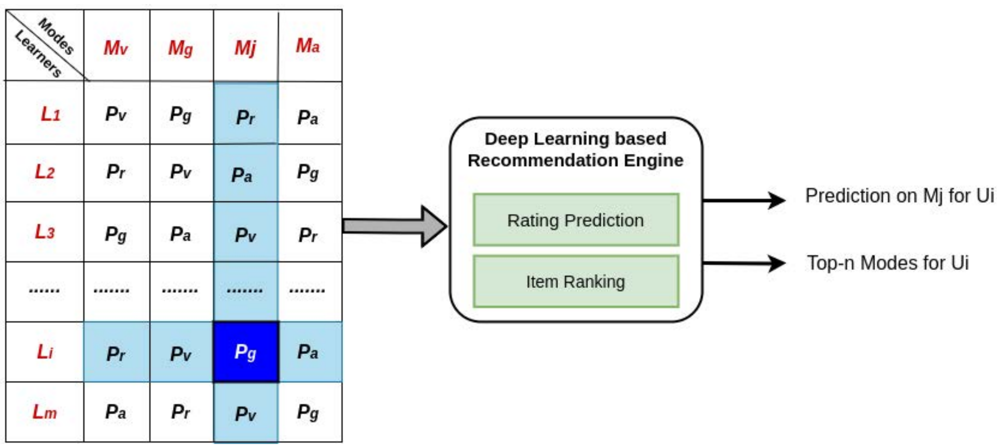

FIGURE 10. Recommender module.

E. CONTENT AND ASSESSMENT DELIVERY MODULE

The main task of the content and delivery module is to deliver the content as per output of the Recommendation Module. The module delivers appropriate content to a learner and sends information related to performance and other attributes to the data module. Depending upon the recommendations, the module also selects personalized content.

Our proposed framework encompasses five modules which are capable to deliver efficient personalized learning to an individual. The framework incorporates state-of-the-art techniques, which are capable to determine needs of an individual learner and deliver content accordingly.

VI. FUTURE RESEARCH DIRECTIONS

Technological advancements have led us to identify a few research directions, which can be explored by the community to further strengthen the AI personalized learning domain. Below, we describe a few research directions for the benefit of the community:

1) **Counterfactual Evaluation**
There is intrinsic bias present in the functionality of recommendation systems due to the fact that the data these systems are trained on are observational data and not experimental. Also such recommendation systems often do not perform well due to the concept drift between the data of the training phase and the testing phase. Therefore, there is a need to perform counterfactual evaluation of recommender systems [151], in which different possible scenarios of the student learning process are evaluated to assess the response of the recommender system.
2) **Learner Activity Data**
Most of the e-learning systems do not have tools and mechanism in place to record the necessary information

related to a learner's journey. This information is essential for the development of personalized e-learning systems. This data and information need to be gathered at an appropriate level of granularity. The higher the granularity, the finer the trained machine learning based personalized e-learning system.

3) **Learner Evaluation Metrics**
Conventionally, learners are being evaluated in terms of their assessment scores in order to move them further through the learning path. While the assessment scores provide an important measure of ones' learning, it does not totally reflect the skill set of each learner or the problems that learner faces during the e-learning process. In that sense, definition and identification of significant as well as measurable evaluation metrics also need to be done in order to better map the aforementioned traits. These parameters may include time taken to attempt a specific problem, number of attempts on a given problem, user behaviour or performance on different devices, type of evaluation etc.

4) **Evaluation of the Recommendation**
One of the most prominent issues that exist in adaptive learning systems is the evaluation of each recommendation that is being provided to each learner during a specific session. This refers to the analysis of each recommendation in terms of its efficacy and contribution towards the learning goal of each learner. Currently, there are no evident ways to evaluate the recommendations provided, at each point during the user journey, other than going back to the user and gathering their feedback or assess the overall performance of the user after the completion of the learning path. General methods of evaluations are Mean Absolute Error (MAE), precision, F-measure. Context aware recommendations systems can be evaluated through contextual precision and contextual Receiver Operating Characteristic curve (ROC). Other recommendation systems can be evaluated using questionnaires, user-studies and interviews.

5) **Latency (real-time)** The personalization of content in an adaptive e-learning system should be run-time and response should not be delayed. This issue has been one of the key factors of the increasing drop out ratio where the increased time to receive response from the system could distract the learners' attention and result in lack of motivation towards the e-learning process.

6) **Continuous Evaluation** Continuous Assessments can help us to identify skill set and personal traits for each learner as an individual characteristic that signifies the persona of that learner and her progressive evolution. While the assessments are important, it is also required to identify the frequency of assessments which can be used to balance the overall learning of the learner. Also, identification of the assessment type for each specific learner after any give n learning content is also significant in order to implement the adaptivity in true sense.

This work can be extended further by creating different user/learner personas in order to understand their attitudes and behaviour. It can help to effectively map the implementation of the personalized e-learning systems.

The above-mentioned directions are significant in strengthening AI-based personalized e-learning systems. We anticipate that contributions from the community will continue to enhance personalized learning.

VII. CONCLUSION AND DISCUSSIONS

The development of AI-based personalized e-learning systems require a holistic approach, comprising of thorough analysis of available data and e-learning data sources. These requirements should be properly synthesized and the necessary data should be extracted from the e-learning databases. Understanding the student learning process is essential for the development of an adaptive and personalized e-learning system. A good starting point for the understanding of this process is to model the sequential assessments' responses using a recurrent machine learning model. The trained model will explain the past student behaviour along with the forecast of the performance on future assessments, as demonstrated by the "Adaptive Learning Module" of the proposed framework. This basic model can be improved with the introduction and enrichment of the existing e-learning data by incorporating diverse variables related to consumed learning resources. Such relevant data variables will aid in implementing the "Adaptable Learning Module" and the "Recommendation Module" as discussed in Section V. Integrating different intelligent e-learning components this way provides a basis for the overall personalized e-learning solution.

We have outlined a set of requirements and associated challenges and subsequently presented a holistic framework for personalized e-learning. The presented framework is designed to be an example of an intelligent e-learning system that integrates complementary components in order to first learn to determine comprehension levels of a student and then suggests learning resources as per the determined student level.

We have also presented a few research directions, which are open to the community to the community for exploration and research. For this purpose, continuous implementation and utilization of personalized learning framework can iteratively improves the personalization model. Utilization of data should also follow compliance to ensure data privacy. Evaluation of learner and the overall framework is significant. For this purpose, iterative rounds of evaluation of the framework may help towards improvement of the overall system.

We anticipate that efficient mechanisms for personalized e-learning can be extremely beneficial to cater the needs of imparting quality education and training for masses. For this purpose, a broader collaboration between different communities can be beneficial.

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