Context Aware Recommender Systems and Techniques in offering Smart Learning: A Survey and Future work

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***Abstract*— There exist several context aware recommender systems (CARS) that have been designed to perform specific tasks in facilitating smart learning. Such context aware recommender systems have potentially played important roles in education, especially in recommending to a learner certain activities. In this research we reviewed existing context aware recommender systems used in facilitating pedagogical smart learning. Our survey paper addressed the following research questions; which contexts are used in smart learning, how the contexts are collected, recommended activities, data mining techniques, and future work in CARS for smart learning. In our findings we addressed the research questions with reference to smart learning. We identified that there are numerous context aware recommender systems; but despite all existing CARS in smart learning, there are several challenges and gaps that are still existing. Such challenges include: - Absence of CARS that perfectly fits the ever changing learner's needs and preferences, and lack of standard database for smart learning, among other issues highlighted in our future work.**

Index Terms* — *Artificial intelligence, Context aware recommender system, Technology enabled Learning

I. Introduction

Author [16], [25], and [40], explain that there is massively huge educational content that has been digitised in digital libraries and other learning platforms globally. On contrary there are insufficient mechanisms put in place to recommend relevant and personalized learning content to learners. Specifically based on the learners' ever changing preferences, that we consider to be smart learning.

Reference [5], [45], and [9], point out that context aware systems collect a variety of information from their environment and adapt their behavior according to the collected data. The collected bits of information is what the system interprets into a meaningful action, based on the current status of the entities that interact with the system. Context information that the system collects could refer and not limited to identity, time, temperature, mood, location, activity, environment, etc. In order to recommend relevant learning content to learners in smart learning environment, there is need to incorporate CARS to pick learners preferences and likes.

Author [24], [13], [58], and [40], all clarify that currently learning activities have gone digital in most learning institutions, with most of the learners preferring to use smart learning platforms. Thus calling for the need to automatically recommend to a learner certain activities at any particular time of learning. This would in turn reduce the time taken to manually searching for the relevant learning activity. The recommended activities could range from books for a certain level, courses to undertake, professionals in a certain field etc.

These activities are recommended based on the contexts collected from a learner. Such that to recommend professional to assist a learner, we may collect the location details and level of expertise of a learner. Hence pointing out that there are diverse contexts and context variables that can be used in context aware systems. There are several research that have been done in CARS in smart learning, with each research addressing a particular research problem. In this paper we surveyed existing literature in CARS for smart learning that were in line with our research questions.

II. Background

In our background we gave an insight of smart learning, context aware recommender systems, environment and techniques in smart learning. Context aware recommender system components, how smart learning contexts are collected from the environment and considerations when designing smart learning context aware recommender systems.

A. Overview of smart learning

Reference [10], [47], [22], and [42], all point out that smart learning is student concentric strategy mode of learning in provision of learning materials, where a learner will have diverse choices of learning at his fingertip, and learning can be achieved at home, field, school, etc. All these depends on the learner's choice of learning.

Author [37], [52], and [8], explain that a smart learning system should be able to learn the users' preferences based on the environment of the learner. This is due to learners' ever changing demands, hence it is imperative to keep collecting the learner's choice of preferences every time. The collected learner preferences, can then be automated based on the way that data was collected and the expected results.

Source [9], [27], [44], and [57], suggest that technology enabled smart learning process usually takes the following salient steps.

1) *Sensing*

   It entails scanning the user and his environment then collecting/sensing his particular requirements.

2) *Reasoning*

   An array of artificial intelligence tools that analyze the collected data using the sensors

3) *Acting*

   It evolves around reacting to the environment, based on the solutions offered by the reasoning stage

B. Context aware recommender system components, environment and techniques

Papers [34], [22], [17], and [5], all show that models of context awareness systems starts by first sensing their environment or contexts. During the sensing, they will collect the contexts that they are adapted to collect. They will then use their artificial intelligence to give an output, or adapt to the environment in a manner that is proportional to the collected contexts. Thus different contexts collected will necessitate the context aware model to behave in a particular fashion. Likewise [26], [49], and [3], suggest that there are a number of environment awareness that context awareness systems could perceive. These context aware environments could be grouped as: -

1) *Physical environment context*

   This is where the context awareness data is one that is related to physical world parameters. Such as location of user, body temperature of user etc.

2) *Human environment context (user context)*

   These contexts are pertaining to the user; such as: -User's identity, habits of the user, to-do-list of the user etc.

3) *ICT context or virtual environment context.*

   This is where the context awareness data is data relating to a device in the distributed system. Such as GPS location etc.

Reference [60], [33], [12], research suggest that there are several recommendation techniques that have been proposed and used by a number of research. These recommendation techniques include group-based, knowledge-based, content-based, demographic-based, utility-based, context-aware, trust-aware, collaborative filtering, social network-based, and hybrid technique. The choice of a technique depends on the way contexts are to be collected and processed.

Such that for group based recommendation, the recommendation made are similar for members of a particular group, while knowledge based will differ depending on learner's knowledge level. Demographic based recommendation will focus on some demographics, say how many times you have rated a certain item. While hybrid recommendation, combines more than one recommendation technique.

C. How smart learning contexts are collected from the environment

Papers [23], [41], [33], and [39], all point out that there are several ways that have been put across to collect contexts for learning systems. The collection depends on the environment and type of context to be collected. These contexts can be collected through: - Wi-Fi networks, RFID (Radio frequency identification), wireless sensor networks (WSNs), internet, mobile agents, mobile and wearable sensors, and computer systems.

D. Considerations when designing smart learning context aware recommender models

Reference [28], [50], [51], [16], and [4], all point out that when designing smart learning context aware recommender system, then the following factors are vital to consider for a more comprehensive and user-friendly recommender system. These considerations are diversity of recommendations, recommender persistence, user privacy, user demographics, recommendations serendipity, and trust.

III. LITERATURE REVIEW

Due to the evolution of MOOC (Multiple Open Online Courses) available in the internet, with each course having its own objective. There exist several CARS in smart learning systems, each addressing a pertinent goal, justifying the complexity and the several activities that can be recommended in smart learning. Hence we restricted our survey to CARS papers that addressed the following research questions in pedagogical smart learning: -

- Which contexts are used in smart learning,
- How are the contexts collected,
- What data mining and recommendation techniques used to processes the contexts,
- What are the recommended activities,
- Future work in CARS.

During our literature search we identified several articles on context aware recommender systems in learning.

A. Selection of articles for review

As outlined by [4], and [45], there are several research that have been carried out in CARS smart learning; with each recommending an activity and addressing their own gap.

We searched through various journals, and conference proceedings using the following terminologies: -

- Context aware recommender systems in learning,
- Recommender systems in smart learning
- Context aware in education

Several journal articles and conference proceedings were availed. We selected journals published within this decade and specifically addressing majority of our research questions.

B. Surveyed papers on context aware recommender systems for smart learning

Below are some of the papers that we reviewed in smart learning contexts aware recommender systems. Where we had more than one author with similar research but different findings, we documented all their findings under one title.

1) Context-Aware Recommender Systems for E-Learning: A Survey and Future Challenges

Author [15], [32], and [53], all argue that several research have been conducted, on technology enabled learning recommender systems. Majority of the studied models use knowledge-based filtering, collaborative filtering and hybrid techniques. These techniques depend on recommendations that are to be suggested to a learner. There are diverse contexts that are usable in smart learning. These contexts are categorized as physical condition contexts, computing contexts, user contexts, resources contexts, time contexts, situation contexts etc.

Several activities were recommended with these recommender systems. These recommender systems were to suggest any of the following activities:- teachers, peers, learning content, knowledge levels, training needs, books, institutions, lighting levels, learning styles, courses to undertake etc.

Their research identified some challenges and future work, which include: - combining more than one context groups to have a hybrid, contexts that have not yet been used, automatic capturing of learners' contexts, user interests, and standard dataset for smart learning recommendations. They also suggested other data mining methods other than the mostly used nearest neighbour, crowdsorcing, pattern matching and association rules.

2) Automatic learner needs identification using context awareness and artificial intelligence

Reference [9], [29] and [56] explain that context awareness could be used to investigate learners' behavior pattern and offer them relevant solutions with regard to their learning behavior. Their systems uses artificial intelligence and context awareness to provide learners with their specific likes. These likes, depends on their past data and the data collected from their ubiquitous devices. However, these systems are limited to recommending to a learner, the reading content based on their previous likes unfortunately their systems do not support dynamic learner preferences.

3) Ubiquitous computing technologies and context aware recommender systems for ubiquitous learning

Papers [35], and [46], Developed ubiquitous learning system. The system integrates context aware and ubiquitous computing technologies. Their system, a 2D or a QR bar code that enabled students in getting recommendations on the best herb that can be used for a particular ailment. The various plants have an attached QR code, from which the students can scan the plants QR code with their mobile devices to identify the herb and to an extent the medicinal values of the herbs. They used clustering algorithm and association rules to unearth relationships in databases. Collaborative filtering approach assists the algorithm to identify the relationships.

4) Keywords Learning Materials Recommendation Framework

Reference [21], and [59], explain that there are a number of E-learning material recommendation frameworks. In their framework an instructor uploads learning content in the database. Each content was given a keyword which will be used for recommendation purposes. The keyword will have content attributes such as title, author etc. A student will be given recommendations based on the keyword that the student has requested. There was a learner's ratings for these keywords. Further recommendations are given based on average learner ratings of these keywords. Otherwise, the recommender system will predict a good learners' ratings for the item.

5) Book Recommender System using Fuzzy Linguistic Quantifier and Opinion mining

Author [2], [14], and [57], proposed a book recommender system where learners give opinion and rate books, thus a customer review for the available books. The customer will give their opinion review online. The reviews will be aggregated, and an ordered weighted average (OWA) will be determined. A book with the highest OWA is usually the one with the highest recommendation. This context aware recommender suggests a number of books, and let a user rate the books. It then recommends books with similar OWA ratings as those that the learner rated highly in his ratings. This is not practical where there are several books.

6) Fuzzy Logic Based Context Aware Recommender for Smart E -learning Content Delivery

Reference [22], and [39], suggest that Fuzzy logic-based context aware recommender for smart E-learning content recommender, is a model that collect learner's context and give suggestions of relevant learning material to a learner. A learner will be provided with an assessment test. The time taken to complete the test and the assessment test score, will form the learner's contexts.

The collected contexts will be analyzed using type 1 fuzzy logic, to output a learner's knowledge level. The output knowledge level from the fuzzy logic will be assigned to a learner, which will then be used to recommend relevant learning content for the learner. There will be a database with learning contents OWA scored with the professionals of that learning subject. Thus learning content with OWA of ± 10 from a learner's knowledge level will be recommended to the learner.

7) Dynamic context aware learning objects in e-learning environment

Reference [38], [2], and [43], elaborate that in context aware E-learning environment, we could have either a random user or an adequate user of E-learning system. We have three modules that support the interpretation of user contexts for all the users. These are the system contexts, user contexts, and environment contexts.

The existing context aware systems for E-Learning have no standardized set of context parameters, hence the selection of contexts is based on randomly considered set of parameters. Some of the context parameters include: - Learner's personal profile, level of expertise, preferences, intention, quality of learning service, learner's devices, pace, state etc. That are used for recommendations.

They suggest that there is need to have a standard model incorporating all the three modules, in order to integrate all the eLearning learning objects to achieve dynamic contexts.

8) SMS based E-Assessments enabling better Student Engagement, Evaluation and Recommendation Services in E-Learning using Fuzzy Rules and Course Ontologies

Author [6], and [36], research proposed models where students interact with teachers as usual in class or using e-learning platforms. The models suggest that students will answer quizzes pertaining to their interactions with the teacher. The way a student answers the quizzes will now guide the student on whether to proceed or revisit the earlier topics. The model mines a student SMS response on a fuzzy logic, which then gives the student personal recommendation whether to proceed to the next topic or not. The research is limited to course topics, and whether the student is competent to proceed to the next topic based on the SMS E-assessment score.

9) E-learning group recommender systems: Combining User-User and Item-Item Collaborative Filtering Techniques

References [48], [1], and [11], proposed that a group recommender system has combined a hybrid of item-item and user-user collaborative filtering techniques to build their recommender systems. Implying that instead of recommending based on similar users only, they also incorporate both similar users and similar items in their group collaborative filtering recommendations. They further argue that majority of recommender systems were group recommenders and not personal recommenders. Noting that it would be difficult to build personal recommenders for each user. Their have not built context aware recommender system for every individual, but have built a recommender system that consider the preferences of a group of users and recommend to a user with reference to a group that a user best fits.

10) Enhanced Recommendations for e-Learning Authoring Tools based on a Proactive Context-aware Recommender

Author [19], [20], and [30] suggest that authoring tools are powerful systems in the area of e-Learning. They assist teachers to create new learning objects by reusing or editing existing educational resources that are stored in learning repositories. However, due to large number of resources these tools access, it is usually difficult for teachers to find the most suitable resources for their target level.

The papers propose models that could generate proactive context-aware recommendations on resources during the creation process of new learning objects. The models use context topics of the learning object and the target audience. The models would then suggest suitable resources without explicit user request being needed. Therefore, the user would discover the resources during the creation process.

11) A Fuzzy Approach to Multidimensional Context Aware e-Learning Recommender System (CA-ELRS)

Reference [18], and [55], point out that majority of the learners context include: - mood, emotion, duration of study, place, time, and social interaction. The paper thereby works towards developing an effective multidimensional CA-ELRS using mood and time duration as fuzzy logic input concepts. Then through use of fuzzy logic, the crisp output can be given, which will then be used to match the relevant learning content.

12) Context-aware recommender for mobile learners

Author [10], and [54], research entail building mobile recommender systems with semantic-rich awareness information. Their content recommendations are tailored to a learner's background, context, and task at hand of the mobile learner. These content recommendations are also integrated with different operational characteristics such as varying network bandwidth and limited mobile devices resources. In incorporating all the above factors in one way or the other, it was therefore necessary to consider a proactive context awareness mechanism that can sense both system-centric and learner-centric context and adapt the accessed services on the go. The models use shared ontology space and unified reasoning mechanism.

13) Constructing a User-Friendly and Smart Ubiquitous Personalized Learning Environment by Using a Context-Aware Mechanism

Author [31] and [7] developed intelligent personalized context-aware recommendation learning systems. The systems comprised of multimedia streaming learning subsystem, and context-aware learning subsystem. The learning content being recommended change with the learner's location and environment change. They provided dynamically adjusted learning that is location-based. The study used broadly defined term personalized mobile learning due to various sensor technologies that is usually incorporated in mobile equipment. These recommendations were personalized learning, that change according to the learner's environmental information such as history, regional traits, nearby buildings etc.

IV. RESULTS AND DISCUSSIONS

A. Results

From the above literature review, we managed to tabulate the result in table 1 below for easy visualization and quick follow-up, based on each CARS studied in smart learning.

TABLE 1
A SUMMARY OF LEARNER CONTEXTS, RECOMMENDER SYSTEMS, DATA MINING TECHNIQUES, RECOMMENDED ACTIVITIES AND FUTURE RECOMMENDATIONS USED IN THE DEVELOPMENT OF SMART LEARNING CARS

Main research Publication(s)	**Contexts collected**	**How contexts would be collected**	**Recommender system (s)**	**Recommendation / data mining Technique(s)**	**Recommended Activities**	**Challenges and Future work**
[32] Verbert, K. et al. and [15] Chughtai M.W, et al.	- Software - Task - Proximity - Knowledge - Learning styles – Interest etc.	- Computers - GPS - Mobile phones - Sensors - Mobile agents	- Location based learning. - System based learning. - Time based etc.	- Nearest neighbour, - Crowdsorcing, - Pattern matching - Association rules	- Suggest teachers, peers, knowledge levels, - Lighting styles - Learning content, levels etc	- Use of hybrid recommendation techniques - Standard dataset - Automatic context capture
[9] Aztiria, A., et al.	- Past likes & behavior data - Current behavior data	- Timers - Computer - Social media - RFID	- Keywords Learning Materials	- Pattern matching	- Learning content based on learners likes and behavior	- Incorporate several behaviors - Cold start, especially when few past learner behavior are available
[35] Thiprak, S., and Kurutach, W.	- QR barcode - 2D bar code	- Bar code reader - Computer - Internet	-UbiCARsUL	- Clustering algorithm	- Identify a herb - Identify extent of medicinal values in herbs	- Integration with other capturing devices
[21] Ghauth, K. I., and Abdullah, N. A.	-Learner ratings - Keywords	- Computer - Search engines	- learner needs identification	- Context awareness - Normal search	- Reading content - Reading content ratings	- Automatic context capture
[2] Adnan, M., N., et al.	- Learner's book opinion - Book ratings	- Computer - books in database ratings	- Book recommender system	- Aggregated ordered weighted average on a book	- Suggests reading book	- Capturing several and diverse opinions -Challenges during information overload
[22] Gogo, K. O., Nderu, L. and Mwangi, R. W.	-Learner test assessment score -Time to complete assessment test	- Learner assessment - Computer - Timer	-Smart e-learning content recommender	- Context aware - Fuzzy logics	- Relevant and personalized learning content recommendation	-Use of interval type 2 fuzzy logic - Incorporate other learner contexts - Learning information overload -Network delays
[38] Zarrad A., and Zaguia, A.	-User context, Environment context, -System context	- GPS - Computer - Smart phone - Wireless networks - Wearable sensors	- Dynamic learning objects in e-learning	-Unspecified	- Relevant e-learning content	-Need for a standard model that would be able to integrate all the eLearning learning objects - Standard location based database.
[6] Antony, J., et al.	- SMS E-assessment score - Teacher interaction	- Learner assessment - Computer - Smart phone	-SMS based E-Assessments Recommendation Services in E-Learning	-Fuzzy logic	- Suggest learning topic to visit	- Research is only limited to course topics. It needs to be expanded to capture other learning items
[48] Pujahari, A., and Padmanabhan, V.	- User preferences on item	- Preference ratings on learning content - Computer	-E-learning group recommender based on User-User and Item-Item	-Hybrid of similar users and similar items - Collaborative filtering	- E learning content based on similar users and similar items	-Build personal recommenders for each user
[19] and [20] Gallego, D., et al.	- User context (idle, eyes open, reading, etc.) -Learning object context (level, topic language,)	- Mobile device - Camera - Computer - learning content access -Internet	-Proactive Context aware Recommender for e-Learning Authoring Tools	-Aggregating context scores for each collected context, then compare with the most closest score	- Proactive relevant authoring tools for e-learning	- Need to integrate several real world learning contexts

[18] Dwivedi P., and Bharadwaj K.K.	-Learner moods (happy, sad, moody, etc.)	- Mobile device - Camera - Computer	Multidimensional Context Aware e-Learning Recommender	- Item based collaborative filtering	- Suggest learning content with regard to learners moods	- Incorporation of several moods and emotions contexts
[10] Benlamri, R., and Zhang, X.	-Mobile learner surrounding contexts (GPS, wireless nets, security, etc.)	- GPS - Computer - Google maps - Smart phone	Context-aware recommender for mobile learners	- Ontology reasoning	-Recommend learning content to mobile learners, depending on mobile surrounding context	- Efficient context integration and adaptation - Sufficient context change adaptation
[31] Yao, C.B.,	-GPS location -QR code	- Barcode - GPS - Computer - - Wi-Fi - Wearable sensors	-Personalized context-aware recommendation (PCAR) learning system	-Intelligent personalized context-aware learning algorithm - Aggregations of contexts	-Location based M-learning, for recommending learning content based on location	- Dynamic location changes - Mapping several locations.

B. *Discussions*

As explained by Author [18], [40], [54], [46], and [55], as well as from the results in table 1 of our study. We identified that smart learning incorporates e-learning, mobile learning, pervasive learning as well as ubiquitous learning. Each of the above learning has its own set of tools and architectures. With the evolution of MOOC and the various learning styles and learner preferences. There exists several contexts that can be used in designing context aware recommender systems, depending on the contexts that can be collected, as well as the learning architecture to be developed.

These learning contexts can be grouped as *user context* (preference, intention, moods, knowledge level, expertise, frequency, goals, keywords, language, background etc.). *Environment context* (GPS location, region, temperature, time, proximity, day etc.), or *System context* (hardware, software, network, system speed, etc.).

Due to the various contexts in CARS in smart learning, there are diverse strategies of collecting user contexts in smart learning. These strategies depend mainly on the CARS architecture and environment from which the contexts are to be collected. Such collection methods include: - the use of computers, Wi-Fi, wearable sensors, QR code, internet, RFID, touch screens, etc. User contexts tends to use majorly wearable devices and computers. Environment contexts tend to use gadgets that can collect environmental contexts, such as GPS, Wi-Fi, thermometers etc. As system contexts tend to use computers, timers, internet etc.

We also noted that there are various recommendation and data mining techniques, which extracts useful information from learner contexts and guide the recommendation intelligence. These recommendation techniques used include content-based, group-based, knowledge-based, demographic-based, utility-based, trust-aware based, social network-based, fuzzy-based, collaborative filtering, and hybrid recommendation. On the other hand, the data mining techniques that can be used in mining learning content in smart learning include: - nearest neighbour, regression, crowdsorcing, pattern matching, association rules, clustering algorithm, normal search, ordered weighted average and collaborative filtering.

Our results in table 1 further indicate that each and every context aware recommender system in learning is addressing a particular goal, thus diverse future work with regard to their individual goals. Some of the items that have been recommended in smart learning include: - recommendations of learning material, teachers, peers, topics, learning content, lighting styles, levels of learning, etc. In our survey, we noted that there exist several recommender systems that recommend similar activities, say learning content; but with different contexts collected from a learner. This then confirms that, we do not need to collect same contexts for similar recommendations.

Similarly, same contexts could be collected from learners using different CARS, but lead to different activities being recommended to a learner. For example, in order to recommend relevant books to a particular learner, any or a combination of the following contexts can be collected from learners: - learner preference, keywords, level of study, expertise, etc. The contexts collected depend entirely on the architecture, data mining method, user profiles, context variables, and strategies for collecting learners' contexts.

There are still several areas of research that have not been fully exhausted regarding CARS in smart learning, especially with the evolution of MOOC and learner centric learning. For example, in a research to recommend relevant books to a learner, when one has picked similar contexts. Then the following could be issues of concern.

Taking:-

- Strategies for collecting learners' contexts …….…….A
- Recommendation techniques and data mining techniques used in CARS ……………..……………..……..……. B

If there are 7 strategies through which specific learner contexts can be collected, and 6 data mining techniques that can be used for the research. ***So*** *A=7, and C=6.* ***Then*** this research alone would have *7x6 = 42 possibilities*. If we decide to diversify the contexts, then even more possibilities will be available exponentially for the same research.

Following the fact that there are several parameters to be addressed in CARS in smart learning, then there arises several possibilities, challenges, and future work.

V. Conclusion and Recommendations

A. Conclusion

This survey justifies that there are several context aware recommender systems in smart learning, with several areas that have not been fully researched. This can be attributed by the several learner contexts available; various recommendation and data mining techniques, various strategies through which contexts can be collected, and the numerous activities that can be suggested in smart learning.

This study further points out that due to the evolution of MOOC and learner centric learning, the aspect of CARS in offering smart learning is even being complicated with technological advancements. These are due to the random set of parameters, several existing context variables that a CARS can choose, and diverse learner preferences. Hence there is no set standard for building CARS in smart learning, but open to individual researcher.

The survey further illustrate that there exist numerous contexts, context variables, data mining techniques, strategies for collecting contexts and CARS for smart learning. But despite the various context aware recommender systems in place, there is no recommender system that fully fits every learner's preference. This is due to the ever changing learner preferences, contexts and learning environments.

B. Recommendations and future work

There exists different CARS research in smart learning as indicated in table 1, although each context aware recommender system is addressing a specific goal. Even though the CARS could have same goals, they would have utilized different set of contexts, diverse recommendation techniques, or different strategies through which contexts are collected.

Due to the dynamic and ever changing learners' preferences and contexts, the following gaps arise: -

- Automatic extraction of learner contexts especially for big databases without cold start problems,
- Capturing ever changing learners' contexts in real time,
- Development of a situation aware CARS that can be able to perceive every context situation (i.e. if the environment is noisy / unconducive for learning hence postpone learning),
- Mapping of several locations in context aware data,
- Sharing of recommendations or contextual information over big data databases,
- Standard context capturing devices in smart learning,
- Developing a proactive CARS other than the traditional user requests and response given scenarios.

From the above gaps, we recommend building of a smart learning CARS that would be able to have a universal framework / model and platform for smart learning, with a standard database for contextual data and recommended data for every learner in smart learning.

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