

# Toward Embedding Robotics in Learning Environments With Support to Teachers: The IDEE Experience

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**Abstract**—Nowadays, there is an increasing interest in using different technologies, such as educational robotics in classrooms. However, in many cases, teachers have neither the necessary background to efficiently use these kits nor the information about how students are using robotics in classroom. To support teachers, learning environments with robotics tools should monitor the students' interaction data while they are interacting with the different resources provided. With the analysis of this data, teachers can obtain valuable information about students' learning progress. In previous work, we presented integrated didactic educational environment (IDEE), an integrated learning environment that uses robotics to support physics laboratories in secondary education. Students' interactions with IDEE are stored and analyzed using the additive factor model to show the teachers the most significant skills in the learning process and those students who have difficulties with these skills. Now, our goal is to enhance the information given to the teachers to allow them to focus on the specific needs of each student on every different skill involved in the activities and not only the significant skills. To this end, we use a conjunctive knowledge tracing model based on a hidden Markov model. In this article: first, we describe how the CKT model has been adapted to the pedagogical model of IDEE, second, we show that this model can identify the skills that each student masters, and thus, support teachers in identifying learning criticalities in students.

**Index Terms**—Computer-assisted instruction, intelligent tutoring systems, learning environments, science, technologies, engineering and mathematics (STEM).

## I. INTRODUCTION

**I**NTegrating new technologies in classroom implies changes in the traditional teaching paradigm. Nowadays, students are expected to follow their paths and pace of study. Among the so-called new technologies, robotics is gaining more prominence in education. Real-world problems can inspire and motivate students [1] and educational robotics is a suitable approach to apply STEM methodology in classrooms [2], [3], [4], [5], [6]. With the increased use of educational robotics, it has been noticed the importance of computational thinking in

education [7], [8]. A trend in the research area of educational systems is the development of learning programming environments, which make the programming tasks more friendly to beginner students [9].

However, the introduction in traditional classes of new technologies is not effortless as it opens new challenges that have to be addressed and solved to help teachers in exploiting their advantages:

- 1) classes are transformed into unstructured learning environments;
- 2) teachers do not feel secure in the management of their classes;
- 3) the technological tools are not easy to use by the teachers and the activities are often not adapted to the learning curriculum contents [10], [11];
- 4) teachers find difficult to assess their students because they lack information about each student's learning path [12], [13].

Nowadays, it is more evident that there is a need to adapt learning platforms to the educational context by providing the necessary tools for teachers to evaluate the learning process of their students. For example, with Google Classroom,<sup>1</sup> teachers can create automatic correction tests. However, these tools are limited when students work on exercises involving different contents and skills. Since educational resources are usually based on multiple skills, the goal should be to analyze students' progress in each skill involved in the educational activities.

To address this issue, web-based learning environments store students' interactions to be further analyzed in order to obtain the performance, the level of knowledge in the concepts of the course or the main mistakes and difficulties. This analysis is performed by using techniques from the research area of educational data mining [14]. Nevertheless, these learning environments do not usually use peripheral tools (e.g., robotics) or their use is isolated from the curriculum [11]. In these cases, data about students' interactions with the robotics artifacts are not gathered nor analyzed. This fact prevents the analysis of students learning progress in educational activities using robotics. The analysis of the whole learning process of the students, when they interact both with robotics and activities within the learning environment, may help teachers in the assessment of the learning process [15], [16].

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<sup>1</sup>[Online]. Available: <https://support.google.com/edu/classroom>

To this end, we have implemented integrated didactic educational environment (IDEE) [17], [18], a web-based learning environment specially designed to be used in classroom to help teachers in physics classes with the support of robotics. IDEE aids teachers by offering information about the students learning progress [18]. This information is obtained by analyzing students' interaction data using the additive factor model (AFM). This model analyzes the difficulties of students only on significant skills. However, in IDEE, the exercises proposed are based on multiple skills, and it would be advisable to analyze students' performance in any skill involved in the learning activities. To fulfil this objective, in this article, we show how to enrich the information provided to the teachers by using the conjunctive knowledge tracing (CKT) model [19].

The rest of this article is organized as follows. In Section II, we review some related work about the application of new technologies in education and learning process analysis. An overview of IDEE is given in Section III. Section IV describes the data analysis of students' interactions with IDEE using the CKT model. The results obtained are shown in Section V. Finally, Section VI concludes this article.

## II. RELATED WORK

The digitalization of the didactic processes and the use of learning environments and technological tools allow us to obtain data about how students carry out the activities proposed by the teacher. The analysis of this data provides valuable information about the learning process, such as, for example, what concepts appear more difficult to the students [20], [21].

The research area of educational data mining and learning analytics offers methods to analyze data collected by learning environments. This analysis helps us to better understand the learning outcomes of student engagement [14], [15].

For example, machine learning techniques have been used to analyze data collected in programming activities to help teachers to predict students' performances in a block-based programming environment [22]. Recent temporal patterns in conjunction with support vector machines and logistic regression are used for early prediction of students' success or difficulties in open programming problems [23]. Unsupervised clustering techniques are applied to automatically identify students' programming abilities [24]. A  $k$ -means algorithm is used to analyze the data generated by the clicks of the students in scratch to classify their learning in the programming activities [25]. Logistic regression is also used to assess students learning in massive open online courses [26].

Learning analytics are widely used in online learning environments with different goals. For example, educational data analysis is used for self-reflection [27], as support to teachers [28], or to build dashboards to support collaborative learning [29].

When using external educational artefacts (such as robotics), actions done by the students are usually observed and registered manually by humans or are automatically recorded and analyzed by video taping. The features considered are called observables. Several drawbacks may arise when dealing with observables, such as subjective inferences [30].

Thus, it is advisable to gather all this data automatically [15]. For example, researchers have presented how to gather different students' problem-solving pathways when using the EV3 Lego Mindstorms robot by a modified version of the software in the EV3 Lego brick [16]. These data are further analyzed using the  $k$ -means algorithm for clustering the different problem-solving pathways. Nevertheless, the learning path analysis when robotics environments are used in other subjects (e.g., maths or physics) is still an open issue [31], [32].

Educational data can be analyzed both to obtain useful information about students' learning process and to help the teacher to identify the recovery actions according to the individual needs of the students [33]. For example, machine learning techniques are used to predict students' lack of motivation in early times. This prediction provides the teachers with information regarding students' withdrawal [34]. Unsupervised learning techniques are also used to group students with similar interaction patterns. The groups are shown to class instructors, who can provide some additional recommendations only to the groups they deem appropriate [35]. A systematic review on how learning analytics is being used in online learning environments can be found in [28].

The teacher plays a fundamental role in the teaching-learning process of the students; for this reason, it is essential to provide the teachers with information about how the students are carrying out the activities, as well as on the difficulties and the progress made by each student. To perform this analysis, teachers need tools that are easy to use and whose results are easily interpretable [36], [37]. In particular, graphical techniques help users analyze and understand data [38]. Visual representations allow users to see, explore, and understand large amounts of information at a glance. Dashboards for teachers may also include methods to visualize and inspect predictive models of students' performance built using machine learning techniques [39].

These dashboards proved to be useful as they allow teachers and students to be aware of the learning process [29], [40], [41]. However, in secondary education, neither learning environments nor dashboards for teachers are effectively used in class [18], [27]. To overcome this limitation, we propose IDEE, a web-based learning environment that uses robotics to teach physics in secondary education [18]. In the following sections, we describe how the information given to the teachers can be enriched by the use of a CKT model [19].

## III. IDEE OVERVIEW

IDEE is a learning environment that provides a framework to study learning activities in physics through robotics. In IDEE, students use the EV3 Lego Mindstorms educational kit as the robotic component.

IDEE conforms to the architecture of an intelligent tutorial system described in [42]. This architecture is composed of the following parts (see Fig. 1).

- 1) *Student interface*: It contains the activities shown to the student. The interface of IDEE is composed of different areas (see Fig. 2): statement of the activity, table, and graphic display for students' answers, robot activation

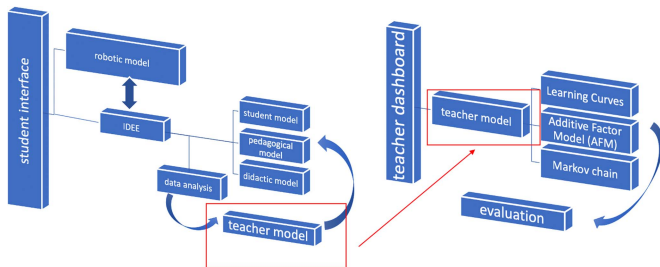


Fig. 1. IDEE architecture.

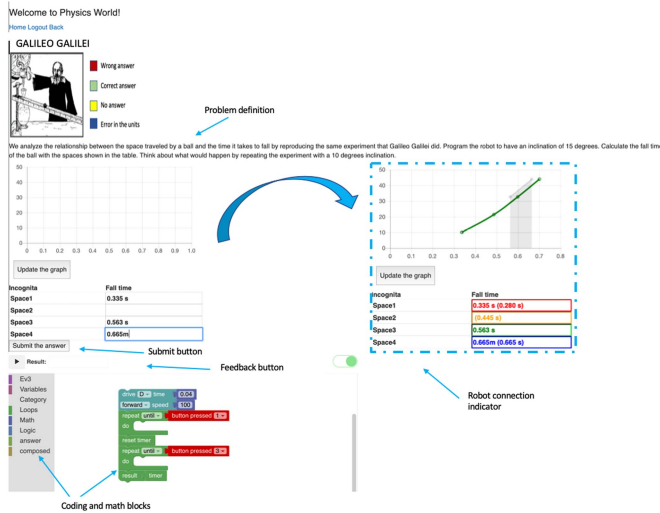


Fig. 2. General Interface and automatic assessment of students' solutions in IDEE.

button, area for data returned by the robot, toolbox with programming blocks, the programming area for students and an evaluation area of the solutions provided by students.

- 2) *Student model*: It represents the level of knowledge of each student and its evolution.
- 3) *Pedagogical model*: It refers to the teaching methodology applied and the way the problem is presented to the student to optimize the learning process. The problems in IDEE are presented according to the level of knowledge of each student stored in the student model. More details about this model are given in the following section. A more complete description can be found in [18]. The concepts that students must acquire are grouped in IDEE into learning units and defined in the didactic model.
- 4) *Didactic model*: In IDEE, the didactic model contains the knowledge about how the experiences are structured in activities. Concepts and skills that students may acquire are defined in this model for each experience and activity. Currently, IDEE contains the following four experiences: *uniform rectilinear motion*, *uniformly accelerated motion*, *inclined plane*, and *free fall*. Each experience is composed of four different activities. In the initial activity, students learn how the robot works. For this, a set of predefined robots are provided, one for each available experience (see Fig. 3). The second activity is a laboratory in which

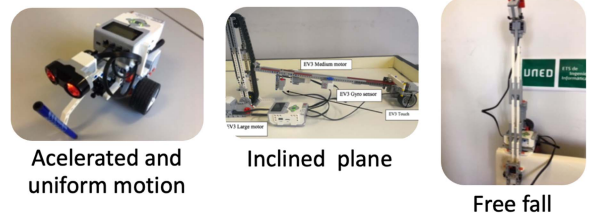


Fig. 3. Predefined robots proposed in IDEE: the robot on the left side of the figure is used for the *accelerated and uniform motion* activity. The robot in the central image is used for the *inclined plane* activity, and the robot on the right side of the figure is used for the *free-fall* activity.

students have to use a block programming language to program an action in the robot (e.g., drop a ball on an inclined plane). During the laboratories, the robot returns certain values needed to solve the activity (for example, the time spent by the ball to roll down the inclined plane). The students have to submit such data to IDEE using its interface. The third activity is a test defined to make students reflect on the physics concepts involved in the experiment. At the end of the experiment, the students have to solve a final problem without using robots to carry out the theoretical analysis of the phenomenon.

Each learning unit is characterized by several skills needed to acquire the contents. These skills may appear in different learning units, and each skill may have different relevance in different learning units. Thus, a skill can be considered as the competence that the students have to acquire when studying a particular learning unit. The relevance of each skill is represented in the didactic model with a parameter called *score*. More details about this parameter are given in the following section.

The skills of the learning units have been defined taking into account both the independence assumption required by the AFM model and our teaching experience. In our experience, some students owned some skills and did not have others. For example, some students, although demonstrating the ability to interpret graphs (skill *graphics interpretation*), did not correctly carry out the activities that required fixing the origin of the motion (skill *reference system*). The skill *graphics interpretation* refers to the ability to interpret plots of mathematical functions and is mainly a mathematical competence. The skill *reference system* refers to the ability to transform physical quantities, such as lengths, times, or weights, into numerical quantities to later work with them as data. This requires the definition of a reference point for the units of measure for all physical quantities in the real environment (e.g., distances). IDEE was created to allow students to develop mathematical, theoretical, and practical skills in the same environment. More examples of skills are *uniformly rectilinear motion* (skill\_13), *relate magnitudes* (skill\_3), and *acceleration* (skill\_9). These skills are related to the *inclined plane* activity.

In Table I, we show some examples of the skills defined for the learning unit of the *kinematic study of movement* [18].

TABLE I  
SKILLS INCLUDED IN THE LEARNING UNIT OF KINEMATIC STUDY OF  
MOVEMENT IN IDEE

Skill	Name
Graphics interpretation	skill_1
Reference system	skill_2
Relate magnitude	skill_3
Operation maths	skill_7
Uniformly accelerated movement	skill_8
Velocity	skill_10
Time	skill_11
Knowledge in robotics	skill_12
Uniform rectilinear motion	skill_13

By working with this learning unit, students should be able to describe the rectilinear motion of a body using the equations that connect space, speed, and time. The contents of this learning unit are *uniform rectilinear motion*, *velocity*, *distance and displacement*, *uniformly accelerated movement*, *free fall*, and *acceleration*. Through the activities included in IDEE, the student can work on the contents of the learning unit.

The skills currently considered in IDEE cannot be modified by the teachers. Nevertheless, although it is not the focus of this article, IDEE allows teachers to create new learning units and their corresponding skills.

Besides, each skill has a different relevance in different activities. Their relevance is represented in the didactic model with a parameter called *score*. This score has been defined and validated by the authors of IDEE. When teachers define new learning units and skills, they have to define their corresponding scores. For example, in the laboratory activity of the inclined plane, the student must calculate the time for a ball to fall on an inclined plane. This activity is related to the following skills: skill\_13, skill\_3, and skill\_9. So, for skill\_13, the value of the parameter score is 10 (representing that this skill is essential in this activity); for skill\_3, the value of the parameter score is 8 (representing that this skill is useful for the student's understanding of the relation between space and fall time); for skill\_9, the parameter score is 5 (representing that students work on this skill but it is not essential in this activity). More details about this parameter are given in the following section.

- 5) *Robotic model*: It allows the communication of the system with the EV3 Lego system.

In IDEE, students interact with the robot using the programming area. The instructions for the robot are coded using programming blocks. To implement the programming area, we used Blockly.<sup>2</sup> Regarding Blockly, our goal is not to teach students programming skills but to let them use the programming blocks to operate with the robot in the experiment. We have developed two new blocks to make the toolbox easier to use. One block is for the communication between IDEE and the EV3 brick and the other one is for the communication between the robot and

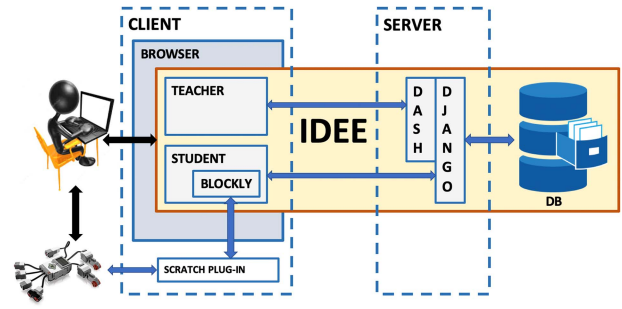


Fig. 4. IDEE architecture.

the system. In particular, the latter is especially important since it avoids the latency time in the communication between the robot and IDEE. It allows maintaining the brick's operating system without additional installations by downloading the program in the brick.

- 6) *Teacher model*: It refers to the analysis of the progress of the student's knowledge. This analysis is shown in the teacher dashboard. The teacher dashboard includes information about the learning process of the students. It serves as an interface between the teacher and the teacher model. Thus, the information stored in the teacher model is shown using different visualizations.

In the following section, it is described an overview of how this analysis is performed by using the AFM, its limitations and how we have enriched it by using the CKT model.

The architecture of IDEE has been implemented using Django<sup>3</sup> for the web infrastructure, PostgreSQL<sup>4</sup> for the database, Dash<sup>5</sup> for the teacher dashboard, Blockly to allow the students to implement programs during the learning activities and a Scratch Plug-in to enable the communication between the Blockly program and the Lego EV3 system through a Bluetooth connection. This architecture is shown in Fig. 4 [18].

#### IV. ANALYSIS OF THE LEARNING PROCESS IN IDEE

##### A. Overview

The student model represents the learning of the student through the skills. Each activity is associated with the skills that the student proves to own when correctly answering. This relationship is weighted through the scores. The student model contains the score accumulated in each skill by the student. Thus, accumulated score allows IDEE to obtain the student's level of knowledge.

When a student gives a correct answer, IDEE determines the value of the *accumulated score* for each skill in the following way [18].

- 1) If the activity is a test, the accumulated score is equal to the score of the skill in the activity.
- 2) If the activity is a problem or a laboratory exercise, the accumulated score ( $AS_{i,j}$ ) for the skill\_i and the student j

<sup>3</sup>[Online]. Available: <https://www.djangoproject.com>

<sup>4</sup>[Online]. Available: <https://www.postgresql.org/>

<sup>5</sup>[Online]. Available: <http://www.dash-project.org>

<sup>2</sup>[Online]. Available: <https://developers.google.com/blockly>



is calculated as follows:

$$AS_{ij} = \frac{n_j}{N_j} * W_i \quad (1)$$

where  $n_j$  is the number of correct answers given by the student  $j$  in the activity,  $N_j$  is the number of total answers in the activity, and  $W_i$  is the score parameter of the skill\_i in the activity.

The analysis of students' progress and the identification of the difficulties faced during the activities, is done using the AFM, see [43]. By the AFM, we obtain a set of significant skills together with those students who had difficulties applying these skills. The teacher can visualize the coefficients of the AFM, namely, a coefficient  $\alpha$  that shows the students' abilities in the skills, a coefficient  $\beta_i$  for each skill\_i that represents its easiness and the coefficient  $\gamma_i$  that indicates the faster students who learned skill\_i. A complete description of how this analysis is performed is described in [18].

Since this analysis does not consider the parameter score and the type of activity in which the student is working (test or problem) in IDEE, an extension of this model has been implemented. This model is called eAFM for *enhanced AFM*. The analysis obtained using the eAFM is shown to teachers with interactive graphs and tables. Thus, teachers can have a global overview of the learning process of their students and identify those skills that are more significant to improve the learning process and require appropriate recovery actions [18].

However, the AFM and the eAFM only identify those skills most significant in the activity. Having this information, teachers have to find by themselves information about students' learning process on the dashboard. This inspection requires a lot of time. To let teachers focus on the critical skills and support students in overcoming their difficulties, it is advisable to directly provide them with information on the students' progress. If a teacher cannot focus the recovery on the essential concepts, all the information on the student's progress could be ineffective.

To help the teacher to focus the recovery action only on the critical skills of each student, a new model based on Bayesian inference has been implemented in IDEE: the enhanced conjunctive knowledge tracing (eCKT) model.

### B. CKT in IDEE

To obtain information on those skills in which students make mistakes, IDEE implements the eCKT model based on the CKT model introduced in [19]. The CKT model is based on the reference *Bayesian knowledge tracing* model [44] and, it allows us to identify the skills mastered by the student and those in which they need to improve. This CKT model uses a hidden Markov model, as shown in Fig. 5. It consists of two hidden states, *skill knowledge* ( $CS$ ) and *no skill knowledge* ( $\overline{CS}$ ).

In the model, there are the following three parameters; a *slip probability* ( $S$ ) (it is the probability that a student is incorrect knowing the skill); a *guess probability* ( $G$ ) (is the probability that a student is correct without knowing the skill), and a *learning transition probability* ( $T$ ) (it is the probability that a student learns in a particular tutoring opportunity). The CKT model considers constant these three parameters. The student's knowledge is given by the probability of being in the state  $CS$ . We

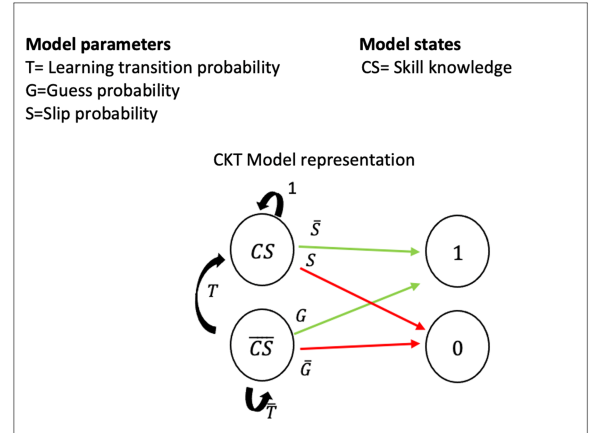


Fig. 5. Representation of the CKT model for a given skill with the descriptions of the parameters and the nodes.

call this probability  $K$  and it evolves according to the student's performance during the activities. When a student participates in an activity, the system obtains an outcome 1 if correct and 0 if error, and it can update, a posteriori, the probability  $K$ . Now, we show how it works in a system with multiple skills (skill\_i with  $i \in \{1 \dots I\}$ ). Assume, for example, that a student makes a mistake, then the probability  $K_i$  where  $i$  refers to the skill\_i is updated according to the following equation:

$$\begin{aligned} P(CS_k/\text{Error}) \\ = P(\text{Error}/CS_k) * P(CS_k)/P(\text{Error}). \end{aligned} \quad (2)$$

The probability of error is calculated as the complement of the probability to be right.

The student can be right, knowing the skill and getting it right, or not knowing it and guessing, therefore, the probability of error is expressed by the following equation:

$$\begin{aligned} P(\text{Error}) &= 1 - P(\text{Correct}) \\ &= 1 - \prod_{i=1}^I [K_i(1 - S_i) + (1 - K_i)G_i]. \end{aligned} \quad (3)$$

The probability of error knowing skill\_i ( $P(\text{Error}/CS_i)$ ) is obtained when either the student makes a mistake about skill\_i or if the student does not make a mistake about this skill but makes a mistake in another skill. This probability is expressed by the following equation:

$$\begin{aligned} P(\text{Error}/CS_i) &= S_i + (1 - S_i) * \\ &\times \left( 1 - \prod_{\substack{j=1 \\ j \neq i}}^I [K_j(1 - S_j) + (1 - K_j)G_j] \right). \end{aligned} \quad (4)$$

A skill is considered acquired by a student if the probability of knowing it is greater or equal to 0.95 [19]. The teacher can inspect, for each student, the learning progress in each skill and decide to support those students that have not acquired certain skills.

TABLE II  
Q-MATRIX OF THE LEARNING PERFORMANCE OF A STUDENT RECORDED IN FOUR ACTIVITIES AND THE RESULTS OF THE CKT MODEL

Activity	Q-matrix			Results CKT	
	skill_1	skill_2	answer	$K_1$	$K_2$
1	1	1	false	0.500	0.500
2	0	0	true	0.843	0.869
3	1	1	true	0.964	0.975
4	1	1	true	0.892	0.975

Equation (2) of CKT model is applied on a binary Q-matrix, which represents the iterations of each student with each skill while performing the proposed activities. As an example, Table II shows the results of the CKT model on a student who has worked on four activities related to skill\_1 and skill\_2. In this case, the student has acquired knowledge about the skill\_2 but needs to improve on the skill\_1.

### C. Adaptation of the CKT Model to the IDEE Cognitive Model

The pedagogical model included in IDEE represents the goals of the learning units with multiple skills and considers the relevance of each skill in the proposed activities with the score parameter. The CKT model takes into account the student's interactions with the different skills without considering the relevance of each skill. The improved model considers the relevance of the skill by the score parameter.

While the CKT model considers the parameters  $S$ ,  $G$ , and  $T$  constant, IDEE implements an eCKT model, where the  $S$  and  $G$  are variables that depend on the  $score$  parameter. This is done by taking into account that an activity related to a certain skill with a high score, requires the student to have good knowledge.

Thus, for each activity, the parameters are fixed in the following way.

- 1)  $S$  is the probability of making a mistake knowing the skill. When the skill appears in the activity with a high  $score$ , it means that the student needs a good knowledge of it to get the answer right and has a higher probability of making a mistake. This suggests that the value of  $S$  has to be as greater as the relevance that the skill has in the activity as follows:

$$S = \begin{cases} (\text{score}/10) \times 0.05 & \text{score} \neq 10 \\ 0.05/10 & \text{score} = 10. \end{cases} \quad (5)$$

- 2)  $G$  is the probability for the student to guess the answer without knowing the skill. For each student,  $G$  represents the probability of guessing the answer. This probability has to be as lower as the relevance of the skill in the activity

$$G = \begin{cases} (1 - \text{score}/10) \times 0.2 & \text{score} \neq 0 \\ 0.2/10 & \text{score} = 0. \end{cases} \quad (6)$$

As an example, Table III shows on the:

- 1) left side; the Q-matrix representing an example of data on how a student has worked on four different activities in the *inclined plane* learning unit;
- 2) right side; the results of the CKT model and the improved eCKT model.

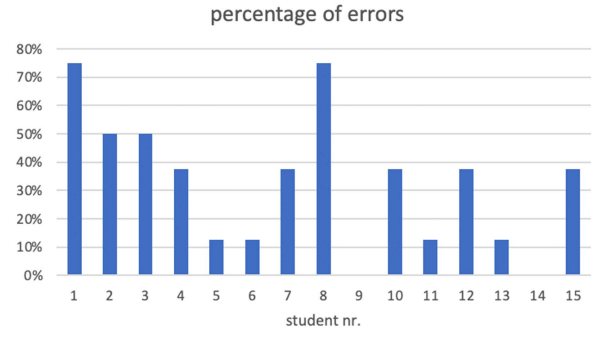


Fig. 6. Bar graph showing the percentage of students' errors in the initial knowledge of the students.

In the left part of the table that refers to the data, it can be seen that the student makes activity\_3 and activity\_4, right. Let us look at the skill\_1, which is not so relevant in these activities (the  $score$  parameter is only 2). On the right side, it can be seen that when the student's answer is correct in activity\_3, the inclusion of the parameter  $score$  in the model determines a decrease in the result (0.869) concerning the 0.964 value of the CKT model.

This behavior is desired since the value of the  $score$  parameter of skill\_1 is low. Therefore, when the student gives a correct answer, the model considers a lower increment in the knowledge acquired by the student.

Let us now look at the skill\_2. This skill is essential since the parameter  $score$  has a high value. It is observed that when the student answers correctly in the activity\_3, the inclusion of the parameter  $score$  in the model determines an increase in the result (0.999) concerning the 0.975 value of the CKT model.

## V. EXPERIENCES AND RESULTS

### A. Overview

A preliminary evaluation of the feasibility of using IDEE was described in [18]. In this article, we describe the experience of using IDEE in the Italian School in Madrid.<sup>6</sup> A group of 15 students aged between 13 and 14, without any selection of study preferences, background knowledge, or gender, have used IDEE. The proposed activity lasted 2 h with five EV3 kits working with the experience of the inclined plane implemented in IDEE. Another group of 13 students study the same concepts following a traditional class and making exercises on their notebooks with a teacher explaining the contents.

To evaluate the initial level of knowledge, the first group of students were asked to make a pretest before the experience. The results of this pretest show that students present difficulties with the concepts about uniformly accelerated rectilinear movement (UARM) and when the proposed exercise requires to relate concepts of speed and space with the uniformly accelerated motion.

In Fig. 6, it is shown the percentage of student errors, and Fig. 7 shows the distribution of the percentage of errors on the topics of uniform rectilinear movement, free fall, and how these concepts are related. Students 1, 2, 3, and 8 make 100% of the

<sup>6</sup>[Online]. Available: <http://www.scuolamadrid.org/>

TABLE III  
EXAMPLE OF LEARNING DEVELOPMENT IN A STUDENT WORKING ON FOUR ACTIVITIES WITH THE CKT AND ECKT MODELS

Activity	data				Results			
	skill_1	skill_2	skill_3	answer	CKT		eCKT	
					$K_1$	$K_2$	$K_1$	$K_2$
					0.500	0.500	0.500	0.500
1	4	1	0	false	0.843	0.869	0.902	0.984
2	0	0	1	true	0.843	0.869	0.902	0.984
3	2	8	0	true	0.964	0.975	0.869	0.999
4	2	8	0	true	0.892	0.975	0.856	0.999

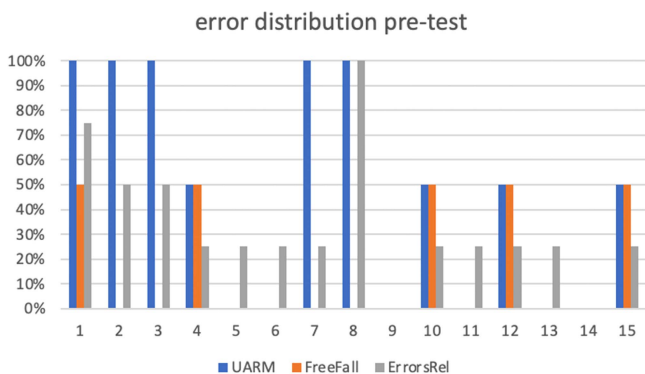


Fig. 7. Graph showing the percentage of students' errors on the different topics assessed in the pretest.

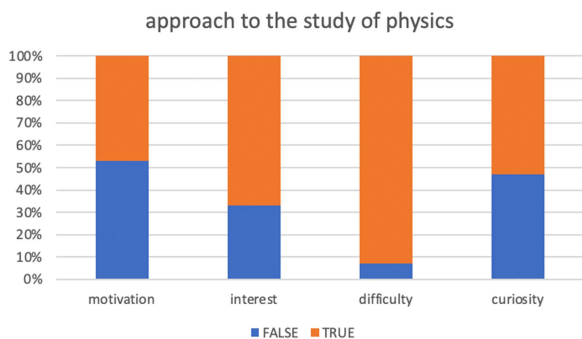


Fig. 8. Graph shows the interest of the class group in the subject of physics.

exercises on the UARM and at least 50% of the exercises about the relationships between these concepts.

Fig. 8 shows the interest in physics of the class group. It is possible to notice that students consider difficult the physics subject.

After the experience, a post-test was presented to the students to evaluate their understanding of the uniform accelerated rectilinear movement.

The same post-test was presented to the control group composed of the 13 students who did not interact with IDEE. Although, for the control group, we do not have the results of a pretest study, we rely on the fact that the two groups belong to two different classes of the Italian School of Madrid. In this school, students start in elementary school and exit at the end of secondary school. During this long period, they are rearranged at least two times to preserve didactical equilibrium. So, we may expect there should not be significant statistical differences between the average outcomes of the two groups.

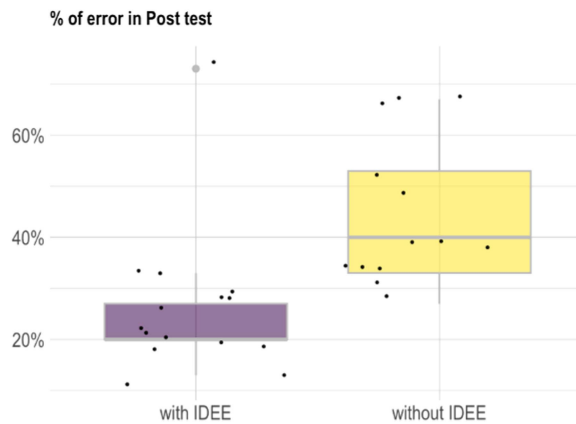


Fig. 9. Graph shows the percentage error in the post-test for the two class groups.

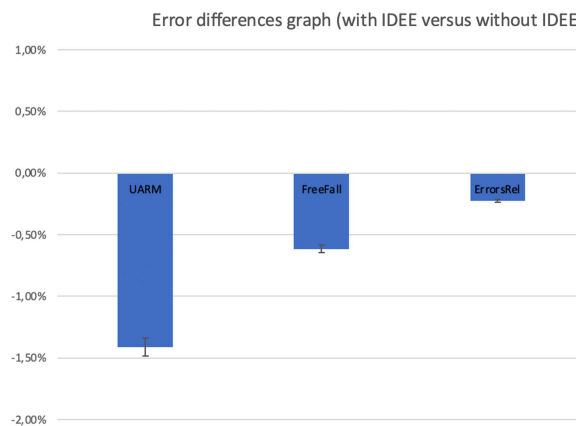


Fig. 10. Graph shows the difference between the means of the two groups (with IDEE versus without IDEE) over the number of errors.

Fig. 9 shows the percentage of errors in the post-test for the two class groups. Students who have worked with IDEE show that they have a better understanding of the topics studied; the statistical significance of this statement is demonstrated with a  $t$ -student test ( $p \leq 0.05$ ). In Fig. 10, the graph shows the difference between the means of the two groups over the number of errors. It is possible to observe how the use of IDEE (since all differences are negative) allows students to be more confident when they have to relate the UARM to the fall of a grave or the inclined plane and in the understanding of UARM and free fall concepts.

To determine the degree of fulfilment of the objectives proposed in this experience, the results have been analyzed by conducting surveys to the students to obtain information to measure:

TABLE IV  
INDICATORS OF THE LEARNING PROCESS WITH THE eAFM

(a) THE SKILL INTERCEPT IS THE INITIAL DIFFICULTY FOR EACH SKILL AND SLOPE IS THE LEARNING RATE OF EACH SKILL.

skill id	skill name	skill intercept ( $\beta$ )	Pf(>  z )	slope ( $\gamma$ )	Pr(>  z )	Probability
skill_1	Graphics interpretation	0.61	0.05	-9.61	0.022	0.00003
skill_3	Relate magnitude	0.43	0.033	-0.94	0.004	0.12
skill_7	Uniformly accelerated movement	5.66	0.002	-2.56	0.000	0.83
skill_10	Velocity	0.75	0.006	8.1	0.001	0.99

(b) THE SKILL INTERCEPT PARAMETER FOR SIGNIFICANT STUDENTS (IN BOLD ARE SHOWN THOSE STUDENTS WITH LOW LEARNING).

student	student intercept ( $\alpha$ )	Pf(>  z )
<b>user_id_779</b>	-1.79	0.009
user_id_780	1.98	0.021
<b>user_id_788</b>	-1.16	0.045

The skill intercept is the initial difficulty level for each skill, the slope is the learning rate and probability is the success probability to use a skill once the experience is over.

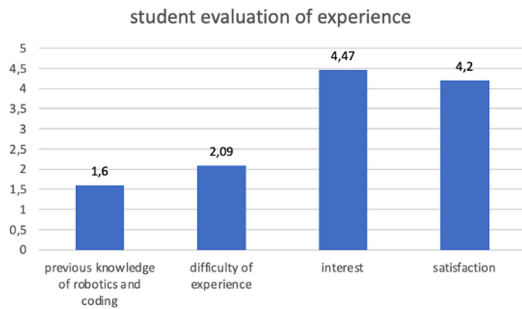


Fig. 11. Graph to determine the degree of fulfillment of the objectives proposed in this experience. The student can express his opinion by answering with a number between 1 and 5.

their previous knowledge in robotics and computer science, their difficulties in performing this experience concerning the planned objectives, their level of interest and their degree of satisfaction.

The results shown in Fig. 11 are encouraging. The class group has no initial knowledge of robotics and programming but considers the experience interesting and not complex. Overall, students are satisfied with the experience.

### B. IDEE Student Evaluation

Students' responses during the experience are stored in the database of IDEE in the table named `data_table`, which is made up of 257 records. The `question_table` and `versionproblem_table` store the relationships between questions or problems with skills and scores. These tables, with the answers given by the students, allow the definition of the `profile_table`, which includes the score accumulated by the student in the various tasks. The `profile_table` includes 250 records. In the following, we show the results obtained by applying both the eAFM and eCKT analysis. The results from the eAFM, help the teacher to find information about the students' learning. The eCKT results directly provide the model with the required information about the student's learning.

The quantitative data of the database are converted into qualitative data to obtain the Q-matrix on which the statistical method of the eAFM works. The Q-matrix is made of 242 entries. Each entry is composed of the `student_id`, the skill which the student

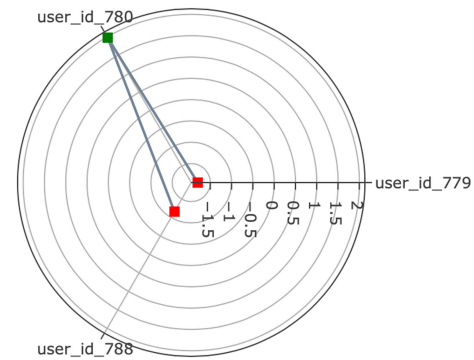


Fig. 12. Graphical analysis of the student intercept parameter  $\alpha$  with a polar graph.

has worked on and the number of attempts previously done in each skill.

The data analyzed by the eAFM are summarized in Table IV. The higher the intercept of each skill, the lower the initial difficulty the skill has. The higher the slope of each skill is, the faster students learn the skill. *Relate magnitude* (skill\_3), *graphics interpretation* (skill\_1), and *velocity* (skill\_10) are skills on which students have little knowledge. *Uniformly accelerated movement* is the easiest skill with an intercept of 5.66. The high slope parameter 8.1 for skill\_10 allows us to observe that the practice with IDEE improves the knowledge of this skill. The success probability in this case is high (0.99). Also, for the skill\_7, the success probability is high but for the student's initial knowledge and not for the practice with the system.

In Fig. 12, [Online]. Available: the teacher can observe the students with difficulties in red and students with good learning in green.

With the information provided by the eAFM, the teacher can analyze the individual path of knowledge of the students on the dashboard. A possible analysis the teacher can do, when observing the learning of the student with ID 779 in IDEE, is as follows:

- 1) the value of the accumulated score in the significant skills shows that the student has low values. It means that the student has acquired limited knowledge (see Fig. 13);
- 2) the different learning curves, show a decrease in the number of errors in skill\_3 and uncertainties in skill\_1 (see Fig. 14).



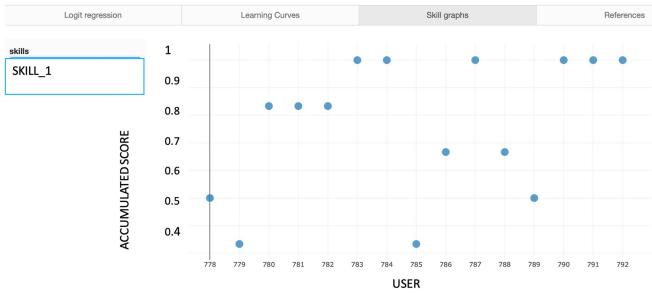


Fig. 13. Graphical analysis of the student's score on skill\_1.

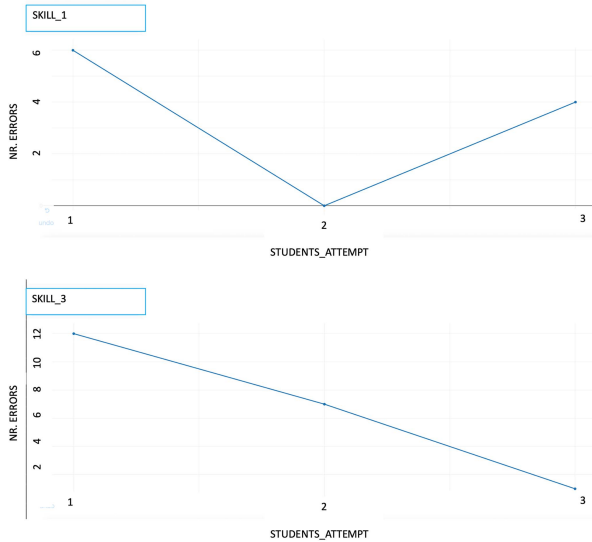


Fig. 14. Learning curves on skill\_1 (image above) and skill\_3 (image below)

TABLE V  
RESULTS OF eCKT MODEL FOR THE STUDENT WITH ID 779

Activity	data				Results eCKT		
	skill_1	skill_3	skill_10	answer	$K_1$	$K_3$	$K_{10}$
1	0	8	0	false	0.50	0.50	0.50
2	0	8	0	false	0.50	0.23	0.50
3	0	8	0	true	0.50	0.90	0.50
4	0	8	7	false	0.50	0.87	0.32
5	0	8	7	true	0.50	0.99	0.90
6	0	8	7	false	0.50	0.98	0.67
7	5	0	0	false	0.19	0.98	0.67
8	10	5	0	true	0.93	0.99	0.67
9	5	5	0	false	0.65	0.99	0.67
10	10	5	0	false	0.39	0.98	0.67
11	0	0	8	true	0.39	0.98	0.63
12	0	0	8	true	0.39	0.98	0.62

Thanks to the application of the eCKT model, the teacher can visualize the knowledge acquired by the students in the different skills detected by the eAFM as significant. The results for the student with ID 779 can be seen in Table V.

In the eCKT model, a skill is mastered when the value of 0.95 is obtained. Then, the teacher may focus on the skills where the student has not achieved this value. Looking at the student with ID 779, the teacher will focus the recovery only on skill\_1 and skill\_10. The teacher will provide the student with new activities on *graphic interpretation* (skill\_1) and on the concept of *velocity* (skill\_10).

Thanks to the eCKT model, the evaluation of the student's learning is synthesized in a table. Thus, the teacher does not need to invest time to get this information from the dashboard. Additionally, the teacher can consult and view the results provided by the model also in the dashboard. The coherence between the output of eCKT model and the results available in the dashboard support the confidence in the model as an aid for the teacher to understand the student's learning progress. Thus, IDEE is enriched with a new tool capable of helping the teacher to interpret the evolution of students' learning.

## VI. CONCLUSION

Although activities involving educational robotics motivate students, they are often only used as extracurricular activities. This is due to the lack of teachers' experience using educational robotics kits. To support teachers, it is necessary to embed robotics into learning environments and to provide the teachers with information about the learning process of their students. In IDEE, teachers are supported with the enhanced AFM that gives information about students' learning process.

In this article, we have also described how we have enriched the information provided to the teachers using the eCKT model.

IDEE has been tested in a real setting, a class in the Italian School in Madrid. Although more experiences should be carried with more students, the results at the moment show that the methodology applied allows students using IDEE to have better results on the post-test and make students more confident when they have to relate the concepts involved in the experience. The results show that students had no difficulties using IDEE even if they have no previous knowledge of robotics. Thus, results show the feasibility of this learning environment as well as the usefulness of the information about the analysis of the learning process given to the teachers.

The main limitations of the presented study are the size of the sample group of students that have used IDEE and the reduced size of the experiments currently included in IDEE. The promising results encourage us to go in this line.

We foresee several lines for future work. First, to assess the contributions of IDEE, it would be convenient to carry out an experiment in which IDEE is compared with similar tools.

The domain application of IDEE may be extended to other physics topics included in secondary education. In addition, we should test if IDEE can be applied in other subjects, such as mathematics or biology (extending the type of robots used in the experiments).

Regarding the analysis tool, we plan to work on the interface to make more user-friendly to teachers the interpretation of the results. In addition, new models may be included. For example, unsupervised techniques can be used to recommend the teacher, which groups of students are similar or have complementary behaviors.

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