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Abstract. Awarding gaps have been commonly observed between different socio-demographic categories of students, especially in the domains of sociology and learning science. Recent research has shown that using Learning Analytics models could be exploited to reduce these gaps, and therefore contribute to making the learning process more inclusive and equitable. This demonstration paper presents CERSEI, a new web-based learning prototype that aims to enhance inclusiveness by exploiting two Learning Analytics models: a cognitive effort model and an activity recommender built upon the cognitive effort model. Previous research has indeed shown a strong interplay between socio-economic status, effort and motivation, e.g., families from higher socio-economic status tend to mobilize more resources to prevent their children from falling down the social ladder. Some categories of students might therefore have fewer sources of motivation and exert less effort, or a higher tendency to exert effort on specific activities that are not the most relevant for succeeding. CERSEI allows students to track their effort by assigning ratings on their activities using the RSME scale and to receive engaging recommendations of learning activities. This will allow us to collect the relevant data to better understand how effort is exerted by different categories of students and how recommendations can impact them. Based on the outcomes of the related analysis, we will then aim at creating better Learning Analytics models. We expect that these models will help to provide more inclusive and equitable learning.

Keywords: Cognitive Effort · Activity Recommendation · Inclusiveness

1 Introduction

According to research, students from privileged backgrounds generally have a greater chance of success compared to their underprivileged peers [1, 2]. The phenomenon of different socio-demographic groups having different learning outcomes is generally referred to as the awarding gap [3], also called achievement gap [4]. One means of reducing this gap is to exploit the potential of Learning Analytics models. Recently, Hlosta et al. [5] studied the effects of asking teachers to contact students based on predictions from a Learning Analytics model that indicated which students were likely to fail. Using this method increased the learning success of ethnic minority students by 10% and that of students from low IMD (Index of Multiple Deprivation) band by 4%.

We believe that effort modeling is one very promising Learning Analytics approach towards that goal, especially because effort and motivation have been found to be particularly important factors of the success of students from privileged backgrounds [2]. The underlying hypothesis, called compensatory advantage hypothesis, states that the achievement gap is stronger among students with a lower ability and can be explained in terms of effort and motivation, i.e., students from a privileged background tend to exert more effort and to have more sources of motivationt [6]. Providing students with a means to give feedback about their effort and receive effort-based educational recommendations could therefore contribute to reduce this gap.

We therefore developed CERSEI (Cognitive Effort based Recommender System for Enhancing Inclusiveness), a learning platform that allows students to assign effort ratings to the activities they complete on a Virtual Learning Environement (VLE) and to receive effort-based recommendations. More precisely, students can use CERSEI to keep track of the effort they exerted on previous activities and to estimate how much effort they think would be required for them to complete the next available activities. Based on these ratings and on students' behavioural data (mouse and keyboard usage, page views, submitted work, etc.), the platform computes predicted effort ratings and provides activity recommendations that the students can choose to accept or reject. When they accept, they are directed to a local Moodle-based VLE deployed on the same server on which they can perform the corresponding activity and submit their work.

From a research point of view, CERSEI allows us to collect behavioural data and subjective effort ratings that can be used to train our effort model. The first version of our effort model is built upon the work of Moissa et al. [7], which focused on modelling students' cognitive effort using similar learning data collected during 45-minute series of activities. The study demonstrated the relevance of using mouse and keyboard usage data as a means of measuring and predicting the effort, and the even higher relevance of also incorporating longer-term past student data as input of the models, i.e., mouse and keyboard usage data from previous activities.

Overall, our goal is to test the hypothesis that the effort is different for different categories of students (as indicated previously in the literature), to have a better understanding of how different categories of students exert effort while learning, and to have a better understanding of the extent to which engaging recommendations of learning activities can be useful depending on the categories of students. As a first step however, we are currently preparing a pre-study to assess the usability and design of the platform, and to make sure it is fully functional, especially in terms of data access. This process includes applications for ethical and data privacy approvals from our university, which are currently being conducted. A separate study will be made in a future work, which will be built upon the results of the pre-study.

2 Overview of CERSEI

CERSEI takes the form of a web platform that can be linked to a VLE to connect students' learning data to our effort model and recommender system. The platform has three main functionalities: (1) Online Activities, (2) Effort Tracking and (3) Activity Recommendations.

2.1 Online Activities

In order to have a pool of activities that can be used as recommendations by the recommender system, CERSEI includes a simple Moodle-based learning environment on which activities can be created by teachers. Students can then access these activities and submit their work using the Moodle online interface. Currently, the platform only contains a few initial activities for the purpose of evaluating the usability of the platform. These activities are related to the topic of web technology, and go from short HTML and CSS exercises to the development of advanced PHP and JavaScript applications.

While students perform these online activities, their behavioural data is recorded (mouse and keyboard usage). These data are then used by our effort model to predict effort ratings of future activities. These activities can be accessed from the different views of the platform related to effort tracking and activity recommendations, which are presented next.

2.2 Effort Tracking

CERSEI categorizes the activities that the student can perform according to two dimensions: the type of learning environment (the VLE to which CERSEI is linked, or CERSEI itself) and the completion of these activities (whether an activity was completed or not). In other words, four views are related to effort tracking: (1) Completed from VLE, (2) Remaining from VLE, (3) Completed from CERSEI and (4) Remaining from CERSEI, see Figure 1. Initially, all VLE activities are in the second category, and all activities from CERSEI are in the fourth category. Each time an activity from the VLE is completed, it becomes visible in the first category, and each time an activity from CERSEI is completed it becomes visible in the third category.

Students can use these views to provide effort estimates for remaining activities, and perceived effort rating for the completed ones. Both types of ratings can be changed or removed any time. When no ratings have been provided by a student to an activity, the value predicted by our effort model is displayed instead. The platform therefore handles three types of effort ratings: estimated

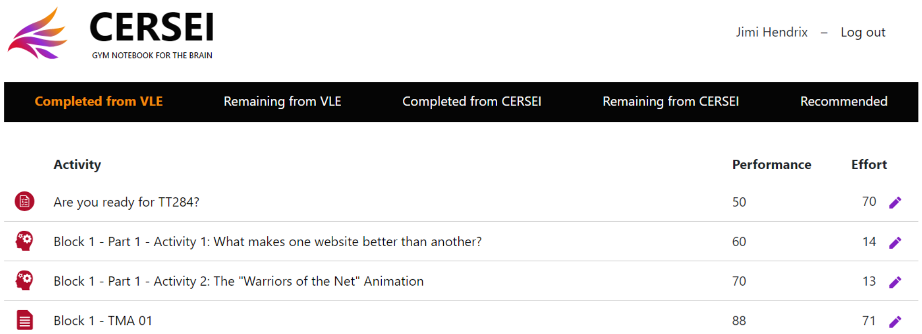

Fig. 1. The different views of CERSEI. Students can click on the pen icons to change the effort ratings and the individual activity links to access them either on the VLE or on the local Moodle.

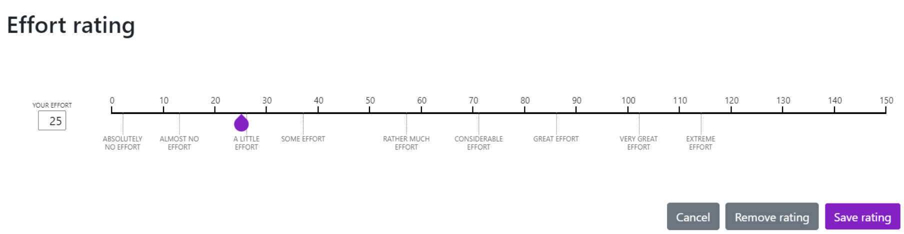

Fig. 2. The RSME modal window used to assign ratings. The modal window appears when students click on the pen icons from the effort tracking views and allows them to assign, change or remove their ratings.

ratings, perceived ratings and predicted ratings, which are all stored separately in our database. Making this distinction is important because some low effort tasks may seem to require a high effort and vice versa, which could have an impact on the acceptance of recommended activities.

All estimated and perceived effort ratings are assigned by students using the RSME, see Figure 2. This instrument provides students with a scale from 0 to 150 on which several verbal labels were precisely positioned based on a user study [8]. Compared to the more widespread NASA-TLX instrument [9], it is similar to the "Effort" dimension of the instrument, but has the advantage of being precise in terms of intervals between the labels. Predicted ratings are currently computed based on the effort model from Moissa et al. [7].

2.3 Activity Recommendations

The last view of the platform is dedicated to activity recommendations. Recommendations are displayed in a relatively large box that contains a precise description together with an illustration. Students can either accept the recommendation, in which case they are directed to the corresponding online Moodle interface, or reject the recommendation, in which case, the decision is simply recorded in the database.

The recommendations are computed based on the effort based model and use of a technique from the domain of social psychology called the foot-in-the-door. The idea is to first make recommendations of activities that require a low effort, and if these activities are accepted and completed, to make a subsequent recommendation of a similar activity[4] that requires a comparably high effort. This technique seems particularly relevant for educational purposes because it is compatible with the the zone of proximal development [10], which states that activities should increase the challenge little by little.

3 Pre-study

We are currently preparing a user study to assess the usability and design of the first version of the platform using the AttrakDiff questionnaire[5]. We are recruiting students of the current presentation of a module on Web technologies from our university. The learning data of the student will be sent to our servers once a day, and will be used to determine the list of activities the students have completed and the ones they still have to complete.

The study will start in May 2023 and will last until June 2023. The main axes of the experimental protocol are the following:

- Step 1: The student accesses the platform and creates an account
- Step 2: The student provides effort ratings to 20 - 30 of his previously completed VLE activities
- Step 3: The system provides the student with a first low effort recommendation
  - Step 3a: The student assigns an estimated rating (how much effort will be required)
  - Step 3b: The student accepts or rejects the recommendation
  - Step 3c: If the recommendation is accepted and completed, then the effort rating is refined by the student
- Step 4: The system provides the students with a second higher effort recommendation
  - Step 4a: The student assigns an estimated rating (how much effort will be required)
  - Step 4b: The student accepts or rejects the recommendation
  - Step 4c: If the recommendation is accepted and completed, then the effort rating is refined by the student
- Step 5: The student answers the AttrakDiff questionnaire.

[4] Currently, the similarity between the activities is a simple cosine similarity based on their meta-data and text content.

[5] https://www.attrakdiff.de/index-en.html

4 Conclusion

The current version of CERSEI is able to be connected to the VLE of a university, and allows students to track their effort and receive activity recommendations. At this stage, our models are still relatively rudimentary, as our current goal is only to assess the usability and design of the platform.

In future work, we will undertake a larger study with a much higher number of students from the next presentation of the same module. The number of students who register each year to this module is around 1,500. We hope that more than 300 students will participate, which will allow us to collect a high amount of effort ratings. We will also collect socio-demographic data from the data repository of the university and will study how effort is exerted by different categories of students and how recommendations can impact them. Based on the outcomes of the related analysis, we will then propose different effort models that we will test using the usual offline information retrieval methodology. Subsequently, we will use the best-performing model to study different aspects related to our recommender system, such as the influence of the elapsed time between consecutive recommendations and of different effort gap values between subsequent recommendations.

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