Memory Load and Performance-based Adaptive Smartphone E-learning Framework for E-commerce Applications in Online Learning

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Abstract

The term e-commerce is not confined to the purchase and sale of goods only. There are several occasions where students are not able to comprehend any idea on their own. With the availability of online learning platforms such as Massive Open Online Courses (MOOCs) and Virtual Learning Environments (VLEs), students may visit online Internet sites, where various articles are made available with a single click. With mobile devices in their hands, they can also listen to the presentations of different academics from anywhere and at any time. In an online learning environment, it is challenging to provide tailored learning content to students that fulfill their needs and requirement. Therefore, we in this research paper propose an adaptive smartphone learning framework. The framework first considers students' academic performance, preferred learning content, and memory load i.e., cognitive characteristics. Based on students' academic performance, preferred learning content, and memory load, appropriate adaptive and motivational triggers are sent on students' smartphones to guide and motivate them in their learning process. We have introduced ten types of adaptive triggers that in different scenarios will be presented to students to help them in remembering important learning points. Furthermore, performance-based motivational triggers in connection with adaptive triggers are also introduced. These motivational triggers are sent on students' smartphones for giving them a suggestion, hope, appreciation, and warnings during their studies. In this study, we also show how different students' learning scenarios are created and how our framework deals with those scenarios in students' learning process.

Keywords: E-commerce, Adaptive triggers, Performance-based triggers, Smartphone learning

1 Introduction

The emergence of e-commerce and related technologies has enabled students to access learning material from anywhere and at any time. Students can order books from several websites such as liberty books, Amazon, etc. In case, if the books or other type of learning content is expensive then the students have the option of reading books online or watching educational lectures for free. With the emergence of smartphones, students now have more freedom to access learning material and can learn on the move. The tremendous popularity and success of online learning platforms such as Massive Open Online Courses (MOOCs), Virtual Learning Environments (VLEs), and Learning Management Systems (LMS) has triggered the exponential growth in the volumes of online learning material [1]. With a large amount of learning content available online in the form of text, animations, videos, quizzes, and exercises, students are often confused in accessing the preferred and right learning content.

According to the Pakistan Advertiser Society (PAS), the number of mobile phone users has crossed the 139.2 million mark where 81% of smartphone users are teenagers and youth have aged between 21 to 30 years[1]. Research studies divulged that 53% of college students have smartphones and 92 percent of those students use smartphones during their idle time at college or home [2]. This high percentage of smartphone usage among the youth makes smartphones a perfect platform for learning.

However, encouraging students to use smartphones for learning purposes is a challenging task [3]. Students use smartphones primarily for entertainment and communication purposes. Among other activities the most common students' smartphone activities are social networking, playing games, sharing videos and pictures, enjoying music and entertainment [4]. Therefore, the designers of smartphone learning apps should carefully and wisely develop apps that are adaptive, easy to use, and consider students' memory load.

Advances in smartphone technologies have made smartphones more authoritative, lightweight having faster processors and larger Random Access Memory (RAM), Wireless enabled technology, Near Field Communication (NFC) technology, high-definition videos, and 3G and 4G Internet-enabled technologies [5-6]. With 3G and 4G technologies, students can access the Internet at anytime and anywhere. This allows students unrestricted location and time-based access to Learning Management System (LMS) resources in the university campus, outside the university campus, from home, and from anywhere. However, it is also

1 https://pas.org.pk/mobile-phone-users-in-pakistan-cross-139-2-million-mark

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important that among many learning resources, students get proper guidance, appropriate suggestions, and appreciation based on their memory load and performance.

Adaptive learning is an educational technique that considers students learning styles, cognitive abilities, learning preferences, learning goals, and academic state before providing educational material to a student [7]. The adaptive learning method uses a computer as an interactive learning device to orchestrate and organize learning resources according to the needs of each learner [8].

Memory load (cognitive load) refers to the mental strength that a student can use during the learning process [9]. It also refers to the human brain's ability to interpret and remember concepts during learning [10]. BJ Fogg asserted that two elements must be present at the same time for a learning behavior to occur i.e., 'ability' and 'motivation' [11]. Ability refers to brain cycles that can interpret and remember a concept whereas motivation refers to the human will to do a particular behavior. Triggers can be prompt, call to action, clue, reminder, or informative messages. It is one of the key elements in urging and encouraging human beings to perform a particular behavior.

In this paper, we introduced triggers for increasing students learning ability (memory load) and motivation. Our proposed Framework introduces a mechanism based on students' learning material types and preferences, memory load, and academic performance state. Students are presented with different learning material like content, quizzes, video, and audio tutorials, animations, and exercise solving based on their partialities and preferences. Then different types of adaptive triggers (recommendations, clues, messages) are presented to students on their smartphones during the learning process in different amounts based on their memory load to help each student in interpreting and memorizing a topic. Different types of motivational triggers are also presented to students based on their academic performance state. Subsequently, students are guided, appreciated, praised, suggested, warned, and directed in these motivational triggers. Finally, these triggers are presented in such a way that they remain concise, useful, and handy so that students are not overwhelmed and distracted from their learning objectives. The rest of the paper is organized in the following manner. Section 2 discusses previous studies, their outcomes, and their limitations. Section 3 is about students' features and working of smartphone learning framework. Section 4 discusses various learning scenarios for students with different preferences and performances. In section 5, framework implementation and the experimental procedure is detailed. Section 6 summarizes the research study along with its limitations and the improvement that can be performed in future work.

2 Literature Review

More than 95% of the worldwide population live in a zone covered by mobile-cellular networks allowing instructors to keep in touch with students at any time and from anywhere [12]. In the past decade, numerous studies of mobile learning have been carried out each contributing essential information to researchers and scholars about knowing the use of mobile devices in the educational domain. H. Crompton and D. Burke performed a comprehensive and systematic literature review on the use of mobile devices in the education sector particularly in higher education institutes [13]. The prime target of most research studies is directed towards finding the impact of mobile learning on students' accomplishments. Using mobile devices as a language learning tool was the most often researched and implemented matter.

Though the phenomenon of mobile technologies and mobile learning is new, the effectiveness of mobile devices is countless in terms of providing instant just-in-time education and making the learning process easy and flexible [14]. Although mobile devices nowadays are used primarily for communication and entertainment, they can educate people at their own will and at the time convenient for mobile users. More often mobile learning is also called ubiquitous learning as digital mobile technology used for learning purposes is the prime target of expanding streams of mobile learning studies. With mobile learning instructors are exploring these new technologies to combine them with collaborative learning environments to make learning easy and interesting [15].

With the emergence of mobile technology, various m-learning models, frameworks, and systems have been incorporated in educational institutes [16]. The primary requirements for the acceptance of m-learning systems in educational environments are usability and user satisfaction [17]. Few studies in the past have addressed the issues related to usability and user satisfaction in the real environment with students and instructors [18]. For effective Mobile Learning Systems (MLS), the evaluation and analysis of the usability of MLS are necessary. A study carried out by [19] performed a usability assessment of a Context-Aware MLS with the help of 6 instructors and 48 students in real learning settings. The result obtained showed that 82.4% of students accepted the services offered by the Context-Aware MLS. The learning reinforcement services provided by the SMS messages were having the highest acceptance rate for the instructors with a positive opinion of 91.5%. The high school students showed 81% acceptance of the suggestion services provided by Mobile Learning Objects (MLOs). The generated results showed that the assessed MLS holds broad recognition, acceptance, contentment, and applicability from instructors' and students' viewpoints.

With improvement in mobile technologies, mobile devices now can detect the environmental and contextual features of students through software, geofencing, cameras, and using different sensors. Considering environmental and context features, a study was carried out by [20] that proposed a mobile learning model called Dynamic Mobile Adaptive Learning Content and Format (D-MALCOF). D-MALCOF first considered students' background knowledge, performance, preferences, learning habits, and contextual features to provide tailored and suitable learning content to various students. To measure the effectiveness of the D-MALCOF model, an Android mobile app was developed and tested in the Moroccan higher education system. The D-MALCOF model was evaluated on how it has increased the students' knowledge level and learning outcomes. The test results of students who were using the mobile app were compared to those who have learned through traditional web-based online settings, which concluded that the proposed model has the potential to boost students' skills in the JAVA programming language.

N. Ahmad et. al. employed the interpretive structural modeling (ISM) method to model critical success factors (CSFs) in cloud-supported mobile learning environments [21].

With the help of experts in the field of education, various important features and their relationships were identified with the help of the ISM technique. For classifying features into independent and dependent features, Matrice d'Impacts Croisés-Multiplication Appliquée á un Classement (MICMAC) analysis was carried out. The most important features identified in increasing students' performance were related to management support. Finally, a theoretical model was created that discusses how mobile learning models can help instructors and management staff in supporting students at the right time during their studies.

Recently, many educational institutions have started integrating and using Massive Open Online Courses (MOOCs) to support traditional classroom procedures. Many MOOC platforms provide the facility to instructors to create their own Small Private Online Courses (SPOC) to support them in providing distance-learning education [22-23]. However, despite supporting a large volume of data and students, these platforms are limited in creating certain online classes with no collaboration among students. A study carried out by [24] addressed the limitations of traditional classroom settings and Massive Open Online Courses (MOOCs) and proposed a game-based mobile application called MyMOOCSpace. The MyMOOCSpace application provided several opportunities to students to support the collaborative learning activities of MOOC platforms. The MyMOOCspace application was developed by leveraging the power of CSCL and gaming aspects to make learning easy, interesting, and riveting. The evaluate the application and to demonstrate its usefulness, a case study comprising 25 students was carried out and the result showed that MyMOOCSpace increases the performance and interaction of students while using it.

Mobile devices can help students in learning a foreign language in those situations where the several challenges and students are not aware of the new language [25]. M-learning can provide optimal conditions for students to enhance their engagement while learning the target language. H. Avci and T. Adiguzel presented a Mobile-Blended Collaborative Learning model to support students in making collaboration while learning English [26]. The model was integrated with classroom learning settings and outside of classrooms to enable language learners to rehearse English utilizing authentic language activities, collaboration, problem posting all based on a project-based learning methodology. The research study aimed to investigate the effects of WhatsApp instant messaging applications on the English proficiency of students. A total of 85 students were enrolled in five intermediate classes at the foundation university, Istanbul and the training lasted for seven weeks. The data collected from the WhatsApp log file and semi-structured interviews revealed that practicing English in a real setting facilitated students in language learning, improving their communication skills and increasing vocabulary knowledge. Moreover, instant messaging proved to be very effective in an informal learning platform to increase the language learning performance of students.

Mobile computing devices such as smartphones and tablets can provide various educational opportunities for students for collaboration, accessing educational content, communication, content creation, and interaction with colleagues and instructors from anywhere [27-28].

Several research studies have been conducted to measure the effect of mobile phone messages on the learning process. Considering the anytime and anywhere nature of mobile phones, researchers are making their efforts in facilitating mobile phones, especially smartphones to enhance learners' study behavior [29].

S. Srirama et al., have presented smartphone-focused mobile Web Services architecture for collaborative learning where contrary to centralized learning management systems, an architecture based on collaborative learning is presented [30]. In collaborative learning architecture, the use of mobile phones has been emphasized in sharing and enhancing knowledge.

Woodcock et al., have investigated that the ubiquity, multi-functionality, and connectivity of mobile phone devices offer a novel and influential learning environment [31]. Their study found that students possessing smartphones are generally unaware of learning apps and do not know about the potential of smartphones in learning.

Hossain et al., in [32] consider learners' sensory, physical, and cognitive level through smartphones for appropriate and targeted learning. A reconfigured Android interface is presented to the learner based on their cognitive load level. Their study proved that a re-configurable mobile Android phone (R-MAP) interface could be very effective especially for visually impaired learners.

Authors in [33] stated that more and more instructors are adapting smartphones for collaborative and active learning in classrooms. They asserted that smartphones could become a very effective tool in high order thinking, mutual understanding of concepts, problem-solving, online participation, developing teamwork skills, and improving learning satisfaction. They successfully installed and tested Smartphone-Supported Collaborative Learning System (SSCLS) and successfully addresses mobile learning issues and how mobile phones can be used to increase collaborative and interactive learning.

Furthermore, in a study [34] conducted by Heyoung Kim et al., it was revealed that 87 ESL mobile apps are very effective in mobile-assisted language learning. Key features in mobile-assisted language learning apps were content presentation, design, learner-centered learning opportunities, and flexible practices.

Machine learning and deep learning models such as generative adversarial network (GAN) [35], long short-term memory (LSTM), and Artificial Neural Networks (ANN) along with their variants have been recently used to capture students learning behavior via videos, online learning features for needed feedback and guidance [36-37]. To allow autonomous vehicles to accurately predict the right context, generative adversarial network (GAN) architecture has been proposed [38]. The GAN architecture allows autonomous vehicles to learn on their own and make autonomous decisions. Internet of Things (IoT) has become an integral part of online education with many exciting features that enable a student to learn on the go at any time and any place [39-40]. With improvements in IoT technologies, it is expected that students will be facilitated more in accessing relevant learning content and timely feedback [41].

We in this study present an adaptive smartphone learning framework, different types of adaptive and motivational triggers, and some learning scenarios that demonstrate how smartphones can be used in increasing students' study behavior.

3 Features and Working of Smartphone Learning Framework

The proposed framework revolves around two types of triggers, namely adaptive triggers, and motivational triggers. Adaptive triggers are disseminated on students' smartphones based on their memory load, learning material types, and academic performance state. Their purpose is to direct students in the learning process, increase their memory load capacity, and guide them on what to do after a particular study goal has been achieved. Motivational triggers encourage, suggest, and appreciate students based on their academic performance state. In the next section, we discuss the functions of the five stages of the proposed framework. The details are presented in Figure 1.

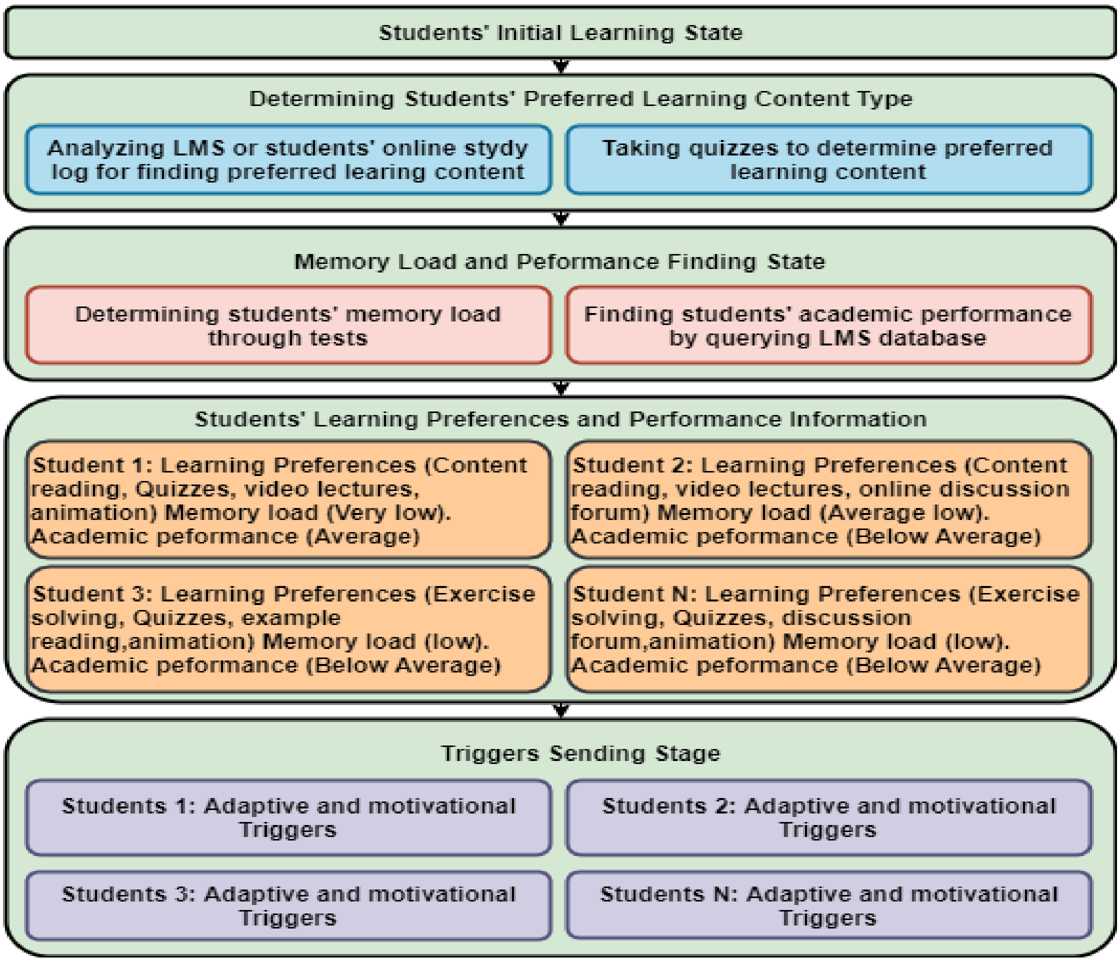

Figure 1. Memory load and performance based adaptive smartphone learning framework

3.1 FrameWork Stages

The initial learning stage refers to newly registered students in some courses. At this point, our framework mechanism has no information about students' memory load or academic performance. Therefore, in the second stage, the first student's preferred learning material and content types are determined. The framework suggests that this can be achieved either by analyzing Learning Management System (LMS), analyzing students' online study logs or by taking a short quiz that determines the preferred study material types. Subsequently, the third stage is dedicated to eliciting students' academic performance states and memory load statistics. Academic performance is revealed by querying the LMS database where students' assignments, quizzes, and examinations result are stored. Memory load is that characteristic which changes from time to time. Therefore, it should be determined on regular basis i.e., after one week or after one month by taking a short online memory load finding quiz from students on their smartphones.

The framework's fourth stage is the dynamic and summarizing stage. Information about students' preferred learning material types, academic performance, and memory load are summarized here, and later, based on this information different triggers are distributed to students. It is dynamic as overtime, students' academic performance, learning material types, and memory load change. The fifth stage is the triggers sending stage. This stage determines what adaptive and motivational triggers should be sent to various students on their smartphones.

Next, we discuss memory load scale values and their relationship to the number of learning material objects and adaptive triggers.

3.2 Memory Load (Cognitive Load) Scale Values

Our Framework mechanism presented in Figure 1 rely on dynamic memory load of each student. This memory load can be determined by a quiz on weekly or monthly basis. The minimum and maximum points/values for memory load is between 0 (minimum) and 100 (maximum). Between these extreme values students' memory load is categorized as follows: Very Low (0 <= ML < 15), Average Low (15 <= ML < 35), Low (35 <= ML < 50), Balance = 50, High (50 <= ML < 65), Average High (65 <= ML < 85) and Very High (85 <= ML < 100).

The numbers of adaptive triggers to be presented to each student are based on the above-mentioned memory load categorization. For example, it is likely and expected that students having Very Low memory load needs more triggers and guidance as compared to the students who have Average High or Very High memory load. It is also possible that a student having a Very Low memory load gets overwhelmed or annoyed by adaptive triggers if it is presented to him/her after every learning activity. To handle this situation, the framework mechanism assigns appropriate numbers of triggers to their corresponding learning material types. It is to be noted that the number of triggers to be presented to each student is always based on the student's memory load values. Table 1 shows the correspondence between students' memory load and the number of topics to study and the number of adaptive triggers to be presented to students.

Table 1. Memory load scale values and number of adaptive triggers assigned to learning topics

Student memory load	Number of topics to be studied per week/month	Assigned number of triggers to learning topics
Very low (0 <= ML < 15)	20	90% of learning material = 18
Average low (15 <= ML < 35)	20	80% of learning material = 16
Low (35 <= ML < 5)	20	70% of learning material = 14
Balance = 5	20	60% of learning material = 12
High (5 <= ML < 65)	20	50% of learning material = 10
Average high (65 <= ML < 85)	20	40% of learning material = 8
Very high (85 <= ML < 1.0)	20	30% of learning material = 6

3.3 Learning Material Types

The considered learning material types are content, video lectures, audio lectures, animations, quizzes, learning by examples, exercise solving, online discussion forum, and additional learning material. Additional learning materials are websites and an online Learning Management System (LMS). Below we show learning material types along with their allotted adaptive triggers. In the next section, we will discuss these adaptive triggers.

3.4 Adaptive Triggers (Smartphone Messages)

Students are presented with different adaptive triggers conferring to their preferred learning material types and according to assignments of adaptive triggers to each learning material. The key purpose of adaptive triggers is to help students in increasing their memory load capacity and aiding them in remembering important learning points. Due to the nature of learning material types, they cannot be applied with all types of adaptive triggers. Except for content learning material type, all other learning material including a video tutorial, audio tutorials, animations, quizzes, learning by example, exercise solving, online forums, and additional learning material have specific triggers allocated to them. For example, exercise solving learning material type cannot be assigned with T1, T2, T3, T4, T5, T8, and T9 triggers because after solving an exercise, a student is in no position to write key points, or to summarize the topic, or do revision or memorized key points. Likewise, normally, reading the blog or having a discussion in an online forum, or consulting additional learning material on the internet is a casual learning material type where a student is searching for some extra information or problem-solving help. Therefore, an online forum or additional learning material cannot be assigned with triggers through T1 to T7.

Table 2 shows ten types of adaptive triggers along with their timings. Timings for each adaptive trigger are before and after. Before timing means presenting trigger to the student before he/she has started learning and after timing means presenting trigger to the student after he/she is finished learning the topic. It is once again important to note that the key purpose of these adaptive triggers is to help students exhaustively interpret the topic and remember key points about it. The description of each of these adaptive triggers is detailed in Table 2.

3.4.1 T1: Writing Key Points During Learning

According to the author in [42] writing key points and ideas during learning helps students in reducing memory load. They are in a better position to establish a connection among different ideas. It is the best choice for students having a low memory load to divide the topic into subtopics and then to master each one step by step.

3.4.2 T2: Topic Revision Trigger

C Wehlburg asserts that the only way to know about weakness in learning is through doing revision and enhancing academic engagement [43]. This trigger encourages students having a low memory load to revise the topic an appropriate number of times as revision reinforces learning ideas [44].

3.4.3 T3: Summarizing Topic

Authors in [45] suggest that students should be motivated to engage in summary activity after learning. T3 is about encouraging students to summarize the learned topic at the end as it will help them in constructing a memory connection between already learned knowledge and novel knowledge.

3.4.4 T4: Remembering the Topic

T4 trigger is also dedicated to students having a low memory load. As compared to students having a good memory load or interpretation capability, low memory load is more vulnerable to distraction and diversion as they complete a specific learning goal [46]. Therefore, this trigger is a reminder to students having a low memory load to rethink and reanalyze what they have learned so far.

3.4.5 T5: Sharing of Interpretations and Thoughts

T5 is primarily for good consistent students having very high memory load capacity. After achieving a particular learning goal, a student may explain it more simply than it is already presented in a book or some article. This way, a student helps his colleague and reinforces his/her concepts.

3.4.6 T6: Helping Other Students Online

T6 extends T5. In this type of trigger, students having strong memory load-bearing capability are directed and encouraged to visit online learning forums, LMS, and email groups and help other students who have posted problems and are waiting for answers.

3.4.7 T7: Posting Learning Goal Problems

Students having low memory load encounter more problems as compared to students having cognitive ability during the interpretation of new concepts [47]. Therefore, T7 is about motivating students to share their problems and concerns online and request their peers or instructors to help them out. This trigger is always presented at the end of learning. Students should be careful to post questions as they should be concise, clear, targeted and in simple words otherwise, it will lose its trustworthiness.

3.4.8 T8: Attempting Quiz after Learning

To further strengthen, enrich and reinforce the learning topic, T8 is presented to the student at the end of learning and is challenged to go for a quiz if he/she is sure about his/her understanding of the topic. This way student knows about his/her strength and weaknesses.

3.4.9 T9: Problem's Identification and Sharing with the Tutor in Class

T9 is particularly for those students who study alone and are reluctant in sharing problems online.

3.4.10 T10: Encouraging for Solving Chapter Exercise

All the above nine adaptive triggers related to students' memory load mentioned so far have in common one goal: giving guidance at the right time, suggesting the next learning activity, helping students in improving their memory load capacity, and preparing them for the end semester examinations. Most often, questions given in final examinations are from chapter exercises or identical to them. Therefore, the T10 trigger is dedicated to encouraging students to solve chapter exercises and get prepared for the final examination. Solving chapter exercise is a kind of rehearsal as without practice students normally forgets new knowledge and information [48]. In the next section, we discuss academic performance states along with their motivational triggers.

Table 2. Adaptive triggers along with their timings

No.	Triggers guiding students	Timings
T1	It will be better if you write down key points on one hard paper. It will help you in remembering and interpreting the same topic during revision.	Before
T2	Please try to revise this topic and make sure that you have memorized it.	After
T3	If you have mastered these topics, then do write a summary of them so that it can help you in future references.	After
T4	Please make sure that you have covered and remembered all important points of the current learning material.	After
T5	Please share your interpretations, thoughts, and understanding of this topic with your colleagues on LMS, blogs, class email group or online forums.	Before/ After
T6	If you are confident that you have mastered the current learning object then please see the online class forums and help your class colleagues if they have problems with the same topic.	After
T7	If you have questions or problems related to the current learning the topic then post your questions on the online forum and request to teachers or class fellows to help you out.	After
T8	If you are sure that you have memorized the current topic then attempt a short quiz related to the same topic.	After
T9	Please note down the difficult points on paper and discuss them with tutor or class fellows in the next class.	Before/ After
T10	To make sure that you have understood the current learning topic then solve chapter exercises. It will increase your self-assurance and will prepare you for the upcoming exam.	After

3.5 Students' Performance States and Motivational Triggers

For brevity, we have divided students' academic performance into three categories i.e., ***Below Average***, ***Average***, and ***consistent Excellent***. Different types of motivational triggers are assigned to students based on their academic performance.

Table 3 shows students' performance states, their assigned motivational trigger types, and motivational triggers examples.

Adaptive triggers aimed to increase the memory load i.e., the ***ability*** of students while they study. On the other hand, Motivational trigger types are targeted towards increasing students' ***motivation*** toward learning. In Table 3 we have presented different types of motivational triggers for different students based on their educational performance. Table 3 also shows students' performance states or categorizations with corresponding motivational trigger types and their examples. For presenting these motivational triggers, opportune time will be an important factor. Here opportune time is the right time at which motivational triggers should be presented on students' smartphones. One of the examples of an opportune time at which motivational triggers should be present to students is right after the quiz result has been announced. Similarly, sending praise and appreciation triggers to good consistency once in one week would be more effective and suitable. Too many motivational triggers may overwhelm or annoy students during the learning process. Figure 2 presents the workflow of the smartphone learning framework at the abstract level.

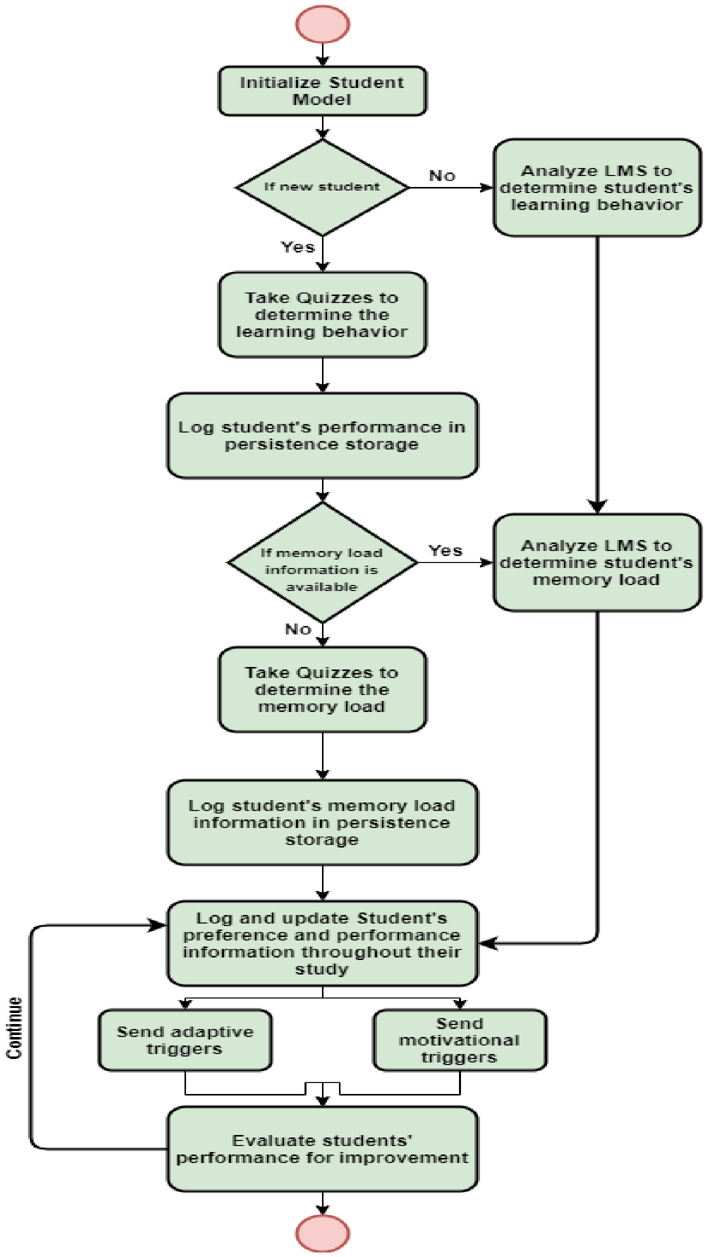

Figure 2. Workflow of smartphone learning framework at the abstract level

Table 3. Students' performance states, motivational trigger types and their examples

Students' academic states	Motivational triggers types	Motivational triggers examples
Below average i.e., fragile (weak students)	Fear	You may get relegated if you continue to show poor performance.
	Hope	Four hours of day learning will move you to the top students of your class.
	Suggestion	Please refer to LMS for newly video tutorial made by you instructor.
Average improving students	Praise	Congratulation. You are now among the top 10 students of a class. You can be in the top 10 if you work a little more.
	Appreciation	Today all instructors appreciated your improving performance in meeting.
	Social acceptance	Your position in class in 1st. You must feel proud of it but it would be better if you maintain it throughout the semester.
Consistent (good students)	Reward	Your department chairman will give you a certificate for showing good performance.
	Praise	You showed commendable performance in Quiz. Well-done.
	Appreciation	I as your instructor appreciate your good consistent performance throughout the semester. Well done.

4 The Student Learning Models (Scenarios)

Table 4 to Table 7 show four students learning models i.e., scenarios along with their recommended adaptive and motivational triggers. These four models represent hypothetical instances of the different scenarios shown in stage four of our framework. Next, we explain each student model and how different types of triggers are presented to them on their smartphones.

Table 4. Student 1 learning model

Student 1 learning model: Scenario 1				
Preferred learning content types	Memory load	Academic performance	Recommended adaptive triggers	Recommended motivational triggers
Contents Video lectures Quizzes Animations	Very low	Average	T1-T10 T4, T5, T6, T7, T9 T5, T6, T7, T9 T4, T5, T6, T7, T9	Praise, Appreciation, Social acceptance

Table 5. Student 2 learning model

Student 2 learning model: Scenario 2				
Preferred learning content types	Memory load	Academic performance	Recommended adaptive triggers	Recommended motivational triggers
Contents reading Video lectures Online discussion forum	Average Low	Below Average	T1-T10 T4, T5, T6, T7, T9 T8, T9, T10	Fear, Hope and suggestion types triggers

Table 6. Student 3 learning model

Student 3 learning model: Scenario 3				
Preferred learning content types	Memory load	Academic performance	Recommended adaptive triggers	Recommended motivational triggers
Exercise solving Example reading Animations	low	Below average	T6, T7, T10 T5, T6, T7, T9 T4, T5, T6, T7, T9	Fear, Hope and suggestion types triggers

Table 7. Student N learning model

Student N learning model: Scenario N				
Preferred learning content types	Memory load	Academic performance	Recommended adaptive triggers	Recommended motivational triggers
Exercise solving Discussion forum Quizzes	Low	Below average	T6, T7, T10 T8, T9, T10 T5, T6, T7, T9	Reward, Praise and appreciation

4.1 Scenario 1

With a low memory load and average academic performance, this scenario suggests that a student is eager and enthusiastic about learning. Therefore, wisely, at the appropriate time, this student is praised and appreciated through concise motivational triggers. Furthermore, based on preferred learning material types, different adaptive triggers are presented to the student during learning. It is to be noted that at some specific point in time, only one type of learning material is consulted by the student. Thus, only those types of triggers are presented to a student which is assigned to that learning material. Table 4 summarizes this scenario.

4.2 Scenario 2

In this scenario, a student is having few learning material types with content reading, video lectures, and discussion forums. The scenario infers that the student memory load is better than the student in situation 1. This also means that a student in scenario 2 is not giving appropriate time and concentration to learning. Consequently, these types of students should be motivated by fear, hope, and suggestion types of motivational triggers. As discussed earlier, adaptive triggers are bound to the type of learning material. Therefore, if the student in this scenario is doing some learning activity in an online discussion forum, then only T8, T9, and T10 adaptive triggers will be presented to him/her. Table 5 illustrates this scenario.

4.3 Scenario 3

The learning model in scenario 3 shows that this student is struggling hard both with his/her memory load and academic performance. The preferred learning material types indicate that the student believes in learning by revision and examples. These types of students need special monitoring by his/her instructor as they go along with their semester study. Table 6 shows the corresponding recommended adaptive and motivational triggers presented to this student.

4.4 Scenario N

This scenario represents students having exercise solving, discussion forum, and quizzes as preferred learning material types. With a moderate-high memory load and consistent academic performance, this student gets a reward, praise, and appreciation type triggers on his/her smartphone. Moderate high memory load means that the student is good with his/her memory load so he/she will not be astounded with so many adaptive triggers. Table 7 shows this scenario. The main working steps of student learning models are presented below in the form of the algorithm.

```
Procedure StudentBehaviorModel ()
Begin
Initialize student's features
Do
        If ( student ← NewStudent ) {
        DetermineStudentLearningBehavior
                RealizeQuiz()
                }
        Else {
        AnalyzeStudentProfile()
        }
        EndIf
Do
        If ( student ← NewStudent ) {
        DetermineStudentMemoryLoad
                RealizeQuiz()     // for determining memory load and student's performance
        }
        Else {
        AnalyzeStudentProfile()
        }
        EndIf

Procedure AnalyzeStudentProfile() {
        Begin
        ElicitLearningPreferences()
        ElicitLearningMemoryLoad()
        ElicitPerformanceInformation()
        ProcedureMatchingAdaptiveTriggers()
        ProcedureMatchingMotivationTriggers()
        Adaptation()
        Indexing()
        End
}
Procedure RealizeQuiz() {
        computeBehaviorModel()
        computeMemoryLoad()
}
Procedure Adaptation() {
        ComputeAdaptiveTriggerMatch()
        ComputeMotivationalTriggerMatch()
}
…..
```

5 Framework Implementation and Experimental Procedure

To evaluate the effectiveness of our proposed framework, a prototype application called memory load and performance model (MLPM) was developed and tested for 30 days at Kohat University of Science and Technology, Kohat, Pakistan. The main objective of the experimental study was to reveal whether adaptive and motivational triggers persuade, guide, and motivate students in increasing their learning performance.

5.1 Implementation

For this pilot study, 80 undergraduate students participated which further were divided into two independent groups i.e., the control group having 40 students and the experimental group having 40 students. The control group received normal learning content independently of their learning behavior, preferences, and performance whereas, on the other hand, the experimental group received the learning material according to their need, preferences, and performance. Before carrying out the experimental study, a brief 20-minute tutorial was presented to all participants regarding the working of the MLPM system. The MLPM system was able to run both on the Android platform and the web. Over time the control group received normal learning content and no adaptive and motivational triggers were presented to them on their cell phones whereas the experimental group received tailored learning material and motivational/adaptive triggers were presented to them on their cell phones for guidance and needed help.

5.2 Results and Discussion

Throughout the experimental study, we were interested in knowing the difference in performance between the two groups after using the MLPM system and how much the MLPM system helped make the learning process engaging and helpful. After 30 days, a posttest was piloted for both control and experimental groups which revealed that the MLPM system was successful in improving the performance of the experimental group. The significant (2-tailed) P-value for the posttest was 0.0034 (<0.05), which shows a significant difference between the mean performance score of the experimental group and the control group at a 5% significance level. The posttest result demonstrated that the learning performance of the experimental group was better than that of the control group.

To determine the effectiveness of the MLPM system, an updated version of the End-User Computing Satisfaction (EUCS) model questionnaire was realized. Using Google forms, an online EUCS survey was conducted with 40 experimental group participants. Using the EUCS, six dimensions of the MLPM system namely ease-of-use, timeliness, usefulness, engagement, adaptiveness, and attitude towards using MLPM were measured. The mean score for all of their perimeters was greater than 4 (out of 5) which asserted that overall the experimental group students were satisfied with the use of the MLPM system and will use a similar type of system in the future.

6 Conclusion, Limitations, and Future Work

The online learning environment offers plenty of opportunities for economical and reasonable e-commerce businesses. Instructors and students do not need to search for the physical stores and do not have to consume a generous amount of money on its setup. However, in the online learning environment, it is crucial to know students' preferred learning content to provide necessary guidelines and feedback.

In this study, we presented a smartphone-based learning framework that considers students' academic performance and memory load capabilities before recommending them meaningful motivational and adaptive triggers. Students' preferred learning material types, memory load, and academic performance are identified first, and then adaptive and motivational triggers are presented to them on their smartphones. Any university or college that is interested in keeping their students up-to-date and motivating and helping them in their learning process can implement this framework in their online software system like LMS.

In the future, our focus will be on priority orders of different adaptive triggers. Further, we will work on finding the opportune time i.e., the right time on which the adaptive and motivational triggers should be presented to students. We will also try to work on additional suggestions and adaptive learning activities that can help students in improving their learning behavior.

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