DOI: 10.15388/infedu.2022.04

The Expectancy-Value-Cost Light Scale to Measure Motivation of Students in Computing Courses

Pablo SCHOEFFEL, Vinicius F. C. RAMOS, Cristian CECHINEL, Raul Sidnei WAZLAWICK

Software Engineering Departament – University of Santa Catarina State (UDESC)
Ibirama, Brazil
Department of Information and Communication Technologies, Federal University of Santa Catarina
Araranguá, Brazil
Department of Informatics and Statistics, Federal University of Santa Catarina
Florianópolis, Brazil
e-mail: pablo.schoeffel@udesc.br, email@viniciusramos.pro.br, contato@cristiancechinel.pro.br, raul.wazlawick@ufsc.br

Received: January 2021

Abstract. This paper proposes and validates a short and simple Expectancy-Value-Cost scale, called EVC Light. The scale measures the motivation of students in computing courses, allowing the easy and weekly application across a course. One of the factors related directly to the high rate of failure and dropout in computing courses is student motivation. However, measuring motivation is complex, there are several scales already carried out to do that job, but only a few of them consider the longitudinal follow-up of motivation throughout the courses. The EVC Light was applied to 245 undergraduate students from four universities. The Omega coefficient, scale items intercorrelation, item-total correlation, and factor analysis are used to validate and measure the reliability of the instrument. Confirmatory and exploratory factor analyses supported the structure, consistency, and validity of the EVC Light scale. Moreover, a significant relationship between motivation and student results was identified, based mainly on the Expectancy and Cost factors.

Keywords: computer science education, social factors, higher education, student perception, motivation.

1. Introduction

The issue of failure and dropout in computing courses is still relevant to many researchers of the field of computing science education (Watson and Li, 2014, Bennedsen and Caspersen, 2019). There are several papers that discuss the factors to the (sometimes high) unsuccessful rate, including specific factors from the computing area, such as students' difficulty with programming (Bergin and Reilly, 2005, Niitsoo *et al.*, 2014) and lack of familiarity with the computing contents (Carter, 2006). Another factor is that even though freshmen students consider STEM courses as cross-disciplinary and innovative, it frequently cause disappointment and doubt (Peters and Pears, 2013).

According to (Sinclair *et al.*, 2015), more qualitative data and other measures (such as the expectation of the student) are required for a broader understanding of the Computer Science student. Another factor associated with the success and retention of students is their motivation, i.e., the stimulus for the desire to learn something or to participate and succeed in the process of learning. There is plenty of works that try to correlate and present interventions to enhance them (Hulleman and Barron, 2016).

According to (Kori *et al.*, 2016), low motivation to study is one of the reasons for students to dropout. The lack of motivation can cause a strong discrepancy between potential and actual success in learning. This explains why highly qualified students may have poor performance, whereas students with average potential can be among the best (Figas *et al.*, 2013).

Few studies discuss the social factors and aspects to motivate students in computing courses and programs (Muñoz-Organero *et al.*, 2010, Serrano-Cámara *et al.*, 2014, Velázquez-Iturbide *et al.*, 2017, Schoeffel *et al.*, 2018, Tek *et al.*, 2018). Related studies that measure or consider motivational aspects to predict performance (or dropout) normally focus on measuring motivation only at one specific time (e.g. (Muñoz-Organero *et al.*, 2010, Gray *et al.*, 2014)). To the best of our knowledge, there are no studies that consider the change in motivation over time as a factor for predicting students' performance. Turner and Patrick (2008), for example, suggest that motivation researchers should focus more on development and change in motivation—issues that are central to fostering motivation to learn in the classroom, and that can be related to specific classroom interactions and activities.

In order to evaluate whether the change in motivation has a significant variation in students of introductory computing courses, we propose to measure weekly the motivation of students and, for this, a simple and quick instrument to apply was necessary. In addition, the instrument needed to be consistent with learning motivation theories. In this sense, according to (Brophy, 1983), the expectation-value theory is one of the most understandable theories to perceive the motivation of students. Considering that the EVC (Expectancy-Value-Cost) scale proposed by (Kosovich *et al.*, 2014) is based on this theory and is one of the most simplified instruments for measuring motivation, we initially adopted the EVC scale as an instrument for measurement.

However, although the original scale had only ten items, we found that the scale had repetitive items and, for each factor, a different number of items. In addition, the scale was created for basic science and mathematics subjects. We realized that these situations could hinder the students' understanding and the answers analyses. At this point, therefore, the hypothesis arose that the scale could be adapted to the context of computing disciplines and reduced even more, maintaining the adequacy to the original theory and reliability, besides reducing the application time, since the goal was to apply weekly to a large number of students.

In this context, this paper aims to present and validate a light instrument to measure the student motivation. The validation uses data from a weekly measure from 245 computing students. The paper also aims to confirm the relation between motivation and student's performance and propose to answer the following research questions (RQ):

- **RQ1:** How do underlying factors influence the responses to the items of the questionnaire?
- **RQ2:** Is there a relationship between students' motivation and performance?
- **RQ3:** Is there a relationship between the weekly variation of motivation and student performance?

The remainder of this paper is structured as follows, Section 2 presents a the-oretical contextualization about student motivation and Section 3 describes the related works. Section 4 describes the methodological procedures used and Section 4.1 detail the questionnaire proposed and its validation. Section 5 presents the results related to the use of the instrument, Section 6 discusses the findings, and Section 7 concludes the paper.

2. Theoretical Background

Since the 50s, several theories of motivation have been created to explain what moves people to act (Maslow, 1954, Herzberg, 1968). In the educational context, there are various theories and models that try to explain and measure students' motivation (Eccles, 1983, Pintrich *et al.*, 1991, Tuan *et al.*, 2005, Appleton *et al.*, 2006). According to (Entwistle, 1998), the main findings of the existing research on motivation in higher education describe motivation as: i) the amount of effort put into activity and its goals; ii) something that has some consistency, but it may change; iii) something that affects, but it is also affected by the level of performance; and iv) something that appears in contrasting ways.

According to (Brophy, 1983), among several theories of motivation, the Expectation-Value (EV) is more comprehensible to understand students' achievement motivation. This theory proposes that motivation consists of two factors that predict the outcomes: expectation and value, as the name suggests. The former reflects how much the student believes he can succeed in a task (related to grades, for example), while the second reflects how the student perceives a given task as important and worth of be accomplished (related to future interests, for example) (Eccles, 1983). In the EV theory, proposed by (Atkinson, 1957), individual expectancies for success and the importance of the course perceived by students are important determinants of their motivation to perform different tasks (Wigfield, 1994). Based on EV theory, several researchers proposed models to measure student motivation (Pintrich *et al.*, 1991, Guay *et al.*, 2000, Tuan *et al.*, 2005, Appleton *et al.*, 2006, Martin, 2007). Likewise, Flake (2012) proposed a 36-items scale including the factor cost, which can be defined as how much a student has to sacrifice to engage in a task. Grays (2013) investigated the factor structure and longitudinal invariance of a 16-items measure of motivation for coursework using the Expectancy, Value, and Cost Scale (EVaCS) for incoming and mid-career college students. Later,

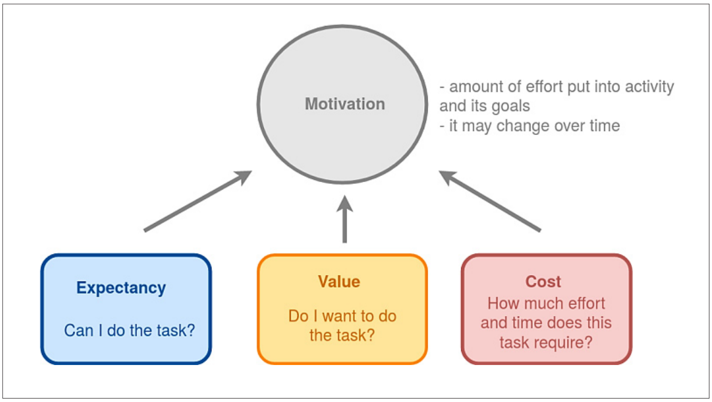

Fig 1. Overview of the EVC scale proposed by (Kosovich et al., 2014).

(Kosovich *et al.*, 2014) created a brief 10-items scale to measure middle school students' expectancy, value, and cost for math and science. Fig. 1 summarizes the EVC model proposed by (Kosovich *et al.*,2014).

In the EVC model, the essence of the expectancy component can be summarized in one question: "Can I do the task?" When students believe that they can do something, they are more likely to engage in that behavior (Barron and Hulleman, 2014). Similarly, the essence of the value component is captured with the question: "Do I want to do the task?" When students hold the belief that they value something, they are more likely to engage in that behavior (Barron and Hulleman, 2014). At last, the cost component reflects the negative aspects of engaging in an activity, such as perceptions of the effort and time required to be successful, or negative psychological states such as struggling or failing at the activity (Kosovich *et al.*, 2014).

Students' perceptions about themselves change during their college experi-ence, and these perceptions are related to aspects of motivation (Benson *et al.*, 2017). According to (Turner and Patrick, 2008), it is only by unfolding patterns of how individuals change in response to their contexts, and how these contexts change in response to individuals' actions, that one can illuminate the development of motivation. Gillet *et al.* (2017) founded evidence for a substantial level of within-person changes over time, suggesting that the time interval was sufficient to study change at the individual level.

In order to repeatedly measure students' motivation during the course time frame, the practical scale proposed by (Kosovich *et al.*, 2014) is adapted in this work. Besides that, the original questionnaire is reduced and simplified from ten to six items, in order to accelerate and simplify the process. This new scale proposal is named EVC Light.

3. Related Work

Some works in the literature discuss the concepts of computing students' motivation. However, most of them describe the use of methodologies or teaching tools. There are some works that propose scales/models to measure student motivation, but not exclusively restricted to computing courses, such as, the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich *et al.*, 1991), the Students' Motivation Toward Science Learning (SMTSL) (Tuan *et al.*, 2005), the Academic Motivation Scale (AMS) (Vallerand, 1992), and the Student Experience Survey (SES) (Whiteley *et al.*, 2015).

The MSLQ is a questionnaire based on a cognitive vision of motivation and learning strategies (Pintrich *et al.*, 1991). This questionnaire consists of two sections: i) the first with 31 items to evaluate the student's values, expectations, and effect; and ii) the second section has 31 items to evaluate the use of different cognitive and metacognitive strategies by students, in addition to 19 items to evaluate the management of different resources by students. Moreover, the SMTSL is a questionnaire to measure the motivation of students for learning science (Tuan *et al.*, 2005). It consists of 36 questions divided into five groups: i) effectiveness – belief in their ability to perform activities well; ii) active learning strategies – the use of various strategies to build new knowledge based on prior understanding; iii) value of learning science – finding the relevance of science in everyday life; iv) performance objectives – compete with other students and gain attention from the teacher; and v) stimulating learning environment – curriculum, faculty, and student interaction.

Besides, the l'Èchelle Scale of Motivation in Education (EME) was developed in French by (Vallerand *et al.*, 1989). This scale is composed of 28-items divided into: i) intrinsic motivation; ii) extrinsic motivation; and iii) amotivation. EME was subsequently translated into English, originating the AMS (Vallerand, 1992).

At last, the SES, also known as University Experience Survey, was created to measure the level of engagement and satisfaction of first and last year students at Australian universities (Whiteley *et al.*, 2015). It consists of five groups of questions: student engagement, teaching quality, learning resources, student support, and skills development. Despite the importance given to the motivation and engagement in the success of students, few works in this context were found in the area of Computing.

In this context, a systematic mapping of literature identified 32 relevant studies (Schoeffel *et al.*, 2018). However, little bit more than half of the studies (53%) use some of the models/protocols previously proposed in the literature. Only two models/protocols were used in more than one study (two, to be specific). The other thirteen studies were based on thirteen different models/works, meaning that there is no reuse of tools regarding the measurement of motivation in the computing field. This reinforces the need of a validated instrument, for instance, the one proposed in this paper.

Furthermore, all mapped works are restricted to the measurement at a particular time, thus not covering the possible changes of motivation during the entire time frame of a course. The uniqueness of this work is the adaptation of the EVC Model (Kosovich *et al.*, 2014), to simplify and to allow the longitudinal application of a scale, to measure student motivation in introductory computing courses. Despite the possibility of using it in all courses, the focus of this work and the scope of validation is restricted to the introductory computing courses due to their particularities and history of high dropout and failure rates (Medeiros *et al.*, 2019).

4. Methodology

This work validates an instrument to measure motivation in computing students across introductory courses, based on the EVC Model (Kosovich *et al.*, 2014). In order to perform an evaluation of the questionnaire, a case study was conducted as it is presented in Fig. 2.

As it is shown in Fig. 2, the first step is the construction of the instrument, which is related to the definition of the study and the questions to be included in the questionnaire. The next step is related to the data collection. Here, the following steps are taken: i) apply the instrument to computing students; and ii) collect and organize data from case studies. The experiment involved 245 undergraduate students from traditional courses (face-to-face courses, not online learning) belonging to four undergraduate programs. The third and fourth steps are related to the instrument validation and data analysis. Internal consistency reliability (Omega coefficient), and the convergent and discriminant validity (intercorrelation of the scale items) of the instrument are evaluated. Moreover, to test the congruence between the theoretical and observed scale structure, a Confirmatory Factorial Analysis (CFA) was performed. CFA allows for the assessment of the fit between observed data and a priori conceptualized, theoretically grounded model that specifies the hypothesized causal relations between latent factors and their observed indicator variables (Mueller and Hancock, 2001).

To analyze the adjustment of the data to the previous models, the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) indicators were analyzed from CFA. The CFI is an incremental adjustment index, which considers the complexity of a model, comparing the model under study with a more restrictive one, which does not specify relationships between variables. The CFI compares the discrepancy between the data and the most restrictive hypothetical model (Hu and Bentler, 1999). The values of RMSEA measure the discrepancy or adjustment error of the sample matrix under study and population covariance. The SRMR index roughly assesses the average standardized discrepancy between observed and model-implied variances and covariances, that is, it is a measure of the average of unexplained correlations in the model (Mueller and Hancock, 2001).

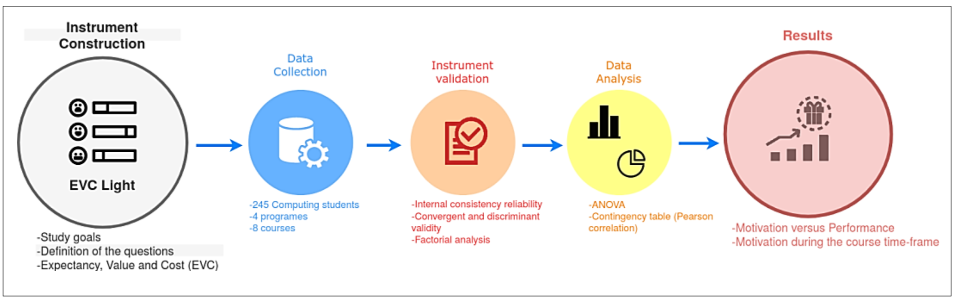

Fig 2. Methodology overview.

For the data analysis of the relationship between the motivation index and students' performance, it was used ANOVA and contingency table using Pearson correlation. The last step is related to the interpretation of the results.

4.1. *Instrument Construction*

To create the proposed motivation scale, it was built a questionnaire based on the EVC practical scale proposed by (Kosovich *et al.*, 2014). The original scale was created to measure the motivation of basic education math and science students. The EVC scale has ten items divided into three factors: expectation, value and cost. The proposed EVC Light scale maintains the original factors, but reducing the number of items and changing the description of the items to be more generic and cover any subject. Some items of the instrument were joined, because we understood that they were very similar, would not bring additional information and can cause confusion for the students. For example, the items "I believe that I can be successful in my class" and "I am confident that I can understand the material in my class" were grouped into a single item "I am confident that I am going to learn the content and have success in the course", as shown in Fig. 3.

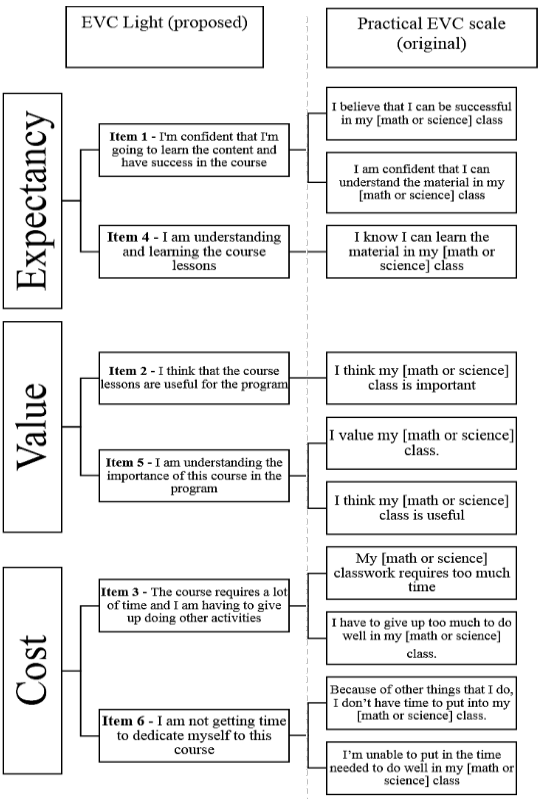

Fig 3. Relation between original EVC scale and EVC Light.

Each factor consists of two items, as shown in Fig. 3. The new scale is called EVC Light. It is important to note that reducing the scale from 10 to 6 items further simplifies the questionnaire, easing the weekly evaluation.

Although the scale is created for introductory computing disciplines and validated with students of these disciplines, it is generic and can be used in any context. However, we emphasize that validation occurred only in the context of computing courses in undergraduate programs.

The questionnaire was written in Portuguese and it contains the items described in Fig. 3 that also shows the relation between the original practical EVC Scale and the proposed EVC Light scale. Each possible answer has 5-option Likert-scale item.

4.2. *Data Collection and Context*

In total, 245 students from four different universities (two publics and two private) from Brazil answered the instrument weekly during the first and second semester of 2018 (see Table 1). In the first semester, it was conducted a pilot in three classes from one of the universities. In the second semester, the experiment was expanded to other courses, programs, and universities.

The instrument was applied to the same classes during 18 weeks of the course. In most cases, students answered an online questionnaire at the end of each of the weekly classes. The courses of the first semester were conducted by three different teachers, one for each course. The courses of the second semester were conducted by six different teachers.

Ao final do semestre foram coletadas as notas de cada aluno em cada disciplina, para fazer as análises e correlações. At the end of each semester, we collected the grades of each student in each course to perform the analyses and correlations.

Table 1

Participants by program and university

University	Course	Period	Students
A	Introductory Programming	20181	53
A	Programming I	20181	21
A	Programming II	20181	38
A	Introductory Programming	20182	47
A	Programming I	20182	17
B	Algorithms	20182	30
C	Algorithms and Programming	20182	16
D	Algorithms and Programming Techniques	20182	24

The courses “Introductory Programming”, “Algorithms”, “Algorithms and Programming” and “Algorithms and Programming Techniques” are distinct names but similar to CS101.

4.3 *Instrument Validation*

The internal consistency of the questionnaire was measured by calculating the Omega Coefficient (McDonald, 2013), which measures the reliability of the multidimensional questionnaire. The Omega total coefficient was satisfactory (0.90), considering the three original factors. To confirm the appropriateness of the EVC theory for the sample, it was used Confirmatory Factor Analysis (CFA) (Mueller and Hancock, 2001). For the purpose of analyzing the fit of the data, comparisons were made with four different models, as performed in (Kosovich *et al.*, 2014). Table 2 presents the analysis of the following models:

- Model 1 – tests a one-factor structure in which all of the items represent a (Motivation);
- Model 2 – tests an additional two-factor structure with an Expectancy factor, and a combined value-cost factor (Eccles, 1983);
- Model 3 – tests a two-factor structure in which expectancy and value form a single factor (positive motivation), and Cost as a separate factor; and
- Model 4 – tests a three-factor structure with distinct Expectancy, Value, and Cost factors as proposed by (Kosovich *et al.*, 2014).

According to (Brown, 2015), CFA is almost always used in the process of scale development to examine the latent structure of a test instrument. CFA verifies the number of underlying dimensions of the instrument (factors) and the pattern of item-factor relationships (factor loadings). CFA can give the investigator valuable information regarding the fit of the data to the specific, theory-derived measurement model (where items load only on the factors they were designed to measure), and point to the potential weakness of specific items (Mueller and Hancock, 2001). (Hu and Bentler, 1999) consider that the CFI value must be greater than 0.95, RMSEA values below 0.06 indicate a good fit, and a cutoff value of SRMRclose to 0.08 or less. The CFI value of three-factor EVC model was 0.988, indicating a good adjustment of the data to the model. The RMSEA for the model 4, presented in Table 2, indicates a good adjustment for the proposed scale (RMSEA = 0.057, P-value < .05), which means that the RMSEA does

Table 2

Confirmatory factor analysis of models

Model	x^2	df	RMSEA	CFI	SRMR	P-value
Model 1[1]	862.45	9	0.34	0.57	0.17	< .001
Model 2[2]	618.39	8	0.30	0.70	0.17	< .001
Model 3[3]	398.32	8	0.24	0.81	0.10	< .001
Model 4[4]	29.39	6	0.07	0.99	0.01	< .001

[1] the one factor model
[2] two-factor model of expectancy versus Eccles's value
[3] two-factor model of positive motivation versus cost
[4] three-factor EVC model

not reject the proposed model. The value of the SRMR index of the EVC model was 0.014, showing a satisfactory adjustment.

In order to detail the evidence of the convergent and discriminant validity of the items of the questionnaire, intercorrelations of the items were calculated. If the correlation coefficient is greater than 0.29, it is considered medium correlation, and greater than 0.5 is considered high correlation (Cohen, 1988). Table 3 shows all correlations between the factors groups. The degree of correlation between the items determines the degree of convergent and discriminant validity. The expectation and value factors have an average correlation, and the correlations within each factor are strong (bold values in the Table 3), indicating the presence of three factors. To confirm that, an Exploratory Factors Analysis (EFA) was performed to identify the number of factors (quality factors or dimensions) that represents the responses of the six items of the questionnaire.

Following the Kaiser-Guttman criterion (Kaiser, 1956), the results show that three factors should be retained, explaining 74.00% of the data. Fig. 4 shows the eigen value for each factor number (representing each item) for Principal Components and EFA. In order to identify the factor loadings of the items, the Varimax with Kaiser Normalization rotation method was used, because it is the most widely accepted (Cohen, 1988). Table 4 shows the factor loadings of the items associated with the three retained factors. The highest factor loading of each item, indicating to which factor the item is most related, is marked in bold. The Chi-Square statistical test proves that three factors are sufficient (P-value < .05).

Table 3
Intercorrelations of the Item

	Item	it1	it4	it2	it5	it3
Expectancy	it1	-				
	it4	**0.701**	-			
Value	it2	0.465	0.421	-		
	it5	0.392	0.421	**0.691**	-	
Cost	it3	-0.208	-0.277	-0.018	-0.036	-
	it6	-0.244	-0.293	-0.075	-0.078	**0.677**

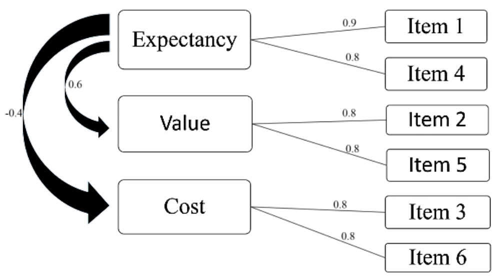

Fig 4. Factor analysis of adjusted questionnaire.

Table 4
The Factor Loadings

Item	Factor 1	Factor 2	Factor 3
it1	0.210	**0.956**	-0.121
it2	**0.650**	0.367	-
it3	-	-0.103	**0.862**
it4	0.318	**0.659**	-0.220
it5	0.985	0.158	-
it6	-	-0.146	**0.768**

5. Results

5.1. *Motivation versus Performance*

The relation between student motivation and student performance was analyzed by the ANOVA method (see Table 5). This table presents the variance of the average of the motivation indexes (see Equation 4) according to the final student's status in the course (success or fail). Indexes presented in equations (1), (2), (3), and (4) are converted to values between 0 and 1. The item 1 to item 6 make reference to the answers to the items shown in Fig. 4. EI, VI, CI, and EVC Index refers to Expectancy, Value, Cost, and Expectancy-Value-Cost indexes, respectively.

$$EI = \frac{item1 + item4 - 2}{12} \tag{1}$$

$$VI = \frac{item2 + item5 - 2}{12} \tag{2}$$

$$CI = \frac{item3 + item6 - 2}{12} \tag{3}$$

Table 5
The Relation Between Motivation Factors and Status

Factor	Status	Mean	SD	n	*P*-value
Expectancy	Success	0.800	0.187	127	< .0001
	Fail	0.686	0.227	118	
Value	Success	0.860	0.171	127	.9950
	Fail	0.860	0.197	118	
Cost	Success	0.450	0.268	127	.0250
	Fail	0.532	0.303	118	
EVC Index	Success	0.737	0.147	127	.0007
	Fail	0.671	0.153	118	

Table 6
The Relation Between Motivation Factors and Grade

Factor	Grade	Mean	SD	n	*P*-value
Expectancy	A	0.837	0.193	41	<.0001
	B	0.800	0.185	69	
	C	0.733	0.155	30	
	D	0.676	0.234	105	
Value	A	0.882	0.138	41	.3830
	B	0.843	0.195	69	
	C	0.903	0.133	30	
	D	0.851	0.204	105	
Cost	A	0.364	0.252	41	.0074
	B	0.479	0.280	69	
	C	0.575	0.258	30	
	D	0.521	0.302	105	
EVC Index	A	0.785	0.146	41	.0003
	B	0.721	0.142	69	
	C	0.689	0.124	30	
	D	0.669	0.158	105	

$$EVCIndex = \frac{(EI + VI + CI) + 1}{3} \tag{4}$$

The results confirmed the relation between motivation and final status (success or failure), showing that successful students have greater motivation index. Furthermore, unsuccessful students have significantly lower expectancy indexes and higher perception of the course cost.

It was also analyzed the variation of the motivation indexes according to the student's final grade level, using the ANOVA method (see Table 6). As expected, one can perceive a positive relationship between the index of motivation and student performance. In general, as better is the student final grade as higher is his/her motivation index. Additionally, students with lower grades also have lower expectancy indexes and higher perceived cost. On the other hand, it was not possible to identify the significant variation of the value factor neither with respect to the student's status nor to the level of the grade. One can see that the students' performance had a significant variation compared to the levels of expectancy and cost. However, the value factor has no significant variation compared to the performance.

5.2. *Motivation During the Course Time-Frame*

To identify the variation in motivation over the semester of the course, the t-student test was used to analyze the significance of the difference between the motivation indexes for each week. In general, it is possible to see a small variance, negligible. For the few situations with significant variance, there were divergent results. For example, in one week, the index variation is positive, and in another one it is negative. To calculate the variance, the difference between the subscales indexes of each week was analyzed (see Fig. 5). The analysis showed significant variation only between week three and week two (P-value = .046) and between the end of the course and week four (P-value = .003). Both variations were positive.

To analyze the variance in student success, the results of successful and failed students were compared. No significant differences or any relevant pattern in the variation was found. The correlation between the weekly indexes of motivation and the final grade of the students was also analyzed (see Fig. 6). It was identified a medium correlation (0.29 to 0.50) between subscales expectancy and cost and the final grade, mainly in the two first weeks and after the eighth week. To better illustrate this correlation, Fig. 7 shows the correlation between expectancy and the final grade in the first week. Similarly, it was analyzed the evolution of the motivation indexes over the weeks and the

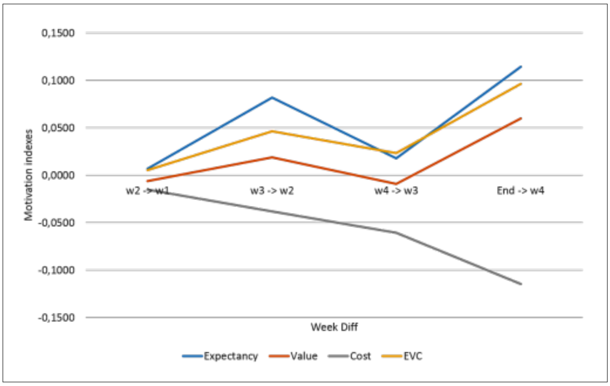

Fig 5. Variation in the motivation indexes (all students).

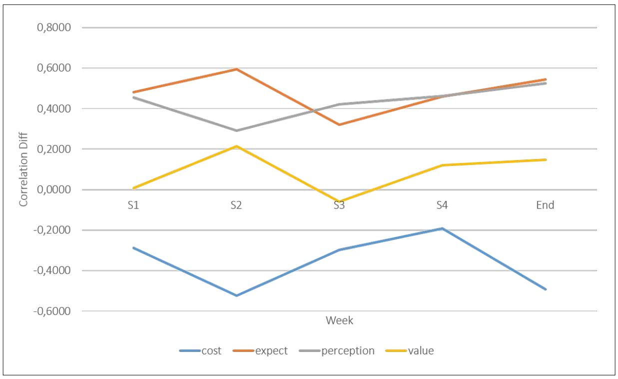

Fig 6. Correlation variation between motivation and final grade.

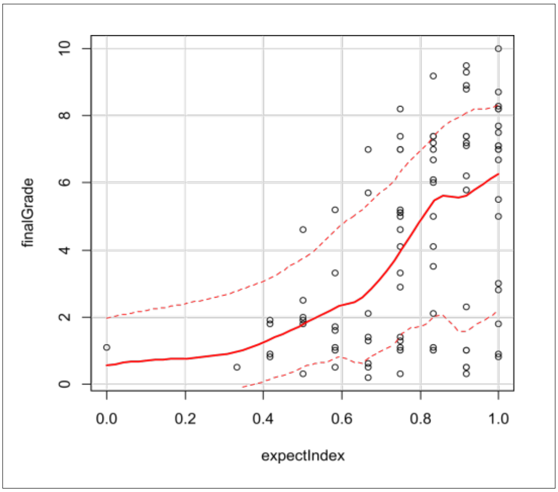

Fig 7. ScatterPlot of the correlation between "expectancy" and the final grade in the first week.

variance according to the students' final status (success or fail). The analysis identified that there is a significant difference in the subscales expectancy and cost, especially in the two first weeks and after the fifth one.

Table 7 shows that the expectancy decreases significantly after the fourth week, mainly in the case of students who failed. The value factor does not change significantly between failed students and successful students, but it also decreases after the fourth week. About the cost factor, successful students do not change their perception. However, failed students decrease their cost perception between the first and fourth week, increasing after the fourth week. This variation is possibly related to the moment of the first assessment.

Table 7

Relation between motivation factors and status by week

		Expectancy		Value		Cost	
Week	Status	Avg	*P*-value	Avg	*P*-value	Avg	*P*-value
1	Success	0.877	< .0001	0.915	.235	0.439	.007
	Fail	0.687		0.875		0.603	
2	Success	0.760	.055	0.846	.893	0.405	.001
	Fail	0.690		0.851		0.552	
3	Success	0.790	.166	0.847	.065	0.436	.142
	Fail	0.745		0.901		0.504	
4	Success	0.828	.010	0.909	.897	0.438	.224
	Fail	0.689		0.913		0.542	
Others	Success	0.722	< .0001	0.823	.667	0.455	< .0001
	Fail	0.557		0.809		0.604	

6. Discussions

The analysis also helped to state that the instrument is consistent and reliable, according to the Omega coefficient. Moreover, the factor analysis confirmed the convergence and discriminant validity between items, considering three distinct dimensions: expectancy, value, and cost. This indicates that the EVC Light scale can be used to measure motivation in the context of students of introductory computing courses, considering the factors expectation, value, and cost. A reduced scale facilitates the application, especial-ly if it is performed repeatedly.

- **RQ1:** How do underlying factors influence the responses to the items of the questionnaire?

The experiments confirmed the fit of data to the EVC model, indicating three dimensions that influence the responses. However, a medium correlation was found between the expectation and value factors, in addition to a low variation in the value factor among students. This partially corroborates with the findings of (Mitchell et al., 2000) that claim that students with strong motivation for studying a subject perceive more clearly the amount of practical work involved (cost factor) and their final grades (expectancy factor). Contrarily to the results presented in the current paper, the authors say that strong motivation leads to a more positive perception of the subject and the clarity that it matter, paying due attention to the course (value factor).

- **RQ2:** Is there a relationship between student motivation and student performance?

Yes. There is a relation between motivation and performance of students, specially in the first two weeks. It was also identified that expectancy and cost factors had significant variation depending on performance. In the context of programming courses, these findings corroborate previous results from (Bergin and Reilly, 2005), where the authors found that intrinsic motivation has a strong correlation with performance. In a wider scope survey, (Afzal et al., 2010) positively related both extrinsic and intrinsic motivation to students' academic performance. The results also endorse (Alipio, 2020) research, who conducted a large survey (12,452 college freshmen on 70 different high schools) to verify the connections between psychological factors, expectancy-value beliefs, and academic performance. He says, "academic overload (cost factor) affect negatively on expectancy-value beliefs and academic performance, while expectancy-value beliefs had a positive influence on academic performance" (Alipio, 2020).

- **RQ3:** Is there a relationship between the variation of motivation and student performance?

Although there is a correlation between motivation over time and students' performance, no significant difference between the weekly variation of the motivation indexes and the students' performance was found. It was identified that there is a significant difference in the subscales "expectancy" and "cost", especially in the first and after the fourth week. The expectancy decreases significantly after the fourth week, mainly for students who have failed later.

The value factor does not change significantly between failed and successful students, but it also decreases after the fourth week. About the cost factor, successful students do not change their perception over the course. However, failed students decrease their cost perception between the first and fourth week, and then increased.

It was identified that, in general, students strongly perceive the importance of the course in the curriculum (value factor), also discussed by (Mitchell *et al.*, 2000), but the expectancy of the successful student in the course gradually decreases throughout the semester. On the other hand, the perception of the effort required for the course is relatively high, increasing even more in the fourth week of the course. Thus, it is possible to assume that students demotivate from the introductory computing courses, mainly due to the level of difficulty encountered. Soh *et al.* (2007) also encountered that students demotivate from the beginning to the end of the course. For instance, in the researched sample of this paper, only 17% of the students already knew computer programming before entering the course and less than 24% had computation in basic education. Still, almost half of the students (48.8%) assume they have regular or poor performance in mathematics. Similarly, (Gomes, 2010) identified that the personal perception of capacity and accomplishment has a relationship with the performance of the programming students. This result corroborates the results found here, where a strong relationship between the expectancy and performance of the students was perceived.

A good starting point to think about how to act to enhance motivation during the semester is to follow (Hulleman and Barron, 2016) suggestions. The authors suggest a variety of works to target motivations interventions into four areas that motivates students into classrooms: expectancy and control beliefs, interests and values, goals, and the psychological costs of engaging in academic tasks.

There are other aspects to be researched in order to understand the impact on motivation, such as, students' interaction inside the learning management system (Macarini *et al.*, 2019, Muñoz-Organero *et al.*, 2010), and pre-university factors (Schoeffel *et al.*, 2017). All these findings indicate that one can use the EVC Light scale to identify at-risk students according to their motivation since the first few weeks of their enrollment. This can be done by applying machine learning algorithms using the motivational factors as input to make predictions of student outcome or performance.

It was observed that the results in the first few weeks tend to have similar behavior during all weeks of the semester. A positive aspect of the instrument is to allow identifying motivation or lack of motivation and, consequently, students at-risk of failure since the first weeks of the course. Another positive aspect is the simplicity of the instrument, which can be applied in few minutes. The instrument consists of a simple questionnaire that needs only six responses in a Likert scale, which greatly simplifies its application in class and it seems to be less costly than other models.

It is important to note that there is still an open question about the perceived costs that is whether to consider multiple kinds of costs in the research (Perez *et al.*, 2019), since (Eccles, 1983) presented three kinds of costs in their paper (effort, opportunity, and psychological costs). So far, those results were expected, because previous experiments already proved the relation between student expectancy and performance (Afzal *et al.*, 2010, Bergin and Reilly, 2005, Alipio, 2020). However, the variation along the weeks is not significantly different between students with higher performance from those with lower performance. With these results, it is possible to accept the null hypothesis that there is no correlation between motivation variation and performance of freshmen computing students.

7. Conclusions

This paper evaluated a new instrument to assess students' motivation in computing courses. The goal was to create and to validate a simple and easy to apply scale, in order to identify students at-risk of failure. The EVC Light scale, adapted from (Kosovich *et al.*, 2014), proved to be consistent and valid. It contains only six questions about expectancy, value, and cost factors. The CFA analysis showed the EVC Light scale measures satisfactorily the same constructors than the original scale. The validation of the scale indicates that it is possible to measure student motivation, based on the expectation, value and cost components, using a smaller scale than that proposed by (Kosovich *et al.*, 2014). A smaller scale speeds up and facilitates the application of the instrument, especially if the objective is to measure frequently, and if the scale is applied repeatedly. Thus, EVC Light is an instrument that can periodically provide input data about motivation for further usage by machine learning algorithms, for example, to predict students at-risk of failure.

The results of experiments performed with 245 computing students also showed that motivation indexes had a significant relation to student performance (status and final grade), mainly related to the expectancy and cost factors. In general, students with better results have a greater expectancy and lower perception of course cost, in first few weeks of their enrollment. On the other hand, the weekly variation in motivation was not significant. This has a positive aspect, because from the first weeks the measured motivation can use to predict the performance of students and, with this, identify previously students at risk. However, it also has a negative aspect, because it was not possible to identify specific moments or pedagogical strategies that may affect the motivation of students of introductory computing courses. One hypothesis for this is that the value factor (importance of the course) is high from the beginning and has little variation, that is, students understand, as expected, that course is important for the program. The expectation is high at the beginning of the course, as opposed to the perception of cost, which is lower. This is possibly due to more complex content not have started and the cost changes over the weeks, possibly due to increased complexity and application of assessments. At the end of the course, the expectation returns to rise moderately, possibly because the students are already safer and some have given up along the way. This inverse correlation of the expectation and value aspect causes the motivation indexes to do not have a significant variation over the weeks. With these data, we can assume that the increase in the complexity of the subjects and the load of activities can be important factors to maintain the high motivation of students of introductory computing courses and, consequently, increase success and retention rates.

There are some threats to the validity of this research: i) the limited number of participants; ii) other factors not considered in the study that may have affected the results, such as pre-university factors (knowledge in programming, performance on Math, taste for Informatics, etc.) or out class factors (health problem, job change, etc.); and iii) the student self-assessment allows bias in responses according to the student's current state of mind. It is also important to conduct more and new studies to better assess the impact of motivation variation on the students' performance, and to investigate why the relation between value perceived and performance is not significant.

Hulleman and Barron (2016) present different kinds of works to make interventions in education to enhance learning outcomes. For example, there are a num-ber of works focused on the improvement of the confidence of the students in learning and achievement in a specific academic context, or how students can engage in some aspects of the academic tasks (cost factor). Future work should check initial assumptions to justify the reasons there is no variation in the motivation indexes over time. It is also important to conduct more and new studies to investigate why the relation between value perceived and performance is not significant. Furthermore, there are other attributes besides motivation that can be evaluated, such as professor perception, LMS interaction, and pre-university factors. At last, the use of machine learning predictors to identify students at-risk of failure based on students motivation over time is another possibility.

Future work will evaluate other attributes besides motivation, such as professor perception, Learning Management System (LMS) interaction, and pre-university factors. Moreover, the use of prediction techniques to identify students at-risk of failure based on those attributes is also considered. At last, interviews with outlier students will be conducted to understand behaviors out of patterns, to aim to improve the present method.

References

Afzal, H., Ali, I., Khan, M.A., Hamid, K. (2010). A study of university students' motivation and its relationship with their academic performance. *International Journal of Business and Management*, 4(5), 80–88.

Alipio, M. (2020). Predicting academic performance of college fresh-men in the philippines using psychological variables and expectancy-value beliefs to outcomes-based education: A path analysis.

Appleton, J.J., Christenson, S.L., Kim, D., Reschly, A.L. (2006). Measuring cognitive and psychological engagement:Validation of the Student Engagement Instrument. *Journal of School Psychology*, 44(5), 427–445.

Atkinson, J.W. (1957). Motivational determinants of risk-taking behavior. *Psychological Review*, 64(6), 359–372.

Barron, K., Hulleman, C. (2014). Expectancy-value-cost model of motivation. In: *International Encyclopedia of the Social and Behavioral Sciences*, 8, 503–509.

Bennedsen, J., Caspersen, M. E. (2019). Failure rates in introductory programming: 12 years later. *ACM In roads*, 10(2), 30–36.

Benson, L., McGough, C., Kuzbary, D.M., Sharp, J.L. (2017). Longitudinal study of changes in student motivation and attitudes in engineering. In: *2017 ASEE Annual Conference & Exposition, Columbus, Ohio. ASEE Conferences*. P. 10. https://peer.asee.org/28634

Bergin, S., Reilly, R. (2005). The influence of motivation and comfort-level on learning to program. In: *Proceedings of the 17th Workshop of the Psychology of Programming Interest Group (PPIG 05)*. Sussex University, Brighton, UK, pp. 293–304.

Brophy, J. (1983). Conceptualizing student motivation. *Educational Psychologist*, 18(3), 200–215.

Brown, T.A. (2015). *Confirmatory Factor Analysis for Applied Research*. New York, NY: The Guilford Press, 2nd edition.

Carter, L. (2006). Why students with an apparent aptitude for computer science don't choose to major in computer science. *ACM SIGCSE Bulletin*, 38(1), 27–31.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. Academic Press, Inc, New York.

Eccles, J.S. (1983). Expectancies values, and academic behaviors. In: Spence, J.T., editor, *Achievement and Achievement Motives: Psychological and Sociological Approaches*. W. H. Freeman, New York, pp. 75–146.

Entwistle, N. (1998). Motivation and approaches to learning: motivating and conceptions of teaching. In: Brown, S., Thompson,G., Armstrong, S. (Eds), *Student Motivation*. Kogan Page, London, pp. 15–24.

Figas, P., Hagel, G., Bartel, A. (2013). The furtherance of motivation in the context of teaching software engineering. In: *2013 IEEE Global Engineering Education Conference (EDUCON)*, pp. 1299–1304.

Flake, J.K. (2012). *Measuring Cost: The Forgotten Component of Expectancy-value Theory*. Master's thesis, James Madison University.

Gillet, N., Morin, A.J., Reeve, J. (2017). Stability, change,and implications of students' motivation profiles: A latent transition analysis. *Contemporary Educational Psychology*, 51, 222–239.

Gomes, A.J. (2010). *Dificuldades de Aprendizagem de Programação de Computadores: Contributos Para a Sua Compreensão e Resolução*. PhD thesis, Universidade de Coimbra.

Gray, G., McGuinness, C., Owende, P. (2014). An application of classification models to predict learner progression in tertiary education. In: *2014 IEEE International Advance Computing Conference (IACC)*, pp. 549–554.

Grays, M. (2013). *Measuring Motivation for Coursework across the Academic Career: A Longitudinal Invariance Study*. Master's thesis, James Madison University.

Guay, F., Vallerand, R.J., Blanchard, C. (2000). On the assessment of situational intrinsic and extrinsic motivation: The situational motivation scale (SIMS). *Motivation and Emotion*, 24(3), 175–213.

Herzberg, F. (1968). One *More Time: How do you Motivate Employees?* Harvard Business Review.

Hu, L., Bentler, P.M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55.

Hulleman, C.S., Barron, K.E. (2016). Motivation interventions in education: bringing theory, research, and practice. In: Corno, L., Anderman, E.M. (Eds), *Handbook of Educational Psychology*. Routledge, New York and London, 3rd edition, pp. 160–171.

Kaiser, H. (1956). The *Varimax Method of Factor Analysis*. University of California, Berkeley.

Kori, K., Pedaste, M., Leijen, A., Tõnisson, E. (2016). The role of programming experience in ICT students learning motivation and academic achievement. *International Journal of Information and Education Technology*, 6(5).

Kosovich, J.J., Hulleman, C.S., Barron, K.E., Getty, S. (2014). A practical measure of student motivation: Establishing validity evidence for the expectancy-value-cost scale in middle school. *Journal of Early Adolescence*, 35(5–6), 790–816.

Macarini, L.A.B., Cechinel, C., Machado, M.F.B., Ramos,V.F.C., Munoz, R. (2019). Predicting students success in blended learning – evaluating different interactions inside learning management systems. *Applied Sciences*, 9(24), 5523.

Martin, A.J. (2007). Examining a multidimensional model of student motivation and engagement using a construct validation approach. *British Journal of Educational Psychology*, 77, 413–440.

Maslow, A.H. (1954). A theory of human motivation. *Psychological Review*, 50(4), 370–396.

McDonald, R.P. (2013). *Test Theory: A Unified Treatment*. Psychology press.

Medeiros, R.P., Ramalho, G.L., Falcão, T.P. (2019). A systematic literature review on teaching and learning introductory programming in higher education. *IEEE Transactions on Education*, 62(2), 77–90.

Mitchell, M., Sheard, J., Markham, S. (2000). Student motivation and positive impressions of computing subjects. In: *Proceedings of the Australasian Conference on Computing Education, ACSE '00*. New York,NY, USA. Association for Computing Machinery, pp. 189–194.

Mueller, R., Hancock, G. (2001). Factor analysis and latent structure, confirmatory. In: Smelser, N.J., Baltes, P.B. (Eds), *International Encyclopedia of the Social & Behavioral Sciences*. Pergamon, Oxford, pp. 5239–5244.

Muñoz-Organero, M., Muñoz-Merino, P.J., Kloos, C.D. (2010). Student behavior and interaction patterns with an LMS as motivation predictors in e-learning settings. *IEEE Transactions on Education*, 53(3), 463–470.

Niitsoo, M., Paales, M., Pedaste, M., Siiman, L., Tõnisson, E. (2014). Predictors of informatics students progress and graduation in university studies. In: *Proceedings of INTED 2014*. Valencia, Spain. IATED Academy, pp. 2521–2529.

Perez, T., Wormington, S.V., Barger, M.M., Schwartz-Bloom, R.D., Lee, Y.-k., Linnenbrink-Garcia, L. (2019). Science expectancy, value, and cost profiles and their proximal and distal relations to undergraduate science, technology, engineering, and math persistence. *Science Education*, 103(2), 264–286.

Peters, A., Pears, A. (2013). Engagement in computer science and it – what! a matter of identity? In *2013 Learning and Teaching in Computing and Engineering*, pp. 114–121.

Pintrich, P.R., Smith, D.A.F., Garcia, T., McKeachie, W.J. (1991). *A Manual for the Use of the Motivated Strategies for Learning Questionnaire (MSLQ)*. Technical report, University of Michigan.

Schoeffel, P., Wazlawick, R.S., Ramos, V. (2017). Impact of pre-university factors on the motivation and performance of undergraduate students in software engineering. In: *2017 IEEE 30th Conference on Software Engineering Education and Training (CSEE&T)*. Savannah, GA, USA, pp. 266–275.

Schoeffel, P., Wazlawick, R.S., Ramos, V.F.C. (2018). Motivation and engagement factors of undergraduate students in computing: A systematic mapping study. In: *2018 IEEE Frontiers in Education Conference (FIE)*, pp. 1–5.

Serrano-Cámara, L.M., Paredes-Velasco, M., Alcover,C.-M., Àngel Velazquez-Iturbide, J. (2014). An evaluation of students' motivation in computer-supported collaborative learning of programming concepts. *Computers in Human Behavior*, 31, 499 – 508.

Sinclair, J., Butler, M., Morgan, M., and Kalvala, S. (2015). Measures of student engagement in Computer Science. In: *Proceedings of the 2015 ACM Conference on Innovation and Technology in Computer Science Education, ITiCSE'15*, New York, NY, USA. Association for Computing Machinery, pp. 242–247.

Soh, L., Samal, A., Nugent, G. (2007). An integrated framework for improved computer science education: Strategies, implementations, and results. *Computer Science Education*, 17(1), 59–83.

Tek, F.B., Benli, K.S., Deveci, E. (2018). Implicit theories and self-efficacy in an introductory programming course. *IEEE Transactions on Education*, 61(3), 218–225.

Tuan, H., Chin, C., Shieh, S. (2005). The development of a questionnaire to measure students motivation towards science learning. *International Journal of Science Education*, 27(6), 639–654.

Turner, J.C., Patrick, H. (2008). How does motivation develop and why does it change? Reframing motivation research. *Educational Psychologist*, 43(3), 119–131.

Vallerand, R. (1992). The Academic Motivation Scale: A measure of intrinsic, extrinsic, and amotivation in education. *Educational and psychological measurement*, 52(4), 1003–1017.

Vallerand, R.J., Blais, M.R., Briere, N.M., Pelletier, L.G. (1989). Construction et validation de I'echelle de motivation en education (EME). *Canadian Journal of Behavioral Sciences*, 21, 323–349.

Velázquez-Iturbide, J.A., Hernán-Losada, I., Paredes-Velasco, M. (2017). Evaluating the effect of program visualization on student motivation. *IEEE Transactions on Education*, 60(3), 238–245.

Watson, C., Li, F.W. (2014). Failure Rates in Introductory Programming Revisited. In: *Procceedings of ITiCSE '14, ITiCSE '14*. New York, NY, USA. ACM, pp. 39–44.

Whiteley, S., Iarossi, D., Bricknall, R. (2015). *2015 Student Experience Survey Methodology Report*. Melbourne, Australia.

Wigfield, A. (1994). Expectancy-value theory of achievement motivation: A developmental perspective. *Educational Psychology Review*, 6(1), 49–78.

P. Schoeffel holds a Ph.D. in Computer Science at the Federal University of Santa Catarina (Brazil). He is currently an Associate Professor in the Software Engineering Departament of the University of Santa Catarina State (Brazil). His research interests include educational games, learning analytics, software engineering, and computer science education.

V.F.C. Ramos holds a Ph.D. in Systems and Computer Engineering at the Federal University of Rio de Janeiro (Brazil) jointly with the Eindhoven University of Technology (Holland). He is an Associate Professor in the Sciences, Technologies, and Health Center of the Federal University of Santa Catarina (Brazil). His research interests include the use of intelligent systems in education, learning analytics, social network analysis, and computer science education.

C. Cechinel received the bachelor's and master's degrees in computer science from the Federal University of Santa Catarina, Brazil, in 1998 and 2000, respectively, and the Ph.D. degree in information and knowledge engineering from the Computer Science Department, University of Alcalá, Spain, in 2012. He is currently an Associate Professor in the Sciences, Technologies and Health Center, Federal University of Santa Catarina. His research mostly focuses on the development and analysis of digital learning technologies, learning analytics, and distance learning. He is an Active Member of the Latin-American Community on Learning Technologies and a Former Member of the Special Committee on Computers and Education, Brazilian Computer Society. He is a former Associate Editor of the Brazilian Journal of Computers in Education (2016–2018).

R.S. Wazlawick is Dr. Eng. by the Federal University of Santa Catarina and Full Professor at the same institution. He coordinates the Bridge Lab that produces country-wide solutions for public primary healthcare in Brazil. He was chairman of the IFIP WG3.2 (Higher Education) and trustee of the Brazilian Computer Society. His main research interest is Software Engineering, especially object-oriented systems and agile development.