Adoption and impact of a learning analytics dashboard supporting the advisor-student dialogue in a higher education institute in Latin America

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Abstract

This paper presents a case study on the adoption and impact of new modules in a learning analytics dashboard supporting the dialogue between student advisors and students when advising on a study plan for the next academic semester in ESPOL, a higher education institute in Ecuador.

of the impact of the new dashboard modules was assessed using a mixed-methods approach. The *quantitative approach* builds on data of 172 advisors in 34 programs and 4481 advising sessions in 2019 (post) and 4747 advising sessions in 2018 (pre) to assess the adoption and use of the dashboard, the level of support experienced by the advisors, the impact of the new dashboard modules on the difference between the advised study plan and the plan students register for, and students' academic achievement. A *qualitative approach* with observations of 14 staged advising dialogues and semi-structured interviews with eight advisors was used to assess how the dashboard was used and to get deeper understanding of the perceived usefulness and impact of the dashboard.

The results show that an institution-wide deployment of dashboard modules tailored to the needs of the advisors can be achieved and increased the level of support perceived by the advisors and significantly decreased the gap between the suggested study plans in advising dialogues and the study plans students

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actually register for. On the short-term however, no significant changes in academic achievement were observed.

Keywords: learning analytics, learning dashboard, case study, learning technologies, impact, academic advising

A set of structured practitioner notes

What is already known about this topic?

1. Academic advising can positively impact retention, academic achievement, and study completion.
2. Learning analytics dashboards are promising pieces of educational technology for academic advising as they can trigger reflection and sense-making of educational data.
3. Evaluation of learning analytics dashboards is often still immature and not well-connected to the actual goals of the dashboards. Large-scale evaluations looking at impact of dashboards are even more scarce.

What this paper adds

1. This paper adds, to the scarce scientific evidence on academic advising dashboards, a large-scale case study on a dashboard supporting the advisor student dialogue during the composition of well-balanced study plans.
2. The papers presents research evidence of the impact of the dashboard on the support advisors experience, the study plans suggested by the advisors and the ones actually registered by the students, and students' academic achievement. Evidence is based on a quantitative analysis, using data of 172 advisors from 34 programs representing more than 9000 advising dialogues, and a qualitative analysis using observations and interviews.

Implications for practice and/or policy

1. Dashboards to support academic advising dialogues can be realized institution-wide at scale. Training of student advisors supports such a large scale deployment.
2. Well-designed dashboards that focus on addressing needs of advisors, increase, once implemented, the level of support that advisor experience when advising students.
3. Dashboard accommodating the simulation of study plans and the workload associated with them, succeed in decreasing the variance in suggested plans between advisors and reduce the gap between the study plans advisors suggest to student, and the study plans students actually register for. Short-term impact on academic achievement was not observed.

Biography

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1 Introduction

The goal of this paper is to share a a large scale case study regarding the adoption of Learning Analytics Dashboards (LADs) for academic advising in higher education and the impact on the advising and academic processes (perceived support, suggested and registered study plans, and academic achievement). Below, we introduce academic advising, LADs, the evaluation of LADs, the particular context, and the goal and contribution of this paper..

When studying in higher education, students have to make a lot of decisions regarding their study plan. Academic advising assists students in the clarification of their career/life goals and the development of an educational plan for the realization of these goals through communication and information exchanges with an advisor. Academic advising often occurs during a face-to-face-meeting between the student and their advisor, the so-called advising dialogues. Students typically consult their advisor when they have to make academic decisions, when they have doubts regarding their current career, or when they experience difficulties during their studies. Academic advising can have positive impact on retention, academic achievement, and study completion (Young-Jones et al. (2013); Drake (2011); Bahr (2008); Sharkin (2004)). Currently most higher education institutions (HEI) offer academic advising programs, and accreditation agencies such as ABET specify criteria related to advising.

Learning Analytics (LA) was defined by Erik Duval as "collecting traces that learners leave behind and using those traces to improve learning". LA has been growing as a research field since 2019 and an increasing number of reports are published of LA interventions in educational practice. Nevertheless, only few scientific reports tackle LA at institutional scale (Ferguson et al. (2014); Dawson et al. (2019)) as difficulties, such as resistance to change, hinder scaling. Recently, both the technology acceptance model (Davis et al. (1989)) and academic resistance models (Piderit (2000)) have been used to better understand the difficulties in taking LA to an institutional scale.

Within the LA domain, Learning Analytics Dashboards (LAD) specifically focus on visually presenting educational traces, often supplemented with outcomes of educational data mining or predictive analytics, to end-users such as teachers and learners. The first LADs related to academic advising focused on the identification of students at risk (King (2012); Wolff et al. (2014); Calvert (2014); Gasevíc et al. (2016); Choi et al. (2018); Herodotou et al. (2019a,b)). Recently, LADs have also been used to support advising dialogues (Charleer et al. (2018); Millecamp et al. (2018); Gutíerrez et al. (2018)), still keeping the research evidence on LADs focusing on advising very limited (Gutíerrez et al. (2018)).

One important open issue related to LADs in general is evaluation. Bodily & Verbert (2017), Jivet et al. (2018), and Verbert et al. (2020) formulated important criticism towards the evaluation of LADs. They stress the need to better articulate the evaluation goals and to match the evaluation goals to the goals of the LADs.

In our work, we focus specifically on a LAD to support academic advising dialogues, adopted at an institutional scale at the Escuela Superior Politecnica del Litoral (ESPOL) in Guayaquil, Ecuador. We first elaborate on the context before introducing the goals of the research, the methodology, and the contributions.

The main objective of academic advising in ESPOL is to support students in their academic career by advising them about career options and subjects to select as well as redirecting them if necessary to other ESPOL offices such as the student-welfare departmentIn 2013 ESPOL developed a supporting LAD and scaled it to the entire university as part of the Undergraduate Student Accompaniment Program. . In 2017, ESPOL entered the LALA Erasmus+ project aiming at building LA capacity in Latin America, which provided an important stimulus to further develop the existing LAD. Initial interviews, surveys, and focus groups to understand the current situation indicated that advisors require more data-based support to make sound decisions when advising students (Ortiz et al. 2019).

This paper reports on the adoption process, evaluation, and impact of three new modules introduced in the existing ESPOL LAD to address the need for more data-based support during the dialogue between an academic advisor and a student when advising on a study plan for the next semester. Hereby our paper aims at sharing a particular case-study of LA at scale to inspire other higher education institutions. With this paper, we advance the state of the art by the presentation of a large-scale mixed-methods evaluation regarding both use, perceived usefulness, impact on the support advisors experience, impact on the actual study plans suggested and registered, and impact on students' academic achievement.

2 Related work

As related work, this paper focuses on three very recent LADs targeting HEI, of which two are dashboards supporting academic advising dialogues (Charleer et al. (2018), Gutíerrez et al. (2018)), and one is a dashboard to identify at-risk students (Herodotou et al. (2019a)). These three were selected as they have a strong focus on advising, included a predictive LA component, used a combination of qualitative and quantitative evaluation, and were deployed and evaluated at medium or large scale. Table 1 summarizes the main characteristics of the three LADs and their evaluation and compares them with the LAD modules and evaluation presented in this paper.

The "Learning dashboard for Insights and Support during Study Advice", or LISSA in short, is a dashboard supporting the dialogue between academic advisors and first-year students, developed and used by KU Leuven, a general university in Belgium (Charleer et al. (2018); Millecamp et al. (2018)). LISSA was the result of intensive user-centered design approach and driven by the goal of empowering advisors by providing them with visualisations of data underlying the student's career path and the program of study. The LISSA dashboard includes predictive modules visualizing the probability of in-time graduation and the probability of success of plans composed for the re-sits in summer. These predictive modules rely on visualization of data of past cohorts rather than on machine learning (Charleer et al. (2018)). The evaluation of LISSA did not involve pre or post measurements nor A-B testing, so no proves for “hard” impact with respect to previous years was presented.

Gutíerrez et al. (2018) also presented a LAD supporting academic advising, named Learning Analytics Dashboard for Advisors, or LADA in short. In contrast to LISSA, LADA builds on predictive analytics using machine learning to present advisors with so-called “chances of success” when composing study plans for the next semester. LADA can be used both in an advising dialogue or individually by the advisor. The evaluation of LADA did involve a pre and post setup in the staged observations, which provided indicators for impact on the advising dialogue of the LAD, but the impact remains to be shown in actual advising sessions.

Herodotou et al. (2019a) presented a large-scale implementation of a LAD in HEI to support teachers in the identification of students at risk in online courses of an open university. The dashboard called, OUA, short for Open University Analyse, presents teachers with the outcome of machine learning algorithms predicting which students are at risk of not submitting the next assignment and not completing the course. The quantitative analysis of the paper showed that teachers’ increasing engagement with OAU was associated with a higher likelihood of completing the course. Yet, the authors themselves already indicate that a causal interpretation can’t be done (yet) as teachers engaging more in OUA may be better teachers anyway, also causing an increasing course completion rate.

The ESPOL dashboard presented in this paper focuses on the advising dialogue, (just as LISSA and LADA) and contains a predictive component (similar to LISSA, LADA, and OUA), in the ESPOL dashboard predicting the difficulty of the study plan. Just as the evaluation of LISSA, LADA, and OAU, the evaluation in this paper focuses on use and perceived usefulness using questionnaires and semi-structured interviews. Similar to LADA, observations of staged dialogues were used. Different from LISSA, LADA, and OUA this paper additionally presents a pre-post quantitative evaluation setup at large scale, allowing to assess the impact of the ESPOL dashboard on the study plans suggested by the advisors, the plans actually registered by the students, and students’ academic achievement.

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	goal	impact studied	evaluation methods	evaluation scale
LISSA	support student- advisor dialogue focus on first-year students	use perceived usefulness usability impact on advising	questionnaire advisors questionnaire students observations real dialogues semi-structured interviews	1 HEI *quantitative:* 26 advisors, 101 students, 11 STEM programs *qualitative:* 15 advisors, 15 + 20 dialogues, 2 STEM programs
	References: Charleer et al.(2018);Millecamp et al.(2018)			
LADA	support advice on study plan by advisors (not necessarily in dialogue)	use perceived usefulness usability comparison with old system	questionnaire advisors staged observations (think-aloud)	2 HEIs 26 advisors 78 staged observations 2 STEM programs
	References: Gutíerrez et al.(2018)			
OAU	helps teachers identify at-risk students in online course	use perceived usefulness usability correlation with student performance impact on teaching & support	log data academic records semi-structured interviews	1 online university *quantitative:* 59 teachers, 1325 students, 9 courses *qualitative:* 6 teachers
	References: Herodotou et al.(2019a)			
ESPOL	support student- advisor dialogue when advising study plan any student	use perceived usefulness impact on study plans	log data academic records questionnaire advisors thematic analyses staged dialogues semi-structured interviews	1 HEI *quantitative:* 172 advisors, 4747+4481 students, 34 programs *qualitative:*8 advisors, 14 dialogues, 4 programs
	This paper			

Table 1: Overview of the dashboard described in journal papers and most related to the presented ESPOL dashboard. Relevant characteristics of the study are summarized.

3 Advising sessions and advising dashboard

The ESPOL dashboard aims at providing support to advisers during an advising dialogue with a student when composing a study plan for the next semester. In ESPOL, academic advising is done by teachers of the study program. Typically, 20 students are assigned to each available teacher. Advising sessions, also called advising dialogues, are organized twice every semester during a fixed two-week period at the beginning and in the middle of the semester. This paper focuses on the beginning-of-semester advising sessions organized before the registration for the actual subjects, to advise students on a study plan for the upcoming semester. These sessions are mandatory for students who have already studied at least one semester. Typically, advising sessions take around 15 minutes.

The dashboard supporting the advising sessions is well-integrated in university practices and IT: it is the tool that each advisor uses when advising students. While the original dashboard (Figure 1) had a module to select courses for the next semester plan, no data-based support was provided. As advisers expressed the need for such support (Ortiz et al. 2019), three new modules were integrated in the dashboard in 2019 focusing on data-based support when advising study plans for the next semester. The first module (Figure 2) focuses on the student's academic history. Based on the lessons learned from the LISSA dashboard of Charleer et al. (2018), the module visualizes the entire pathway in a single screen. The second module (Figure SI.2) supports the composition of a well-balanced study plan by offering a simulation of the workload and difficulty of a suggested study plan for the next semester. The third module (Figure SI.3) offers a comparison of the student's study pathway with other students as well as welfare information.

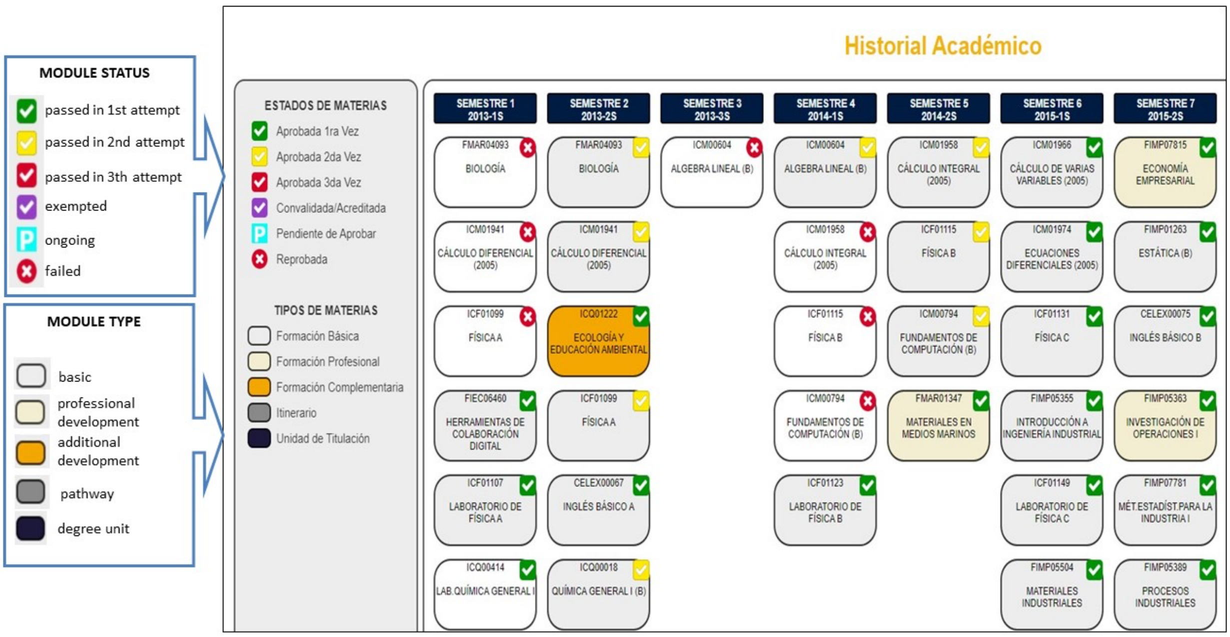

Figure 2: Screenshot of the first new module of the ESPOL advising dashboard, visualizing a student's academic pathway. Clicking a tile triggers details on the module (Figure SI.2)

Figure 1: Overview of the old ESPOL advising dashboard.

4 Methods

To support the introduction of the new modules in the ESPOL advising dashboard in 2019, voluntary training workshops were organised. At the start of the workshops the advisors were asked to indicate the level of support they experienced from the existing dashboard (pre) on a 5-point Likert scale. A 3-question knowledge test at the end of the training, indicated that the advisors achieved the training objectives. Next, the new modules were introduced in the advising dashboard during the actual advising sessions. After the first semester advising period, advisors were requested to report the perceived level of support (post). Both before (2018) and after (2019) the introduction of the new dashboard modules, the dashboard activity, including the study plan suggested by the advisor, was logged.

From the university's data warehouse, the study plan that students actually registered for and the academic achievement (grade point average (GPA) and number of subjects passed) in the next semester was retrieved. The data of 2018 (pre) and 2019 (post) was used to assess the impact of the new dashboard modules on the suggested and registered plans, the difference between the suggested and registered plans, and students' academic achievement. The **quantitative analysis**, with permission of the university (no ethical commission at ESPOL), was performed between advisors. To this end the data obtained from 2018 (pre) and 2019 (post) was filtered to obtain a consistent dataset by only keeping first-semester dialogues from advisors who advised a minimum of 10 students in both 2018 and 2019 and whom on average advised more than 15 hours of workload (proxy for suggesting of a valid study plan). Finally, eight outliers were removed (inter-quartile range of 1.5) and for each advisor, the data of all their advising dialogues in one year was averaged. This resulted in a dataset of 172 advisors (52 trained and 120 non-trained), who on average held 27.6 advising sessions in 2018 (pre), accounting for a total of 4747 sessions, and 26.05 advising sessions in 2019 (post), accounting for a total of 4481 sessions. The **qualitative evaluation** of the new dashboard modules was done using observations of staged advising dialogues where a researcher acted as a student but where the advisor was real. Advisors provided informed consent. In each qualitative evaluation session with an advisor, taking around 70 minutes, two advising dialogues were staged and a semi-structured interview was done. Details of the staged dialogues and the semi-structured interviews are available in Supplemental Material II. The evaluation session took place at the end of the semester in which the new dashboard modules were introduced. Eight advisors were selected from all advisors that satisfied the following criteria: participated in the training, were in the quantitative analysis dataset, and reported a 4 out of 5 level of perceived support. The selection was done such that two advisors belonged to the same program, diverse programs were selected (both STEM and non-STEM), and selected advisors had diverse levels of use of the new dashboard modules in the actual 2019 advising sessions. Table 1 summarizes the main characteristics of the eight selected advisors.The entire evaluation sessions were video-taped, including a screencast of the advisors' screens, and log-data was retrieved. A thematic analysis, of which the details are elaborated in Supplementary Material IV, was used to analyse the semi-structured interviews.

5 Results

To evaluate the impact of the dashboard, the evaluation was done in four stages. In the first stage the **adoption and use** of the new dashboard modules were evaluated. Adoption and use should be evaluated before proceeding to other impact measures. Moreover, to understand the potential impact of the modules on the advising process and academic achievement, understanding how the dashboard modules were used was key. The second stage tackled the impact on the **perceived support**. This was already an important aspect of impact as good support of advisors and their perception of being well-supported already impacts advising. The third and fourth stages tackled the more ambitious impact on the **study plans** and student's **academic achievement.**

5.1 Adoption and use

To assess the adoption of the new dashboard modules, the average time that each advisor used the new modules during the advising sessions was derived from log data (Figure 3). On average, the advisors used the dashboard during 35% of the advising dialogue (5.290 out of 15 minutes).

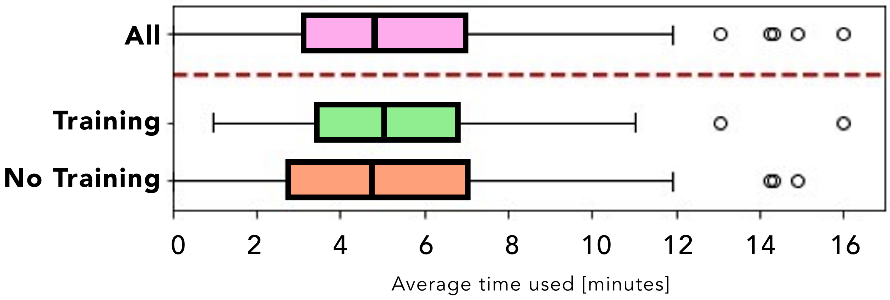

Figure 3: Average time in minutes that all advisor, trained advisors, and non-trained advisors used the new modules during their 15 minutes advising dialogues. The 52 trained advisors (M=5.676 minutes, σ=3.079 minutes) on average used the new modules more than the 120 non-trained advisors (M=5.122 minutes, σ=3.130 minutes), this difference was not significant when testing using a paired-samples t-test: t(119,51)=-1.071, p =0.286).

The thematic analysis of the staged observations resulted in a sequence of (sub)themes handled chronologically, supplemented with a duration and the dashboard module used, for each staged dialogue. Figure 4 visually presents the results of the thematic analysis. The quantitative analysis of the results , presented in Supplemental Material III confirmed that the new modules of the dashboard were mainly used during *Planning* and when discussing *Academic History*, which matches the goals of the new modules (see also

Table SIII.3). Within these themes, the new modules were mostly used when the advisors were talking about the *Performance* of particular *Subjects*, *Difficulty*, and *Workload* (Table SIII.4). Typically, Academic History is handled in the beginning of the sessions, followed by Planning, and ending with the Advising Process (Figure 4).

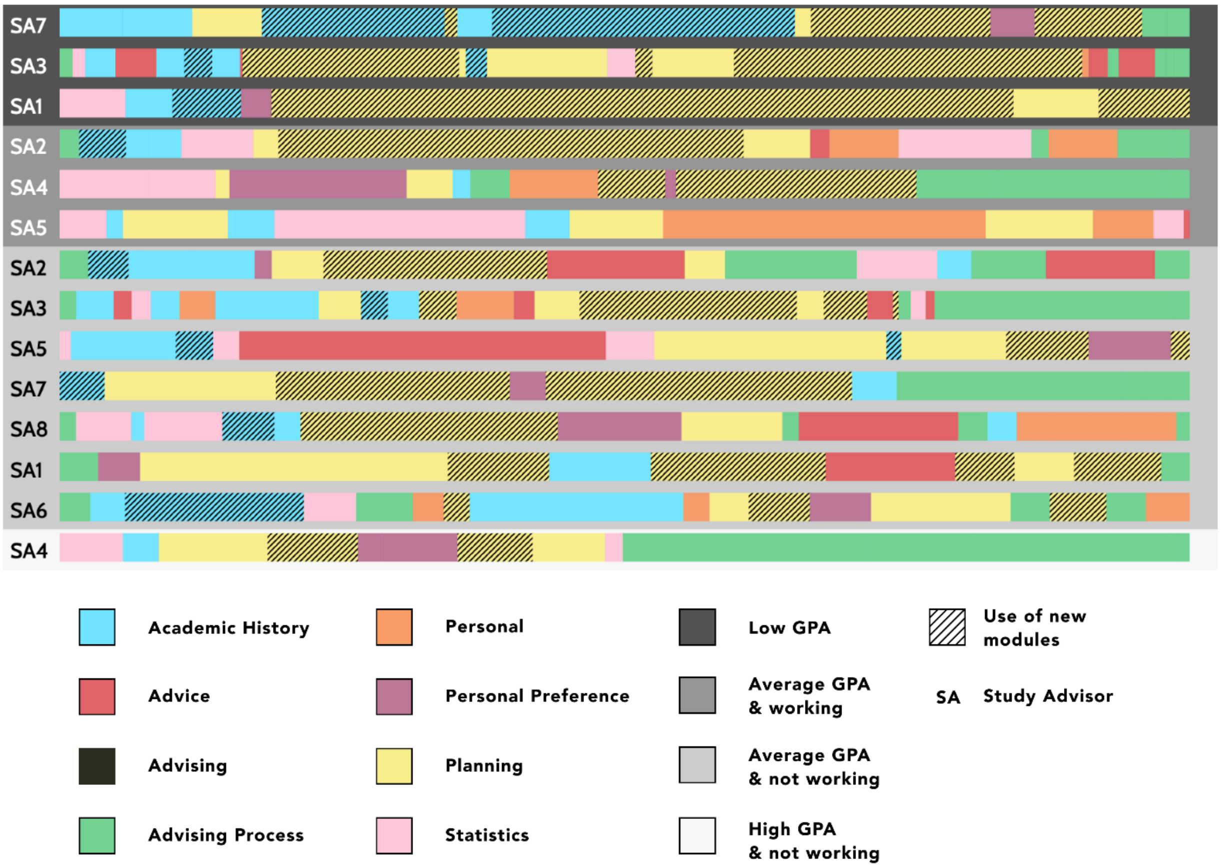

Figure 4: Visualization of the identified themes in the 14 staged advising dialogues, with an indication of whether the new dashboard modules were used (dashed), and the type of student profile (Table SII.2, different shades of green in the background). Each row represents one staged dialogue. The different colours represent the chronological sequence of themes discussed, their length is proportional to the percentage of the time spent in that particular advising session.

As the results regarding adoption and use confirmed that the new modules are actually used by the student advisors and that they were used for the purpose they were designed for (academic history & planning), the impact of the new modules on perceived support was analysed next.

5.2 *Perceived support*

An analysis of the perceived support in 2018 (pre) and in 2019 (post) reported by the 52 advisors whom received training indicated that the perceived support in 2019 was significantly higher than in 2018 (see Figure 5).

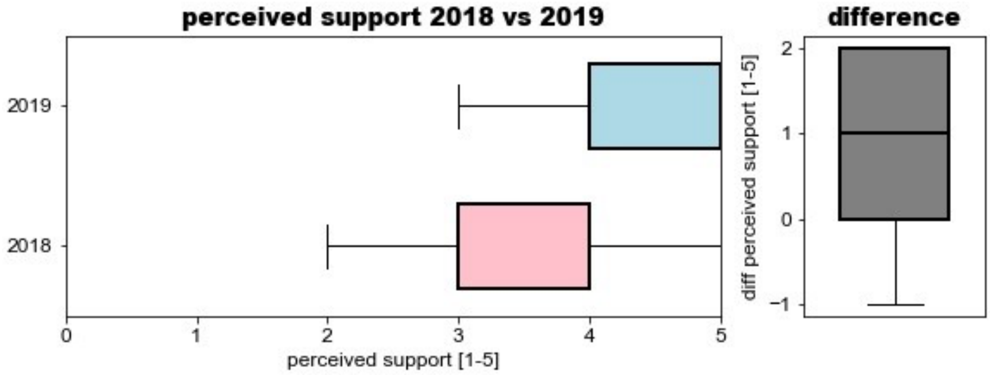

Figure 5: Impact of new modules on dashboard on perceived support of advisors (5=highest perceived support). A Wilcoxon Signed-Ranks test indicated that the perceived support in 2019 (M=4.346, σ=0.590) was significantly higher than in 2018 (M=3.558, σ=0.872): Z=18.0 and $p=3.298 * 10^{-6}$.

Furthermore, the perceived level of support by the new dashboard is related to the level of use: advisors who feel better supported by the dashboard used the new modules more (average time dashboard modules were used during advising), although no statistically significant differences could be retained (see Figure 6).

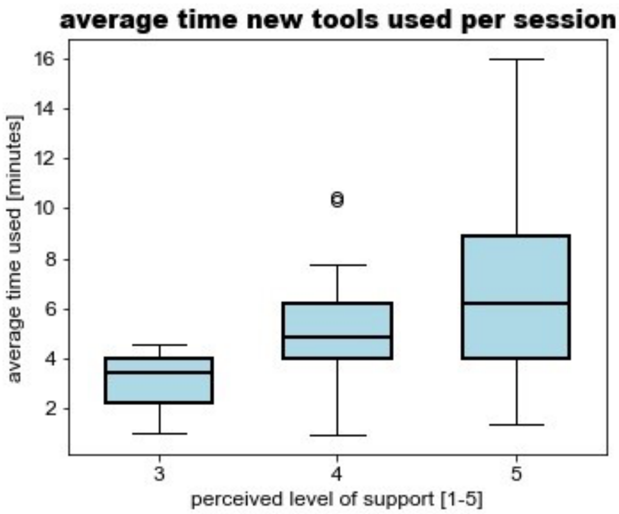

Figure 6: Relation between perceived support and average time the new dashboard modules were used. The average time spent by advisors reporting the highest level of support (M= 6.764, σ= 3.754) was higher than the average time spent by advisors reporting the one but highest level of support (M= 5.146, σ=2.285): t(27,20)=-1.869, p =0.0679.

The semi-structured interviews after the staged dialogues provide deeper understanding on why the advisors feel better supported by the new dashboard modules and what could still be improved. Supplemental Material IV contains all quotes from the advisors that could be extracted from the interviews, which were used to generate the summary below. Most advisors indicate they were happy about the new modules and found them useful and supportive. The new modules support advisors in the following challenges they encounter: lack of information (regarding advising in previous years, personal challenges, and follow-up of referrals) and user-friendliness (lack of overview and number of clicks needed to see information). Advisors mainly request improvements regarding more data on the students' personal situations and better support regarding the personal aspect of the advising dialogue. This is also reflected in the thematic analysis of the staged dialogues: when talking about Personal aspects and Personal Preferences (Table SIII.2) advisors do not use dashboard modules. The training that was offered addresses the need for explanations regarding advising, especially for new advisors. Advisors however still expressed the desire for additional support for advising students on top of the one they received from the university. They believed the university level is still not doing enough to support them, but indicated they do feel supported by peers or the faculty.

5.3 Study plans

The final goal of the advising session in the first semester is to support the advising of well-balanced study plans with a manageable workload. The second new module of the dashboard provided a simulation of the workload of study plans. Even if advisor and student agreed on a study plan during the advising session, the student was still free to register a different plan. The workload gap, the difference between the workload between the advised plan and the registered plan, is therefore a measure for how well the students comply with the advice given.

Figure 7 shows how the new dashboard modules impacted the workload of the advised plans, the workload of the registered plans, and the workload gap. A paired-samples t-test exposed a statistically **significant decrease of the workload gap** between 2018 (no new dashboard modules, M=-4.6987 hours, σ=5.577 hours) and 2019 (new dashboard modules, M= -2.504 hours, σ=4.229 hours): t(171)=-4.926, p =$1.9650*10^{-6}$. A Shapiro-Wilk test indicated that the null hypothesis of normality could be retained: W(171)= 0.991, p=0.379. This is due to the increased suggested workload rather than a decrease in the registered workload.

A Levene test showed a **significant decrease** from 2018 to 2019 **of the variance of the suggested workload** (f(171,171)=11.04, p=0.001) and the **variance of the workload gap**: (f(171, 171)=10.78, p=0.001), indicating increased consistency between advisors.

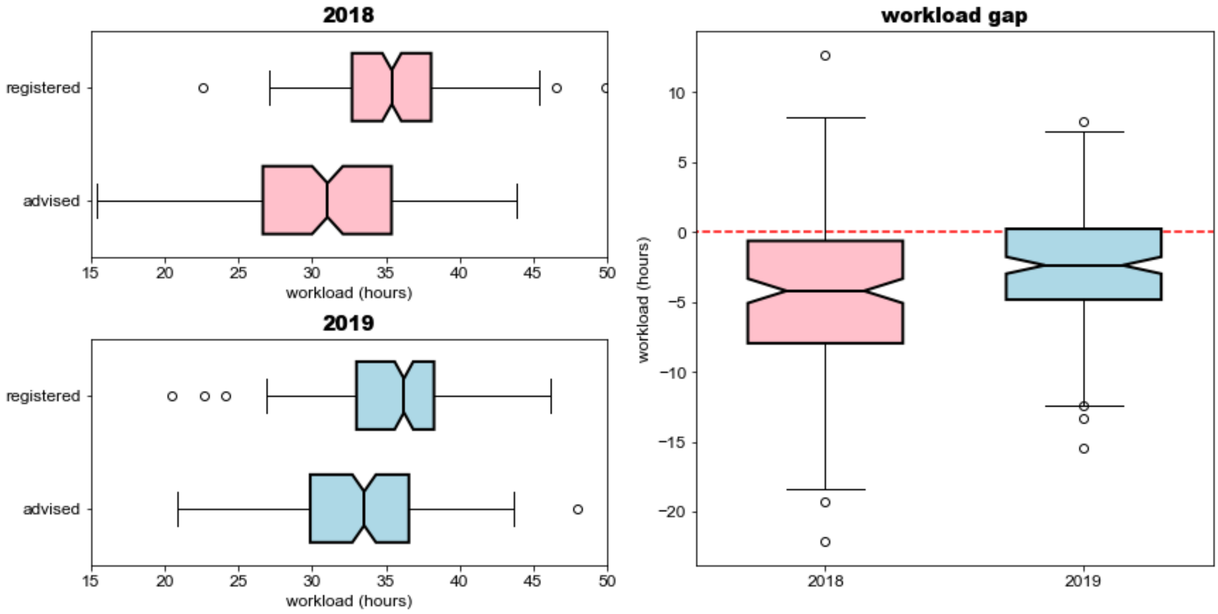

Figure 7: Changes in workload between 2018 (before new modules) and 2019 (after new modules) of the advised and registered study plan, and the difference between the two (workload gap) averaged per advisor Statistical tests are included in the paper.

Academic achievementBetween 2018 and 2019 an average increase in both the average GPA (2018: M=6.948, σ= 0.459; 2019: M=6.982, σ= 0.553) and average number of subjects passed (2018: M=3.948, σ= 0.498; 2019: M=3.959, σ= 0.591) was observed, a paired-samples t-test indicated this increase was not significant (Figure 8).

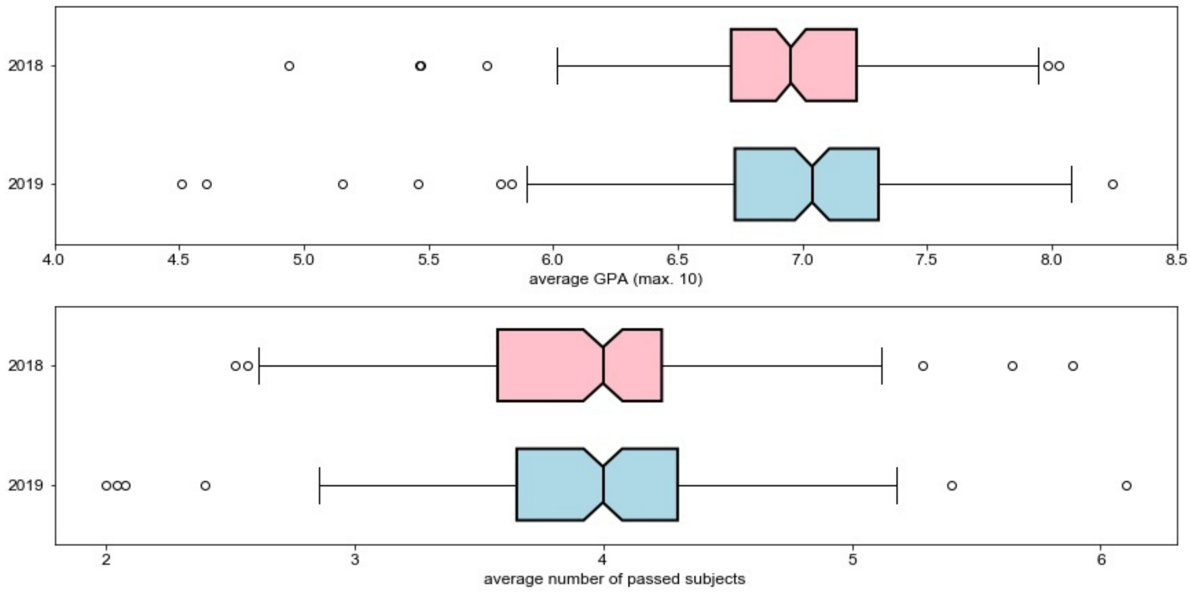

Figure 8: Changes academic achievement (GPA and number of passed subjects) between 2018 (before new modules) and 2019 (after new modules) averaged per advisor.

6 Discussion

This paper presented the impact of three new modules in the ESPOL advising dashboard supporting the advising of a well-balanced plan for the next semester. On the short-term the goal was to realize adoption of the new dashboard modules during the advising dialogues in order to better support the advisers and increases student success on the long-term. Below we discuss the results, also connected to existing literature on LAD, and elaborate on the implications of the obtained results. Before entering into the discussion we want to highlight that the evaluation plan of the new dashboard modules, leading to these results, was designed to ensure that the evaluation goals were well-aligned with the goals of the dashboard, hereby meeting the criticism of Bodily & Verbert (2017) and Jivet et al. (2018). Additionally, as the dashboard was deployed at institutional scale, reaching more than 296 student advisors responsible for 6668 student, this paper adds to the scarce scientific reports of LA at scale (Ferguson et al. (2014); Dawson et al. (2019)). The pre-post design of the evaluation and the large scale of the dataset (172 advisors in 34 programs and 4481 advising sessions in 2019 (post) and 4747 advising sessions in 2018 (pre)) is unique: previous research on academic advising learning dashboards often either did not handle a comparison with the old situation (Charleer et al. (2018)), only relied on observations of staged dialogues with old and new advising approaches (Gutíerrez et al. (2018)), or used an approach preventing causal interpretations of the findings (Herodotou et al. (2019a)). Finally, the scale of the evaluation exceeds the scale of any previous scientific evaluation of academic advising dashboards. The discussion below is structured according to the goals of the LAD modules: adoption & use, perceived usefulness, suggested & registered study plans, and academic achievement.

6.1 Adoption and use

When implementing LAD at institutional scale, one has to overcome resistance to change (Piderit (2000)). This paper both evaluated **if** and **how** the new LAD modules were used. Some contextual aspects supported the adoption of the new LAD modules: they were part of an existing LAD already deployed at institutional scale, and advisors were obliged to use one of the new modules for logging the suggested plan. Additional measures are believed to have strengthened the adoption and decreased resistance to change. First, the modules were designed based on the specific needs expressed by advisors for additional data-based support to compose well-balanced study plans. Second, a voluntary training was organized to support advisors in their use of the new modules. The results indicate that the adoption of the dashboard was successful (the new modules were used on average during 35% of the time in advising sessions). The training was well-received by the advisors, but proved not be essential towards adoption as the level of usage was not different between trained and non-trained advisers. The former findings can support HEI when deciding which strategies are most important to obtain institution-wide adoption of LAD dashboards.

To assess **how** the new modules were used and if the use was in line with the goals of the LAD modules, staged advising dialogues were analysed both quantitatively and qualitatively. Results indicate that advisors use the new modules during the dialogues in line with the goals of the modules, i.e. predominantly for discussing the academic history of the student and for composing a plan for the next semester. As these results were obtained using staged advising dialogues with trained advisors where both the staging and the training could have biased the results, further research should focus on how the modules are used in real advising dialogues and if training has any impact in this respect. Furthermore, future research should more deeply investigate which dashboard modules trigger which insights, questions, and discussion topics (Charleer (2017)). Finally, new iterations of the ESPOL LAD shall take into account the feedback of student advisors.

6.2 Perceived support

From the questionnaire data and the interviews we can conclude that advisors perceived a significantly higher level of support by the dashboard after introduction of the new modules. These results indicate that a HEI's investments in educational technology can at least partially address the support that advisors request from their university, provided that the educational technology is tailored to the particular needs they expressed. The interviews indicated that advisors, while being positive about the new modules, still expect support from the HEI beyond the dashboard. Furthermore, they indicate that the usefulness of the dashboard should be further improved regarding interpretability of the predictive components and statistics and surveyability (all information in a single overview). The former connects to the findings of Gutíerrez et al. (2018), where advisors were concerned about the lack of interpretability of predictive components. The latter connects to the recommendations of Charleer (2017) to provide both overview and detail in LADs. Advisors still indicate that the dashboard does not sufficiently provides them with support regarding a more personal dialogue, especially when discussing a student's challenges that go beyond the academic level. This contrasts with the findings of Charleer et al. (2018), who found that a fact-based dashboard provided advisors with a narrative that enhances a personal dialogue. Future research should focus on which aspects of advising dashboard trigger personalization.

According to the Technology Acceptance Model (TAM, Davis et al. (1989)), higher perceived support would lead to higher acceptance. Therefore, the increased level of perceived support connects to the adoption of the dashboard modules as discussed above The results presented in this paper support the TAM as we found that advisors reporting higher level of support, use the new dashboard modules more intensively than advisors reporting lower levels. Therefore, based on the results, we recommend that HEI wanting to adopt LAD should invest in addressing the needs of their users and interventions should take into account the usefulness as perceived by the advisors, even if these perceptions are influenced by subjective feelings and emotions.

Future iterations of the LAD will tackle the requests of advisors to include additional data on the students' personal situations and for better support regarding the personal aspect of the advising dialogue.

6.3 *Study plans*

The quantitative evaluation demonstrated the **impact** of the new modules on the **study plans**. First, in the semi-structured interviews advisors indicated that the modules, similar to the LISSA dashboard (Charleer et al. (2018)), supported then in making data-based recommendations in study-plans and no longer required them to only rely on their experience. Second, it was shown that the variability of the workload of the suggested plans between the different advisors decreased after the introduction of the new modules. This indicates that the modules created more consistency in the suggested plans between the advisors, which would be welcomed when assessing the quality of the advising process in HEIs. Third, the results showed that the workload gap, i.e. the gap between the workload of the suggested study plans and the study plans students actually register for, decreased significantly. This effect was at first sight surprisingly not caused by changes in the plans students register but rather in the plans that advisors suggest: after the introduction of the new modules, advisors are better capable of suggesting a plan that suits the needs and expectations of the students. One hypothesis is that advisors get a more realistic view on the workload and the difficulty of the composed plans thanks to the additional modules and as a result no longer suggested under-ambitious but safe study plans, which students were not registering for anyway. As we still believe that on the long term a change in the study plans students register is required to impact student success and retention, future research shall more deeply investigate the changes in the suggested and registered study plans. On the long term offering advices better matching students' expectations has the potential of increasing students' satisfaction with the advising process, and realizing more behavioural change especially considering the rather prescriptive setting the advisers are currently operating in (Burns B. Crookston (1994)).

Gutíerrez et al. (2018) showed that the number of future scenarios student advisors can explore increased after the introduction of a LAD. Our evaluation setup did not include an observation of advising sessions with and without the new LAD modules. Future work focusing on observing real dialogues with and without the new dashboard modules should be undertaking to assess if similar impact on the advising process is observed.

6.4 *Academic achievement*

After one year, the introduction of the new dashboard modules did not yet result in reaching the long-term objective of increasing student success. Results indicated that the introduction of the new dashboard modules did not result in a significant effect on the GPA nor on the number of subjects passed was observed. This is not unexpected as it was also shown that the new modules did, at a population level, not have an impact on the workload of the study plans students registered for. Additionally, we want to emphasize that student success is impacted by many more factors than just the advising of study plans. As a result, even if changes could have been observed it would not have been possible to causally relate them to the new dashboard modules. Finally, impact on student success is rather far-fetched and, according to the LA process model of Verbert et al. (2013), such impact could only be obtained after awareness and reflection is induced. By focusing on the adoption and use this paper mainly focused on the stepping stones of awareness and reflection, which on the long-term might induce impact. In contrast, Herodotou et al. (2019a) did find that teacher's increased engagement due to the LA intervention was related to a higher likelihood of completing the course, but they\ authors themselves warn that this could not be interpreted (yet) as impact as a causal interpretation could not be made.

HEI should not be discouraged by the so-far absence of impact on student success. First, this paper did show that the introduction of new dashboard modules does improve the support advisors experience from the HEI and decreases the variance between different advisors. Both aspects are beneficial to the quality of the advising process and can suffice to create the required return-on-investment, especially when taking in the account the rather technology-low dashboard modules as presented in this paper which rely on data readily available at any HEI. This paper, and the honest reporting of the obtained results, urges HEI to have realistic expectations regarding the outcome of LA rather than the currently prevalent inflated expectations.

7 Conclusion

This paper presented a large-scale case study focusing on the adoption and impact of new modules in a dashboard supporting the dialogue between student advisors and students when advising on a study plan for the next academic semester. A first limitation of this study is that it focuses on the point-of-view of the advisor and that the voice of the students is still missing. A second limitation relates to the qualitative analysis which, due to ethical reasons is based on observations of staged rather than real advising dialogues. While the staged observation on the positive side allowed to carefully select student profiles, they on the negative side can at best be an approximation of a real dialogue. For future work the research team will seek permission of the ethics committee to observe real dialogues. A third limitation is that the evaluation has only a short-term perspective as the dashboards have only been implemented one year so far. Future work will focus on a longitudinal assessment and long-term impact. While not necessarily a limitation, we want to stress that the dashboard and its evaluation is only limited to one university so far. As Stoneham (2015) indicated that a "one-size-fits-all" approach does not work and that LADs should be adapted to the particular context, we warn that the ESPOL advising dashboard and the results obtained in the particular context should not just be copied to other HEIs. This particularly holds for HEI using a different advising model.

Despite the above limitations, this paper allows to conclude, based on the qualitative and the large-scale quantitative analysis, that an institution-wide deployment of modules in an advising dashboard increased the perceived level of support by the advisors, decreased variance between advisors, and significantly decreased the gap between the suggested study plans in advising dialogues and the study plans students actually register for.

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Statements on potential conflicts of interest, open data and describing the ethical guidelines and approval for reports of empirical research.

The anonymised data will be made available, after final acceptance of the paper, on figshare (https: //figshare.com).

The advisors taking part in the advising dialogue gave informed consent prior to the start of the evaluation. The data of both advisors and students was anonymised.

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