Student's characteristics and programming learning – A Macanese perspective

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***Abstract*—Results in introductory programming courses are often disappointing. Several possible causes for this situation have been reported. This paper reports some results of an experiment where we tried to find correlations between novice student's performance in an introductory programming course and some of their characteristics, namely previous programming experience, past grades (in general and in Mathematics), learning styles and motivation to the study area. The study took place during the academic year of 2016-2017 involving a group of Macanese students. A comparison with a similar experiment done previously in Portugal, involving two different groups of students, is also presented.**

Keywords—introductory programming learning; motivation; student's bacckground

I. INTRODUCTION

Novice students usually experience difficulties when learning to program. There are several reasons that can explain those difficulties [1]. Many authors have proposed different tools and strategies to facilitate initial programming learning, but the fact remains that the initial programming courses often prove very difficult to many students, while others don't seem to find it particularly difficult and show a good and fast progress. This situation is often reported by computer science teachers all over the world. It happens both with computer science majors and non-majors. So, it is necessary to deepen the knowledge about the reasons why some students can learn programming easily, while many others find it so difficult that they dropout or fail to pass initial programming courses.

This paper reports a study where we tried to find relationships between novice students' learning characteristics and their performance in an initial programming course. In the next sections, we will present the study and discuss the results obtained. We also present a short comparison of the results with the conclusions of a similar study made in 2007/2008 with two Portuguese samples.

II. THE STUDY

This study took place during the academic year of 2016-2017 and involved 30 novice students enrolled in the Bachelor of Science in Computing of the Public Administration School of the Macao Polytechnic Institute (MPI). This group followed an introductory programming course that uses the Java language. We wanted to investigate the impact that some personal characteristics could have in programming learning performance. The characteristics investigated were previous programming experience, learning styles and motivation to the study area. In this work, we didn't evaluate information on study methodologies or the time students dedicated to study for the course.

The study included three surveys, one focusing on the student's background information, another about learning styles and a third one about motivation. The first survey allowed us to get some demographic and academic data and some information about the student's background knowledge. The second survey intended to determine the students learning style. In this case, we used the Index Learning Style – ILS [2]. The third survey focused on motivational aspects. The first and third surveys were done in a regular classroom setting using pen and paper. The ILS was answered on-line.

III. STUDENT'S BACKGROUND

This section has information about the students' academic background, and about some characteristics that may influence programming learning performance. We analysed different items, namely the students' higher education access grade, their previous mathematics grades, their previous experience in programming and some motivational aspects. The main idea was to look for correlations between each of these items and the marks students got in their initial programming course.

A. Programming Background

The students' previous programming experience was determined through a question where students had to auto-classify their knowledge level (none, basic, medium or advanced) in several programming languages. The students declared heterogeneous backgrounds: some had earlier programming experience with different levels of knowledge, some did not. The results can be seen in Table I.

TABLE I. PREVIOUS PROGRAMMING LANGUAGES EXPERIENCE.

	C	*VB*	*Java*	*Python*	*Other*
None	81%	64%	80%	94%	81%
Basic	13%	33%	17%	3%	3%
Medium	3%	0%	0%	0%	3%
Advanced	3%	3%	3%	3%	3%

It is possible to observe that most students declared having no previous knowledge of programming. Only one of them declared to have advanced proficiency in the programming languages mentioned in the survey. A few students declared to have a basic knowledge, especially in VB and Java programming. Those who mentioned other languages pointed out PHP and Javascript.

We used these results to analyse a possible relation between the students' previous programming experience and the results they obtained in the initial programming course. We wanted to know if the students who declared some previous programming experience would perform significantly better than their colleagues that had no previous experience. That was not the case. Strangely, the student that declared to have advanced programming experience in several programming languages had one of the lowest grades in the course.

B. Access Grade

To apply for the Computing programme at MPI the students must take an access exam. In the case of students coming from mainland China, the results of the national Chinese exam "Gao Kao" are considered. Students from Macao must take a local exam for selection purposes. This exam focuses on Mathematics and English. The results for our sample are shown in Table II (we use a 0 – 20 scale). It is possible to see that, in general, MPI can recruit good students for its Computing programme.

TABLE II. ACCESS GRADES.

	Access Grade
Average	15.24
Median	15
Std. Dev.	1.44
Minimum	13.10
Maximum	18.50

We wanted to know if there was any correlation between the students' access grade and the mark obtained in the introductory programming course. However, no correlation was found. Nevertheless, we found some other correlations (Table III) with the Access Grade that are worth mentioning. To note that assessment consist in 1 closed book test during the course which weights 20%, a final closed book exam which weights 50% and open book exercises that jointly with the students' class participation correspond to around 20% of the final grade.

TABLE III. ACCESS GRADES AND OTHER VARIABLES.

	TOP	**Test**
Access_Grade	.465*	-.428*

We found a negative correlation between the access grade and the marks students obtained in the first test made in the introductory programming course. This means that the students who had better access grades had worst results in this initial test. Maybe these students had more difficulties in their initial adaption to higher education, as this negative correlation was not found when considering the course final grades.

We also asked students where their secondary school grades ranked in the context of that school. They could classify their grades in the top 10%, top 25%, top 50%, top 75% or top 90% of their school. Having in mind that only 28 students answered this question, we can consider that most of them were good students in secondary school, as 4 students declared to be in the TOP10, 12 students in the TOP 25 and 6 students in the TOP 50. The remaining 6 students declared they belonged to TOP 75 and TOP 90. As would be expected, we found a correlation between the Access Grade and the students' classification in the TOP, as the students with the highest marks were those who were better placed in their schools.

C. Mathematics Grades

One aspect that interested us was the possible relationship between the student's mathematics grades in secondary education and their performance in introductory programming. Maybe the student's grades in mathematics could be used as an indicator of their problem-solving abilities, which are fundamental to learn programming. However, we didn't find any significant correlation between the two variables. The results for our sample are shown in Table IV (we use a 0 – 20 scale).

TABLE IV. ACCESS GRADES.

	Access Grade
Average	15.8
Median	15.8
Std. Dev.	1.6
Minimum	13.2
Maximum	19

D. Motivational Characterization

To succeed in any task, an individual must be motivated to it. Unfortunately, motivation is a concept that is difficult to measure in a meaningful way [3]. It is possible to observe a person's behaviour and to infer their likely motivation, but it is never possible to be certain. We tried to evaluate the dominant type of student motivation, based in three types defined by Jenkins, namely extrinsic, social and achievement motivation [4]. A fourth category, corresponding to "null motivation" was also used to accommodate cases falling outside the previous three categories. To evaluate this, we asked the following question to the students:

Which of the following statements best describes your attitude concerning the Computing degree you are following:

a) I want to do well for my own satisfaction.

b) I want to do well to please my parents, family and friends.

c) I want to do well to please my teacher.

d) I want to do well so that I will get a good job.

e) My main goal is to pass.

Choice a) reflects the achievement (personal) motivation, b) and c) the social motivation d) the extrinsic motivation and e) the null motivation. The results are shown in Table V (the sum is higher than 100% because the students could tick more than one answer).

We tried to find correlations between the type of motivation and the student's results in the introductory programming course, but we couldn't find one (in some cases the number of answers was not enough to obtain statistics). However, it was possible to note a few interesting aspects. For instance, only one student chose option c, which means that social motivation doesn't seem to be very important for these students. On the other hand, as expected, all the students with higher marks in the introductory programming course (>=16 points) chose option a) or options a) and d). This suggests that the students that had higher marks are possibly more intrinsically motivated. However similar results emerged from the students with lower results.

TABLE V. MOTIVATION TYPES.

Extrinsic	26%
Social	9%
Achievement	65%
Null	13%

We also used two motivation related instruments (CIS - Course Interest Survey and IMMS - Instructional Materials Motivation Survey), both developed by Keller [5], trying to get a more in depth picture about student's motivation.

CIS is a multidimensional questionnaire consisting of 34 items divided in four dimensions/categories (Attention, Relevance, Confidence and Satisfaction). It measures the motivational effect of course interest. It includes 8 questions for Attention, 9 for Relevance, 8 for Confidence and 9 for Satisfaction. Hence, the maximum that can be obtained is 40 points for Attention, 45 points for Relevance, 40 points for Confidence and 45 points for Satisfaction.

IMMS measures the motivational effect of instructional materials based on 36 related questions (12 questions for Attention, 9 for Relevance, 9 for Confidence and 6 for Satisfaction). The maximum that can be obtained is 60 points for Attention, 45 points for Relevance, 45 points for Confidence and 30 points for Satisfaction.

The CIS and MMIS internal consistency has been estimated high. Cronbach's alpha of CIS is 0.953, which indicates a high level of internal consistency for this instrument with this specific sample, while the Cronbach's alpha of IMMS is 0.964. Analysing separately each of the dimensions, in our sample the results were good for CIS: α=0.844 for Attention, α=0.856 for Relevance, α = 0.813 for Confidence, α=0.887 for Satisfaction and α=0.947 for the total. The results were also good for IMMS: α=0.897 for Attention, α=0.814 for Relevance, α=0.937 for Confidence, α = 0.924 for Satisfaction and α =0.961 for the total.

Both instruments are situational measures of students' motivation to learn regarding a specific learning condition, such as an instructor-facilitated learning environment. Furthermore, they were designed following a specific model of learner motivation, called the ARCS Model [5]. As situational instruments, they are not intended to measure student's generalized levels of motivation toward learning. The goal with these instruments is to find out how motivated students are, were, or expect to be, by a particular course.

CIS - Course Interest Survey

We could not find correlations between any CIS category and the grades in the introductory programming course. However, considering that the minimum points in this instrument is 34, the maximum is 170 and the mid-point is 102, it is possible to conclude from Fig. 1 that many students in the sample had a good general motivation level. However, there are a few with lower marks, bellow the mid-point.

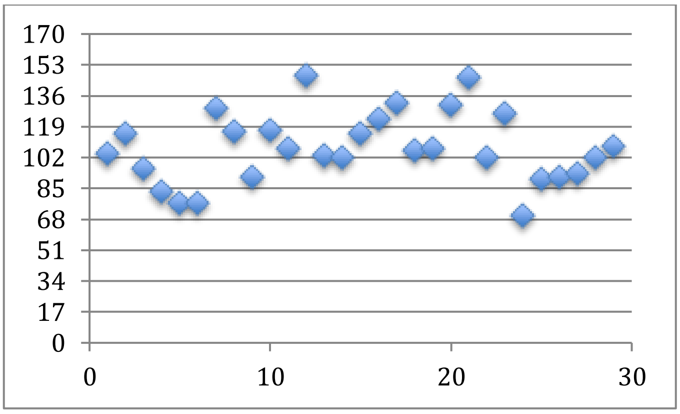

Fig. 1. Course Interest Survey – Global assessment

Fig. 2 to Fig. 5 show the results obtained for the different categories of CIS.

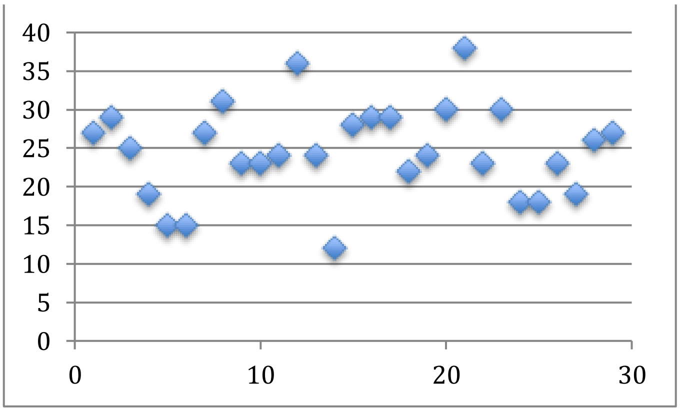

Fig. 2. Course Interest Survey – Attention category

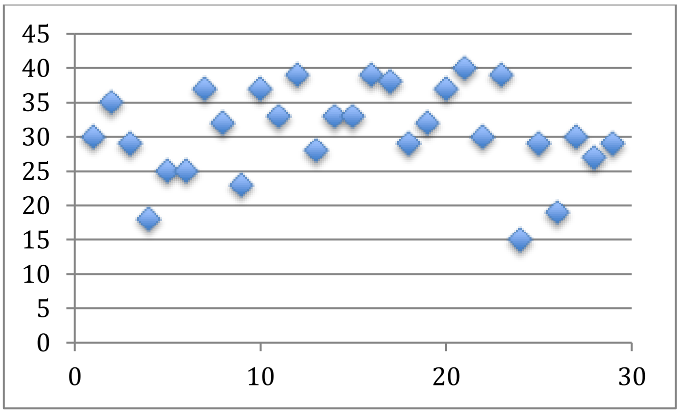

Fig. 3. Course Interest Survey – Relevance category

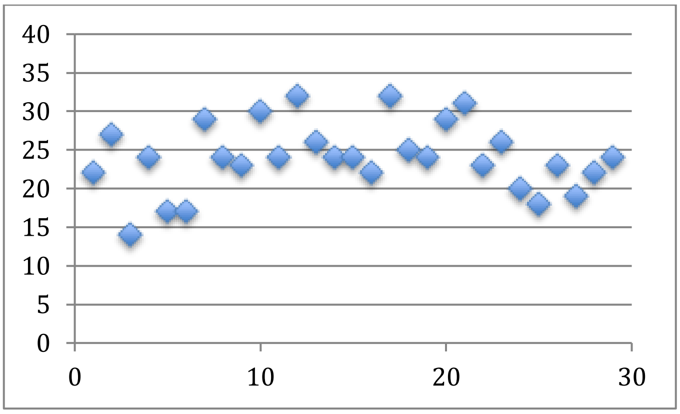

Fig. 4. Course Interest Survey – Confidence category

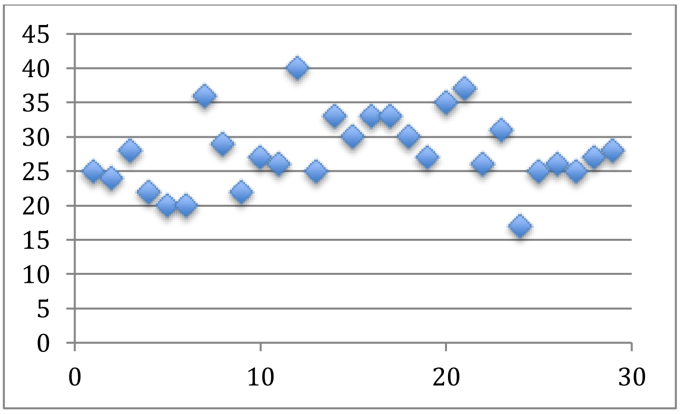

Fig. 5. Course Interest Survey – Satisfaction category

Table VI shows the descriptive statistics for each category of the CIS instrument.

TABLE VI. DESCRIPTIVE STATISTIC OF CIS RESULTS

	Attention	Relevance	Confidence	Satisfaction
Average	27	29.5	23	26.5
Std. Dev.	6	6.6	4.5	5.4
Minimum	12 (6)	15 (9)	14 (8)	17 (9)
Maximum	38 (40)	40 (45)	32 (40)	40 (45)

Taking into consideration the maximum possible value in each category, we can observe that most students show high motivation levels. The lower levels were obtained in the Confidence category. This is an important aspect to consider, as previous studies showed the importance of motivation and personal perceptions of competence to the success in introductory programming courses [6]. Maybe this is an issue that should be addressed by course instructors.

IMMS- *Instructional Materials Motivation Survey*

We could not find correlations between any IMMS category and the results the students obtained in the introductory programming course. However, considering that the minimum is 36, the maximum is 180 and the mid point is 108 we can consider that most students showed satisfactory motivation levels towards the materials used in the course (Fig. 6). However, the values were not as high as those concerning the motivation towards the course. Of course, this issue requires further study, but maybe the course instructors should try to find more innovative materials to stimulate their student's motivation.

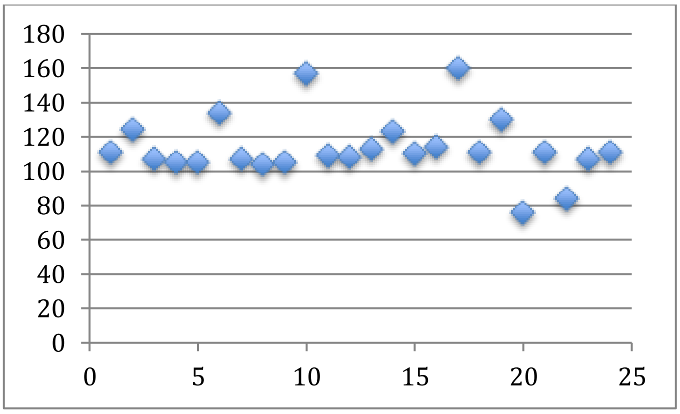

Fig. 6. Instructional Materials Motivation Survey– Global assessment

Fig. 7 to Fig 10 show the results obtained concerning each category.

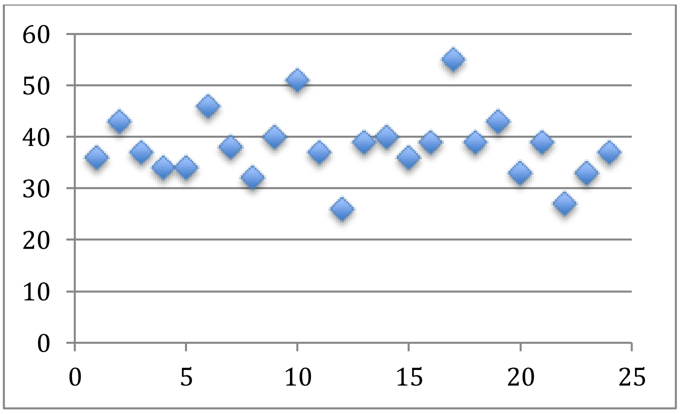

Fig. 7. Instructional Materials Motivation Survey– Attention parameter

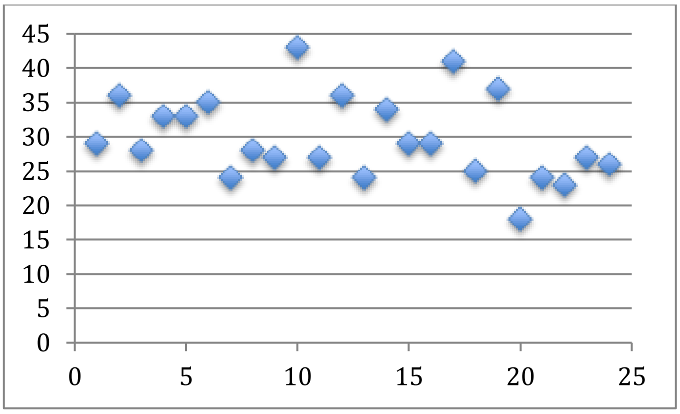

Fig. 8. Instructional Materials Motivation Survey– Relevance parameter

Having in consideration that the maximum in each category is 60 for Attention, 45 for Relevance, 45 for Confidence and 30 for Satisfaction, we verify that most students have high motivation levels concerning the used materials. Again, the confidence parameter shows comparatively lower values.

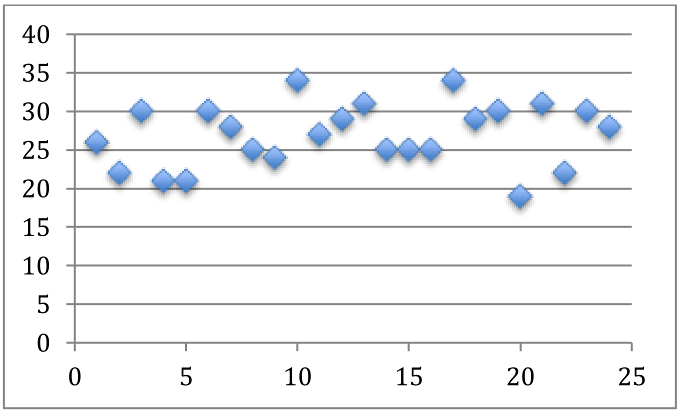

Fig. 9. Instructional Materials Motivation Survey– Confidence parameter

Fig. 10.

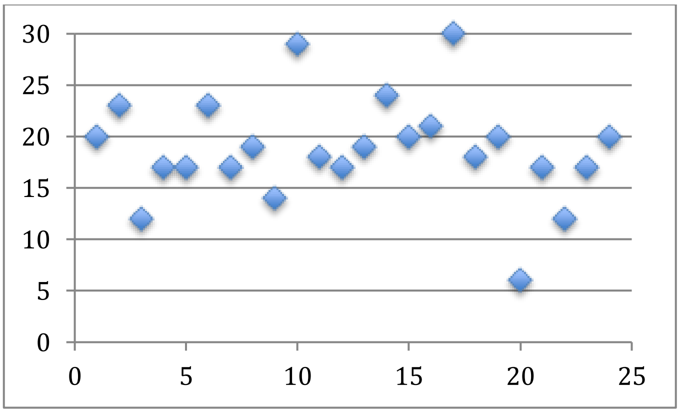

Fig. 11. Instructional Materials Motivation Survey– Satisfaction parameter

Table VII shows the descriptive statistics for each category of the CIS instrument.

TABLE VII. DESCRIPTIVE STATISTIC OF IMMS INSTRUMENT

	Attention	**Relevance**	**Confidence**	**Satisfaction**
Average	37	26	28	20
Std. Dev.	6.6	6.0	4.6	5.1
Minimum	26 (12)	18 (9)	18 (9)	6 (6)
Maximum	55 (60)	43 (45)	36 (45)	30 (30)

The correlations obtained with the different categories of the two motivational instruments can be found in Table VIII. It can be observed that all CIS categories are strongly correlated with each other, meaning that the students with higher values in one category also had higher values in the other categories. The same is true for the IMMS.

The students who showed more confidence in the course were also those that showed more confidence about the used materials. The students who had more satisfaction with the materials were those who showed more attention and confidence in the course, which highlights the importance of the materials used in the course.

We looked for correlations between each category of the two motivational instruments and the final grades in the introductory programming course. We also looked for correlations between the instruments categories and the different assessment components used in the course. We only found a correlation between the confidence and the scores obtained in the final exam ($p = 0.371$ at 0.05 level (2-tailed)). This means that most students who obtained better marks in the final exam were the most confident in class. This result also stresses the importance of student's confidence to their success.

TABLE VIII. CORRELATIONS BETWEEN THE CIS AND IMMS INSTRUMMENTS

	Interest Attention	Interest Relevance	Interest Confidence	Interest Satisfaction	Material Attention	Material Relevance	Material Confidence	Material Satisfaction
Interest Attention	1	.779**	.786**	.806**				.406*
Interest Relevance	.779**	1	.783**	.891**				
Interest Confidence	.786**	.783**	1	.828**			.368*	.399*
Interest Satisfaction	.806**	.891**	.828**	1				
Material Attention					1	.938**	.950**	.937**
Material Relevance					.938**	1	.913**	.948**
Material Confidence			.368*		.950**	.913**	1	.902**
Material Satisfaction	.406*		.399*		.937**	.948**	.902**	1

E. Learning Styles

Learning styles are "characteristic cognitive, affective and psychological behaviours that serve as relatively stable indicators of how learners perceive, interact with and respond to the learning environment" [7].

To characterize the student's learning styles, we used the Felder-Silverman model [8], due to its good performance [9,10], namely with respect to (i) ease of implementation, as the corresponding instrument can be answered online; (ii) automatic generation of results, based on the answers students give in the online instrument and (iii) straightforward interpretation of results.

To Felder “a student’s learning style profile provides an indication of probable strengths and possible tendencies or habits that might lead to difficulty in academic settings. The profile does not reflect a student’s suitability or unsuitability for a particular subject, discipline, or profession” [11]. The emphasis in Felder-Silverman Model is on preferred learning style, not in ability [12]. According to this model a learner is classified in five categories, Sensing/Intuitive, Visual/Verbal, Active/Reflective, Sequential/Global, Inductive/ Deductive.

The categories Sensing/Intuitive and Visual/Verbal refer to the mechanisms of perceiving information. The categories Active/Reflective and Sequential/Global concern how the information is processed and transformed in understanding:

- Sensory/Intuitive – Sensory learners like to study facts and solve problems by using known methods. They tend to be more oriented to details, like practical work and are good to memorize things. Generally they don’t like surprises and complications. Intuitive learners feel comfortable with abstract concepts. They like to find out new possibilities and applications to the studied topic. They tend to be innovative and don’t like repetitions.

- Visual/Verbal – Visual learners easily remember things they see as figures, maps, diagrams, films, and flowcharts. Verbal learners prefer written or spoken explanations.

- Active/Reflective – Active learners absorb information by trying things out and working in teams. They tend to focus on the outer world. Reflective learners prefer to think about the information and like to work alone.

- Sequential/Global – Sequential learners learn in orderly, incremental steps. Generally they have more success in the studies because the majority of books used by professors are sequential. Global learners tend to learn in large steps after accumulation of all the facts.

- Inductive/Deductive – Inductive learners organize the information starting from particular reasoning toward generalities. They infer principles. The deductive learners organize the information so that the solutions for the problems are consequences of a general idea. They deduce principles. The traditional teaching method is deduction, starting with theories and proceeding to applications.

To identify the student’s learning preferences, we used the Index Learning Style – ILS. It does not include the Inductive/Deductive category, as the author believes that the best method of teaching is induction, whether it is called problem-based learning, discovery learning or inquiry learning. This instrument is a set of 44 sentences, 11 for each of the four categories. The classification of the student according to his/her score in a dimension of a category (e.g. Visual or Active) can be fairly (1-3), moderate (5-7) or strong (9-11). A person classified as fairly does not show preference for any dimension of that particular category. The moderate indicates that the learner has a moderate preference for a dimension of the scale and will learn better in a teaching environment which favours that dimension. The strong indicates the learner has a very strong preference on a dimension on the scale. This learner may have real difficulties in learning in an environment, which does not support that preference.

Table IX shows the different learning styles found in our sample, according to each dimension of Felder’s model. Most of the students are sensory (82%), visual (83%) and sequential (77%). These results are coherent with previous studies involving engineering students [13 – 16].

TABLE IX. LEARNING STYLES

Sensory (82%)			**Intuitive (18%)**		
Weak (1-3)	Moderate (5-7)	Strong (9-11)	Weak (1-3)	Moderate (5-7)	Strong (9-11)
31.58%	42.11%	26.31%	40%	60%	0%
Visual (83%)			**Verbal (17%)**		
Weak (1-3)	Moderate (5-7)	Strong (9-11)	Weak (1-3)	Moderate (5-7)	Strong (9-11)
40%	35%	25%	50%	50%	0%
Active (50%)			**Reflective (50%)**		
Weak (1-3)	Moderate (5-7)	Strong (9-11)	Weak (1-3)	Moderate (5-7)	Strong (9-11)
75%	8.33%	16.67%	83.33%	16.67%	0%
Sequential (77%)			**Global (23%)**		
Weak (1-3)	Moderate (5-7)	Strong (9-11)	Weak (1-3)	Moderate (5-7)	Strong (9-11)
58.83%	29.41%	11.76%	57.14%	42.86%	0%

We tried to establish correlations between introductory programming learning performance and each learning style dimension (visual or verbal, active or reflective, sensory or intuitive and sequential or global). However, that was not possible. A similar result had already been reported in [17]. However, other studies reached different conclusions, as they concluded that reflective and verbal learners performed better in programming courses than active and visual learners [18,19].

We also looked for correlations between student’s learning preferences and the results obtained with CIS and IMMS instruments. We found the correlations shown in Table X.

TABLE X. LEARNING PREFERENCES AND MOTIVATION

	Material_ relevance	**Material_ confidence**	**Material_ satisfaction**
Sensorial	-.563*	.513*	-.469*

The negative correlations between the sensorial students and the "Material relevance" and "Material Satisfaction" IMMS categories mean that the students that have a clearer sensorial tendency gave lower valuations to the relevance and satisfaction dimensions concerning the learning materials used in the course. The instructors can improve the learning materials, so that sensorial students find them more useful. On the other hand, the same students (more sensorial), showed more confidence in the materials used.

It was curious to find a correlation (.428*) between the sensorial dimension and the student's access grade. This means that most students with best access grades had a strong sensorial tendency. On the contrary, it was also verified that the students with lower access grades were all verbal (-1.00**).

IV. DISCUSSION

As mentioned before, in the academic year 2007/2008 we conducted a similar study involving two groups of novices computing Portuguese students, one included 51 students from the University of Coimbra (UC) and another included 87 students from the Polytechnic Institute of Coimbra (IPC) [20]. Although nine years have passed since that study, we thought that it might be interesting to compare the results and see if we could find similarities or differences.

Even though the Macanese and the Portuguese groups have a very different cultural background, they also share some common characteristics. The three groups included a clear majority of male students, with an average age of 19 years. They were novice students registered in an introductory programming course included in the first year/first semester of a Computer Science degree. Those courses used different programming languages, Java in Macao, and Python and C in each of the Portuguese cases.

A comparison of the student's higher education access grades shows some difference. While the average access grade in the MPI group was 15.24, the average of the Portuguese samples was lower, 13.97 for UC students and 13.17 for IPC students.

The results produced by the ILS were analogous in all groups. This means that most students were visual, sensory and sequential in similar proportions in all the samples. The only clear difference appeared in the Active/Reflective category, as about 2/3 of the Portuguese students were active and only 1/3 was reflective. On the contrary, in the Macao group we found about 50% of students in each of these dimensions. A more detailed analysis showed some more differences. In the Sensory/Intuitive category, the trend for sensorial students is stronger in the MPI group, since almost 70% of the sensorial students had a moderate or strong tendency to the sensorial dimension. This preference was less evident in the Portuguese students, as most of them showed only a weak tendency to the sensorial dimension. The same could be observed in the category Visual/Verbal.

We used the same questions in both studies to determine the type of motivation that was stronger in each group. In this point we found some difference, as the intrinsic (achievement) motivation seems to be dominant for 65% of the MPI students, while in the Portuguese groups these numbers were lower, 58.33% and 44.07% respectively to UC and IPC groups.

Table XI includes the most important correlations we found in both studies. As stated before, we couldn't find any significant correlation between the final results of the MPI students and the variables we studied (programming experience, access grade and mathematics grade). However, in the study with Portuguese students we found a strong correlation with the previous programming experience in both groups. Also, we could establish correlations with the access grade in both groups and with the mathematics grade, only in the case of the UC group. In that study, we also tried to correlate the final grades of the students without previous programming experience with their calculus abilities. A correlation was established in both groups.

TABLE XI. VARIABLES AFFECTING PROGRAMMING LEARNING PERFORMANCE * AT 0,05 LEVEL (2-TAILED), **AT 0,01 LEVEL (2-TAILED)

	Pearson correlation		
	Group_IPC	Group_UC	Group_MPI
Mathematics grade	—	*p*=0.373**	—
Access grade	*p*=0.282*	*p*=0.451**	—
Programming experience	*p*=1	*p*=1	—
Calculus	*p*=0.492**	*p*=0.416*	—

We don't have a clear explanation for the differences found between the Portuguese and Macanese groups. Maybe the smaller size of the Macanese group and its more homogeneous grades had a role in the results. In fact, looking at the student's final grades, it is notorious that the UC and IPC students had much more disperse grades, with some having very high grades, while others had very low marks. This is not the case of the MPI students.

We also looked for correlations between the Portuguese student's grades in the introductory programming course and their motivation, as measured with the same instruments used in the MPI case. No correlation could be established. A more intuitive analysis showed results very similar in the Portuguese and Macanese groups. For example, no Portuguese student chose option c) (*I want to do well to please my teacher)* and only one Macanese student did chose this option. However, in the three groups, the students with higher marks in introductory programming (>=16 values) chose option a) or options a) (*I want to do well for my own satisfaction*) and d) (*I want to do well so that I will get a good job)*. This seems to suggest that the students that had higher marks in programming were possibly more motivated. However, also in all groups, similar results emerged from the students with lower grades.

V. CONCLUSION

We conducted a study involving novice students from the Macao Polytechnic Institute. These students were enrolled in the introductory programming course included in the Bachelor of Science in Computing. We tried to look for relations between student performance in that course and some variables that according to the literature and our own experience may have influence in student's performance. Although we couldn't establish correlations in many cases, we were able to get some insights on some context and teaching aspects that might be improved.

As we had conducted a similar study with two groups of Portuguese students, we compared the results. In some cases, the results were similar, but there were important differences, as several correlations could be established in the Portuguese study and not in the Macanese study. Although we can't have a proved explanation for these differences, we believe that the high homogeneity of the grades obtained by MPI students can be part of the explanation. As referred by Lahtinen, programming is a versatile skill that demands mastering numerous schemas and sometimes it becomes difficult to determine what influences some results [21].

We plan to repeat the experiment in the next academic year, both in Portugal and Macao, trying to have bigger sample groups, so that we can achieve more reliable results. Knowledge about what affects, positively and negatively, programming learning is very important to define the best learning contexts and pedagogical strategies that may help most students to overcome the natural difficulties of learning to program.

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