Emotional Impact for Predicting Student Performance in Intelligent Tutoring Systems (ITS)

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Abstract—**Current Intelligent Tutoring Systems (ITS) provide better recommendations for students to improve their learning. These recommendations mainly involve students' performance prediction, which remains problematic for ITS, despite the significant improvements made by prediction methods such as Matrix Factorization (MF). The present contribution therefore aims to provide a solution to this prediction problem by proposing an approach that combines Multiple Linear Regression (Modelling Emotional Impact) and a Weighted Multi-Relational Matrix Factorization model to take advantage of both student cognitive and emotional faculties. This approach takes into account not only the relationships that exist between students, tasks and skills, but also students' emotions. Experimental results on a set of pedagogical data collected from 250 students show that our approach significantly improves the results of Student Performance Prediction.**

Keywords—*Intelligent tutoring system; student performance prediction; matrix factorization; emotional impact; achievement emotions*

I. INTRODUCTION

Computer learning systems, in particular Intelligent Tutoring Systems occupy a preponderant place today. These systems are IT environments that aim to best imitate the behavior of a human tutor in his capacity as a field expert and educational expert. Current researches are based on some domains such as student modelling in general and student performance prediction in particular. Let's mention that the student performance prediction in learning systems remains a major research issue because it predicts its performance for different skills over time [1]. In addition, it makes it possible to determine the next content to be presented to the student to give continuity to his learning [2]. Indeed, in the absence of a good prediction, presenting students with activities that are too easy for example can limit learning on the one hand, and on the other hand, presenting difficult activities can also lead to a misunderstanding and demotivation that are too strenuous also risk leading to poor understanding and loss of motivation [3].

Therefore, for student adequate learning, it is important that current systems have relevant information or attributes (characteristics) to refine the results of performance prediction. Besides, for a better understanding of the educational paths of students, it is useful not to limit information taking only to cognitive or economic areas, but to also have information on the emotional state of students. The emotion, not being always taken into account in the systems of prediction, it generally leads to less efficient systems. Indeed, for specialists in Educational Psychology and neuroscience such as Immordino-Yang [4], emotions are almost essential at the neurobiological level to create memories, engage complex thoughts or even come to significant decisions. They are important for our physical survival as well as our social or intellectual life [4]. Giving systems the ability to integrate emotional aspect will allow them to better understand the student's needs and to react accordingly. This is, moreover, the objective of the research area in affective computing [5] [6]. Our objective is therefore to provide our model with significant data such as emotion to increase the quality of performance prediction.

This paper is organized according to the following order: Section 2 provides a State-of-The-Art of techniques and attributes used to predict student performance. Section 3 in turn presents classic Matrix Factorization techniques and the emotional data acquisition method used, while Section 4 describes our Multi-Relational and Emotional approach to predicting student performance. Section 5 presents an evaluation of this approach and provides a comparative study of our results with those of State-of-The-Art. Section 6 concludes this paper.

II. STATE-OF-THE-ART

Personalized learning improves not only the learning process itself but also the overall learning outcomes [7] [8]. But this personalization is only possible by adapting the content of the learning and applying a learning strategy adapted to each individual. Also, with regard to current ITS, it is necessary to have, on the one hand, relevant information on student and, on the other hand, to predict his performance at each stage of his learning. A great deal of research on student performance predicting is available in the associated scientific literature. Student performance prediction is carried out according to several attributes and methods. The choice of selected attributes and the choice of methods used are decisive for predicting performance, in precise evaluation frameworks. In [9] [10] [11], for example, authors chose attributes such as internal marks, session marks, admission score and students' activities by applying decision trees. Raheel Asif *et al.,* [10] showed that using this approach, we could achieve a

performance prediction accuracy of around 83.65%. Other authors such as Abu Amra *et al.,* [12] extended the choice of attributes to the student's father work, the student's place of residence, the gender, and the past performances by applying two different types of classification algorithms: K-Nearest Neighbors (KNN) and Naïve Bayes. Experimental results have shown that the Naïve Bayes method is better than the KNN method with an accuracy of 93.6%. Okubo *et al.,* [13] proposed a Recurrent Neural Network (RNN) approach to predict students' final grades from journal data stored in education systems.

Besides, several other studies such as that carried out in [14] [15] [16] rather propose methods of Data Mining making it possible to search for attributes which significantly affect student performance. Shana *et al.,* [14] for example have extracted, by applying two statistical techniques which are Pearson correlation coefficient and Fisher test, attributes such as previous school marks, level of difficulty of the subject, income family and the student's interest in the subject. Havan Agrawal *et al.,* [15] showed on the basis of a Neural Network model that the current students' academic performances depends mainly on their past performances. The authors Haixia Lu *et al.,* [16] proposed an algorithm for characteristics (attributes) selection which uses Pearson correlation coefficient and Euclidean Distance to measure the correlation between characteristics. The selected characteristics include, among others: past marks, number of school absences, student's willingness to pursue higher education, student age, number of past failures. In [17] the authors compare the results of the two classifiers Support Vector Machine (SVM) and KNN on the data set provided by the University of Minho in Portugal, in order to predict student's final grade. The data set concerns students' mathematical performance and consists of 395 data samples. Characteristics selection was done by calculating the correlation between each attribute (33 Attributes in all) and the target variable (which is the final score). Empirical studies results have shown that the SVM algorithm performs slightly better than the KNN algorithm. The author Seifedine Kadry [18] has shown through a linear regression analysis that the independent variables studied: height, weight, IQ score, sex and age of a student have no significant impact on the performance of it. But the revision time has a significant effect on his performance on the exam.

Other studies such as those conducted in [19] [20] have used Matrix Factorization, a technique derived from recommendation systems to predict students' performance. The results of these studies have shown that the use of this technique can improve prediction results compared to regression methods by building on the student's past performance. Other authors have proposed improving this method by exploring multiple relationships that may exist between students, tasks and their metadata using Multi-Relational Matrix Factorization (MRMF) and Weighted Multi-Relational Matrix Factorization (WMRMF) models [21]. In [22] we proposed a Social and Weighted Multi-Relational Matrix Factorization model which integrates not only friendship relationships like group work relationships, but also mutual influence values to favor error reduction in student performance prediction.

It is clear from this literature review that the majority of research has relied mainly on socio-economic factors and on student past skills without taking into account of emotional aspect. That is constitutes the object of our present study.

III. METHODOLOGICAL APPROACH

Our approach combines a Weighted Multi-Relational Matrix Factorization model and a Multiple Linear Regression modelling Emotional Impact. Therefore, this session presents some Matrix Factorization approaches as methods that we will use to describe and compare our proposed approach. In addition, it presents the method of self-assessment of emotions through the concept of Achievement Emotions.

A. Matrix Factorization Approachs

1) Classical Matrix Factorization (MF) approach: Consider a set S of students, a tasks set I, and a range of possible performance scores P. Matrix Factorization consists in approximating a matrix R by a product of two matrices W_1 (Students) and W_2 (Tasks) [22] [23] [24] as described by (1)

$$R \approx W_1 \, W_2^T \tag{1}$$

$W_1 \in \mathbb{R}^{S \times F}$ is a matrix where each line s is a vector containing the F latent factors describing the student s and $W_2 \in \mathbb{R}^{I \times F}$ is a matrix where each line i is a vector containing the F latent factors describing the task i. Let w_{1_s} and w_{2_i} be the respective vectors of the matrices W_1 and W_2 such that their elements are designated by $w_{1_{sf}}$ and $w_{2_{if}}$.

In this method, a student *s* performance in accomplishing a task *i* is predicted by (2) :

$$\hat{p}_{si} = \sum_{f=1}^{F} w_{1_{sf}} \, w_{2_{if}} = w_{1_s} \, w_{2_i}^T \tag{2}$$

$\hat{p}_{si}$ is the predicted performance value.

W_1 and W_2 designate the model parameters and can be learned by optimizing (3) using Stochastic Gradient Descent method as suggested in [25].

$$O^{MF} = \sum_{(s,i) \in R} \left(R_{si} - w_{1_s} \, w_{2_i}^T \right)^2 + \lambda \left(\parallel W_1 \parallel_F^2 + \parallel W_2 \parallel_F^2 \right) \tag{3}$$

The symbol $\parallel . \parallel_F^2$ indicates the Frobenius norm and λ is a regulation parameter [26]. Let e_{si} denote the difference between the real performance value and the predicted performance value for each couple (*Student*, *Task*). the prediction error is given by (4) :

$$e_{si} = \left(R_{si} - w_{1_s} \, w_{2_i}^T \right) \tag{4}$$

2) Multi-Relational Matrix Factorization (MRMF) approach: Unlike the MF model, the MRMF model refers to

N types of entities $\{E_1,...,E_N\}$ connected by M types of relationships $\{R_1,...,R_M\}$ that can be strongly correlated with each other. Let $W_1, W_2,...,W_n$ ($n \in N$), be the latent factor matrices (designating the parameters of the model) of each of entity types. Equation (3) thus becomes (5) [26] [21] [27]:

$$O^{MRMF} = \sum_{r=1}^{M} \sum_{(s,i) \in R_r} \left(R_{r_{si}} - w_{r1_s} w_{r2_i}^T \right)^2 + \lambda \left(\sum_{n=1}^{N} \| W_n \|_F^2 \right) \tag{5}$$

With $R_r = \{(E_{1r}; E_{2r})\}(r = 1...M)$

3) Weighted Multi-Relational Matrix Factorization approach (WMRMF): The WMRMF model incorporates a weight factor which gives the importance of one relation compared to another.

Equation (5) thus becomes (6) [21] [27] [28]:

$$o^{WMRMF} = \sum_{r=1}^{M} \Theta_r \sum_{(s,i) \in R_r} \left(R_{r_{si}} - w_{r1_s} w_{r2_i}^T \right)^2 + \lambda \left(\sum_{n=1}^{N} \| W_n \|_F^2 \right) \tag{6}$$

With:
$$\Theta_r = \begin{cases} 1, & \text{if } r \text{ is the main relation} \\ \theta, & si \ (0 < \theta < 1) \end{cases} \tag{7}$$

The model parameters are updated through (8) and (9).

$$w'_{r1_{sk}} = w_{r1_{sk}} + \beta \left(2\Theta_r e_{r_{si}} w_{r2_{ik}} - \lambda w_{r1_{sk}} \right) \tag{8}$$

$$w'_{r2_{ik}} = w_{r2_{ik}} + \beta \left(2\Theta_r e_{r_{si}} w_{r1_{sk}} - \lambda w_{r2_{ik}} \right) \tag{9}$$

The parameter β designates the learning rate.

B. Achievement Emotions

In our Multi-Relational approach, we suggest taking into account the possible emotions felt by students during the evaluation sessions. The consideration of emotions suggests, beforehand, the choice of a category of candidate emotions and the choice of a method of emotional detection.

In context of emotions candidate selection, several research studies have generally focused on those related to learning but in particular on those related to learning evaluation [29] [30]. The aim of this work was, through theoretical and statistical studies, to research different emotions that are aroused in a learning context.

In this study, we based on Pekrun's [31] control-value theory of achievement emotions.

The theory proposed by Pekrun strives to provide an integration framework for analyzing the antecedents and effects of emotions experienced in achievements in an academic environment. These emotions are also called achievement emotions. They occur in different academic contexts such as taking courses, studying and taking tests / exams [32]. Achievement emotions are considered to be emotions directly related to achievement activities and / or achievement outcomes [33] [29]. These activities refer to tests, assignments and performances both in examination conditions

and as mere tasks, whereas achievement outcomes refer to for instance grades and scores [34]. Empirical evidence from Pekrun's theory indicates that achievement emotions have three dimensions [34]:

- Valence (positive / pleasant versus negative / unpleasant);
- Activation (activation versus deactivation);
- Focus on the object (activity versus outcome).

The control-value theory of achievement emotions considers the emotions like sets of interdependent psychological processes, according to which the affective, cognitive, motivational and physiological components are of first importance [32].

In our approach, due to the complexity of emotion detection linked to the test, we used the self-assessment method based on Achievement Emotions Questionnaire (AEQ) to detect students' emotions. The AEQ was developed by Pekrun and his colleagues [32]. It is a self-assessment tool for measuring students' emotions in school situations. The instrument, in its final version, consists of 24 emotion scales which are organized into three sections evaluating both class-related, learning and test-related emotions [32]. The AEQ is made up of 232 items that measure eight different emotions related to the class, eight emotions related to studying, and eight emotions to writing tests and exams. A 5-point Likert scale (1 for completely disagree and 5 for completely agree) is used to assess the emotional experiences of students. The emotional scales related to the test include 77 items and the instruction asks students to indicate what they feel in terms of enjoyment, hope, pride, relief, anger, anxiety, shame, and hopelessness related to the test. These eight emotional scales are those chosen by our approach.

IV. PROPOSED PREDICTION APPROACH

In this section, we present our approach or predicting student performance that takes into account student's emotional state. Fig. 1 presents, in entity-association diagram form, the information taken into account by our model.

A. Problem Formulation

The student performs a task by associating a performance score and the emotions associated with the execution of the task (emotions recovered using the AEQ).
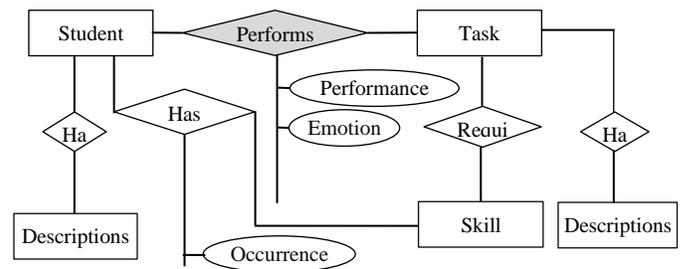
Fig. 1. Entity-Association Diagram for Predicting Student Performance.

Solving correctly the task, student must know specific skills, and task itself is also associated with the skills to be

learned by student. The attribute "Occurrence" gives the number of times student has learned the skill.

B. Emotional Influence Formulation ε_{si}

We hypothesize that any task accomplishment is always accompanied by one or more well-given emotions. We adopt the principle that a student's performance depends not only on their intrinsic abilities (cognitive abilities), but also on his emotions experienced impact.

Note ε_{si} , the emotional impact on the student's performance in completing task *i*. In our approach, ε_{si} is defined as a Multiple Linear Regression model which establishes a linear relationship with the different test emotions of AEQ, relative to task *i*. The different values taken by ε_{si} are reals included in interval $[-1;1]$. The different coefficients are elements of matrix $\alpha = (\alpha_1, \alpha_2, ..., \alpha_8)$. The different variables are elements of matrix $e = (e_1, e_2, ..., e_8)^T$. These elements are respectively the intensities of the eight scales of emotions linked to the test which are: enjoyment, hope, pride, relief, anger, anxiety, shame and hopelessness, and are collected using of the AEQ. Table I presents the different variables and descriptions of variables as proposed.

The different values $e_1, e_2, ..., e_8$ are easily obtained using AEQ. So, we formulate model ε_{si} as follows:

$$\varepsilon = \alpha.e + \alpha_0 \qquad (10)$$

The model ε_{si} was developed on the basis of data collected during the AEQ survey. Unlike the work done in [21], we consider emotion as an additional entity type. Indeed, the relation « *Student – Performs – Task* » does not only take into account performance, but also the possible associated emotions and their valences (Fig. 2).

This relationship generates two matrices: the performance matrix and the emotional impact matrix. The emotional impact matrix has the same dimension as the performance matrix as shown in the example in Fig. 3. In this example, we notice that student S_4 performed task T_5 by obtaining the score of 1. The emotional impact factor on performance, on task T_5 completion is $\varepsilon_{45} = 0.8$. We consider this value as the contribution of emotions to task T_5 achievement. This contribution can either favor task accomplishment, or disadvantage it.

TABLE I.   VARIABLES DESCRIPTION IN MODEL ε_{si}

Variables	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8
Intensity of :	Enjoyment	Hope	Pride	Relief	Anger	Anxiety	Shame	Hopelessness
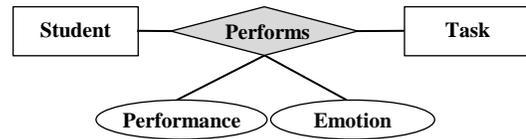
Fig. 2. Relation « Student – Performs – Task ».

In our approach, we combine model ε_{si} with the MRMF and WMRMF models, through the iterative algorithm 1.

Fig. 3. Performance Matrix (P) and Emotional Impact Matrix (ε)

To determine optimal parameters $W_1, W_2, ..., W_n$ of this approach, we proposed the iterative algorithm 1 below using a Stochastic Gradient Descent.

Algorithm 1

Input

N : *number of entities;* M : *number of relations ;* F : *number of latent factors ;* R_r : *for each relations ;* θ : *weight ;* λ : *regulation term ;* β : *learning rate ;* K : *Latent factors.* α_1 , α_2 , α_3, α_4 , α_5 , α_6 α_7 , α_8 : *respectively emotions Enjoyment, Hope, Pride, Relief, Anger, Anxiety, Shame and Hopelessness factors.*

Output

$\{W_j\}_{j=1...N}$: *latent factor matrices for each entity j*

1.   Initialize W_j for each of the N entities using $N(\mu, \sigma^2)$

2.   Initialize Θ_r for each of the M relations

3.   Initialize ε_{si} via (10)

4.   **While** (Stopping criterion is not met) **do**

5.   **for** each relation $R_r = \{(E_{1r}; E_{2r})\}$ in $\{E_1, ..., E_M\}$ **do**

6.   **for** $s = 0$ to number of rows-1 of R_r **do**

7.   **for** $i = 0$ to number of rows-1 of R_r **do**

8. $e_{si} = R_{si} - \hat{p}_{si}$

9.   **for** $k = 0$ to K-1 **do**

10. $W_1[s][k] \leftarrow W_1[s][k] + \beta\left(2\Theta_r e_{si} w_{r2_{ik}} - \lambda w_{r1_{sk}}\right)$

11. $W_1[s][k] \leftarrow W_1[s][k] + \beta\left(2\Theta_r e_{si} w_{r2_{ik}} - \lambda w_{r1_{sk}}\right)$

12.   **end for**
13.   **end for**
14.   **end for**
15.   **end for**
16.   **end while**
17.   **Return** $\{W_j\}_{j=1...N}$

This algorithm proceeds first by initializing the parameters from the normal distribution $N(\mu, \sigma^2)$, taking for expectation $\mu = 0$ and for standard deviation $\sigma = 0.01$. Numerical

simulation through Algorithm 1 also makes it possible to determine the optimal values of matrix $\alpha = \left(\alpha_1, \alpha_2, ..., \alpha_8\right)^T$ parameters. These values are also those which minimize (6).

V. EVALUATION OF PROPOSED APPROACH

In this section, we evaluate our proposed approach in order to show its effectiveness in reducing errors in student performance prediction. We also perform tests to compare our approach performance with certain methods in the literature.

A. Participants and Procedure

To evaluate our emotional modelling approach and study the effect of taking emotion into account in student performance prediction, we carried out studies on upper secondary learners of general education, enrolled in class of Terminal at Lycée Moderne Khalil (Daloa, Côte d'Ivoire). The data were collected by means of the questionnaire distributed to the voluntary student to participate in this research. The sample consisted of 250 students (80 girls with an average age of 16; and 170 boys with an average age of 17). These students were assessed during exams in several disciplines: Mathematics, French, English, History and Geography, Philosophy and Biology Science, for the 2019 - 2020 school year from January to February. The questionnaire was filled out several times for each test in the exam. For our model evaluation, we used the eight emotion scales linked to the AEQ tests. These scales are composed of four emotions with positive valence and four emotions with negative valence.

B. Results and Discussion

We implement two types of models. The first is a Multi Relational and Emotional model noted Emo-MRMF and the second is a Weighted Multi Relational and Emotional model noted Emo-WMRMF. For the evaluation, we reduced the model ε_{si} to three scales of test emotions: Enjoyment, Hope and Anxiety. Indeed, positive activating emotions such as enjoyment and hope can lead to better performance results [35] while negative emotions such as anxiety can lead to poorer performance results when triggered [36]. In [30] [37] the authors have shown that positive emotions such as enjoyment and hope are generally positively correlated with test scores and results. The scale model looks like this:

$$\varepsilon_{si} = \alpha_0 + \alpha_1 e_1 + \alpha_2 e_2 + \alpha_6 e_6 \tag{11}$$

The working environment used for simulations is a 64-bit operating system computer, 8GB of RAM, intel Core i7. The Algorithm 1 development was done in Python language.

To compare our Emo-MRMF and Emo-WMRMF approaches to the MF, MRMF, WMRMF, Global Average, Item Average and User Average methods, we used the RMSE (Root Mean Squared Error) metric. This metric is calculated as follows:

$$RMSE = \sqrt{\frac{\sum\limits_{(r,s,i)\in D^{test}} \left(p_{si} - \hat{p}_{si}\right)^2}{\left|D^{test}\right|}} \tag{12}$$

For referencing, we report the best hyperparameters that we found via cross-validation in Table II.

The experimental results presented in Fig. 4 show that our Emo-MRMF and Emo-WMRMF approaches significantly improve the MFMF and WMRMF approaches by taking into account multiple relationships and the emotional impact factor. The Emo-WMRMF model gives very good results in terms of RMSE reduction compared to simulated comparative methods. Our results show the importance of taking into account emotions in the field of learning in general and in particular in the prediction of student performance. These results also show that emotions have an influence on cognitive abilities such as problem solving and decision making as suggested by Lois Isenman [38]. These results demonstrate the robustness of Multi Relational Matrix Factorization models to ingest a variety of information and relationships.

TABLE II. OPTIMIZING HYPERPARAMETERS

Methods	Parameter
MF	$K = 2$; #iter $= 320$; $\beta = 10^{-3}$; $\lambda = 0.15$
MRMF	$K = 2$; #iter $= 320$; $\beta = 10^{-3}$; $\lambda = 0.1$;
WMRMF	$K = 2$; #iter $= 320$; $\beta = 3.10^{-3}$; $\lambda = 75.10^{-4}$; $\theta \in \{1.0; 0.80; 0.70\}$
Emo - MRMF	$K = 2$; #iter $= 320$; $\beta = 10^{-2}$; $\lambda = 55.10^{-3}$; $\alpha_1 = 14.10^{-3}$; $\alpha_2 = 22.10^{-3}$; $\alpha_3 = -33.10^{-3}$, $\alpha_0 = 0$
Emo-WMRMF	$K = 2$; #iter $= 320$; $\beta = 3.10^{-3}$; $\lambda = 15.10^{-4}$; $\theta \in \{1.0; 0.40; 0.80; 0.70\}$; $\alpha_1 = 3.10^{-3}$; $\alpha_2 = 2.10^{-3}$; $\alpha_3 = -3.10^{-3}$; $\alpha_0 = 0$
Emotional Impact	$K = 2$; #iter $= 320$; $\beta = 3.10^{-3}$; $\lambda = 15.10^{-4}$; $\theta \in \{0.7; 1.0; 0.60; 0.40\}$; $\alpha_1 = 5.10^{-3}$; $\alpha_2 = 25.10^{-3}$; $\alpha_3 = -23.10^{-3}$
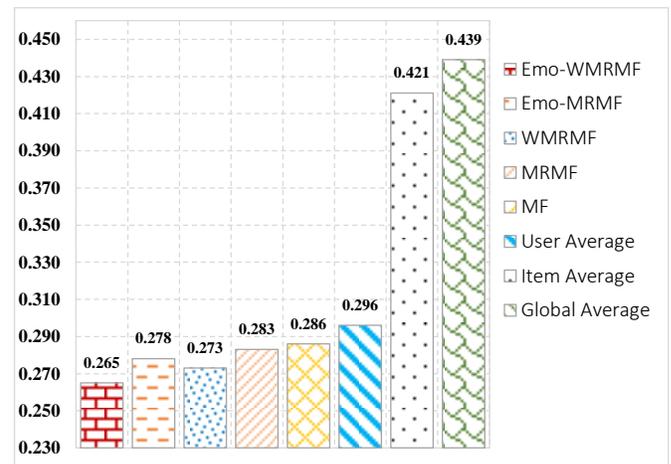
Fig. 4. RMSE Results on our Data Set.

Fig. 5 shows the RMSE results of Emotional Impact factor prediction for different values of parameter iteration. Indeed, the optimization of the model allows, of course, to predict performance, but also to predict the emotional impact of a student *s* when carrying out a task *i*. When the number of

iterations tends to around 320, the RMSE error in predicting emotional impact tends to around 0.232. This reveals the robustness of MF Models to predict all kinds of attributes of the application domain.

Fig. 5 also presents the RMSE evolution of the Emo-WMRMF model. The emotional impact prediction curve decreases rapidly to 80 iteration steps and remains practically constant up to 320. This shows that our model is robust already with an iteration number of 80.
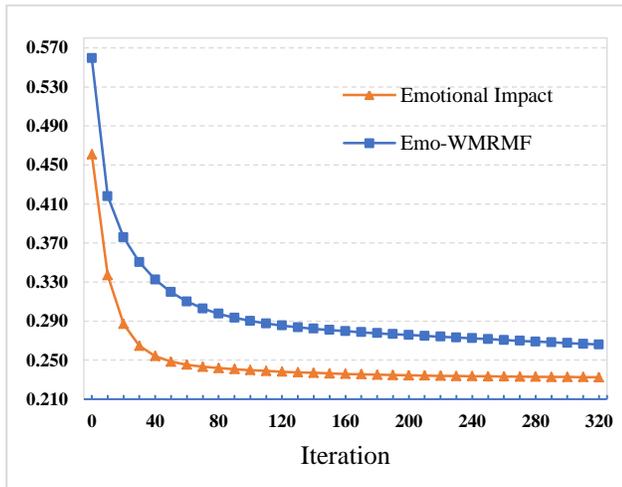
Fig. 5.   RMSE with different Values of Iterations.

VI. CONCLUSION

In this paper, we have proposed an approach which aims at providing a solution to student performance predicting problem in ITS by combining Multiple Linear Regression (modelling Emotional Impact) and a Weighted Multi-Relational Matric Factorization model to take advantage of both student cognitive and emotional faculties. This approach takes into account not only the relationships that exist between students, tasks and skills, but also their emotions. Experimental results on a set of data collected in a general secondary school have shown that our approach makes it possible to more accurately predict student performance.

In future work, we plan to study the impact of the emotional state evolution during assessment sessions and analyze the effect of other emotional scales on student performance prediction results.

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