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Students' Difficulties with Mathematics: Insights from Secondary-Tertiary Transition in a STEM Program

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Abstract. Drop out during the first year at university STEM courses is a plague spreading all around the world and research in Mathematics Education revealed that mathematics is one of its main causes: not only the students' mathematical knowledge, but also affective issues such as attitudes towards learning mathematics, views about mathematics itself, as well as emotions determine the students' success or failure in university career. We investigate the intertwining of cognitive and affective dimensions in freshmen Engineering students attending a bridge course in mathematics at the beginning of the first semester at the Politecnico di Milano.

Keywords: Engineering students · Quantitative nonparametric methods of data analysis · Blended learning · Secondary-tertiary transition · Difficulties in mathematics · Affect-related variables in mathematics education

1 Introduction

Every year, at the beginning of the first semester, in universities all over the world, thousands and thousands of freshmen enrolled at STEM university courses come to attend their first lessons. We know that around 40% of them would not sit in the same classroom a few months later, because of dropout. What kind of information can we get from these first days at university, which can help universities to reduce dropout? In this paper, we aim at contributing to this big, overarching question by: firstly, recalling the main findings concerning mathematics difficulties at first year STEM university courses; and secondly, focusing on the factors that have revealed to be central to understand the issue, and, thus,

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relevant to intervene on dropout. Using regression trees and community analysis, we aim at identifying sub-groups of students (we will call them "profiles") who need differentiated interventions.

The phenomenon of STEM-related dropout has received increasing attention in the literature. In [23], a theory of academic persistence is proposed that is of inspiration for subsequent studies, since students' persistence is affected by a number of factors, as skills, abilities, and prior schooling, as well as by experiences at university. In [16] it is stressed that students should adjust to a new context, a new program, new teaching practices, and a new institution, and different variables that should be considered to understand students' adjustment in the school-university transition are proposed. Among them, gender, students' expectations, coping strategies and school of provenience are the most relevant.

University mathematics, in particular, causes difficulties to students with STEM majors in general and to Engineering students in particular [11]. These difficulties can be traced back to several aspects that generally concern differences between secondary school and university [12]: from the different university courses organization [13] to the different thinking modes that are required at university. In a fundamental study, [5], it is contended that, at the basis of the leap between secondary and tertiary studies, there is a shock *from procedural mathematics to conceptual understanding that university mathematics entails.* For such a reason, it is strongly suggested that transition should be smooth, and communication between school and university should be improved [5]. According to this view, universities from almost all over the world offer preparatory courses whose goal is to bridge the gaps between school and university, supporting freshmen students to recapitulate certain mathematical topics. In the sequel, we name them "Bridge Courses".

The focus of this paper is on sub-groups of students who may find the transition more difficult, compared to their mates. The differences in mathematical attainments between groups of students, and across schools, is a topic of crucial interest for both educators and policy-makers (see e.g. [19]). In the sequel, we briefly recall the main findings to this regard.

Gender Issues. There is an increasing number of studies focusing on the crucial role of social and affective factors, besides the cognitive ones, in undergraduate mathematics learning. [19], for example, underlies that the students' features –such as gender and attitude towards study– influence students' attainment. In particular, it is well acknowledged that women are under-represented in STEM disciplines (see e.g., [8]) and we refer to the model introduced in [7] to capture stability and flexibility of gender differences in social behaviour. This model is social and psychological in its roots and takes into account both the social influences on boys and girls enrolled in STEM courses, and inner disposition.

Mathematical Backgrounds. Students' views of mathematics take also a key role. The study reported in [22] has for us many sources of interest. First of all, it discusses from a theoretical point of view the concept of "views of mathematics" and the related concept of "beliefs about mathematics". The authors state that "students' beliefs, wants and feelings are part of their view of mathematics".

Secondly, the authors argue about the key role of different school backgrounds, different math curricula and different views and expectations in freshmen students attending a Bridge Course. Within this perspective, the role of beliefs (about mathematics) is crucial in determining university success or failure [1,6]. Specific to the Italian context, [17] has proved that the kind of high school influences both cognitive and affective factors in the transition. Also [19] proved that school-level characteristics influence the students' mathematical performances: however, they focused on single schools features such as their size, their Dean's views and management practices, while in our study we focus on the kind of mathematics the students experience at school. In fact, in the Italian context, students who enroll in STEM courses mostly come from three kinds of secondary school: scientific (LS), humanistic (HU), and technical (TE). LS is a type of secondary school with a strong curriculum in math and sciences, while HU is stronger in history, philosophy, languages and arts. And, while LS and HU curricula are specifically designed to prepare students to go to university, TE curriculum is mostly related to workplace, but it is not rare that students from this type of school enroll at university. A focus of this sort [1,17] allows us to understand the role that both mathematical prerequisites (at cognitive level), and views about the importance of mathematics in real life (mirrored by the importance assigned to mathematics in each school type's curriculum) may play in the transition to university STEM courses.

The Digital Turn. The last factor we consider is related to distance learning and e-learning in general. In particular, the students' disposition toward on line teaching material plays a key role in our study, given the organisation of the Bridge Course under investigation. More generally, this factor is related to differences between conceptual and procedural aspects in mathematics, as we argue in the following. Some researchers (e.g. [10]) found that teacher-centred (or teacher-oriented) methods (TO) favour the development of procedural knowledge, while student-centered (or student-oriented) methods (SO) favour the development of conceptual knowledge. A TO lesson provides the students with a linear and organised exposition of knowledge, while a SO one engages students in group-work activities, classroom discussions and in the production of meanings that are inevitably other than final or "authorized", they are personal and provisional, not universal and absolute. A Massive Open Online Course (MOOC) has a SO pedagogical format, in that the students are required to: (a) watch videos and get sense of their content (without any guidance from the teacher); (b) in case parts of the videos are not clear for the student, search for other sources in order to make sense of the content; (c) make interactive exercises and, in some cases, engage in forum discussions. All this entails a production of meanings that is personal and that emerges from the mathematical activity in which the student is engaged. MOOCs are becoming a teaching format common to many universities all over the world. Also the Bridge Course under study takes on a blended learning format, as we will detail more in the section dedicated to the context of the research.

2 The Context of the Research

The Bridge Course, delivered every year at the Politecnico di Milano[1], is a preparatory course before the beginning of the first semester. The Bridge Course recapitulates the basic math knowledge learned at school and is made of an e-Learning part and an attendance part. Students who enroll at university are invited to attend the MOOC course before the attendance one. In the e-learning part, the students are asked to recap essential mathematics on Pre-Calculus MOOC on POK platform (www.pok.polimi.it), where they can watch videos on theory and exercises, and assess their basic knowledge in mathematics through quizzes. In addition, they can interact in a forum. The MOOC course is structured in 6 learning weeks, one for each of the following topics: arithmetics, algebra, geometry, logics, functions, probability. The in-presence part features the students in SO activities, such as group work activity and discussions built upon the syllabus of the Pre-Calculus MOOC. The attendance part consists in 32 h of lessons, spread in the first 2 weeks of September.

We maintain that the Bridge Course combines self-directed (i.e., MOOC) and externally-regulated (i.e., attendance) learning types of instructional formats. There's a need for the latter, since learners are new at the university, they have to acclimatise with the new learning environment and attendance helps them to familiarize with the new didactical contract and the new organisation of courses [21]. There's a need for the former, since learners at university have to be more self-directed and e-Learning helps to adapt their learning behaviour [18].

The data for this study come from a questionnaire, administered at the end of the in-presence part, which investigates affective factors, and from four tests, which assess the students' knowledge on algebra, geometry and logics, calculus, and probability and statistics.

The questionnaire (referred to as Q) is composed by two main sections: 1) the personal data (Q0 in the sequel), and 2) the affective section (QA). Q0 asked about: gender, school type and MOOC attendance. QA is made of 6 questions. Question QA.1 asked whether students faced new math topics in the Bridge Course, while Question QA.2 asked whether they saw exercises or problems formulated in a different way. QA.3 opens a window on the students' expectations about math at the university and QA.4 investigates whether the students have been exposed to SO learning formats at school. QA.5 and QA.6 were dedicated to MOOC/course appreciation and aimed at investigating the students' disposition toward e-learning materials.

The math tests, made up of 10 multiple-choice questions each, provide information about the students' mathematical knowledge and skills. They have been administered on the second day of the attendance course (algebra), on the fourth one (geometry and logics), on the sixth one (calculus), and on the eight and last one (probability and statistics).

[1] Politecnico di Milano is the technical university of Milan with Engineering, Architectural and Designer programs.

3 Theoretical Background

The type of data that we would like to analyse are heterogeneous. Indeed, we have both quantitative variables measuring students' performances, and qualitative ones related to personal-level features and affective aspects. Moreover, there is a plea in Mathematics Education research for studies that do not assume linear correlations between variables that are complex in nature. This is especially true when affective aspects are under scrutiny.

For these reasons, we resort to methods that do not rely on strong modelistic assumptions on the structure of data, nor on linearity of connections. We employ classification trees to investigate the influence of personal-level features (i.e., gender, school type, and MOOC attendance) on mathematical test performances. We recall that previous studies in Mathematics Education have resorted to classification trees to investigate the interplay of cognitive and affective factors in determining students' performances [1].

Parallel to classification trees, in order to identify how students clusterize when they expose their views of mathematics, we resort to network analysis and, specifically, to community detection, a novelty in the educational context [14]. One can wonder whether a more classical unsupervised clustering method was not employed for this purpose. We argue that in qualitative questionnaires the strong limitation of the latter approach is the need of defining a suitable metric to measure differences between students' answers, which can be avoided using a network analysis approach. In the following the two methods are described in detail.

Regression Trees. The regression trees is a method that aims at predicting the value of a numerical target variable on the basis of several input variables, and selecting the input variables that explain the most the target variable. For the analysis presented in this paper, we will use the tree for predicting the students' score in the math tests. Specifically, a tree T is a set of successive splits that group the initial set into C groups, corresponding to the *leaves* of T. A tree is constructed by computing, for each factor to be considered, the information gain (with respect to the target variable) given by splitting the initial population into two groups, using some threshold value of the input variables. In the case of regression trees, the gain is computed as the amount of variance reduction of a split. Every possible split in terms of the input variables lead to a division of the sample units into two separate groups (i.e., their intersection is empty). For growing the tree, an iterative algorithm is used. The algorithm starts with a tree with a single node and successively splits it exploring all possible splits and performing the one that most reduces the variance (see [9]).

Network Analysis. Regression trees allow us to examine the relationship between the students' performance on tests (i.e., a measure of cognitive aspects) and personal characteristics of the students such as gender, school type and MOOC attendance. But we need a different mathematical tool to identify clusters within the set of students who answered the questionnaire Q, which represent a very big and complex set of data. Since the data are qualitative and not quantitative we decided to use the *community analysis*. Community analysis reveals possible sub-networks (i.e., groups of nodes called communities, or clusters, or modules) characterised by comparatively large internal connectivity, namely the nodes that tend to connect much more with the other nodes of the group than with the rest of the network [4].

Hence, we use community analysis to recognise clusters of students and figure out students' profiles according to their attitudes. To that end, a students' network is designed for the set of answers to Q. The method proposed by [4] is used to design the network, where two nodes are linked if they co-participate at the same 'meeting'. In this work, the nodes of the network are the students while the 'meetings' are represented by the same answer to the questions of the affective section QA: the more answers they have in common the stronger the link between two nodes. For example, if students i and j gave 8 same responses to the questionnaire (i.e., select the same items), hence there exists a link between nodes i and j, and its weight is 8. Figure 1 exemplifies such an idea. The personal data collected in Q0 represent further attributes of the nodes. As a consequence of this approach, the network (N in the following) is undirected and weighted.

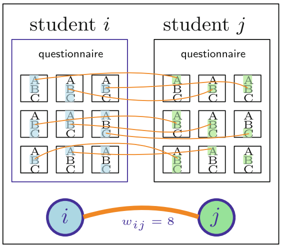

Fig. 1. Schema for the design of students' network: students i and j gave 8 same responses to the questionnaire, hence there exists a link between nodes i and j, and its weight is 8.

Since we are interested in identifying sub-networks of students according to their attitudes, we seek for a specific partition of the set of nodes induced by a certain measurable quantity. To that end, we adopt the so-called "Louvain method" [3] based on the optimization of the *modularity* Q. Roughly speaking, given a partition $\{C_1, C_2, \ldots, C_K\}$ of the network, modularity Q is the (normalized) difference between the total weight of links internal to the sub-graphs C_k, and the expected value of such a total weight in a randomized "null network model" suitably defined [20]. To evaluate the goodness or triviality of each community we adopt the *persistence probability* α_k, that measures the 'cohesiveness' of the sub-graph C_k. A sub-network which has $\alpha_k > 0.5$ can be reasonably defined as a *community*. Obviously, the larger α_k, the larger the internal cohesiveness of C_k. Notice that, since α_k tends to grow with the size N_k of C_k it is necessary to test the non triviality of the community [4]. This can be done introducing the significance of α_k, identified by the standard z-score.

$$z_k = \frac{\alpha_k - \mu(\bar{\alpha}_k)}{\sigma(\bar{\alpha}_k)}. \quad (1)$$

where $\bar{\alpha}_k$ is the persistence probability of sub-graphs of size N_k, so that a large value of z_k (i.e., $z_k > 3$) denotes that the community is not trivially formed on the basis of the size of the sub-graph.

4 Results

Table 1. Number and characteristics of students and number of questionnaires and tests answered by students

Total	Males	Females	LS	HU	TE	Other	Q	T1 day 1	T2 day 4	T3 day 6	T4 day 8
589	402	150	415	57	55	42	369	535	505	500	331

Table 1 shows the number of students, their characteristics and the number of questionnaires and tests answered. We can see that the number of males is greater than the one of females, and that the students coming from LS high school type represent the majority. This confirms a general trend in STEM studies. In the next subsection, we focus on the cognitive variables to see how the students performed in the tests and how gender, school type and MOOC attendance impact test performance.

Test Performances. The students' performances in the four mathematical tests is shown in Fig. 2. Each test consisted of 10 multiple choice questions. Figure 2 shows the histograms of the number of correct answers out of 10 in each test. Even though it is clear that some tests are harder for the students than others, the distributions in the four histograms is similar. In general we have an asymmetric distribution with a heavy left tail and centred in the medium-high range of the scores. Further, it is also clear that the distributions of the scores can not be assumed as Gaussian: first of all, there is only a discrete set of 11 possible score values, and secondly the distributions are asymmetric. We then employ nonparametric statistical tools, e.g., methods that do not assume the normality of data.

We remark that, since all tests were done in different days, and collected anonymously, it is not possible to link the scores within students and the distributions of the scores gained in the four tests are considered separately. In order to understand how gender, school type and MOOC attendance influence the test scores, we performed a Kruskal-Wallis rank test [15] whose results show that the

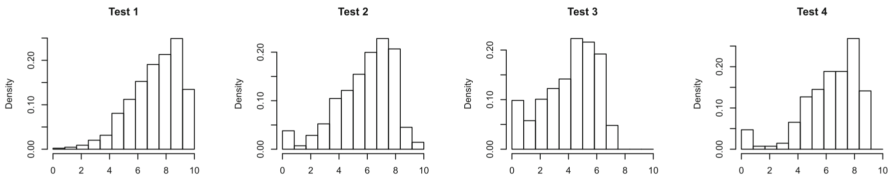

Fig. 2. Histograms of the scores in the four tests. T1 - Algebra, T2 - Geometry and logics, T3 - Calculus, T4 - Probability and statistics

test score is significantly related to the school in the first three tests, it is not related to the gender apart from test 2, and it is not related to the MOOC level.

To that end, we fit four regression trees to estimate the score of each test. We consider the test score as the target variable, which ranges between 0 and 10. We apply the regression tree method to single out which test score "characterizes" different groups of students. We have at our disposal 3 input variables: gender, school type and MOOC attendance. The construction of the tree is controlled by the parameter, our choice $\gamma = 0.5\%$, that is used to decide the minimum information gain to be considered for a split. For the four tests the results are similar, in terms of the order of the splits that are performed. Here we present and comment the tree obtained for the fourth test, that is the one characterized by a less significant relation between the covariates (school type, gender, and MOOC attendance) and the final score, at least when considering one covariate at a time. Our aim is to show that, also in this (say, worse) situation, a regression tree is able to identify a relation between the covariates and the test score and to classify the students into groups with different characteristics. Furthermore, in the context of our research, the students who answered to test 4 were the ones who were present in the last day of the Bridge Course: in this way, we are somehow (and indirectly) able to consider the students who actually attended a significant portion of the Bridge Course. The regression tree for test 4 is reported in Fig. 3.

We read the tree from the top to the bottom and at the top we read that the average test score is 6.7. We can see that the first split is determined by the school type: students from LS perform better (average test score 6.8) than the ones coming from other school types (representing 28% of the sample). In the latter case, no further distinction is made and the average test score for these students is 6.3. Among the students who come from LS, a second split is given by MOOC attendance: those with high attendance (score greater than 3.5 on a scale from 1 to 5) perform better than those who attended the MOOC less (i.e., <3.5). However, those who almost never attended the MOOC (i.e., <1.5) perform better than the students who partly attended it. Who are these students? Two groups of students are identified, at this stage: one group is made by those students who come from LS and dedicated time to watch the videos in the MOOC and to make exercises (these are the ones with the highest test average, namely 7.4); the other group is made of the students who come from LS, a school type where

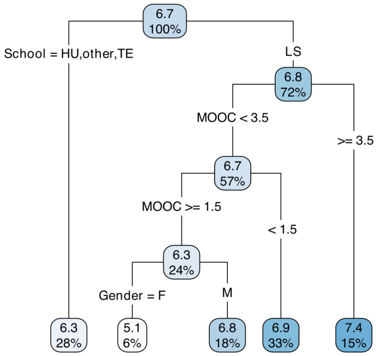

Fig. 3. Regression tree for test 4

math curriculum is strong, and hence they do not feel the need to learn more math on the MOOC. In fact, their performance is good (their average test scores is 6.7, which is higher than 6.3, namely the average of those who come from HU or TE school types). Among those students from LS who partly attended the MOOC, males perform much better than females. From this analysis, we have seen that the school types is the most influencing variable in test scores, but within the same school type we can identify different sub-groups of students who have different attendance at the MOOC. These differences may be better understood by looking specifically at affective variables (beliefs, attitudes, ...). This is the aim of the next subsection.

Community Analysis on Q. The community analysis on network N ($n = 369$ nodes) allows us to identify a partition with three clusters (modularity $Q = 0.0650$), whose details are reported in Table 2. The persistence probabilities (α_k) coupled with the z-score inform that the three identified sub networks of the whole students' network are not trivial.

Table 2. Results of max-modularity community analysis for students' network N

Community	N	N [%]	α_k	z_k
C_1	79	21.409	0.250	8.647
C_2	144	39.024	0.482	17.989
C_3	146	39.566	0.455	12.413

Figure 4 shows the communities' frequency of answers to Q0 in test Q: we can notice that community 3 has more males in percentage, more LS students (and fewer students from other school type), and more students who did not attend the MOOC course. Similarly, community 1 has a relatively higher percentage of male and LS students, while community 2 has a relatively lower percentage of

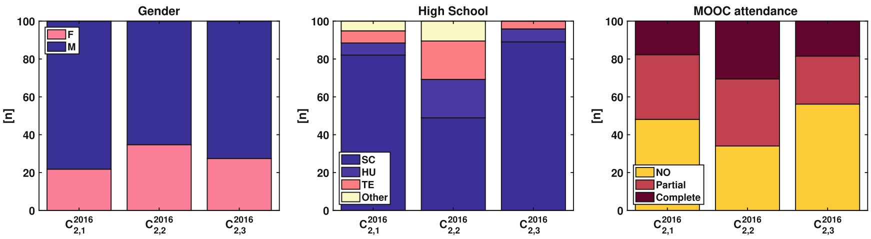

Fig. 4. Percentage of answers to personal data section Q0 grouped by community.

LS ones and the MOOC attendance is almost uniformly distributed among the three level of attendance. A χ^2-tests on the differences between the frequencies of answer to Q according to the identified communities shows that the three personal-level characteristics are statistically different in the three communities. At the same time, it highlights that the students in the three communities have answered in significantly different ways at all the questions but QA.3 and QA.4. The answers mostly given by the students belonging to the different communities to questionnaire QA allow us to characterise the three communities as follows.

Profile P_1: The students of this profile have a strong mathematical curriculum since they did not experience new math during the Bridge Course (QA.1). Since they declare to "have been exposed to problems different from the ones they were used to" (QA.2), they are unfamiliar with problem-based learning and they have a rather procedural approach to mathematics. Their exposition to procedural mathematics and more TO methods is confirmed also by the fact that they appreciated more the attendance part, instead of the e-learning part, the latter fostering more conceptual understanding (QA.5, QA.6).

Profile P_2: The students' sample has a large part of females and the majority of them come from HU, TE and Other schools, moreover two third of them attended the Pre-Calculus MOOC. The students belonging to profile 2 have a weaker mathematical background with respect to the previous profile, indeed they encountered new topics already in the bridge course (QA.1). However these students show a more positive attitude toward the e-learning material and the MOOC (QA.5,QA.6), suggesting a more conceptual approach and a positive attitude toward SO methods (QA.2).

Profile P_3: This profile is characterised by students who declared that they did not see any new topics (QA.1) or problems posed in different ways (QA.2). The sample is almost composed by LS students who have not attended the Pre-Calculus MOOC. However half of them would like a future support to the math exam as the *some extra tutoring as the same style of this course* and even a *support on MOOC* (QA.6). We can infer that students belonging to profile 3 have a very strong conceptual mathematical background and a positive attitude toward SO methods.

In the next subsection we come back to the classification tree and try to connect cognitive and affective variables.

Connections Between Affective Questionnaires and Cognitive Tests How do affective variables influence test performances of the students? If we go back to the classification tree shown in Fig. 3, we can identify the three profiles that emerged from the community analysis. After the first split, it emerges a group of students who come from HU, TE and Other schools and who have a lower test performance (average 6.3). These students can be identified with profile P_2. To the right of the split, LS students are identified and the ones with the highest test performance (average test score 7.4) have also attended the MOOC almost entirely. This group of students, which corresponds to 15% of the sample, seem not to correspond to any of the profiles. Among the students who come from LS and attended the MOOC less, we see another split: the leaf of the tree with the students who attended almost no MOOC identifies profile P_3, whose average test score is pretty high (namely, 6.8). The other leaf of the tree identifies the students coming from profile P_1: males are the majority and perform better that females in the test (average test score is 6.3 versus 5.1).

Even in an anonymous setting, we were able to establish a connection between the questionnaire and the tests by looking at the features of the students that *most characterize* the communities (i.e., gender, school type and MOOC attendance), and by seeing if the same features influence the test scores. It was then possible to identify four overarching, general trends that at a gross grain give a representative picture of well-known phenomena related to dropout.

5 Conclusions

In this paper, we aim at contributing to understand the phenomenon of drop out among first year STEM university students. We, thus, recalled the main factors that can help decision-makers to activate resources in order to reduce drop out by identifying and then intervening on subgroups of students who need personalised intervention at the first year of STEM university studies.

Our findings reveal that three main communities can be identified. The first community is populated by students who had been exposed to a strong curriculum in high school, and who have a rather conceptual view of mathematics. They show good performance in mathematics and they declare that in the Bridge Course they encountered mathematical content that was familiar for them: in fact, their acquaintance with conceptual mathematics allows them to feel comfortable with the new context of university mathematics, and not to live it as a shock. Finally, they seem to be able to discern which online content is useful for them: indeed, they declared to have partly attended the MOOC and our interpretation is that, since these students are good in mathematics, they selected the contents they actually felt "useful" for them to recall-being able to not loosing their time. As pertains this community of students, who represent the strongest group, our suggestion (following upon Clark & Lovric [5]) for policy-makers at STEM university is to promote and reinforce their relationships with high schools, especially focusing on secondary school math teacher training, so that teachers will teach their students more conceptual math, in a student-oriented fashion, and their learners will enter the university "well equipped" to deal with the transition.

A second community is as well populated by students who had been exposed to a strong curriculum in mathematics, but with a procedural approach. These students perform less well than their mates in the first community, they did not attended the MOOC and they are able to appreciate only traditional ways of teaching. A majority of males is present in this group. We can further comment that their math performance in tests is good enough, and they declare not to be shocked by the Bridge Course, because their strong mathematical knowledge sustains them in the transition. However, these students seem not to be ready neither for a self-organised way of studying, nor for student-centred learning formats. We expect that these students will face difficulties in the first semester at university, as observed in [2], a study conducted in a similar context. Andrà, Magnano & Morselli's [2] findings reveal that these students have the highest probability of not taking the degree, with respect to the students with weakest mathematical curriculum in high school-namely, those belonging to the third community.

Students in the third community are aware that their mathematical knowledge is not enough to attend first year STEM university, and they start to work hard in order to bridge the gap: they attend the MOOC and they come to the Bridge Course. They appreciate the new format of learning. According to [2], these students have a probability of getting the degree on time that is comparable to the one of the students in the first community. This tells us that mathematical knowledge is important, but it is also important the student's awareness about her weaknesses. For this reason, we suggest policy-makers at university to make use of (or develop their own) questionnaires that help them detecting the students' attitudes towards mathematics, their beliefs about themselves as learners, and their resilience.

From our findings, it emerges a confirmation of well established findings in analogous contexts. However, there are two elements of novelty in this study: one is the taking into account the students' attitudes towards e-learning materials (MOOCs, in particular), the other one is the idea of clustering students with respect to both personal-level characteristics such as gender and school type, and their views of mathematics, as variables that can explain their mathematics performances.

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