A Digital Environment for University Guidance: An Analysis of the Academic Results of Students Who Practice Self-Assessment in Orient@mente, an Open Online Platform to Facilitate the Transition from Secondary School to Higher Education

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A DIGITAL ENVIRONMENT FOR UNIVERSITY GUIDANCE

An analysis of the academic results of students who practice self-assessment in Orient@mente, an open online platform to facilitate the transition from secondary school to higher education

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Abstract: Open Online Courses contribute to learning in different ways (remotely, blended), but they can also provide guidance in students' choices. Orient@mente service at the University of Turin aims at facilitating the transition from secondary schools to higher education with an open platform that delivers automatic assessments. Students can test themselves in order to understand their capabilities and their attitude towards certain disciplines. Moreover, when appropriate, students can attend remedial courses to fill the gaps in their knowledge. Orient@mente first started in 2014 and, after years of continuous deployment, the online platform has collected many data from students interested in starting a university program. A natural question concerns the effectiveness of the action: is there a difference between the academic results of students who practice self-assessment in Orient@mente in comparison with other university students? In order to answer, we considered the average number of ECTS acquired by university students during the first year, dividing students in two groups: those who attended Orient@mente and those who did not. We selected this measurable because national indicators evaluate the number of students who obtain more than 40 first year ECTS. With proper joining rules, we put together data from different origins, such as platform logs and the university record system. The results of the analysis, viewed from different perspectives, confirm the positive impact of Orient@mente on the average number of ECTS and the average grade, with statistical significance.

Key words: Data Analytics, Learning Analytics, MOOCs, Secondary to Tertiary Transition, University Guidance, University Orientation

1. INTRODUCTION

This chapter is an extension of work originally presented in the 17th International Conference on Cognition and Exploratory Learning in the Digital Age (CELDA) (Floris et al., 2020). Massive Open Online Courses (MOOCs) are a pervasive instrument, appearing now in many aspects of education. Keywords related to MOOCs are open education, open access, interactivity, and digital competencies. Education via MOOCs is where many pedagogical studies on user interaction with online systems were born. In addition to education, MOOCs can also pursue goals that are unrelated to disciplinary contents. As an example, with the help of an automatic assessment system, institutions can enhance students' evaluation and management of their self-regulated learning. With the help of computing environments, teachers can enhance problem-solving skills. With the help of web conference tools, peers can collaborate and enhance team-working skills across different regions and countries.

In the 2010 report, the European Commission "Europe 2020" (European Commission, 2010) provided a strategy for smart, sustainable and inclusive growth of Europe. One of the objectives about education is the reduction of the early

school leaver rate (percentage of 18–24-year-olds in the EU who completed at most a lower secondary education and were not in further education or training) by five percentage points, from 15% in 2010 to a target of 10%. Another objective is the increase in the percentage of young graduates aged between 30 and 34 by approximately 10 percentage points, from 31% in 2010 up to 40%. In 2019, the percentage of early school leavers in Europe averages at 10.2%, with quite large differences across countries, ranging from 3.0% in Croatia to 17.3% in Spain (Early leavers from education and training, 2020). On the other side, in 2019, more than 40% of the 30-34-year-olds in the EU had completed tertiary education (Educational attainment statistics, 2020).

There is a close connection and many similarities between these rates with the difficulties that students encounter in the transition phase from secondary school to university, that is the Secondary to Tertiary Transition (STT). Students radically change their perspectives. They need to be aware of the choice that will affect their future and face the difference between expectations and reality, which can lead to unexpected failures of the learning strategies developed in previous education. The education systems in all countries must make this challenging experience as smooth as possible. Technologies and virtual environments can support students in this phase because students can have a preview of what they will face at university in advance. Online assessments containing feedback allow students to check whether their knowledge or their attitude is adequate to attend a specific university program, and interactive learning materials can help them fill their gaps.

The main mission of university orientation is the reduction of the dropout rate, which is a measure that directly affects the evaluation and the ranking of the university itself. Another mission of university orientation is the balance between the demand for professionals by the job market and the number of new graduates, to secure a successful transition into the world of work. Thus, many degree programs have restricted access: they require students to take an admission test in order to control the number of new students, which can enter the program according to the score they get. Other programs, without restrictions, assess just the minimum requirements, and, in case of failure, they deliver remedial courses to align all the students to a common threshold. These assessments can give students a response on their attitude about the discipline, but this is not their main purpose, which is instead a summative evaluation of the students to evaluate their eligibility. Moreover, universities promote various initiatives and different guidance activities for students. Orientation days, job fairs and open days are the most common initiatives promoted by universities, education offices and secondary schools. In addition, technologies offer a solution for guidance activities, providing a massive dissemination of information and automatic assessment inside Digital learning Environments (DLE), together with multimedia resources and interactive components.

The University of Turin proposes several strategies and actions to facilitate the STT using new technologies. The model consists of a DLE, integrated with an Advanced Computing Environment (ACE), an Automatic Assessment System (AAS) and a Web Conference tool. The DLE delivers self-paced Open Online Courses (OOC). In our model there is no M for Massive since the focus of these strategies is on the single student. Moreover, differently from most MOOCs, there is no restriction on when to access the courses: students can start attending anytime and anywhere, with any device with internet connection. In addition to these advantages on availability, the basin of attraction is larger than other kinds of activities: considering the users of the various actions, more than 80,000 users were involved in 5 years of deployment, with possible duplicate across the platforms, but around 67,000 distinct students, from the most populated platform. On average, every month there are around 1,700 unique logins, corresponding to more than 60,000 sign-ins per month.

Thus, the DLE collects many data, which are extremely useful to analyze and evaluate the impact of the orientation actions and improve and enhance their effect. In this paper, we considered the number of first-year University Credits (ECTS) obtained by students at the University of Turin, comparing this number with subscription, access and attendance of at least one course in the Orient@mente platform. We will analyze and discuss what emerges from data collected from different sources.

Section 2 describes the state of the art about university orientation. Section 3 states the research questions and explains the methodology adopted for the investigation, together with the description of actions performed on data. Section 4 shows the results and discusses the relevant implications.

2. STATE OF THE ART

Every time a student fails or drops out of school or university, the whole education system fails, and this can happen at any level. Thus, all institutions aim at preventing failures and enhancing student success. There are numerous strategies to reach this objective, such as addressing evaluation, grouping, motivation, practices, responsibility, and relationships. According to (Krull and Duart, 2018), interventions in student orientation split in two main branches: academic support, connected to the development of cognitive and learning skills, and non-academic support, which focuses on emotional and

organizational aspects such as counselling and guidance services. When performed correctly, both branches have a positive impact on the students' experience.

Data-driven decisions can guide the choice on which strategy most suits institutions. In a fast-changing world, descriptive analytics, predictive and prescriptive models suggest which changes or strategies are good for preventing failure and enhancing success. When institutions can detect possible failures in advance, interventions prevent students' failure. Prediction algorithms using data mining techniques are one of the latest trends (Marquez-Vera et al., 2013), but also, more in general, Learning Analytics (LA) (Gašević et al., 2015), which are now a trend topic in conferences (Ochoa and Merceron, 2018). In (Schumacher and Ifenthaler, 2018), findings emphasize the need to design highly personalized and adaptable learning analytics systems to meet students' needs. LA approaches make use of machine learning algorithms, too. This kind of algorithms usually work as black boxes: they provide an output without any clue or information on the decision process. Research in this topic needs further investigations, concerning the ethical aspects and fairness (Riazy et al., 2020). Developers should keep in mind that predictions of a student's performance directly affect the student's success. Researchers developed methods and tutorials to detect discrimination (Hajian et al., 2016), even though it is endemic: even with no discrimination intention in the developer, the algorithm has biases.

Some experiences join orientation and LA. In (Lonn et al., 2015), the authors address summer programs designed to improve retention and academic success among at-risk postsecondary students, and they investigate how a learning analytics-based intervention empowers academic advisors during their face-to-face meetings with students. The findings suggest that the design of learning analytics interventions should consider students' perceptions of their goals and formative performance, since they affect students' interpretations of their own data as well as their subsequent academic success.

More power comes from digital technologies and online learning and their importance is stressed in the Digital Education Action Plan 2021-2027 (DEAP, 2020). In (Wozniak, 2013), a learning analytics approach was used to examine student engagement with online resources. The author found that providing pre-semester access and attending their first course in distance learning contributes to greater participation.

Lot of work about students' orientation and LA has been done by STELA (Successful Transition from Secondary to Higher Education through Learning Analtyics) Erasmus+ project. In fact, according to (De Laet et al., 2016), among the most common analytics items, academic achievement (e.g., credits obtained, GPA, timely graduation) is one of the most suitable indicators for a successful transition from secondary to higher education, and it can be characterized by different features. To enhance these measurables, (Hodgson et al. 2010) suggests perceiving assessment during the transition as the basis of a critical environment in which students can develop confidence and become more sophisticated learners. This approach requires immediate and continuous feedback throughout the entire transition phase of each student. This feedback should not be summative, not connected to grades, but formative, so that students can monitor their learning in order to improve their learning process.

At the University of Turin, many of these strategies for preventing failure and improving success build their structure inside a DLE, even if most Italian universities do not consider Digital transformation as one of the top three priorities. In fact, in (OECD/European Union, 2020) it emerges the present perspective about institutions' priorities in Higher Education in Italy. From the OECD Higher Education Institution Leader Survey, to the question "Taking into account the HEInnovate dimensions/components listed below, please indicate the three that are most prominent in your strategy", none of the respondents considers the enhancement of digital transformation as one of the top three priorities for the institution. (OECD/European Union, 2020) also reports that the lowest number of investments in digital technologies and systems performed by Italian Higher Education Institutions is devoted to developing digital skills of professors and researchers, who are the people directly in charge of students' education. It is worth mentioning that online universities did not participate to the survey.

In this context, in the subsequent paragraphs, we are going to describe the main orientation actions at the University of Turin adopting a DLE, addressing the increasing need of digitalization of Higher Education institutions.

One of the first actions carried out by the University of Turin is Orient@mente (https://orientamente.unito.it). Orient@mente consists of OOCs for the interactive exploration of courses and programs. Orient@mente helps in the preparation for admission tests, and in the recovery of gaps in many courses, from natural sciences to humanities. It serves as an effective dematerialized orientation for secondary school students who intend to enroll at university. This action provides three distinct types of intervention divided into specific areas:

- The "Realignment Courses" area (RC), which delivers five OOCs in Mathematics, Biology, Chemistry, Physics and Italian Language to help students review, strengthen and integrate the basic knowledge acquired during secondary school.

- The "Prepare for Tests" area (PT), where students can assess themselves with numerous automatically evaluated tests that provide immediate and interactive feedback; this area helps students in preparing for admission tests to the various degree courses.
- The "Explore the Degree Programs of the University of Turin" area (EDP), which consists of OOCs for the interactive exploration of the Degree Programs. Currently, over 80% of the Degree Programs at the University of Turin have an interactive orientation course on the platform.

Start@unito (https://start.unito.it) promotes and facilitates the STT through the creation and dissemination of a series of OOCs, full university modules in many different first-year disciplines, covering topics that students will meet in most degree programs. Moreover, attending a full university module even before enrolling at the university helps students make a responsible choice about their academic career. Courses deliver interactive paths that facilitate university guidance and preparation for admission tests. Moreover, Start@unito addresses other groups beyond students, namely university professors and high school teachers. Considerably smaller than the traditional student population, both groups attended training sessions and, apart from the action itself, the skills they acquired largely affect the secondary and higher education sector (Marchisio et al., 2019), especially in times of pandemic with forced online education (Bruschi et al., 2021).

Foundation Programme (https://foundationprogramme.unito.it) facilitates the integration of pre-university students coming from countries where compulsory education lasts less than 12 years. These prospective students must attend an additional semester or a year and achieve the corresponding ECTS, according to the national standards. Because of its fully online setting, students can attend Foundation Programme from their home country, temporarily avoiding permissions, visa or travelling. These students must only take the final exam in-person at the university, and they can do it even right before enrollment (Floris et al., 2019).

3. RESEARCH QUESTIONS AND METHODOLOGY

As evidenced by the literature (Barana et al., 2016a; Barana et al., 2016b; Barana et al., 2017a; Barana et al., 2017b), Orient@mente has a great impact on strategies to prevent student failure, both from the point of view of the learning experience, with automatic assessment and courses, and from the organizational point of view, with information on courses and programs, and with interviews to older students or professors. The objective of this research is the evaluation of the impact of Orient@mente on students' path inside university.

The Research Questions (RQ) is: How large is the impact of the orientation action of Orient@mente on students' grades at university?

Since the Orient@mente action takes place in a DLE, the environment collects data about the usage and the interaction of the users. The advantages of the Orient@mente action and the usage of the DLE are part of previous works; on the other hand, in this research we want to measure the correlation between academic grades and results of students who used Orient@mente, compared to students who did not use it. Since the orientation action aims at facilitating STT, every statistically significant improvement in admission tests and exams performed by students who used the platform is worth the effort of delivering such a large number of contents. The analysis considers data from two main sources: the database collecting careers of students enrolled at the University of Turin (restricted to the degree programs that have a course in the Orient@mente platform), and students' data from the interaction with the online platform. The latter kind of data are divided into two main sources: the first one collects students' interaction with the DLE, while the other data source is the database of the AAS, which contains everything about tests, such as grades, number of attempts, time, and other data.

The Null Hypothesis (H0) wonders if there is a significant difference in students' academic performance in relation to their activity on the Orient@mente platform.

We measured academic performance calculating the weighted average grade and the average number of ECTS acquired by university students. These values are the most relevant, since the university evaluation system uses similar indicators. Among other values, the ANVUR (Italian national agency for the evaluation of universities and research institutes) considers the number of students that gain more than 40 ECTS (indicator iA1 about didactics). This value is in fact an excellent aggregator for the dimensions of students who continue their studies and productivity. The analysis considers the previous education of students, such as the type of school attended and the graduation mark. Moreover, the analysis also takes into consideration the differences in users with respect to the area of Orient@mente that they attended.

3.1 Analysis Process

The whole process of collecting, managing, and analyzing data took place according to precise literature and indicators (Marchisio et al., 2019; Scheffel et al., 2014).
The data analysis was carried out following four different phases.

- Phase one (P1). The first action on the datasets was merging them to create a unique large database. The joining feature between the different databases lies in the email field, which is common through the different sources, but may anyway not be unique: users' data collected by the university contain two email addresses, the personal one and the institutional one.
- Phase two (P2). The second action on the merged dataset was cleaning and transforming. This phase gives an overview of the whole population and prepares the data for the further phases (grouping and statistical analysis).
- Phase three (P3). Statistical testing, with t-test, chi-square test and ANOVA, to accept or reject the null hypothesis (H0).
- Phase four (P4). Group the items of the dataset according to variables expressing the use of the platform, which areas the student attended, in correlation with the student's achievement at university level.

Two software supported the four phases: "KNIME Analytics Platform 4.1.1" and "SAS 9.4". "KNIME", used in (P1) and (P4), allows easy access to different data sources, and, with the use of SQL language, it allows easy preparation of the dataset for next phases. In order to act on the merged dataset in phases (P2) and (P3), "SAS" allows cleaning, transforming the database and powerful statistical analysis. In this work, we will focus on the first three phases.

4. RESULTS

The total sample has a size of 29256 observations. Every record is a student who enrolled at the University of Turin from 2010 until the academic year 2017/2018. The dataset is divided into two subsamples: the first one (SS1) consists of students that are Orient@mente users too, 22.38% of the global sample, while the second one (SS2) consists of students who are not Orient@mente users, 77.62% of the sample. Table 1 describes the percentage of users divided into (SS1) and (SS2) and grouped by leaving certificate grade, for which the minimum grade is 60 and the maximum grade is 100.

- R1: First range, students with final examination grade between 60 and 69
- R2: Second range, students with final examination grade between 70 and 79
- R3: Third range, students with final examination grade between 80 and 89
- R4: Fourth range, students with final examination grade between 90 and 100

Table 1 shows that the distribution of students across the various ranges of grades is quite uniform, with percentages varying around 20% and 30%. Even inside every range, the global proportion between (SS1) and (SS2) is respected. A similar procedure, shown in Table 2, was carried out about gender, with no significant difference in the proportion of males and females.

Table 1. Percentages and numbers of users according to the subsample and grouped by the final examination grade.

Group	**SS1**	**SS2**	**Row total**
R1 students	1366 students	5023 students	6389 students
Percentage	4.67%	17.17%	21.84%
Column percentage	20.86%	22.12%	
R2 students	2029 students	6851 students	8880 students
Percentage	6.94%	23.42%	30.35%
Column percentage	30.99%	30.17%	
R3 students	1747 students	6081 students	7828 students
Percentage	5.97%	20.79%	26.76%
Column percentage	26.68%	26.78%	
R4 students	1406 students	4753 students	6159 students
Percentage	4.81%	16.25%	21.05%
Column percentage	21.47%	20.93%	
Column total	**6548 students**	**22708 students**	**29256 students**
	22.38%	**77.62%**	**100%**
	100%	**100%**	

Table 2. Percentages and numbers of users according to the subsample and grouped by gender.

Gender	**SS1**	**SS2**	**Row total**
Male	3246 students	11160 students	14406 students
Row percentage	22.53%	77.47%	100%
Column percentage	49.58%	49.15%	49.24%
Female	3302 students	11548 students	14850 students
Row percentage	22.24%	77.76%	100%
Column percentage	50.42%	50.85%	50.76%
Column total	**6548 students**	**22708 students**	**29256 students**
Row percentage	**22.38%**	**77.62%**	**100%**

Table 3. Percentages and numbers of users according to the subsample and grouped by educational origin.

Educational origin	**SS1**	**SS2**	**Row total**
International	85	124	209
Percentage	0.29%	0.42%	0.71%
Row percentage	40.67%	59.33%	
Column percentage	1.30%	0.55%	
Professional School	437	1314	1751
Percentage	1.49%	4.49%	5.99%
Row percentage	24.96	75.04%	
Column percentage	6.67%	5.79%	
Technical School	1638	4432	6070
Percentage	5.60%	15.15%	20.75%
Row percentage	26.99%	73.01%	
Column percentage	25.02%	19.52%	
Lyceum	3977	14922	18899
Percentage	13.59%	51.00%	64.60%
Row percentage	21.04%	78.96%	
Column percentage	60.74%	65.71%	
Unknow	411	1916	2327
Percentage	1.40%	6.55%	7.95%
Row percentage	17.66%	82.34%	
Column percentage	6.28%	8.44%	
Column total	**6548 students**	**22708 students**	**29256 students**
Row percentage	**22.38%**	**77.62%**	**100%**

As shown in Table 3, data proportion is different with respect to the educational origin. It appears that students from the "Lyceum" high school attended Orient@mente less. This happens because most of the OOCs available in Orient@mente until 2018 deal with scientific disciplines, which are the focus of this kind of school, thus students require less remedial intervention.

As for the students who used Orient@mente, first access inside the DLE of 68.10% of (SS1) students was prior to enrollment at the university. Most of the (SS1) students (79%) registered with the personal email address and did not use the university institutional email to access Orient@mente, even when the first access to the platform occurred after enrollment (16%). Thus, in phase (P1) some (SS1) students did not appear in the merged dataset: they might have used two different personal emails, one for Orient@mente and one to enroll at the University of Turin. Such cases cannot be traced back to the university student and this item will appear in (SS2) in the dataset.

4.1 Hypothesis tests

The hypothesis test checks the equality between the average number of ECTS (which we will indicate with the Greek letter μ) achieved by the students at the end of the first academic year in the subsamples (SS1) and (SS2). The test is one-tailed, the alternative hypothesis entails just a larger average for (SS1) students.

$$H_0: \mu_{SS1} = \mu_{SS2}$$
$$H_A: \mu_{SS1} > \mu_{SS2}$$

The p-value for the test is much less than 0.0001, thus rejecting the hypothesis of equality with high statistical significance. We can state that there is statistical difference between the average number of ECTS achieved by students depending on whether they logged in the Orient@mente DLE.

The same Hypothesis test checked the equality of the weighted average grade of students between the subsamples (SS1) and (SS2). The p-value for the test is almost null, thus we can reject the hypothesis of equality with high statistical significance. Even in this second case, Orient@mente action proved effective.

The various groups of students can bring different features on the global behavior according to the same measurable. We restricted the analysis on the sample considering the four ranges of leaving certificate grade (R1), (R2), (R3), (R4). A significant difference between the average number of ECTS appear in the comparison of (SS1-R1), (SS2-R1) and of (SS1-R4), (SS2-R4) with p-value less than 0.005. On the other hand, for groups (R2) and (R3) we cannot reject the null hypothesis, equality is possible. In particular, the case of (R3) is quite significant, since difference between the two averages (SS1-R3) and (SS2-R3) is very little, below 0.05. Thus, we can infer that Orient@mente action is more effective for users with the high-performing and low-performing students, according to the final examination grade. These two groups contain two completely diverse kinds of students. With a closer look at the behavior of students in (R1) and (R4), we can notice that 35% of (SS1-R1) students logged in after enrollment, while only 25% of (SS1-R4) students did it. This shows that weaker students use Orient@mente DLE for one of its main purposes, to fill the gaps that emerge, even during the first year of university studies.

Given the significant difference between the average of the ECTS between the two samples SS1 and SS2, we performed a more in-depth analysis on courses' subscriptions of Orient@mente users to understand which combination of activities within the platform is more significant.

We defined a new variable called "areas used", assigned to SS1 users to indicate which of the areas of the Orient@mente platform each student subscribed to. We marked records with one or more of the following labels:

- PT for a subscription to at least one course in the area "Prepare for Tests",
- RC for a subscription to at least one course in the area "Realignment courses",
- EDP for a subscription to at least one course in the area "Explore the Degree Programs of the University of Turin",
- Nothing for SS2 students.

Table 4 shows the distribution of the variable ECTS among the various categories.

Table 4. Descriptive analysis of the distribution of the average of ECTS achieved by the students at the end of the first academic year with respect to the values of the "areas used" variable.

Areas used	**Min**	**Mean**	**Max**	**IQR**
Nothing (SS2 students)	0	28.88	116	41
PT	0	30.75	119	41
RC	0	27.12	85	37
EDP	0	31.49	116	42
RC + EDP	0	28.53	73	41
RC + PT	0	26.31	97	39
RC + PT + EDP	0	30.54	82	46
PT + EDP	0	32.72	102	40

Table 4 provides a first look at the most helpful areas. Looking at the single areas, users of EDP gained the largest number of ECTS on average. This is in line with the purposes of Orient@mente: with proper guidance in the choice of future studies, the students can perform better during exams. The reader should keep in mind that it is possible that EDP users can be students who have clear ideas for their future and just subscribed to one course to confirm their existing opinion. On the other side, the area with less ECTS on average is RC, and this is not surprising because this area targets students with more difficulties, also students with additional formative duties.

In order to evaluate the differences, after verifying the hypotheses of applicability, we performed an ANOVA test to compare the average ECTS between these groups. The p-value of the test is much lower than 0.0001 and this leads us to

reject the null hypothesis, there is no equality between the means of the various groups. Analyzing more in depth the internal difference between the two groups, we performed a multiple comparison test with the Bonferroni correction to analyze in which cases the difference in the average number of ECTS is significant. The test showed a statistically positive difference between the following couples:

- PT and "Nothing"
- PT+EDP and "Nothing"
- PT and RC+ PT
- PT+EDP and RC.

This result shows how the "Prepare for tests" area has a large weight in the preparation of students since it always appears as positively higher than other or no areas. From these significant tests, we can infer that PT and EDP are the areas with larger impact, more than RC, which is dedicated to students with more troubles in recovering gaps in the knowledge.

4.2 Focusing on two courses

We have already seen a dependence of the effectiveness of Orient@mente on the final examination grade. Other differences arise when dealing with students enrolled in different degree programs. We are going to focus on two cases with conflicting behavior.

Case 1 (C1) concerns students in Mathematics (1271 students). In (C1), we detect an opposite behavior with respect to the global sample: the average number of ECTS earned by (SS2) students is even 3.5 points higher (p-value < 0.02) than (SS1) students. This is not surprising: a possible explanation could be a greater awareness of students in Mathematics, as this is a well-known topic, and the university choice could be guided by an established knowledge of the intrinsic difficulties of a STEM learning path. Usually only the best school students in Mathematics choose this topic, so they are typically students with less gaps to fix.

On the other hand, Case 2 (C2) concerns students in Biological science (2041 students). In (C2) the global behavior is emphasized: the average number of ECTS achieved by (SS1) students is 4 points higher with respect to (SS2) students (p-value < 0.0001). In many degree programs, four ECTS mean one extra exam during first year. In such programs, modules like mathematics, physics, and chemistry are not the main topics, but basic disciplines and often represent first-year obstacles. They are the first modules that students encounter, but not the main discipline of the program.

We understood that focusing on the conflicts can lead to interesting phenomena, but these are not supported by specific evidence and the analysis should leave the quantitative method in favor of a qualitative one, by using social analysis to discover the real motivation behind these numbers.

We should investigate further to track down which user data can be acquired to enable a clear evaluation of these motivations, so as to better support student in the best choice for their university life.

5. CONCLUSIONS

According to the analysis on students' data, it emerges that the effectiveness of Orient@mente has statistical significance, thus proving that it positively affects students' orientation and first-year outcomes thanks to the OOC, accessible even before enrolling at the university (RQ1). In this research, we described a method that can analyse in the same way the effectiveness of similar experiences. The method could be refined in order to automatically execute and return real time results.

Based on our experience, we can list some recommendations for a digital intervention on university orientation:

- Deliver a system in agreement with the other orientation offices and activities, to maximize the positive effect.
- Let students monitor and track their current progress and knowledge with automatic tests and, more importantly, feedback.
- Develop the system in such a way that it can answer to different needs, adapting the learning activities according to the students' pace and needs.
- Provide students an environment that can help them recover their gaps.

These results guide future orientation actions. Given the results, the analysis and the evaluation of the impact of Orient@mente, the University of Turin immediately took action and decided to invest in this initiative. New Orient@mente OOCs and new test areas cover more than 85% of the university degree programs.

Moreover, the model of Orient@mente is going to be exported in other universities (Marchisio et al., 2020).

Many more parameters guide the evaluation process over the guidance service. Close future research concerns:

- Students' personal profile fields, to provide a personalized orientation experience, suited to individual requirements, to offer students the content they need most when they need it, according to their online activity.
- Design personalized learning paths using Machine Learning techniques to differentiate students' learning paths.
- Cluster analysis to identify "behavior" patterns within the platform and study their effects. In this way, once recognized non-productive behaviors by new users, it is possible to intervene to suggest a more effective learning path.
- Learning Analytics techniques to connect the results of tests carried out with the automatic assessment system to improve the implementation of automatic formative assessment strategies and provide immediate and personalized feedback to students.
- Analysis of other variables, such as age, region of origin, results of the admission test and chosen program.
- The comparison of Orient@mente OOCs quality with the international benchmark and with the standards of MOOC providers (Marchisio and Sacchet, 2020).

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