A DATA-DRIVEN FLIPPED LEARNING MODEL FOR ENHANCED STUDENT OUTCOMES

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ABSTRACT

This study investigates the integration of flipped classroom and learning analytics in the algorithm course through the Data-Driven Flipped Classroom model. This research arises from the backdrop of the traditional teaching model in algorithmic courses, where a one-size-fits-all method was applied. The challenges appear as instructors encountered difficulties managing a class with diverse levels of assimilation, limiting the attainment of learning outcomes. Recognizing the need for a more adaptive and personalized model, the study introduces the Data Driven Flipped classroom model. This model provides a dynamic and personalized learning experience. Experimental research with computer engineering first year students at ESPRIT School of Engineering demonstrates the proposed model's effectiveness. Using this model, new learning activities were designed where we strategically employed pre-class Quizzes, in-class interventions, and post-class discussion forums to guide students through exercises of varying difficulty levels. An experimental study was conducted to evaluate students' results and impressions. Survey results of the students (N=60) who participated in the experiment (experimental group) were compared to the results of the students from the control group (N=60). Significant improvements in students' problem-solving abilities, especially among those with lower starting assessments, demonstrate the model's potential to alter education.

KEYWORDS

Learning Analytics, Data-Driven Flipped Learning, Algorithmic course, Standard 8.

INTRODUCTION

In the world of education, finding new and creative ways to teach is crucial, especially when it comes to subjects as complex as algorithmic courses. Due to its intricacy and logical requirements, algorithm courses have long presented difficulties for instructors and students alike. It becomes essential to investigate and put into practise methods that not only improve learning but also encourage a deeper comprehension of algorithms, critical thinking, and problem-solving abilities in order to successfully navigate this educational landscape.

In recent years, the field of computer science education has witnessed a shift towards innovative teaching methodologies aimed at enhancing student outcomes and engagement. Ásrún & Hrafn's (2019) study emphasized student-centered learning, team-based activities, and the flipped classroom approach in programming education. The findings revealed that students actively engaged with online resources, valued communication with instructors and peers, and had a positive learning experience. The study underscored the role of visual aids like videos and the preference for online resources over traditional textbooks in teaching programming effectively.

On the other hand, Deachrut & Natha's (2019) emphasized the effectiveness of active learning strategies in improving student performance and understanding in computer programming courses. The research provided valuable insights for enhancing teaching methods and promoting student engagement in programming education. By implementing active learning approaches, the study aimed to optimize student learning experiences and outcomes, aligning with the evolving landscape of computer science education.

This study focuses on how to apply the data enabled flipped classroom, a current teaching technique designed to boost student performance and understanding in algorithmic courses.
Data-Driven Flipped Learning (DDFL) takes the flipped classroom concept a step further by adopting learning analytics, which is the collecting and analysis of student data to inform and optimize education (Seng & Chuan, 2023). Within the flipped classroom framework, the use of data-enabled teaching and learning practices has enormous promise for not only increasing student outcomes but also customizing instruction to individual requirements.
Educators may better identify students' strengths and limitations by exploiting data-driven knowledge, tailoring exercises to different difficulty levels, and facilitating a more personalized learning experience. This combination of data and flipped learning has the potential to transform how algorithmic courses are taught, making education more effective, engaging, and responsive to learners' different needs.

This paper is organised as follows: the first section examines relevant literature on the use of flipped learning in algorithm courses, illuminating both its benefits and obstacles. Following that, emphasis will be placed on data-driven flipped learning and its underlying concepts. The next section explores into the methods used for the algorithm course, where student performance will be evaluated, as well as a thorough review of feedback from both students and instructors.

BACKGROUND AND RELATED WORK

The flipped classroom, which has been recognised for its success in utilising technology in education (Chang & Hwang, 2018), is a potential technique for improving student's deep learning (Cui & Yu, 2019). This method emphasises higher-order thinking, resulting in a dynamic learning environment in which students may interact and grow at their own speed. Instead of teaching material, teachers in this paradigm act as facilitators, guiding and assisting students that take on more responsibility for their performance and learning activities.

Flipped learning in algorithm courses

When compared to the traditional paradigm, the flipped classroom has been demonstrated to be a more efficient means of teaching algorithms (Amira, T. 2019). For example, the material delivered in algorithm lectures is dense and difficult for many students to absorb at the speed at which instructors give them (Garg, M. 2015). As a result, from time to time, the learner needs to pause and think on his own in order to keep up with the lecture, but in a traditional lecture, such a pause is impossible because the requirement differs from person to person. Furthermore, the information is sequential and strongly linked to each other, so if the learner's attention wanders for a second, he may miss much of the material from the rest of the lecture and simply waste time by attending the presentation. Both issues are addressed by video lectures, which are assigned to students as homework under the flipped classroom paradigm. The learner may view the video lesson at his own pace, pause it when he needs to think about a subject, or rewind it if he missed something.

A critical evaluation of the Flipped Classroom approach's effectiveness has been conducted, considering the perspectives of instructors and students. Using a flipped classroom approach has been associated with numerous benefits. It is thought to support critical thinking both inside and outside of the classroom (Herreid & Schiller, 2013) and enable active learning (Alhasani, 2015). In addition, it promotes regular feedback exchanges between students and instructors, increases student engagement, and permits a self-paced learning environment (Mok, 2014). On the other hand, several studies have demonstrated that certain students would find it difficult to control their flipped learning, which would cause them to show up to class unprepared to participate fully (Herreid & Schiller, 2013). Some students allegedly had trouble understanding the material from the online lectures, which suggests that early interventions are necessary to improve understanding (Bishop and Verleger, 2013).

The data-driven flipped learning

Data-driven flipped learning (DDFL) is a pedagogical approach that combines the flipped classroom model with learning analytics to personalize and optimize the learning experience. Understanding and improving learning experiences and the surroundings that support them is the main goal of learning analytics (Long & Siemens, 2011). The principal objective of learning analytics is to provide instructors with advanced techniques for gathering and analysing complicated data from interactions between instructors, students, and digital media (Mayer et al., 2009).

Learning Analytics and the Flipped Classroom paradigm together signal the beginning of highly adaptive learning environments. This integrative method fosters a learning environment where students feel comfortable participating in self-regulated learning and developing their metacognitive skills through thoughtful self-evaluation. For instructors, this combination appears as a dynamic feedback loop that seamlessly connects the virtual and traditional classroom spaces. Such iterative feedback allows instructors to assess and adjust to students' growth, understanding levels, and changing learning requirements, resulting in a more thorough and flexible approach to instruction (Klemke et al., 2018).

The advantages of DDFL extend beyond individual expertise. According to this study (Seng & Chuan, 2023), it increases student engagement, leads to better learning gains, and even improves teaching effectiveness. Educators obtain crucial insights on how their students learn, allowing them to modify their approaches and create a genuinely dynamic learning environment.

DDFL, like every other breakthrough, has its unique set of problems. Data privacy necessitates caution, and instructors must be trained to leverage the value of learning analytics. In order to support this data-driven strategy, schools may need to invest in digital infrastructure. However, when evaluated against the possible advantages, these obstacles appear to be minor hiccups on an otherwise bright road. Data-driven flipped learning hints at a future in which learning is individualized, entertaining, and ultimately more rewarding for both students and instructors.

CASE STUDY

In this section, we will dive deeper into the details of the experiment that was carried out using the innovative Data-Driven Flipped Classroom model. We will examine the specific population that was the focus of the study, the criteria for inclusion, and the resources that were utilized on the Blackboard LMS platform to drive this data-driven approach.

Course Description

The algorithmic course serves as the foundation of our first year engineering program, giving students the fundamental knowledge and skills necessary to solve problems and engage in computational thinking in order to effectively deal with the complexities of contemporary engineering. Three years ago, first year student had a one programming course in their syllabus that covered algorithms alongside the C programming language. The emphasis was primarily on the language itself, delving into its specifications, including syntax and lexical features, with relatively less emphasis on problem-solving approaches.

As a result, we decided to add a new course to the syllabus focusing on algorithms and follows the same outcomes schedule of the other C programming course. Both courses have the same learning outcomes. The algorithm course focuses more on fundamental aspects and the problem-solving skill while the C programming course focuses on the application on those fundamental concepts and technical skills. Hence, Students are exposed to the learning outcome one week before the C programming course. Therefore, our challenge is to prepare students well enough to easily master programming courses, to solve complex problems in a pre-prepared way. Students will be more prepared to solve problems using model thinking.

Although the traditional lecture format was used in our algorithms course, we soon realized its shortcomings when it came to fully grasping and applying these intricate concepts. Passive learning, which characterizes traditional classroom, limits active engagement and practical application, which runs counter to the need for algorithmic learning, where students need to be engaged in analysing problems and formulating solutions. In addition, the lack of timely feedback mechanisms hinders personalized learning experiences. The classical approach used in this course is illustrated in figure 1.

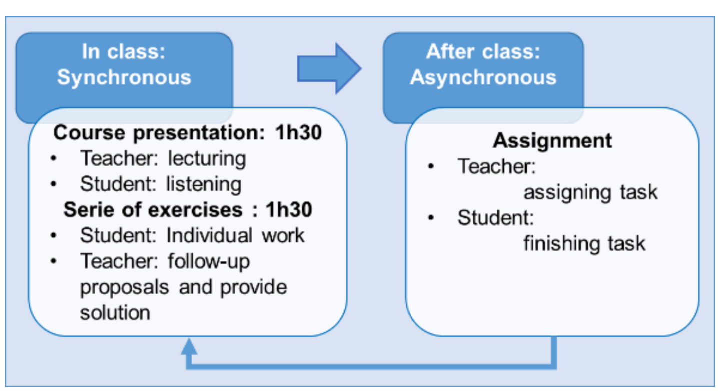

Figure 1. Overview of conventional teaching approach

As demonstrated, the course presents a limited interactivity between students, which reduced opportunities for collaborative problem-solving and diverse perspectives. Hence, we implemented the DDFL method in the algorithmic course and detail the outcomes in this study.

Research questions and methods

The aim of the study was to compare the effectiveness of the data-driven flipped classroom (DDFL) versus the traditional lecture-based teaching method in terms of improving the results of first-year computer engineering students. Research questions included:

The impact of the data-driven flipped classroom on student performance and understanding compared with the traditional lecture-based teaching method. The influence of data-driven personalized instruction on student engagement and academic achievement. The benefits and challenges of implementing the data-driven flipped classroom in a computer engineering teaching context.

To answer the research questions, the experiment involved two groups of First-Year Computer Engineering students at ESPRIT School of Engineering, totaling 120 participants. To ensure comparability with a focus on current learning dynamics, the experimental group (N=60) participated in the Data-Driven Flipped Classroom during this academic year, while the control group (N=60) experienced the traditional lecture-based teaching method in the previous academic year.

Selection criteria were used to maintain comparability between academic years. Students were chosen based on the following criteria: (i) Similar academic backgrounds. (ii) No past exposure to the model. Using these criteria, we hoped to create two comparable groups, even though they were from different academic years. This enabled a more accurate evaluation of the DDFL model's effects on student outcomes.

In summary, the study methodology involved a comparison between two groups of students to assess the impact of the data-driven flipped classroom on computer engineering students' performance and understanding, with a focus on teaching personalization and current learning dynamics.

Design and Implementation of the DDFL Approach

Our Data-Driven Flipped Learning Approach employs pre-class quizzes and in-class activities to customize the learning experience and cater to students with varying levels of knowledge in the classroom. The platform for providing the Data-Driven Flipped Classroom experience was Blackboard LMS.

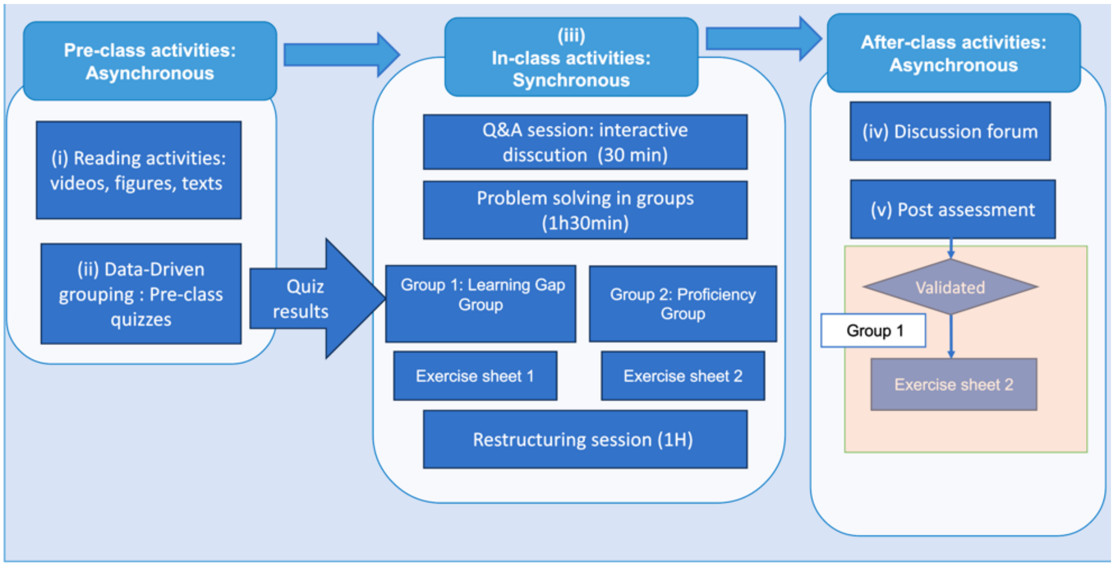

Figure 2. DDFL framework

This strategy consists of five components as illustrated in figure 2:

(i) Pre-class Activities: Reading activities and video to address the learning outcome.
(ii) Data-Driven Grouping and Pre-Class Quizzes: Before each class session, students take short, interactive quizzes to assess their understanding of significant concepts covered in pre-class lectures. Students are dynamically separated into two groups based on their quiz results:
a. Students in Group 1 (Learning Gap Group) score below a specified level, suggesting possible gaps in knowledge.
b. Students in Group 2 (Proficiency Group) have a medium or high level of understanding and score at or above the threshold.
(iii) Activities in the classroom:
a. Q&A session: The instructors provide a clarification on doubts that arose from the pre-classes activities.
b. Collaborative problem-solving: Students work in groups depending on their Pre-Class Quizzes classification on a complementary set of exercises enabling cooperation on difficult tasks, boosting peer learning. Learning Gap Groups will have access to an exercise sheet of medium difficulty allowing the students to achieve the minimum level of learning outcome. While the Proficiency Groups work on a different set of exercises of higher level of difficulty allowing them to work to obtain a better level of understanding. Meanwhile, instructors give tailored help in class based on pre-quiz scores, concentrating on areas of uncertainty identified for specific student groups.
c. Restructuring session: The instructors provide an in-depth explanation on the most crucial parts of the lesson.
(iv) Discussion forums: Students were able to interact and enhance their learning outside of the classroom thanks to ongoing conversations on Blackboard platforms.
(v) After-class Activities: Students will have access to a post assessment if validated by the of Learning Gap Groups, they will have access to the same set exercises previously provided to the Proficiency Groups in order to attaint excellence.

As previously detailed, a variety of methods are used in the algorithmic course to collect extensive data regarding student performance. Pre-class quizzes using the Learning

Management System (LMS) Blackboard are the first step in the process. These quizzes serve as a basic assessment tool, providing an overview of students' prior knowledge acquired through the course materials. During the course sessions, classroom activities adapted to the specific needs and skill levels of each group of students are presented and practiced by the students. This adaptation is based on the results of the initial questionnaire and on ongoing assessments of performance during the course. Continuous monitoring occurs during in-class activities in which the professor supervises and assesses individual and group progress. This dynamic feedback loop helps to refine teaching strategies to meet the unique needs of the students.

Post-class assessments, accessible on Blackboard, provide an overview of course effectiveness. In particular, students in Group 1 with a lower skill level will be automatically directed to a series of additional exercises after passing the post-class assessment. This will ensure a progression in skill level for their ongoing learning path. This ensures an adaptive, data-driven approach to optimizing the learning experience in the algorithmic course. The Data-Driven Flipped Classroom concept seamlessly merged pre-class preparation, data-informed in-class activities, and continuous learning beyond the classroom walls by utilizing Blackboard LMS, allowing students to take ownership of their learning journey.

RESULTS AND DISCUSSION

The rigorous performance evaluation of the DDFL model is based on three main elements: the student survey, the teacher survey, and a detailed analysis of exam results classified by learning outcome. We begin by detailing the results of the surveys.

Student and teacher survey

We conducted an electronic survey of the 16 teachers of the algorithmic module and the students in five first-year classes. We received responses from 67 students, representing 42% of the total. And here below the results of the survey:

1. Pedagogical reform has improved active student engagement?

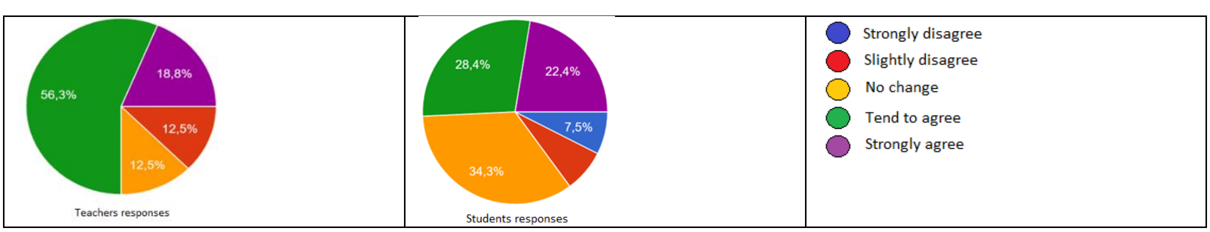

Figure 3. Evaluation of the impact of DDFL on active student engagement

Following on from these responses, we note that 70% of teachers have observed a better level of student engagement. For their part, more than half the students are better motivated. However, 15% of students are not more committed to this reform, which prompts us to launch future improvement actions. Indeed, when we analyze the students' responses more closely, going through their comments one by one, we find that those who are not satisfied with this approach find it difficult to assimilate the course in this phase. This is in line with the responses of a quarter of the teachers who are either neutral or slightly disagree with this approach and who added that in some chapters they found that the students did not assimilate it and they were obliged to repeat the course in class in the traditional way.

2. Flipped classroom activities (pre-assessment, vignettes, course materials) were helpful to prepare students for synchronous courses?

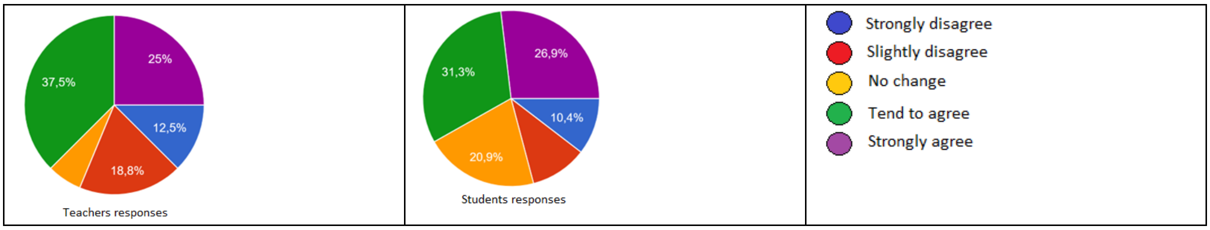

Figure 4. Evaluation of the effectiveness of the flipped classroom activities

Here we find that one-third of teachers would like to improve support. Also 20% of students think that supports are not suitable. This would lead us to better adapt the support to this new model.

3. The new learning activities helped students better understand the concepts.

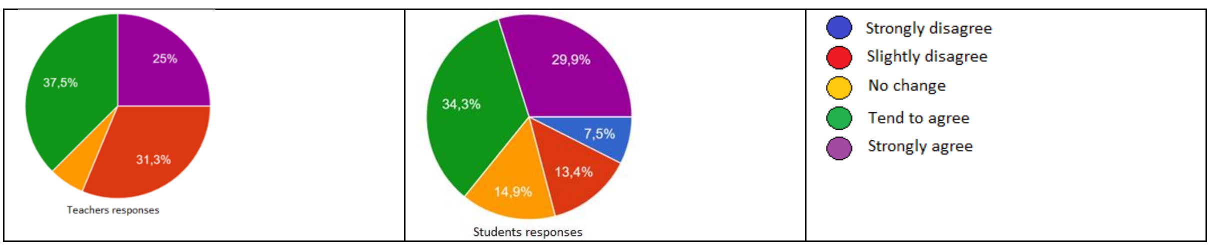

Figure 5. Assessing the impact of new learning activities

Although more than the half of teachers and students think that the new learning activities are suitable for understanding new concepts, we should improve these activities to be more adequate with our new approach. Both students and teachers who disagreed on this issue felt that more time was needed for synchronous sessions.

4. The process for allocating groups for teamwork was clear and fair?

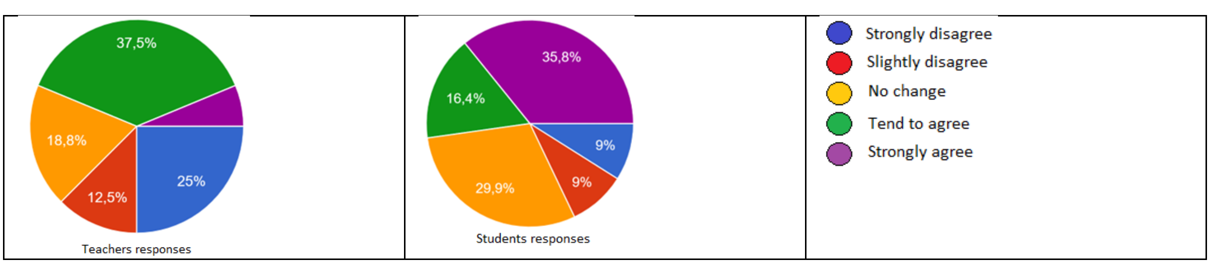

Figure 6. Assessing the process of groups allocation

More than 80% of students agree with the allocation of work groups, since it is based on pre-class results. On the other hand, over 35% of teachers think that the groups should be better distributed. This suggests that the pre-class phase could be improved.

5. The data-driven classroom model enabled appropriate personalization of learning?

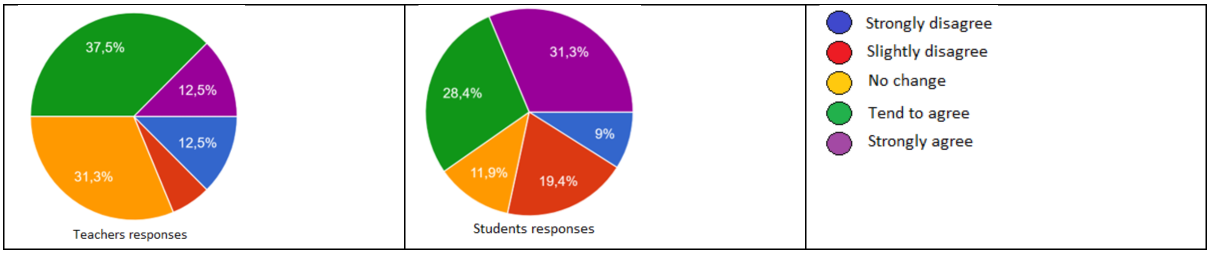

Figure 7. Evaluation of the data-driven model

We note here that students found the DDFL more personalized for them (60%). Indeed, students compare this approach with the flipped classroom approach in other modules such as programming. Although for both students and teachers the DDFL is more efficient, they all agree that more time should be allocated to synchronous sessions. Several students also suggested that correction of exercises not covered in class should be provided.

6. What specific aspects of the reform have been most beneficial in your experience as (a teacher of this module / a student in this module)?

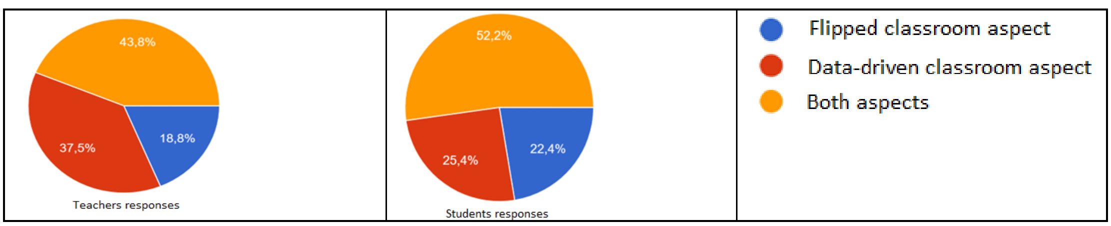

Figure 8. Evaluation of the DEFL approval rate

Teachers find DDFL more beneficial for students, although it involves more student monitoring. For their part, the students all agree that the flipped classroom is beneficial for understanding this module, but almost half are more inclined towards DDFL.

The conclusion of this questionnaire led us to the following results:
1. The students did not object to the group division as it was based on a test.
2. The DDFL requires more time to be allocated to synchronous sessions.
3. The course material needs to be continuously improved to ensure a better student understanding of the course.

Evaluation of the rate of validation of learning outcomes

The aim of the present investigation is to assess the impact of the pedagogical reform, centered on the DDFL approach, on the results of the assessment of students' learning outcomes in Algorithms during the academic years 2022-2023 and 2023-2024. The results, expressed as percentage of validation of learning outcomes (LO - Learning Outcomes), are illustrated in Table 1.

Figure 9 shows the significant changes in student performance following the implementation of this new approach. The overall results show a significant increase in student performance in algorithmics following the implementation of the DDFL approach during the academic years

2023-2024. The emphasis will be on Learning Outcomes 1 and 2, which represent the module's foundational elements.

Prior to the reform, only 55.39% of students validated learning outcome 1, indicating a mixed understanding of basic algorithmic concepts. However, after implementing the DDFL approach, this percentage climbed significantly to 74.2%. This significant improvement suggests that the reform was especially effective at improving students' understanding of fundamental algorithmic concepts. An in-depth analysis also reveals the impact of the DDFL approach on initially struggling students (Group 1: Learning Gap Group). The findings show that this pedagogical approach was effective in targeting the lowest-performing students, providing them with personalised assistance and special attention to fill gaps in their understanding of fundamental algorithmic concepts. This significantly increased the validation percentage.

Table 1. Percentage of validation of learning outcomes before and after DDFL approach

Learning outcomes	Description	Percentage of validation of learning outcomes	
		2022-2023	2023-2024
LO1	Identify the basic concepts of algorithms	55.39%	74.2%
LO2	Establish a high-quality algorithmic solution for problem-solving	44.12%	61.4%
LO3	Use static data structures in programming activities	45.86%	58.69%
LO4	Apply good practices of procedural programming	64.95%	66.6%
LO5	Recognize the role of an algorithm	33.90%	57.43%

Another interesting observation is learning outcome 2, which refers to students' ability to develop high-quality algorithmic solutions. Prior to the reform, the validation percentage was 44.12%, indicating challenges in solving algorithmic problems and developing high-quality algorithmic solutions. After implementing the DDFL approach, the percentage increased to 61.4%, indicating a significant improvement in this particular skill. The DDFL approach allowed personalised teaching to better meet the specific needs of learners, particularly those who had difficulty establishing correct, quality algorithmic solutions.

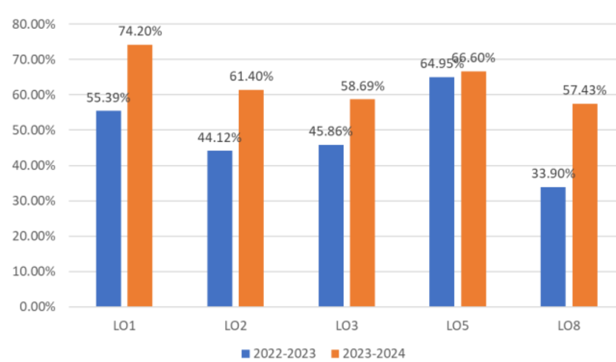

Figure 9. Written exam results before and after DDFL approach

Finally, the overall analysis of the results demonstrates the effectiveness of the DDFL approach in improving student performance in algorithms. The DDFL approach gave the weakest students a great opportunity to improve their understanding and make significant progress in key skills. This highlights the importance and positive impact of DDFL in the teaching context.

CONCLUSION

This study is a significant investigation into the integration of the data-driven flipped classroom within the algorithm course. Faced with the challenges inherent in the traditional algorithmics teaching model, this study proposed an innovative model aimed at meeting students' diverse needs while improving learning outcomes. The initial context demonstrated the limitations of a one-size-fits-all approach to managing classes with varying levels of assimilation, which limited the achievement of learning objectives. The proposed data-driven flipped classroom model is a step towards a more adaptive, personalised learning environment.

Experimentation with first-year computer engineering students at the ESPRIT engineering school has provided valuable insights. The careful planning of learning activities, which included pre-class quizzes, in-class interventions, post-class discussion forums, and evaluation, proved successful. The experimental study's results, which compared the experimental group to the control group, revealed significant improvements, particularly among the students who had previously performed unfavourably. The positive impact of the data-driven flipped classroom model on students' problem-solving abilities, as well as its overall benefits evidenced by written exam results, underline its transformative potential in the field of algorithmic education. The model presented, therefore, positions itself as an effective solution for teachers wishing to stimulate student engagement and improve performance in this key area of computer science.

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BIOGRAPHICAL INFORMATION

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