A Conceptual Framework for Extending Domain Model of AI-enabled Adaptive Learning with Sub-skills Modelling

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Abstract: This paper proposes a conceptual framework of an AI-ALS that extends the Domain Model with sub-skill modelling, to empower teachers with insights, create student awareness of sub-skills mastery level and provide better learning recommendations. The paper also presents the BuildUp Algebra Tutor, an online maths platform for secondary schools based on the proposed framework, that provides step-by-step scaffolding. Results from a pilot study with 5th grade students showed that the scaffolding improved the student success rate by 27.43%, and that the learner model achieves high sub-skill prediction performance with an AUC of up to 0.944. Moreover, survey results show an increase in student self-reported metrics such as confidence.

1 INTRODUCTION

The demand for online and personalized learning is stronger than ever (Docebo, 2020). While the past decade has seen a multitude of online courses, the scale of online learning reached a massive and unprecedented scale in 2020 with over 1.2 billion students impacted by the COVID-19 pandemic and many schools and universities moving their classes online (Li & Lalani, 2020). In this context it has become more important than ever to enable effective teaching and learning in online environments.

While personalised and adaptive learning has been a research topic for a few decades, it only started to be the focus of industry over the past decade (Alamri et al., 2020). Previous research showed that students enjoy the benefits of personalization, the freedom of inquiry-based learning, but they also require structure and guidance (Wanner & Palmer, 2015). Personalised and adaptive learning has several benefits for students (e.g., increase learning efficiency, increase students' motivation, engage students in active learning, promote higher level of learner confidence, etc.), as well as for educators (e.g., help educators to obtain insights on learners' needs and preferences, help educators to manage and track student progress via learning analytics, etc.) (Alamri et al., 2020; Ghergulescu et al., 2016; Kurilovas et al., 2015; Wanner & Palmer, 2015).

Adaptive and personalised learning solutions are increasingly integrating artificial intelligence (AI) algorithms to orchestrate greater interaction with learners, to deliver personalized resources and learning activities, to gather learner data to help identify skills gaps, and to provide tailored learning (Docebo, 2020).

AI-enabled Adaptive Learning Systems (AI-ALS) have the potential to empower teachers as well as to support students in achieving their potential. AI has been adopted extensively in education, helping educators to improve their efficiency with repetitive tasks such as assessment, and to improve the quality of their teaching. Moreover, AI-ALS foster student uptake and retention, improve the learner experience and overall quality of learning (Chen et al., 2020).

The classical architecture of an AI-ALS is based on Domain Model (DM), Learner Model (LM) and Adaptation Engine (Ghergulescu et al., 2019). The DM represents the foundation of an overlay approach to knowledge modelling and includes a representation of the knowledge domain and content metadata.The Learner Model maintains information about the learners such as knowledge level, preferences, etc. The AI Engine is responsible for updating the models and for performing the adaptation.

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Mathematics is one subject where personalised learning could be improved through sub-skill modelling. Solving a maths problem is a multi-step process that requires learners to have good conceptual knowledge, as well as good procedural skills or the ability to correctly apply procedures and strategies to solve problems (Liljedahl et al., 2016). A number of publications have showed that maths learners hold many misconceptions and gaps related to conceptual knowledge which can lead to errors during problem-solving (Booth et al., 2017; Feldman et al., 2018; Hansen et al., 2020; Muzangwa & Chifamba, 2012).

This paper proposes a conceptual framework of an AI-ALS that extends the Domain Model with sub-skill modelling. Modelling sub-skills will enable a system to empower a teacher with insights into the student's (lack of) mathematical sub-skills, to create student awareness of sub-skills' mastery level and to provide better recommendations what to do next. The paper also presents and evaluates the BuildUp Algebra Tutor, an online maths platform for secondary schools based on the proposed framework.

The rest of this paper is organized as follows. Section 2 presents the proposed conceptual framework. Section 3 presents the BuildUp Algebra Tutor AI-ALS that was developed based on the proposed framework. Section 4 presents the evaluation case study methodology and results, while section 5 concludes the paper.

2 CONCEPTUAL FRAMEWORK

2.1 Framework Overview

Figure 1 presents the proposed conceptual framework of an AI-enabled Adaptive Learning System (AI-ALS), whose main components are: Domain Model (DM), Learner Model (LM) and AI Engine. The DM represents the foundation of an overlay approach to knowledge modelling. DM makes a separation between the curriculum model and the content model.

The curriculum model is a representation of the "knowledge domain". It includes knowledge items (concepts) and the relationships between them. The curriculum prerequisite network (also called the curriculum map) defines the prerequisite relationships between the knowledge items. For example, 'multiplication and division of integers' is prerequisite for the knowledge item 'order of operations'. Furthermore, concepts may have other metadata that affects to whom they are relevant (e.g., exam level). Some previous theoretical frameworks for domain modeling divide the abilities to be taught

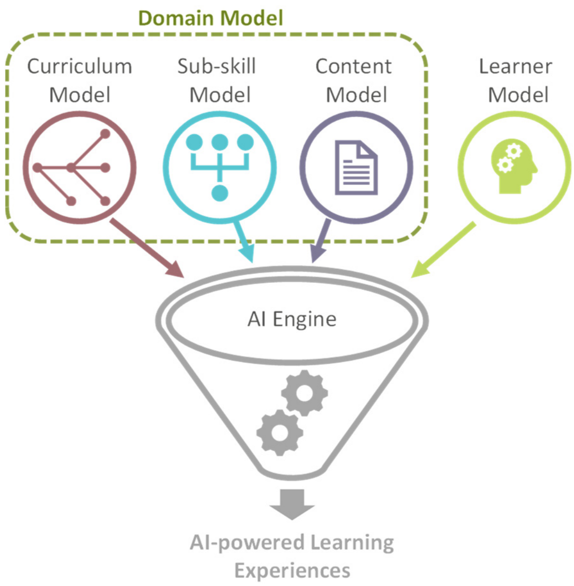

Figure 1: Conceptual AI-ALS framework.

into concepts (knowledge) and skills (know−how) (Kraiger et al., 1993; Schmidt & Kunzmann, 2006). Previous research works have used ontologies to model relations between concepts (Capuano et al., 2009, 2011).

The content model is defined by all the metadata about the content. Content objects are individual pieces of content, activities, quizzes, questions, etc. Content objects can have metadata that reflects how they are used (e.g., type of activity such as exercise, quiz, etc.) or skill used (e.g., listening, writing, etc.). Content objects are linked to curriculum concepts to build a course.

The sub-skill model is a representation of sub-skills. Sub-skills are micro-evidence within a content object like steps in a question. The sub-skills are defined in a taxonomy and typically derived from response analysis of learner interactions. DM enables to create and update a complex learner model and to enable multiple layers of personalisation and adaptation.

The learner model maintains information about the learners such as: knowledge level (i.e., what they know, at what mastery level they know a concept, and what they don't know), preferences, other pedagogy-relevant traits (e.g., self-direction, self-efficacy, motivation, etc.).

The AI engine is responsible for updating the models and for performing the adaptivity across various layers such as content difficulty adjustment, learning loops, and learning path recommendations. Furthermore, the AI engine uses student interactions data and machine learning to infer the sub-skills structure and associations between sub-skills and concepts and between sub-skills and questions, as well as to continuously update the models.

2.2 Enhancing the Domain Model

The proposed conceptual framework enhances the traditional domain model of AI-ALS with a sub-skill model that is a representation of sub-skills. Sub-skills are the formal procedures that a student needs to master to be able to solve non-trivial problems. Examples of maths sub-skills are the arithmetic procedures learned in primary education, as are the procedures to simplify algebraic expressions, expanding brackets, factoring, solving quadratic equations, integration, etc.

The sub-skill model enables to gather deeper evidence from each question at fine-level data below a concept level, data that would be especially powerful for error analysis. Initially the sub-skill model contains a taxonomy of sub-skills organised in a hierarchical view. For example, “Arrage terms with variable to the left and other terms to the right” and “Multiply an equation to remove the fractions” are sub-skill tags in “Solving linear equations using the balance method” tags collection (see Figure 2).


```
{
  "id": "EquationsBalanceMethod",
  "descr": {
    "en": "Solving linear equations using the balance methode",
    "nl": "Lineaire vergelijkingen oplossen met de balansmethode"
  },
  "tags": [
    {
      "id": "EquationsBalanceMethodArrangeTerms",
      "descr": {
        "en": "Arrange terms with variable to the left and other terms to
          the right",
        "nl": "Termen met de variabele naar links en andere termen naar
          rechts halen"
      },
      "errors": [...]
    },
    {
      "id": "EquationsBalanceMethodRemoveFractions",
      "descr": {
        "en": "Multiply an equation to remove the fractions",
        "nl": "Een vergelijking vermenigvuldigen om breuken weg te werken"
      }
    }
  ]
```


Figure 2: Example of sub-skills tags (AlgebraKiT, 2020).

Other possible structures between sub-skills are learned by the AI engine based on response analysis of learner’s interactions with the system on both positive and negative evidence of the student's mastery of sub-skills. Positive evidence of mastery is generated when a student solves a maths problem, while negative evidence of mastery is generated when a student makes a mistake or fails to solve a problem.

2.3 Enhancing the Learner Model

Sub-skill tags are generated as the student interacts with the system and solves questions. Evidence on tags can be positive or negative and weighted.

There are three 'sources' for tags:

- finish tags corresponding to successfully applying the sub-skill to solve the problem;
- hint tags corresponding to hints requested on applying a sub-skill;
- error feedback tags corresponding to errors.

The learner’s strength on each sub-skill can be estimated similarly to the rest of the learner model. Sub-skills can be modelled through a probability distribution vector and estimated using a customised Item Response Theory (IRT) (see Figure 3). For example, for each student the engine will maintain a profile for all the sub-skills in the sub-skills model. As a student interacts with a question and there is evidence of a sub-skill, the sub-skill profile, characterised through a probability distribution, is updated given the evidence type (positive or negative) and using a customized IRT (Franzen, 2017).

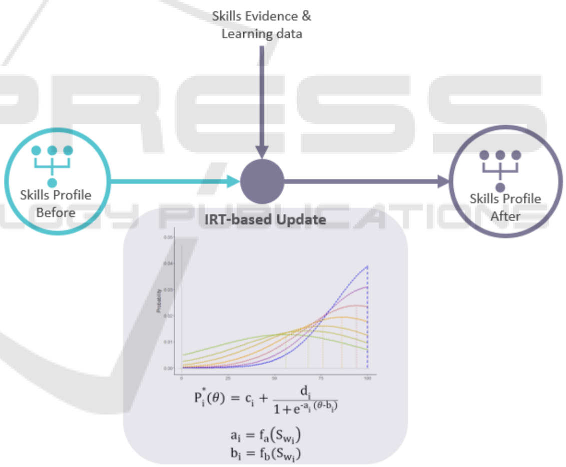

Figure 3: Sub-skills Modelling through Item Response Theory (IRT)-based Update.

3 BuildUp ALGEBRA TUTOR

BuildUp is an online maths platform used by secondary schools throughout Ireland. BuildUp is developed and operated by Adaptemy[2]. BuildUp Algebra Tutor follows on from the BuildUp Junior Certificate course and is developed based on the proposed conceptual framework. It integrates two AI engines: the Adaptemy AI Engine for learner

[2] Adaptemy – www.adaptemy.com

modelling, adaptation and personalisation, and the AlgebraKiT Engine for sub-skill detection and step-by-step scaffolding.

The AlgebraKiT player was integrated into the Adaptemy question player. The AlgebraKiT Engine was integrated with the Adaptemy Content Management System (CMS) and the Adaptemy AI Engine. The two engines communicate using API calls through Adaptemy's CMS. The Learning Data (including sub-skill evidence) is streamed to the Adaptemy AI Engine that updates the Learner Model (including the sub-skills profile).

3.1 AlgebraKiT Engine

AlgebraKiT provides a solution that evaluates each step a student does when solving a maths problem, recognizes and explains errors automatically, and offers immediate hints to the student. The engine was extended to generate sub-skill tags that describe what maths sub-skills are required to solve a problem and to detect what sub-skills are related to mistakes. The sub-skills are defined in the sub-skill taxonomy, which exists separately from AlgebraKiT's evaluation maths engine.

The sub-skill tags are references to the sub-skills in the taxonomy, that are generated by AlgebraKiT's maths engine. So, the maths engine does not use or know the contents of the sub-skill taxonomy. Instead, the engine is built around a large collection of maths rules that are applied in sequence by the engine to solve a problem. This collection of rules represents the procedures a student (should) be able to use. Maths rules and sub-skills are therefore closely related, although multiple rules can be associated with the same sub-skill.

The maths engine applies a maths rule on a mathematical expression to generate a new expression. So, expressions are the result of some maths rule. This is also true for the mathematical expressions that are inputted by a student; these expressions are the result of a mathematical procedure the student performed mentally.

Figure 4 shows how tags are generated when AlgebraKiT generates the worked solution for a problem. The assumption is that the related sub-skills also describe the procedures that the student will apply. This is not completely certain as a student is free to choose his own solution path, but this uncertainty can be handled by the statistical analysis of multiple exercises.

In case a student inputs an incorrect expression, the engine looks to find the mental procedure that the

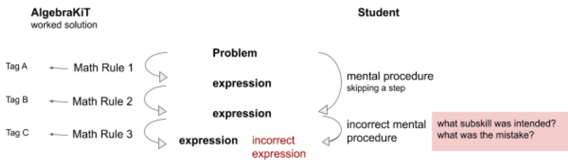

Figure 4: Tags generation workflow.

student applied, to which sub-skill this is related to, and what the mistake is. This information must be bootstrapped from the previous expression and the incorrect expression. When an explanation for the error is found with sufficient certainty, the procedure generates a human-readable description of the mistake and the tags that indicate the related sub-skill.

3.2 Adaptemy AI Engine

Adaptemy's AI Engine is developed based on existing research in the areas of Intelligent Tutoring Systems and Adaptive E-Learning. It makes use of a curriculum model, a content model and a learner model. The rich information from the three models enables the AI engine to personalize the learning and to accurately update the models. For each student, the Adaptemy AI Engine maintains an ability profile on all the concepts in the curriculum. The ability on the concept that has been worked on is updated based on direct evidence using Item Response Theory (IRT). The profile of the other concepts is also updated based on the question outcome as indirect evidence through Bayesian Networks updates. As there is empirical evidence that knowledge depreciation (forgetting) occurs, the engine models forgetting (what was forgotten after it is initially learned for each concept) and updates the student profile overnight. The Adaptemy AI Engine contains several layers of adaptation and personalization. Through this, a system that integrates the Adaptemy AI Engine can provide immediate personalized feedback to the student, engaging content sequencing that adapts to the student's performance, adaptive assessment and scoring, learning paths recommendations and student motivation detection and learning loops.

The Adaptemy AI Engine was evaluated in several previous studies (Dang & Ghergulescu, 2018; Ghergulescu et al., 2015, 2016). The effectiveness of the learning recommendations provided by the Adaptemy AI Engine was evaluated based on data from over 80k lessons (Dang & Ghergulescu, 2018). The results showed that when students followed the recommendations, they had both a higher success rate and a higher average ability improvement as compared to when the recommendations were not followed. The feasibility of integrating adaptive learning powered by the Adaptemy system in the classroom was analysed with 62 schools and 2691 students (Ghergulescu et al., 2015). The results showed that 97% of teachers believe that students enjoy using the Adaptemy system and want to use it at least once per week. A further study with over 10,000 students using the system for more than 6 months in over 1,700 K12 math classroom sessions was carried out to analyse the Adaptemy system's learning effectiveness (Ghergulescu et al., 2016). The students' math ability improved by 8.3% on average per concept for an average of 5 minutes and there was a statistical significant improvement across various ability ranges. Moreover, a 25% problem solving speed increase was observed for the first revision, and 38% increase for the second revision.

The Adaptemy AI Engine was extended as per the proposed conceptual model to work with a sub-skills model. Furthermore, the learner model was extended with a profile per students for all the sub-skills in the taxonomy. When the student finishes the questions, multiple sub-skills are updated based on the sub-skills evidence using a customised IRT for sub-skills. The score of the question, question discriminant and difficulty are computed as functions of the weight of the tag and question metrics.

3.3 Student Learning Journey in BuildUp Algebra Tutor

In the BuildUp Algebra Tutor, students can navigate to different topics and concepts within topics. When selecting a concept, the student can take a self-directed approach and select which concept to practise or they can follow the recommendations provided by the system. Furthermore, teachers can assign concepts as homework and direct students to what concepts to practice.

Encouragements and guidance are presented to students before they start working on questions on concept. Figure 5 shows an example of a question. As it can be seen from the figure, each step is evaluated and feedback is provided to the student.

In the background, the learner profile is updated as students are working through the question. Figure 6 shows the sub-skills dashboard that was developed to illustrate changes in sub-kills in terms of mastery level and accuracy given the sub-skills evidence. Furthermore, recommendations are provided to students.

At the end of each concept, students are presented with a summary of their results and encouragement.

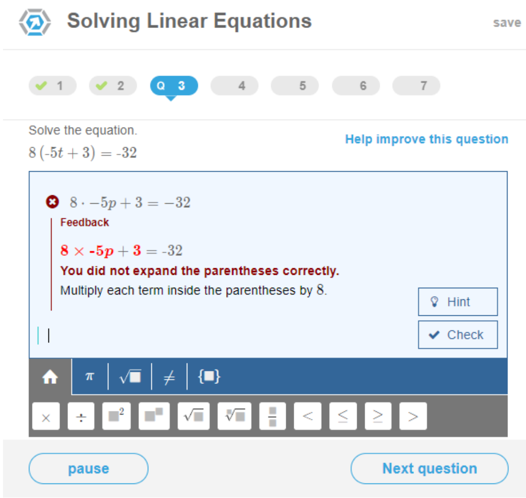

Figure 5: Example of question.

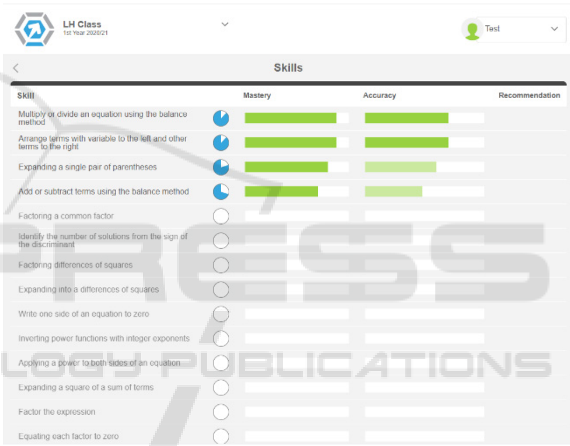

Figure 6: Sub-skills Dashboard.

4 CASE STUDY

4.1 Methodology

A preliminary pilot was conducted to investigate the effectiveness of the BuildUp Algebra Tutor platform. Three classes of 5th grade students (16-17 years old) from one Irish secondary school have participated in the pilot. As part of the pilot the students have practised with Algebra concepts. 26 students worked through a total of 288 questions and previewed another 27 questions.

4.2 Success Rate

Without step-by-step scaffolding students will experience success if they answer a question correctly and fail when making a mistake and entering the wrong answer. With step-by-step scaffolding students receive at each step progressive hints when requested and/or guidance when they make a mistake. Students experience success when they finish the question correctly.

The results analysis showed that for 60.76% of question workings students have provided the correct answer without receiving any scaffolding. For 27.43% of question workings students have received step-by-step scaffolding which helped them to successfully complete the questions, thus increasing the success rate to 88.19% (see Figure 7).

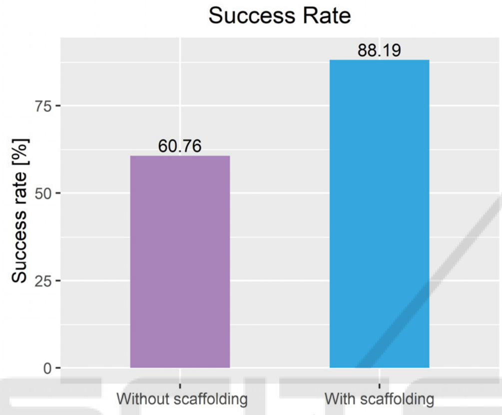

Figure 7: Success Rate Results.

4.3 Scaffolding Effectiveness

When using step-by-step scaffolding students can request hints at any time while answering a question. Scaffolding can be considered successful when the students overcome the challenge and apply the sub-skill to successfully complete the question. As explained in sub-section 3.2, three types of sub-skill tags are generated as the student interacts with the system, namely: finish, hint and error tags.

An analysis was conducted to investigate how students progressed after they requested hints or made errors, respectively. Figure 8 shows that after students requested a hint they have successfully completed the question in 64.44% of cases, requested another hint in 8.89% of cases, did an error in 13.33% of cases, and did not complete the question in 13.33% of cases (i.e., during the pilot duration). The number of hint requests are considered when computing the question score. However, in the pilot, students received only completion status per question and not score details.

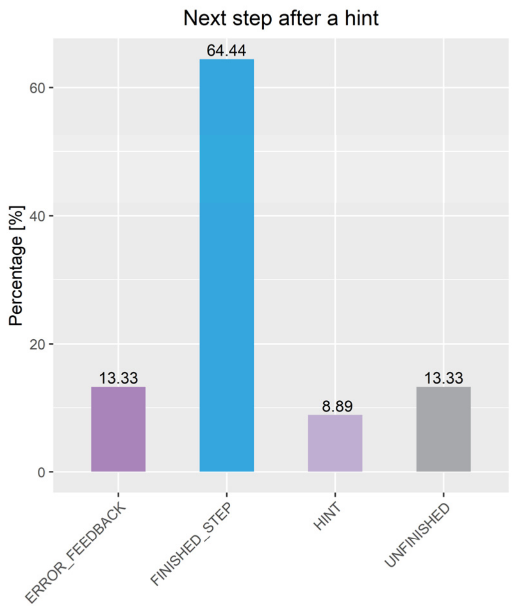

Figure 8: Progress after a hint.

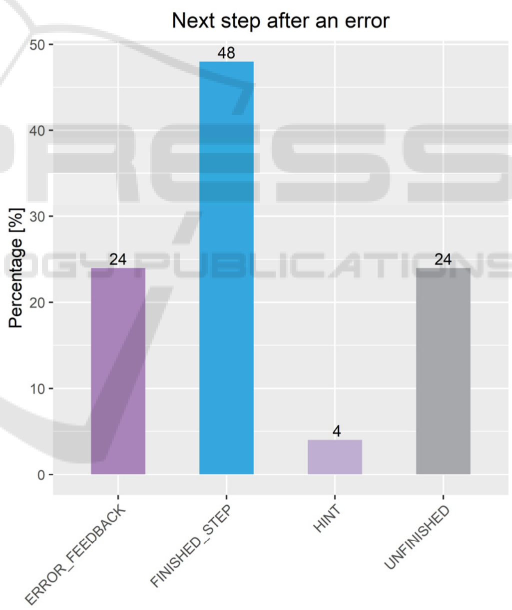

Figure 9: Progress after an error.

Figure 9 shows that after students made an error they have successfully completed the question in 48% of cases, requested a hint in 4% of cases, did another error in 24% of cases, and did not complete the question in 24% of cases.

The results showed that identifying sub-skills and offering related scaffolds was effective as the students successfully completed the questions in most cases after receiving hints or feedback on errors.

4.4 Learner Model Sub-skill Prediction

The learner model estimates the students' strength on each sub-skill using Item Response Theory. AUC (or Area Under the Receiver Operating Characteristic Curve) was used to evaluate the performance of the learner model sub-skill prediction. AUC is commonly used for classification problems in machine learning, where the predicted variable is binary. It is a more stable performance metric than accuracy.

As it can be seen from Figure 10, the sub-skill prediction performance of the learner model is high with an AUC of up to 0.944. Having an accurate learner model prediction is very beneficial as it would make for more effective recommendations to students and teachers.

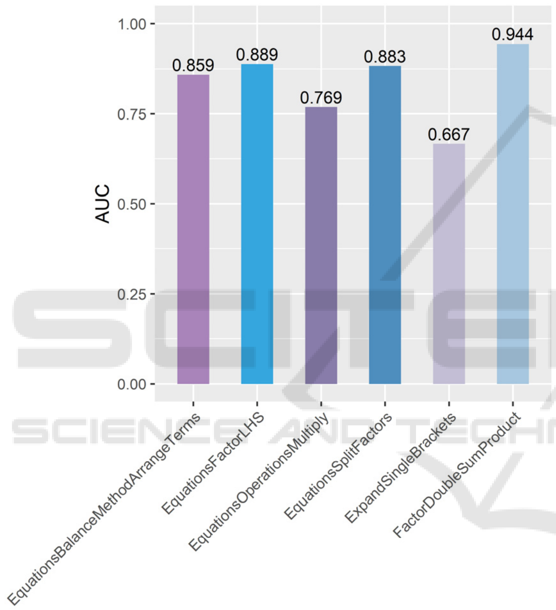

Figure 10: Sub-skill prediction performance.

4.5 Learner Subjective Feedback

Students received a pre-survey and a post-survey to investigate subjective aspects of the learning experience. The students were asked to rate their confidence that they can solve the Maths problems before and after practising with BuildUp Algebra Tutor. A 5-point Likert scale (i.e., 1 – 'not at all confident' to 5 – 'extremely confident') was used. Figure 11 shows that the mean confidence of the students was higher for the post-survey, but the difference was not statistically significant.

Students were also asked to rate if they liked to practice maths using traditional methods (pre-survey) and the BuildUp platform (post-survey), how easy to

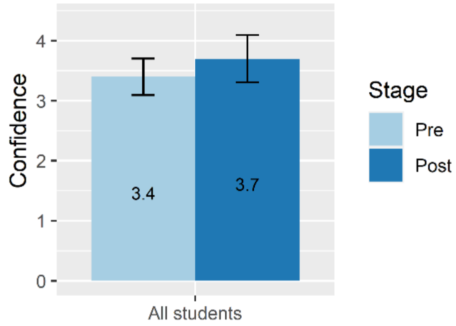

Figure 11: Student confidence results.

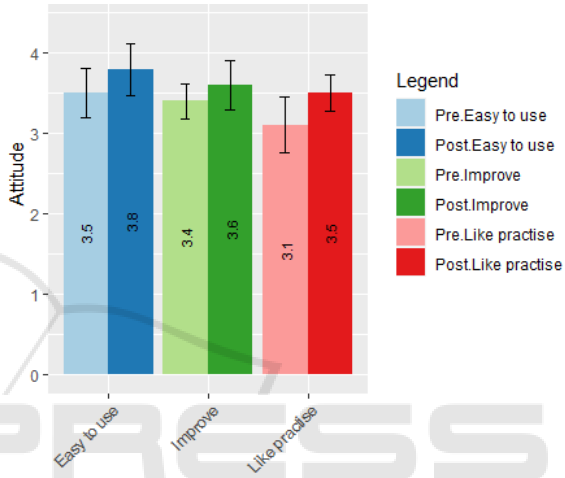

Figure 12: Students attitude results.

use they find them, and if they think they can improve their maths using traditional methods / BuildUp. A 5-point Likert scale (i.e., 1 – 'strongly disagree' to 5 – 'strongly agree') was used. Figure 12 shows that the mean ratings are higher for BuildUp Algebra Tutor than traditional methods.

5 CONCLUSIONS

AI-enabled Adaptive Learning Systems are increasingly adopted due to their potential to empower the teacher through smart dashboards that provide insights into the students' knowledge and progress, as well as to improve the efficiency and quality of teaching. AI-ALS also have the potential to improve the learning efficiency through personalised learning experiences tailored to students' needs, preferences and skillset.

This paper proposes a conceptual framework of an AI-ALS that extends the Domain Model with sub-skill modelling. Modelling sub-skills is very useful for subjects such as Mathematics where learners are required to have good conceptual knowledge and skills in applying problem-solving procedures, but often learners have misconceptions and make errors.

The paper also presented the BuildUp Algebra Tutor, an online maths platform for secondary schools, that incorporates the proposed framework and integrates two AI engines: the Adaptemy AI Engine for learner modelling, adaptation and personalisation, and the AlgebraKiT Engine for sub-skill detection and step-by-step feedback.

A pilot study with 5th year students was conducted to evaluate the benefits of BuildUp Algebra Tutor. The results have showed that the step-by-step scaffolding improved the student success rate by 27.43%. The sub-skill prediction performance of the learner model is high with an AUC of up to 0.944. However, the AUC varied across the different sub-skills which will require further investigation. Moreover, survey results showed an increase in student's self-reported metrics such as confidence.

Future work will investigate how sub-skill modelling can improve the accuracy of the learner model in terms of student's ability on concepts and further improve the adaptive learning solution.

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