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Impact of Pre-University Factors on the Motivation and Performance of Undergraduate Students in Software Engineering

Pablo Schoeffel, Raul Sidnei Wazlawick
Department of Informatics and Statistics
Federal University of Santa Catarina
Florianópolis, Brazil
professorpablos@gmail.com, raul.wazlawick@ufsc.br

Vinicius Ramos
Department of Information and Communication Technologies
Federal University of Santa Catarina
Araranguá, Brazil
v.ramos@ufsc.br

***Abstract*— The significant number of fails and dropouts in computing undergraduate courses, especially in mathematics and programming, remains a challenge. Although the motivation can be directly related to the success of the student, it has only been addressed by a few studies. The purpose in this paper is to assess the impact of factors prior to university on the performance and motivation of undergraduate freshmen students in Software Engineering. Questionnaires were applied to students, and their grades on introduction to programming (CS101) and discrete mathematics (MAT101) were analyzed. Using statistical analysis of variance and correlation, we identified that *motivation* was impacted only by "knowledge and previous experience in programming". *Performance* was impacted by "previous scholar knowledge", "way to access university", "age" and "taste/knowledge of the area". We identified as well, unlike other studies, that the initial motivation had no impact on students' performance.**

Keywords — motivation; performance; student; software engineering education; programming; math

I. Introduction

Despite the demand of the market that suffers a shortage of people skilled in Information Technology (IT) [1] [2], youngsters show little interest in this area, and high dropout rates are perceived especially in computing. Some studies describe worldwide dropout rates up to 40% in computing and technology undergraduate programs [3] [4] [5].

There are specific reasons that are considered as factors for these high drop-out rates, such as "difficulty with programming" [6] [7] and "lack of familiarity with the subject" [8].

According to Sinclair et al. [9], more qualitative data and other measures (such as student's expectation) are needed for the broad understanding of the experience of the computer science (CS) student.

A factor that is associated with the success or retention of students is their motivation and engagement [11] [12]. To improve students' learning and retention in computing, it is important to understand which are the factors that keep them motivated and engaged.

We have verified that motivation and engagement have different definitions and categorizations. This work considers the following motivation categories [10]:

- *Intrinsic motivation*: the main motivation is the interest and taste for computing itself, obtaining knowledge;
- *Extrinsic motivation*: the main motivation is the career and rewards arising with the successful conclusion of the undergraduate program;
- *Social motivation*: the main motivation is to please someone (family, friends, professor, etc.), rising status in classroom;
- *Self-realization*: the main motivation is personal satisfaction to achieve a good performance, fear of failure;
- *Null or amotivation*: there is no particular motivation (a negative view exemplified by the statement "I just want to pass").

Many of the factors that contribute to student retention and success are related to the students' features themselves even before their enrollment in the university, such as their interest in the area, perspective for the future, previous knowledge, etc. [10].

Studies demonstrate that there is a large concern with students' initial motivation [10] and their performance in the first year [13]. However, two things should be discussed more deeply: i) does the initial motivation have direct and exclusive relationship with student performance? ii) which are the other possible factors that may influence on the initial performance of the student?

In this context, we have defined six research questions to be answered in this paper:

RQ1 – Does demographic data and factors related to the enrollment have impact on students' motivation and performance?

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RQ2 – Does prior knowledge of the area and syllabus have impact on students' motivation and achievement?

RQ3 – Does prior experience in computing or programming have impact on students' motivation and achievement?

RQ4 – Does prior high school performance have impact on students' motivation and performance during the undergraduate program?

RQ5 – What are the factors that impact on students' motivation at the beginning of the course?

RQ6 – Does initial motivation have impact on students' performance?

This paper aims to evaluate the impact of demographic data, factors related to student enrollment, and other factors prior to registration in the undergraduate program on the performance and motivation of software engineering students. Section II presents the state of the art; Section III describes the research method used; Section IV presents the results; and Section V discusses the results and presents the conclusions.

II. STATE OF THE ART

The transition from medium to high education is a move from a controlled learning environment to a more autonomous mode. Students with a more academic background may be more comfortable with the transition to autonomous learning than those with a vocational background [14].

Several studies describe factors that impact on the performance of computing students. Many of them are related to the introductory programming course (CS101) [15] [16] [17] [18] [19] [20] [21] [24] [7]. Other studies describe factors related to students' success in the whole undergraduate program [22] [23].

Wilson and Shrock [21] studied the impact of twelve factors on students' performance: math background, alleged motive for success/failure (luck, effort, task difficulty, and ability), domain specific self-efficacy, encouragement, level of comfort in the course, working style preference, previous programming experience (formal and self-initiated), previous non-programming computer experience (internet, games and productivity software), and gender. However, only three factors were shown to have significant impact: level of comfort, math background, and success/failure attributed to luck. Rountree, Rountree, and Robins [19] analyzed gender, age, enrolment status (part or full-time), year of studies at university, major intended, how keen they were to take studies, background in math, humanities, science, and commerce, knowledge in programming language, and expectations. They found that the strongest single indicator of success was the grade the student expected to achieve at the beginning of the course. Other factors that are related to success included whether students think their background is science, commerce, or humanities; whether they have recent university experience with math; and which year of studies they are attending. Pasini *et al.* [24] verified the connection between motivation, emotions, and performance in initial learning of programming for undergraduate students in applied mathematics. The motivation was measured about beliefs on perceived control, task value, and self-concept. Theoretical exam grade was positively correlated with motivational antecedents, specifically perceived control and self-concept. Pappas *et al.* [22] indicate eight configurations of cognitive and noncognitive gains, barriers, motivation for studies, and learning performance that explain high intention to continue studies in CS. The results suggest that *motivation to study CS* and *learning performance* are core factors in explaining high intention to continue studies in the area, but there is no relation between motivation and performance. Longi [18] analyze factors related to students' background, programming behavior, and psychological and cognitive characteristics to predict students' performance in programming, but no clear predictors were identified in this study. Lishinski *et al.* [17] reports on a study that examined the interaction of self-efficacy, intrinsic and extrinsic goal orientations, and metacognitive strategies and their impact on students' performance at a CS101 course. Results showed that self-efficacy was the most important predictor for students' outcome. Idemudia, Dasuki and Ogedebe [16] studied six adapted constructs as predictors for behavioral intention to studying programming: actual usage of programming languages, behavioral intention to program, performance expectancy towards programming, anxiety towards programming, self-efficacy towards programming, and habits towards programming. They demonstrate that performance expectancy, anxiety, self-efficacy, and habits towards programming influence the actual usage of programming languages through behavioral intention to program. Hawi [15] studied business computing students in an introductory computer programming course and found ten relevant factors: "learning strategy", "lack of study", "lack of practice", "subject difficulty", "lack of effort", "appropriate teaching method", "exam anxiety", "cheating", "lack of time", and "unfair treatment". Bergin and Reilly [7] studied the role of motivation and comfort-level in a first-year object-oriented programming course. The study found that intrinsic motivation had a strong correlation with programming performance, as did self-efficacy for learning and performance.

Studies relating previous factors with performance have divergent results. For example, Wilson [12] found no correlation of performance with previous programming experience, previous non-programming computer experience, and gender, but he found correlation with math background. However, Rountree, Rountree, and Robins [19] found a relationship between performance and math background, but they have not found correlation with knowledge of a programming language.

Similarly, few studies correlate performance with the initial motivation, that is, the reason for attending the course or undergraduate program. Studies that correlate performance with motivation also show divergent results. For example, Lishinski *et al.* [17] found no correlation between intrinsic and extrinsic goal orientation on students' performance. Rountree, Rountree, and Robins [19] also found no correlation between the factor "how keen they were to take studies" and performance. However, Pasini et al. [24] demonstrate that theoretical exam grades were positively correlated with motivational antecedents.

In order to find out the previous factors that impact on computing students' motivation and performance, we conducted a systematic review on motivation of computing students, in which we found 17 previous factors, divided into four categories:

- Personal/demographic data: gender [25] [26];
- Taste and knowledge of the area and course: broad and social vision of computing [27], taste for technology and programming [27], correct perception of the area and professionals [28], and knowledge of computing and undergraduate program goals [28];
- Informatics/programming experience: work experience in the area [25] [11] [10], prior knowledge of computing [11] [29], and programming experience in basic education [27];
- Prior school performance: student ability in computing [30], educational history [14] [31] [32] systemic vision, and knowledge about mathematics [27];

Studies also show divergent results about factors that impact on students' motivation. As an example, the "social influence" factor was rated by four studies, and in three of them it had a strong positive impact [33] [29] [34], but on the other one it had a weak impact [35].

Therefore, although there are several studies regarding the previous factors that impact on student performance and motivation in computing courses, there are few studies that measure the correlation between motivation, performance, and pre-university factors. There are divergences in the results of studies in this area, which indicates the need for further research. Besides performing this research, this article also proposes to assess the impact of performance in discrete mathematics (MAT101), which is a subject reported to be difficult for computing students. Another factor that distinguishes this work from others is that it is focused on an undergraduate program on software engineering, and not computer science.

III. RESEARCH METHOD

The proposed study is based on the application of a questionnaire (survey) to 64 freshmen students of the Bachelor Program on Software Engineering at Santa Catarina State University (UDESC) - Brazil. The survey was applied during the second semester of 2016 and first semester of 2017. The development and implementation of this survey was based on the process described by Kasunic [36].

We worked out a questionnaire with 37 items divided into five groups and 20 factors, as shown in Table I. Each item has options following a Likert scale of 4 points. "*Respondents' desires to please the interviewer or appear helpful or not be seen to give what they perceive to be a socially unacceptable answer, can be minimized by eliminating the mid-point ('neither ... nor', uncertain, etc.) category from Likert scales*" [37].

Groups 2, 3, and 4 of the questionnaire were based on a compilation of factors extracted from the literature. The group "initial motivation" is a light scale adapted from Vallerand [38] and Jenkins [10].

In order to assess the impact of previous factors surveyed on the performance of students, we conducted statistical comparisons between all the factors and the final grade in CS101 and MAT101. We chose to use these two courses because they are historically problematic areas with respect to failure and dropout in computing education. "*Math background was second in importance in predicting success in this computer science class.*" [21].

TABLE I. QUESTIONNAIRE GROUPS AND FACTORS

Group	Factor
1. Personal and demographic data	1A – Gender 1B – Quota 1C – Entrance exam position 1D – Year of entrance 1E – Age 1F – Entrance way
2. Taste and knowledge of the area	2A – Taste for programming and technology 2B – Knowledge about the undergraduate program goals 2C – Knowledge about the undergraduate program content 2D – Correct perception about computing professionals
3.Computing and programming experience	3A – Knowledge and experience in computing 3B – Knowledge and experience in computer programming 3C – Programming experience in high school
4. Prior school performance	4A – General educational performance 4B – Prior math performance
5. Initial Motivation	5A – Intrinsic motivation 5B – Extrinsic motivation 5C – Self-realization 5D – Social motivation 5E – Amotivation or lack of motivation

We defined indexes for subscales of motivation to identify the impact of each subscale with greater impact. We also created an index to determine the general rate of motivation (Motivation Index – MI), according to the following formula:

$$MI = \Sigma IM + \Sigma EM + \Sigma SM + \Sigma RI - \Sigma AI$$

where:

IM – Intrinsic Motivation

EM – Extrinsic Motivation

SM – Social Motivation

RI – Self-Realization Index

AI – Amotivation Index

For statistical analysis, we used: comparison of means of independent samples (t-student), comparison of means with more than 2 groups (ANOVA) and quantitative data correlation (Pearson's Coefficient).

IV. RESULTS

To assess the level of internal consistency of the questionnaire, we calculated the Cronbach's Alpha that resulted in 0.768, which can be considered satisfactory. "*There are different reports about the acceptable values of alpha, ranging from 0.70 to 0.95*" [39].

We present in Table II a summary of a statistical analysis related to demographic data. In the following we analyze each of those factors.

TABLE II. STATISTICAL ANALYSIS AND RESULTS (P-VALUE) ABOUT STUDENTS' DEMOGRAPHIC DATA, MOTIVATION, AND PERFORMANCE.

	Factor	Method	Motivation	CS101	MAT101
1A	***Gender***	t-Student	0.5077	0.7490	0.6398
1B	***Quota***	ANOVA	0.8850	0.6150	0.7300
1C	***Entrance exam position***	ANOVA	0.5680	0.6200	0.5950
1D	***Year of student entrance***	t-Student	0.7420	0.7510	**0.0337***
1E	***Age***	Pearson	r=-0.1004 0.4329	r=0.0059 0.9984	r=-0.1944 0.1474
1F	***Way of entering***	ANOVA	**0.0675.**	**0.0962.**	**0.0233***

. p<0.1 * p< 0.5 ** p<0.01

We found no significant differences on motivation and performance between the male (56) and female (8) students, as shown in line 1A of Table II. By applying the t-student test we found a p-value of 0.7490 for CS101, 0.6398 for MAT101, and 0.5077 for motivation. We also found no impact of gender on subscales of motivation.

We also found no significant differences in motivation (p-value: 0.885) and performance on CS101 (p-value: 0.615) and MAT101 (p-value: 0.730) courses, among the students that entered or not by the quota system, as shown in line 1B of Table II. We also do not found impact of quotas on motivation subscales.

The Bachelor Program in Software Engineering studied has 40 vacancies per semester. To fill in these vacancies the university offers admission accordingly to the candidates' admittance grade. Initially, forty candidates are approved considering the classification order. If at least one of those candidates does not enroll, the university makes a new admission offer for each vacancy remaining. This is repeated until the forty vacancies are filled, or when the waiting list is empty, or when first month of class finishes. The university makes three offers on average. As shown in Table II, line 1C, there was no significant difference between students who entered in different offers of admission related to motivation and performance on CS101 and MAT101.

We also analyzed the students' achievements according to the semester of enrollment at the University. Line 1D of Table II shows that the unique statistically significant difference (p-value = 0.0337) was related to MAT101 performance. Students of 2017 have higher grades in MAT101 (6.50) if compared to the students of 2016 (4.94). We believe that this difference is due to the fact that students who enter in the first semester of the year have just finished high school; so they have studied math more recently than students of the second semester that usually spend half a year not studying.

We found no correlation between the age of the students and their motivation (p-value 0.4329) as shown on line 1E of Table II. We also did not found correlation between age and performance in CS101 and MAT101. However, when students are grouped by age range, we found that the younger students (18 years or less) have better performance in CS101.

TABLE III. PERFORMANCE VARIANCE IN CS101 BY AGE GROUP

Age	Mean	SD	p-value
16-17	7,78	1,89	
18-20	4,87	2,54	
21-36	5,82	2,62	**0.0476 ***

* p< 0.5

The most significant variances found in Table II refer to the factor "way of entering". In the program studied there are basically two ways of entering: university entrance exam, a test applied by the own institution that allows access to 30 students sorted by their final grade, and the National High School Exam (ENEM), applied throughout the national territory by the Brazilian Federal Government to those that are concluding high school. This exam allows the enrollment of ten candidates sorted by their final grade. Students enrolled in the past two years of high school or those who have already finished high school can try the exam. There are some exceptions, but they are outside the scope of this work.

Table IV shows in more detail the statistical analysis about motivation, performance, and the way to enter university. We noticed differences in all aspects evaluated according to the entrance exam. For CS101, we found a moderate impact with p-value 0.0962 and strong impact for MAT101 with p-value 0.0233. A moderate impact for motivation also appears, with p-value 0.0675. Students who entered by the ENEM exam had higher average grades in both courses, but they had lower motivation rate.

Table V shows the p-values to mean comparison (ANOVA) for each motivation subscales and ways of university entrance. We noticed a strong difference for the amotivation (p-value 0.0497); and students entering by ENEM had a higher rate of amotivation (4.12) than students entering by the University entrance exam (3.02).

Therefore, about the motivation rate, no factor had a significant impact, considering 95% confidence level. Only the "way of entrance" factor had an impact with a significance level of 0.1 (confidence level of 90%). That way, we cannot reject the null hypothesis that the demographic and student entrance factors do not affect the students' initial motivation.

With respect to the performance factor, the age had significant impact on the CS101 grades and "way of entrance" had significant impact on the MAT101 grades. In addition, the "way of entrance" had an impact with a significance level of 0.1 (90%) confidence in the CS101 grades. Therefore, we rejected the null hypothesis that the demographic and "way of entrance" factors do not impact on students' performance.

TABLE IV. STATISTICAL ANALYSIS ABOUT STUDENTS' ENTRANCE WAY

	University exam	**ENEM**	**Others**	**Transference**
Qty.	53	8	2	1
CS101	5.97	6.84	2.00	1.5
p-value	**0.0962 .**			
MAT101	5.79	7.41	4.3	-
p-value	**0.0233 ***			
Motivation	20.38	17.50	16.00	15.00
p-value	**0.0675 .**			

. p-value < 0.1 * p-value < 0.05

TABLE V. MOTIVATION SUBSCALES AND WAY OF ENTRANCE COMPARISON

Intrinsic	**Extrinsic**	**Self-Realization**	**Social**	**Amotivation**
0.3411	0.7087	0.1337	0.3099	**0.0497***

* p-value < 0.05

A. TASTE AND KNOWLEDGE OF THE AREA

Students responded the self-assessment questionnaire with some questions about the course itself and the area of knowledge (computing). We have grouped the questions into four factors: taste of the area, indicating if the student likes computing; course objectives, indicating the student's knowledge about the objectives of the course itself; subjects of the course, that shows if students know the subjects of the course; and professional vision, which helps to assess if the student understands the course and can visualize his/her profession. Table VI shows the values of the impact of the four course-related factors and their respective area of knowledge on motivation, performance in CS101, and performance in MAT101.

Table VI shows that three factors have values with statistically significant impact: area (line 2A), course objectives (line 2B), and perception of profession (2D line). Regarding the taste for technology, students who agreed to like programming and creating programs performed better than other students, as shown by Table VII. This effect has a statistically relevant value: 0.0157 p-value.

TABLE VI. IMPACT OF FACTORS RELATED TO THE AREA OF KNOWLEDGE AND PROGRAM ON MOTIVATION AND PERFORMANCE IN CS101 AND MAT101

	Factor	**Statistic Method**	**Motivation**	**CS101**	**MAT101**
2A	***Taste for programming and technology***	t-Student	0.4143	0.2395	**0.0157***
2B	***Knowledge of the undergraduate program goals***	t-Student	0.6788	0.2635	**0.0120***
2C	***Knowledge of the undergraduate program content***	Pearson	r = 0.0113 p = 0.9223	r = 0.0479 p = 0.1785	r = 0.2304 p = 0.2077
2D	***Correct perception of the computing professionals***	Pearson	r = 0.0196 p = 0.9587	r = 0.2474 **p=0.09435.**	r = 0.3235 **p=0.0110***

. p-value < 0.1 * p-value < 0.05

TABLE VII. COMPARISON AMONG TASTE FOR PROGRAMMING, MOTIVATION, AND PERFORMANCE

Taste	**Qty.**	**CS101**	**p-value**	**MAT101**	**p-value**	**Motivation**	**p-value**
Agree	45	6,12	0.2395	6,41	**0.0157 ***	20,33	0.4143
Not Agree	19	5,29		4,46		19,37	

* p-value < 0.05

However, the taste for hardware or gaming areas did not present significant difference, despite the different averages, especially in mathematics, according to Fig. 1.

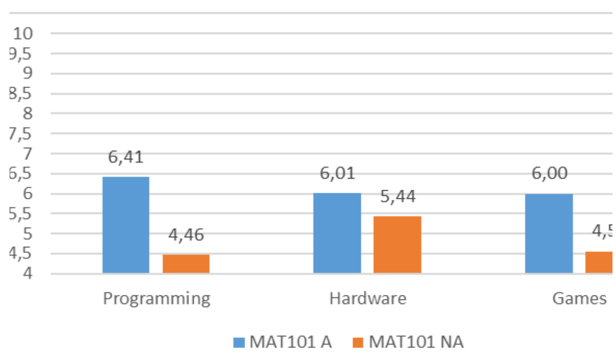

Fig. 1. Comparison between taste for the area and grades in MAT101.

Students who answered correctly about the main objective of computer science and software engineering programs performed better than the others (line 2B of table VI). In CS101 this difference was not statistically significant (p-value =

0.2635); however, in MAT101 the difference between the groups was proved (p-value = 0.01206), demonstrating that students with better knowledge of the goal of the course have better grades (6.41) than the others (4.35). However, the motivation index had no impact (p-value = 0.6788).

It was not possible to establish a correlation between knowledge about the subjects of the course and performance. Evaluating the perception of programming courses, students who believe to have more related disciplines had better performance in CS101 and MAT101, but with low statistical significance (r = 0.0479, p-value = 0.1785 and r = 0.2304, p-value = 0.2077). Motivation had no significance (r = 0.0113, p = 0.9223).

About the knowledge of the course and the area (2D line of table VI), students with a better understanding of the software professional had better performance in CS101 and MAT101 (r = 0.2474, p = 0.09435 and r = 0.3235, p = 0.01097), with moderate effect on MAT101. Motivation again had no significance effect (r = 0.01967, p = 0.9587).

Therefore, we must accept the null hypothesis that prior knowledge of the area and about the undergraduate program do not affect the students' motivation. The null hypothesis that prior knowledge of the area and undergraduate program do not affect student achievement is rejected, being that three factors (taste for the area, knowledge of the undergraduate program, and vision of the professional) have had significant impact on performance.

B. Knowledge and Experience in the Area

We seek to relate the experience and prior knowledge of the student in computer science and general computing, programming, and programming in high school with the motivation and performance in CS101 and MAT101. Table VIII presents the values found for these correlations.

TABLE VIII. Impact of experience and prior knowledge on motivation and performance in CS101 and MAT101.

	Factor	Method	Motivation	CS101	MAT 101
1	Experience in Computing	t-Student	0.8003	0.9301	0.3479
2	Experience on Programming	t-Student	**0.0183***	0.4367	0.9821
3	Programming in High School	t-Student	**7.209e-07***	0.5595	0.5406

* p-value < 0.05

There was no statistically significant effect of these factors on performance in CS101 and MAT101; but strong impact of prior experience in programming on motivation was found. As shown in table VIII, there are very strong effect of programming in high school on motivation with p-value and 7.209×10^{-07}, and students with previous experience have greater motivation (23.85) than the others (19.08). We also found a strong impact of prior experience in programming outside of a school setting on motivation, with p-value 0.0183. Students with experience have greater motivation index (24.25) than the others (19.77).

Therefore, we rejected the null hypothesis that prior knowledge of the area and program do not affect the motivation of the student, since the factors "programming" and "programming in high school" had a significant difference in the results of motivation (t-student test). Furthermore, the null hypothesis that the prior knowledge of the area and of course does not affect the performance of the student is accepted.

C. Previous School Performance

In the self-assessment questionnaires, students were asked about their perception about their general performance in high school and their performance in mathematics. Table IX presents the correlation of in high school performance factors with the motivation and performance in CS101 and MAT101.

TABLE IX. Effect of prior academic performance factors on the motivation and performance in CS101 and MAT101.

	Factor	Method	Motiv.	CS101	MAT101
1	General Performance	t-Student	0.6354	**0.0002 ****	**0.0059 ****
2	Math Performance	t-Student	0.3878	**0.0027 ****	**0.0196 ***

* p-value < 0.05 ** p< 0.01

We found that students with a sense of having better overall performance (in all disciplines) in high school have, really, the best performance in the discipline of CS101 (p-value: 0.0002) and MAT101 (p-value 0.0058). However, we could not demonstrate any difference arising from the motivation factor (p-value: 0.6354).

As for the perception of performance in math, the students with a sense of having better performance also had higher averages in MAT101 (p-value: 0.0196) and CS101 (p-value: 0.0027). Regarding motivation, again, no difference could be demonstrated (p-value 0.3878).

Therefore, the null hypothesis that prior school performance does not affect motivation is rejected. Also, the null hypothesis that the prior school performance does not affect performance is rejected, since both factors had significant difference in both MAT101 and CS101 performance.

D. Motivation and Performance

Table X shows the correlation between motivation and performance in CS101 and MAT101.

Therefore, a negligible positive correlation between motivation and performance in CS101 was perceived, as well as and a negligible negative correlation between motivation and performance in MAT101.

TABLE X. THE PEARSON COEFFICIENT OF CORRELATION BETWEEN MOTIVATION AND PERFORMANCE

	Motivation Index	**CS101**	**MAT101**
Motivation Index	-	0.1470947	-0.1429168
CS101	0.1470947	-	0.5260078
MAT101	-0.1429168	0.5260078	-

We have also measured the correlation of the subscales of motivation in order to check if any specific subscale had an impact on performance. To do this, we calculate the rates of subscales by adding the value of the answers of the constructors of each subscale. In addition, we map the profile of the students regarding the subscales of initial motivation. Fig. 2 shows the general profile of the sample, whereas the average of all students for each subscale. One can notice that the main reasons for students doing the course are intrinsic and social factors.

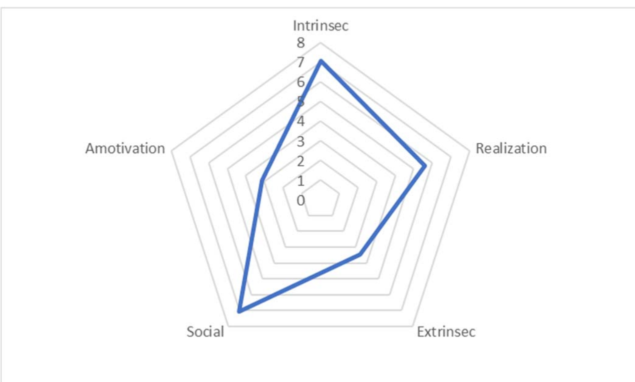

Fig. 2. Profile of students according to subscales of motivation.

Table XI presents the correlation between the subscales of motivational factors and performance in CS101 and MAT101. It also shows the average of the responses of the students in the questionnaire and the respective standard deviation.

TABLE XI. CORRELATION BETWEEN THE SUBSCALE OF MOTIVATIONAL FACTORS WITH PERFORMANCE IN CS101 AND MAT101

	Mean	Standard Deviation	CS101	MAT101
Intrinsic	7.0469	0.9500	r=0.04107 p=0.6375	r=-0.0425 p=0.7448
Extrinsic	3.4687	0.6659	r=0.06719 p=0.4939	r=-0.02608 p=0.8418
Social	7.0625	1.4787	r=**0.24110** p=**0.0398 ***	r=0.00817 p=0.9502
Self-Realization	5.5781	1.9502	r=0.01543 p=0.9506	**r=-0.13882** p=0.286
Amotivation	3.1094	1.2863	r=-0.09011 p=0.3817	**r=0.19475** p=0.1326

* p-value < 0.05

We have found only weak correlations, between social motivation with performance in CS101, and self-realization and amotivation with performance in MAT101. The only correlation with statistical significance was between the social factors and performance in CS101, with p-value 0.0398.

Therefore, the higher the social motivation, higher is the student achievement in CS101. We can say that it has not been possible to prove that motivation impacts on the performance of initial courses CS101 or MAT101.

As an additional result, have identified a moderate correlation ($r = 0.526$ and p-value $= 1.339 \times 10^{-5}$) between CS101 MAT101 performances. This indicates that students with higher grades in CS101 performs better in MAT101 also, as can be seen in Fig. 3.

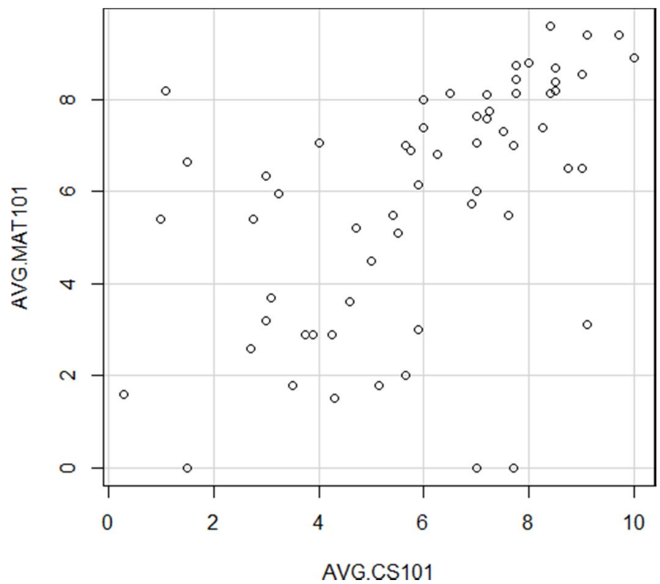

Fig. 3. Scatter plot showing the correlation of the averages in CS101 and MAT101.

V. DISCUSSION AND CONCLUSION

We reported in this paper a study with 64 undergraduate freshmen students in software engineering. We assessed the impact of factors prior to entering the university on performance and motivation of those students.

We evaluated factors related to demographic data, student entrance, taste and knowledge of the area, knowledge and previous experience, previous school performance, and motivation. To identify the initial motivation, we assessed intrinsic, extrinsic, social, self-realization, and amotivation factors.

Table XII shows a summary of the results, evaluating the impact of each factor on the motivation and performance on introduction to programming (CS101) and discrete mathematics (MAT101).

We found in this study only two factors that impact on the students' motivation, both related to knowledge and experience in programming. Most students report that the main reasons for attending the program are related to intrinsic and social aspects. Despite this and the fact that some studies in the literature describe the impact of motivation on performance, it has not been possible to prove that correlation in this study. A possible justification for this is that many studies assess the motivation throughout the program or a specific course. As motivation is something that can vary during the university time, this variation may impact on the students' performance, but not necessarily the initial motivation. Despite many studies also indicate the intrinsic motivation as of greatest impact, only the social motivation subscale has a weak correlation with performance in CS101.

TABLE XII. SUMMARY OF THE RESULTS ABOUT THE IMPACT OF EACH FACTOR ON MOTIVATION AND PERFORMANCE

Group	Motivation	CS 101	MAT 101	Relevant Factors
Demographic and student entrance	ND	D	D	Age (CS101) Way of entering (MAT101)
Taste and knowledge of the area	ND	ND	D	Taste for programming (CS101) Knowledge about undergraduate program (MAT101) Perceptions about computing professionals (MAT101)
Computing and programming experience	D	ND	ND	Knowledge and experience in computing (MOT) Programming experience in high school (MOT)
Previous school performance	ND	D	D	Academic Performance in General (CS101, MAT101) Previous Mathematics performance (CS101, MAT101)
Initial Motivation	-	ND*	ND	* Only the subscale "social motivation" had correlation with CS101 performance

ND – No significant difference / D – Significant difference / MOT - Motivation

With respect to performance, we found that age impacts on performance in CS101. Younger students have better performance, students with intermediate age (18-20) has worse performance and older students have more variation in performance. We also identified that students who entered university by the ENEM national exam have better performance in mathematics.

One interesting aspect we identified was that students with better knowledge of the area and undergraduate program performed better in MAT101. We suppose that students with better knowledge of the area can understand better the importance and need of courses such as mathematics. Some authors define two factors for motivation: value and expectation. Value means the importance, intrinsic value, utility, value or usefulness of the task, and cost [40]. In this case, students who have greater knowledge of the area and undergraduate program can assign a greater value to the math course because they understand its importance and utility.

Another interesting result is that the knowledge and prior experience in computing and programming had no impact on students' performance. It diverges from studies already carried out [12] [41]. On the other hand, the previous school performance had a positive impact in both courses.

We conclude that, for the sample used, the initial motivation has no impact on the performance of students. The results of this study show that the profile of a software engineering student with best performance, as expected, would be a young student (up to 18 years), which likes programming and has a good understanding about the program, courses, and computing professional. In addition, he/she have a good academic history.

Some unexpected results were that knowledge and prior experience in programming have no impact on performance, although it was the only factor that impacted on motivation. In addition, another unexpected result was that initial motivation did not have impact on performance. This may indicate that, as well as several studies already carried out, the motivation throughout the course, but not necessarily the initial motivation, can impact on students' achievement.

A. Limitations and Further Work

There are some threats to the validity of this research: i) the limited number of participants; ii) the limited context that includes only one program in one university; iii) other factors not considered in the study that may have impacted on the results; iv) the student self-assessment allows bias in responses according to the student's current state of mind.

Therefore, it is important to conduct more and new studies to better assess the impact of these factors in freshmen students on software engineering to confirm or not the results found in this study. As future work, we intend to monitor the impact of these factors and the motivation variation over time, verifying the correlation with student’s performance and dropout.

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